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Lattice Reduction-Aided Detection for Overloaded MIMO Using Slab Decoding*

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SUMMARY In this paper, we propose an overloaded multiple-input multiple-output (MIMO) signal detection scheme with slab decoding and lattice reduction (LR). The proposed scheme firstly splits the transmitted signal vector into two parts, the post-voting vector composed of the same number of signal elements as that of receive antennas, and the pre-voting vector composed of the remaining elements. Secondly, it reduces the candidates of the pre-voting vector using slab decoding and determines the post-voting vectors for each pre-voting vector candidate by LR-aided minimum mean square error (MMSE)-successive interference cancellation (SIC) detection. From the performance analysis of the proposed scheme, we derive an upper bound of the error probability and show that it can achieve the full diversity order. Simulation results show that the proposed scheme can achieve almost the same performance as the optimal ML detection while reducing the required computational complexity.

key words: *overloaded MIMO, signal detection, lattice reduction, slab decoding*

1. Introduction

Many research efforts are being increasingly devoted towards the design of future multiple-input multiple-output (MIMO) communication systems. In common MIMO systems, the number of receive antennas are set to be greater than that of transmitted streams. In some cases, however, sufficient number of receive antennas may not be available at the receiver due to limitations in size, weight, cost, and/or power consumption. Such MIMO systems, where the number of receive antennas are less than that of transmitted streams, are called overloaded (underdetermined) MIMO systems [1], [2].

For overloaded MIMO systems, various signal detection schemes have been proposed [1]–[8]. Maximum likelihood (ML) detection can achieve the best bit error rate (BER) performance [9], however, its computational complexity increases exponentially with the number of transmitted streams as it searches over all possible candidates of transmitted signals. In order to reduce the complexity, slab-sphere decoding (SSD), which is based on the idea of sphere decoding [10], [11] for non-overloaded MIMO systems, has been proposed in [1]. SSD firstly splits the transmitted signals into two parts, i.e., the signals containing the same number of signal elements as that of receive antennas minus one, and the remaining signals. The candidates of the latter signals are searched by slab decoding, and then the former signals corresponding to each candidate are obtained by sphere decoding. Although SSD can achieve comparable performance as ML detection, its complexity is still high, especially in the worst case, where the number of possible candidates could not be reduced. On the other hand, lattice reduction (LR) [12], [13]-aided minimum mean square error (MMSE)-successive interference cancellation (SIC) detection [14] with pre-voting cancellation (PVC) has been proposed in [3]. This scheme is composed of three steps. In step 1, it divides the transmitted signals into two parts, the post-voting vector and pre-voting vector. The former contains the same number of signal elements as that of receive antennas, and the latter contains the remaining elements. In step 2, it obtains the estimate of the post-voting vectors for each pre-voting vector candidate by using LR-aided MMSE-SIC detection. Finally, the estimate of the original signal is determined by maximum likelihood among all the possible candidates. Since this scheme searches all pre-voting vectors, its complexity increases exponentially with the difference between the number of the transmitted streams and that of receive antennas.

In this paper, we propose a low complexity signal detection scheme for overloaded MIMO systems, whose preliminary version has been presented in [15]. The proposed scheme, referred as Slab-LR-MMSE-SIC, employs both the idea of slab decoding and LR-aided MMSE-SIC. Unlike the conventional LR-aided MMSE-SIC with PVC [3], the proposed Slab-LR-MMSE-SIC reduces the number of candidates for the pre-voting vector by using slab decoding, which considerably decreases the computational complexity without significant performance loss. Moreover, compared to the conference version in [15], the following contributions have been added in this paper:

- a novel selection criterion for the range of search in slab decoding is proposed. With the proposed criterion, we can determine the range of search by setting an acceptable error probability of slab decoding.

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- a simple method for selecting the indexes of pre-voting vector and post-voting vector is proposed, in order to reduce computational complexity.
- an upper bound for the error probability of the proposed Slab-LR-MMSE-SIC is derived and it is shown that Slab-LR-MMSE-SIC can achieve the full diversity order.

Simulation results show that the proposed Slab-LR-MMSE-SIC can achieve almost the same BER performance as the conventional schemes while significantly reducing the number of candidates of pre-voting vector and hence the required computational complexity.

In the remainder of the paper, we will use the following notations. Superscript T and H denote transpose and Hermitian transpose, respectively. $\boldsymbol{I}_n$ represents an $n \times n$ identity matrix and $\boldsymbol{0}_n := [0, \ldots, 0]^{\mathrm{T}} \in \mathbb{R}^n$. For a vector $\boldsymbol{x} = [x_1, \ldots, x_n]^{\mathrm{T}} \in \mathbb{R}^n$, $\|\boldsymbol{x}\| := \sqrt{\sum_{i=1}^{n} x_i^2}$ denotes ℓ_2-norm of $\boldsymbol{x}$. For a complex matrix $\boldsymbol{A}$, $\mathrm{Re}\{\boldsymbol{A}\}$ and $\mathrm{Im}\{\boldsymbol{A}\}$ represent the real and imaginary parts of $\boldsymbol{A}$, respectively. For a set $\mathcal{V}$, $|\mathcal{V}|$ denotes the cardinality of $\mathcal{V}$. $\mathrm{E}[\cdot]$ stands for expectation operator.

2. System Model

Figure 1 shows the MIMO system model with n transmit antennas and m receive antennas. For simplicity, the number of transmitted streams is assumed to be equal to that of transmit antennas and precoding is not considered. In the transmitter, information bits are mapped to n symbols, converted by the serial-parallel converter, and sent from the transmit antennas. Here, $\tilde{s}_j$ $(j = 1, \ldots, n)$ represents the symbol sent from the j-th transmit antenna and $\tilde{\boldsymbol{s}} = [\tilde{s}_1, \ldots, \tilde{s}_n]^{\mathrm{T}} \in \tilde{\mathcal{S}}^n$ is the transmitted signal vector, where $\tilde{\mathcal{S}}$ denotes the alphabet of the transmitted symbol, with $\mathrm{E}[\tilde{\boldsymbol{s}}] = \boldsymbol{0}_n$ and $\mathrm{E}[\tilde{\boldsymbol{s}}\tilde{\boldsymbol{s}}^{\mathrm{H}}] = \sigma_s^2 \boldsymbol{I}_n$. We assume quadrature phase shift keying (QPSK) or quadrature amplitude modulation (QAM) symbols. The received signal vector $\tilde{\boldsymbol{y}} = [\tilde{y}_1, \ldots, \tilde{y}_m]^{\mathrm{T}} \in \mathbb{C}^m$, where $\tilde{y}_i$ $(i = 1, \ldots, m)$ is the received signal at the i-th receive antenna, is given by

$$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{H}}\tilde{\boldsymbol{s}} + \tilde{\boldsymbol{v}}, \tag{1}$$

where

$$\tilde{\boldsymbol{H}} = \begin{bmatrix} \tilde{h}_{1,1} & \cdots & \tilde{h}_{1,n} \\ \vdots & \ddots & \vdots \\ \tilde{h}_{m,1} & \cdots & \tilde{h}_{m,n} \end{bmatrix} \in \mathbb{C}^{m \times n} \tag{2}$$

represents the flat fading channel matrix. Here, $\tilde{h}_{i,j}$ is the channel gain from the j-th transmit antenna to the i-th receive antenna, and assumed to be constant over at least one symbol time and to be known to the receiver. $\tilde{\boldsymbol{v}} = [\tilde{v}_1, \ldots, \tilde{v}_m]^{\mathrm{T}} \in \mathbb{C}^m$ is a zero mean white complex Gaussian noise vector with covariance matrix of $\sigma_v^2 \boldsymbol{I}_m$.

We also consider the real model equivalent to the complex model (1) as

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{s} + \boldsymbol{v}, \tag{3}$$

where

$$\begin{aligned} \boldsymbol{y} &:= \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{y}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{y}}\} \end{bmatrix} \in \mathbb{R}^{2m}, \\ \boldsymbol{H} &:= \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{H}}\} & -\mathrm{Im}\{\tilde{\boldsymbol{H}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{H}}\} & \mathrm{Re}\{\tilde{\boldsymbol{H}}\} \end{bmatrix} \in \mathbb{R}^{2m \times 2n}, \\ \boldsymbol{s} &:= \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{s}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{s}}\} \end{bmatrix} \in \mathcal{S}^{2n}, \ \boldsymbol{v} := \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{v}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{v}}\} \end{bmatrix} \in \mathbb{R}^{2m}, \end{aligned} \tag{4}$$

and $\mathcal{S} := \left\{\mathrm{Re}\{\tilde{x}\} \,\middle|\, \tilde{x} \in \tilde{\mathcal{S}}\right\} \cup \left\{\mathrm{Im}\{\tilde{x}\} \,\middle|\, \tilde{x} \in \tilde{\mathcal{S}}\right\}$. Note that $\left\{\mathrm{Re}\{\tilde{x}\} \,\middle|\, \tilde{x} \in \tilde{\mathcal{S}}\right\} = \left\{\mathrm{Im}\{\tilde{x}\} \,\middle|\, \tilde{x} \in \tilde{\mathcal{S}}\right\}$ for QPSK or QAM.

3. Conventional Overloaded MIMO Signal Detection Schemes

For overloaded MIMO systems with $m < n$, the conventional sphere decoding [11] and LR-aided detection [14], [16], [17] are not directly applicable given that the channel matrix $\tilde{\boldsymbol{H}}$ is fat, i.e., the number of rows is less than that of columns. In this section, we briefly review the existing methods applying sphere decoding and LR-aided MMSE-SIC detection to the overloaded MIMO systems.

3.1 Slab-Sphere Decoding [1]

The estimate of $\boldsymbol{s}$ with ML detection is expressed as

$$\hat{\boldsymbol{s}}_{\mathrm{ML}} = \arg\min_{\boldsymbol{u} \in \mathcal{S}^{2n}} \|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{u}\|^2. \tag{5}$$

In the same way as sphere decoding, slab-sphere decoding

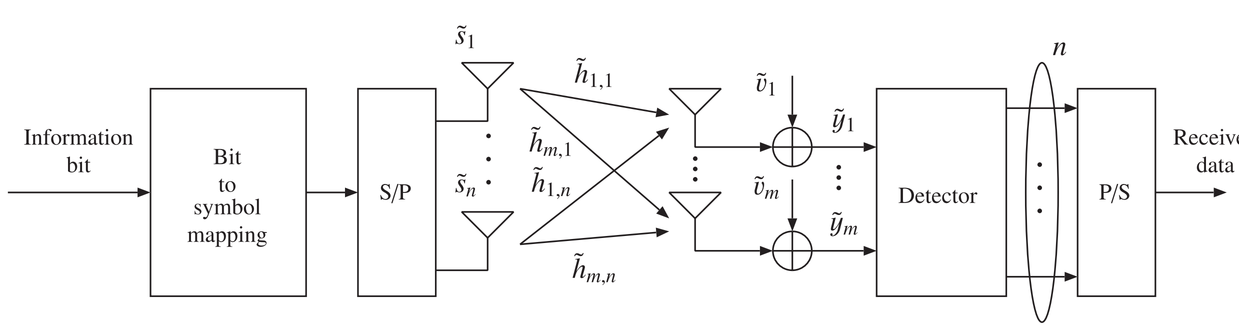

Fig. 1 Model of the overloaded MIMO system.

obtains $\hat{\boldsymbol{s}}_{\mathrm{ML}}$ by solving

$$\hat{\boldsymbol{s}}_{\mathrm{ML}} = \arg\min_{\boldsymbol{u}\in\mathcal{S}^{2n}} \|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{u}\|^2 \text{ s.t. } \|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{u}\|^2 \leq C^2, \tag{6}$$

where C is a constant controlling the range of search. By using QR decomposition of $\boldsymbol{H}$, i.e., $\boldsymbol{H} = \boldsymbol{Q}\boldsymbol{R}$, the constraint in (6) can be rewritten as

$$\|\boldsymbol{z} - \boldsymbol{R}\boldsymbol{u}\|^2 \leq C^2, \tag{7}$$

where $\boldsymbol{z} := \boldsymbol{Q}^{\mathrm{T}}\boldsymbol{y}$. Since $m < n$, (7) can be expressed as

$$\left\| \begin{bmatrix} z_1 \\ \vdots \\ z_{2m} \end{bmatrix} - \begin{bmatrix} r_{1,1} & \cdots & r_{1,2m} & \cdots & r_{1,2n} \\ 0 & \ddots & \vdots & \cdots & \vdots \\ 0 & 0 & r_{2m,2m} & \cdots & r_{2m,2n} \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_{2m} \\ \vdots \\ u_{2n} \end{bmatrix} \right\|^2 \leq C^2, \tag{8}$$

where z_i, u_j, and $r_{i,j}$ represent the i-th element of $\boldsymbol{z}$, the j-th element of $\boldsymbol{u}$, and the (i, j) element of $\boldsymbol{R}$ ($i = 1, \ldots, 2m$ and $j = 1, \ldots, 2n$), respectiely. To search all $u_1, \ldots, u_{2n}$ satisfying (8), we firstly focus on the $2m$-th row of $\boldsymbol{z} - \boldsymbol{R}\boldsymbol{u}$ and find all $u_{2m}, \ldots, u_{2n}$ satisfying

$$|z_{2m} - (r_{2m,2m}u_{2m} + \cdots + r_{2m,2n}u_{2n})|^2 \leq C^2 \tag{9}$$

by using slab decoding algorithm [1]. Next, we search all $u_1, \ldots, u_{2m-1}$ satisfying (8) for each $u_{2m}, \ldots, u_{2n}$ satisfying (9). Once $u_{2m}, \ldots, u_{2n}$ are fixed, we can rewrite (8) as

$$\left\| \begin{bmatrix} w_1 \\ \vdots \\ w_{2m-1} \end{bmatrix} - \begin{bmatrix} r_{1,1} & \cdots & r_{1,2m-1} \\ 0 & \ddots & \vdots \\ 0 & 0 & r_{2m-1,2m-1} \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_{2m-1} \end{bmatrix} \right\|^2$$
$$\leq C^2 - |z_{2m} - (r_{2m,2m}u_{2m} + \cdots + r_{2m,2n}u_{2n})|^2, \tag{10}$$

where

$$w_i := z_i - (r_{i,2m}u_{2m} + \cdots + r_{i,2n}u_{2n}) \tag{11}$$

for $i = 1, \ldots, 2m - 1$. Since the upper triangular matrix in the left side of (10) is square, all $u_1, \ldots, u_{2m-1}$ satisfying (10) can be obtained by using the conventional sphere decoding. Thus, we apply sphere decoding to (10) for each $u_{2m}, \ldots, u_{2n}$ satisfying (9) and obtain all $u_1, \ldots, u_{2n}$ satisfying (8). Finally, we select $\boldsymbol{u}$ minimizing $\|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{u}\|^2$ over the candidate vectors as the estimate of $\boldsymbol{s}$.

3.2 LR-Aided MMSE-SIC Detection with PVC [3]

PVC is an approach to apply LR-aided MMSE-SIC detection [14] to overloaded MIMO systems. In the signal detection with PVC, we divide the index set of the transmit antennas $\{1, \ldots, n\}$ into

$$\mathcal{A} = \{p_1, \ldots, p_{n-m}\} \subset \{1, \ldots, n\}, \tag{12}$$
$$\mathcal{B} = \{q_1, \ldots, q_m\} = \{1, \ldots, n\} \setminus \mathcal{A}. \tag{13}$$

In addition, we divide the elements of the transmitted signal vector $\tilde{\boldsymbol{s}}$ into two vectors as

$$\tilde{\boldsymbol{s}}_{\mathcal{A}} := [\tilde{s}_{p_1}, \ldots, \tilde{s}_{p_{n-m}}]^T \text{ (pre-voting vector)}, \tag{14}$$
$$\tilde{\boldsymbol{s}}_{\mathcal{B}} := [\tilde{s}_{q_1}, \ldots, \tilde{s}_{q_m}]^T \text{ (post-voting vector)}. \tag{15}$$

Similarly, the columns of the channel matrix $\tilde{\boldsymbol{H}} = [\tilde{\boldsymbol{h}}_1, \ldots, \tilde{\boldsymbol{h}}_n]$ are divided into two matrices as

$$\tilde{\boldsymbol{H}}_{\mathcal{A}} := [\tilde{\boldsymbol{h}}_{p_1}, \ldots, \tilde{\boldsymbol{h}}_{p_{n-m}}], \tag{16}$$
$$\tilde{\boldsymbol{H}}_{\mathcal{B}} := [\tilde{\boldsymbol{h}}_{q_1}, \ldots, \tilde{\boldsymbol{h}}_{q_m}]. \tag{17}$$

By the above splitting, (1) can be rewritten as

$$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{H}}_{\mathcal{A}}\tilde{\boldsymbol{s}}_{\mathcal{A}} + \tilde{\boldsymbol{H}}_{\mathcal{B}}\tilde{\boldsymbol{s}}_{\mathcal{B}} + \tilde{\boldsymbol{v}}. \tag{18}$$

We consider all candidates of pre-voting vector $\tilde{\boldsymbol{s}}_{\mathcal{A}}$ and then estimate the post-voting vector $\tilde{\boldsymbol{s}}_{\mathcal{B}}$ corresponding to each candidate of $\tilde{\boldsymbol{s}}_{\mathcal{A}}$ by using LR-aided MMSE-SIC. Thus, the problem is to find all candidates $\tilde{\boldsymbol{u}}_{\mathcal{A}} \in \tilde{\mathcal{S}}^{n-m}$ and $\tilde{\boldsymbol{u}}_{\mathcal{B}} \in \tilde{\mathcal{S}}^{m}$ satisfying

$$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{H}}_{\mathcal{A}}\tilde{\boldsymbol{u}}_{\mathcal{A}} + \tilde{\boldsymbol{H}}_{\mathcal{B}}\tilde{\boldsymbol{u}}_{\mathcal{B}} + \tilde{\boldsymbol{v}}. \tag{19}$$

Let $\tilde{\boldsymbol{u}}_{\mathcal{A}}^1, \ldots, \tilde{\boldsymbol{u}}_{\mathcal{A}}^K$ be all possible candidates of $\tilde{\boldsymbol{u}}_{\mathcal{A}}$, where $K := \left|\tilde{\mathcal{S}}\right|^{n-m}$. Assuming $\tilde{\boldsymbol{u}}_{\mathcal{A}} = \tilde{\boldsymbol{u}}_{\mathcal{A}}^k$ ($k = 1, \ldots, K$),

$$\boldsymbol{r}^k := \tilde{\boldsymbol{y}} - \tilde{\boldsymbol{H}}_{\mathcal{A}}\tilde{\boldsymbol{u}}_{\mathcal{A}}^k = \tilde{\boldsymbol{H}}_{\mathcal{B}}\tilde{\boldsymbol{u}}_{\mathcal{B}} + \tilde{\boldsymbol{v}} \tag{20}$$

can be obtained from (19). Since $\tilde{\boldsymbol{H}}_{\mathcal{B}}$ is an $m \times m$ square matrix, (20) can be regarded as the model of common MIMO systems, where the number of receive antennas is equal to that of transmit antennas. Thus $\tilde{\boldsymbol{u}}_{\mathcal{B}}^k$, the estimate of $\tilde{\boldsymbol{u}}_{\mathcal{B}}$ corresponding to $\tilde{\boldsymbol{u}}_{\mathcal{A}}^k$, can be obtained by applying the conventional LR-aided MMSE-SIC to (20). As the algorithm for LR, complex Lenstra-Lenstra-Lovász (LLL) algorithm [12], which is the complex version of LLL algorithm [13], is employed in [3]. After obtaining $\tilde{\boldsymbol{u}}_{\mathcal{A}}^k$ and $\tilde{\boldsymbol{u}}_{\mathcal{B}}^k$ for all $k = 1, \ldots, K$, we get

$$\hat{k} = \arg\min_{k\in\{1,\ldots,K\}} \left\|\tilde{\boldsymbol{y}} - \tilde{\boldsymbol{H}}_{\mathcal{A}}\tilde{\boldsymbol{u}}_{\mathcal{A}}^k - \tilde{\boldsymbol{H}}_{\mathcal{B}}\tilde{\boldsymbol{u}}_{\mathcal{B}}^k\right\|^2 \tag{21}$$

as the index corresponding to the final estimated vectors of of $\tilde{\boldsymbol{s}}_{\mathcal{A}}$ and $\tilde{\boldsymbol{s}}_{\mathcal{B}}$.

Note that $\mathcal{A}$ and $\mathcal{B}$ are determined in [3] based on the max-min diagonal (MD) criterion [18]

$$\mathcal{B}_{\mathrm{MD}} = \arg\max_{\mathcal{B}} \left\{ \min_{i\in\{1,\ldots,m\}} \left|\hat{r}_{i,i}\right| \right\}, \tag{22}$$

where $\hat{r}_{i,i}$ denotes the (i, i) element of the upper triangular matrix $\hat{\boldsymbol{R}}$ obtained from QR decomposition of $\hat{\boldsymbol{H}}' = \hat{\boldsymbol{Q}}\hat{\boldsymbol{R}}$, which is given by applying LR to $\hat{\boldsymbol{H}} = [\tilde{\boldsymbol{H}}_{\mathcal{B}}^T \; (\sigma_v/\sigma_s)\boldsymbol{I}_m]^T$. Although this criterion gives a good performance, it requires the calculation of LR for each candidate of $\mathcal{B}$.

4. Proposed Signal Detection Scheme

Since LR-aided MMSE-SIC detection with PVC searches all candidates of the pre-voting vector $\boldsymbol{s}_{\mathcal{A}}$, its complexity increases exponentially with $n-m$, i.e., the difference between the number of transmit antennas and receive antennas. In this section, we propose Slab-LR-MMSE-SIC as a low complexity signal detection scheme. Slab-LR-MMSE-SIC reduces the required complexity by decreasing the number of candidates for $\boldsymbol{s}_{\mathcal{A}}$ with slab decoding.

4.1 Signal Detection Scheme with Slab Decoding and LR

In order to reduce the candidates of $\boldsymbol{s}_{\mathcal{A}}$, we consider the real model equivalent to (18) as

$$\boldsymbol{y} = \boldsymbol{H}_{\mathcal{A}}\boldsymbol{s}_{\mathcal{A}} + \boldsymbol{H}_{\mathcal{B}}\boldsymbol{s}_{\mathcal{B}} + \boldsymbol{v}, \tag{23}$$

where

$$\boldsymbol{H}_{\mathcal{A}} := \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{H}}_{\mathcal{A}}\} & -\mathrm{Im}\{\tilde{\boldsymbol{H}}_{\mathcal{A}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{H}}_{\mathcal{A}}\} & \mathrm{Re}\{\tilde{\boldsymbol{H}}_{\mathcal{A}}\} \end{bmatrix},\ \boldsymbol{s}_{\mathcal{A}} := \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{s}}_{\mathcal{A}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{s}}_{\mathcal{A}}\} \end{bmatrix},$$
$$\boldsymbol{H}_{\mathcal{B}} := \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{H}}_{\mathcal{B}}\} & -\mathrm{Im}\{\tilde{\boldsymbol{H}}_{\mathcal{B}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{H}}_{\mathcal{B}}\} & \mathrm{Re}\{\tilde{\boldsymbol{H}}_{\mathcal{B}}\} \end{bmatrix},\ \boldsymbol{s}_{\mathcal{B}} := \begin{bmatrix} \mathrm{Re}\{\tilde{\boldsymbol{s}}_{\mathcal{B}}\} \\ \mathrm{Im}\{\tilde{\boldsymbol{s}}_{\mathcal{B}}\} \end{bmatrix}. \tag{24}$$

Moreover, we transform (23) into

$$\boldsymbol{y} = \bar{\boldsymbol{H}}\bar{\boldsymbol{s}} + \boldsymbol{v}, \tag{25}$$

to implement slab decoding algorithm, where

$$\bar{\boldsymbol{H}} := \begin{bmatrix} \boldsymbol{H}_{\mathcal{B}} & \boldsymbol{H}_{\mathcal{A}} \end{bmatrix}, \tag{26}$$
$$\bar{\boldsymbol{s}} = \begin{bmatrix} \bar{s}_1, \dots, \bar{s}_{2n} \end{bmatrix}^{\mathrm{T}} := \begin{bmatrix} \boldsymbol{s}_{\mathcal{B}}^{\mathrm{T}} & \boldsymbol{s}_{\mathcal{A}}^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}}. \tag{27}$$

By using the QR decomposition of $\bar{\boldsymbol{H}} = \bar{\boldsymbol{Q}}\bar{\boldsymbol{R}}$, we can rewrite (25) as

$$\bar{\boldsymbol{z}} = \bar{\boldsymbol{R}}\bar{\boldsymbol{s}} + \bar{\boldsymbol{\eta}}, \tag{28}$$

where $\bar{\boldsymbol{z}} := \bar{\boldsymbol{Q}}^T\boldsymbol{y}$ and $\bar{\boldsymbol{\eta}} := \bar{\boldsymbol{Q}}^{\mathrm{T}}\boldsymbol{v}$. The equation of the $2m$-th row of (28) is given by

$$\bar{z}_{2m} = \bar{r}_{2m,2m}\bar{s}_{2m} + \cdots + \bar{r}_{2m,2n}\bar{s}_{2n} + \bar{\eta}_{2m}. \tag{29}$$

Thus, by using slab decoding algorithm, we find all $\bar{u}_{2m}, \dots, \bar{u}_{2n}$ satisfying

$$-C_{\mathrm{SLAB}} \leq \bar{z}_{2m} - (\bar{r}_{2m,2m}\bar{u}_{2m} + \cdots + \bar{r}_{2m,2n}\bar{u}_{2n}) \leq C_{\mathrm{SLAB}}, \tag{30}$$

where C_{SLAB} is a constant whose selection will be discussed in Sect. 4.2. It should be noted here that slab decoding gives the candidates for not only $\boldsymbol{s}_{\mathcal{A}}$ but also $\bar{s}_{2m}$ because $\boldsymbol{s}_{\mathcal{A}} = [\bar{s}_{2m+1}, \dots, \bar{s}_{2n}]^{\mathrm{T}}$. However, we utilize the candidates of $\boldsymbol{s}_{\mathcal{A}}$ only, and $\bar{s}_{2m}$ will be estimated as one of the elements of the post-voting vector using LR-aided MMSE-SIC later. From the candidates of $\boldsymbol{s}_{\mathcal{A}}$, we can also obtain the candidates of $\tilde{\boldsymbol{s}}_{\mathcal{A}}$. Let L denote the number of candidates of $\tilde{\boldsymbol{s}}_{\mathcal{A}}$ obtained by using slab decoding algorithm, and we represent the L candidates as $\tilde{\boldsymbol{u}}_{\mathcal{A}}^{k_1}, \dots, \tilde{\boldsymbol{u}}_{\mathcal{A}}^{k_L}$.

Next, we obtain candidates of post-voting vectors $\tilde{\boldsymbol{u}}_{\mathcal{B}}^{k_1}, \dots, \tilde{\boldsymbol{u}}_{\mathcal{B}}^{k_L}$ corresponding to $\tilde{\boldsymbol{u}}_{\mathcal{A}}^{k_1}, \dots, \tilde{\boldsymbol{u}}_{\mathcal{A}}^{k_L}$ by LR-aided MMSE-SIC. Assuming $\tilde{\boldsymbol{u}}_{\mathcal{A}} = \tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell}$ ($\ell = k_1, \dots, k_L$), (19) can be rewritten as

$$\boldsymbol{r}^{\ell} := \tilde{\boldsymbol{y}} - \tilde{\boldsymbol{H}}_{\mathcal{A}}\tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} = \tilde{\boldsymbol{H}}_{\mathcal{B}}\tilde{\boldsymbol{u}}_{\mathcal{B}} + \tilde{\boldsymbol{v}}. \tag{31}$$

In order to obtain the estimate of the post-voting vector $\tilde{\boldsymbol{u}}_{\mathcal{B}}$ corresponding to $\tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell}$, we firstly rewrite (31) as

$$\hat{\boldsymbol{r}}^{\ell} = \hat{\boldsymbol{H}}\tilde{\boldsymbol{u}}_{\mathcal{B}} + \hat{\boldsymbol{v}}, \tag{32}$$

where

$$\hat{\boldsymbol{r}}^{\ell} := \begin{bmatrix} \boldsymbol{r}^{\ell} \\ \boldsymbol{0}_m \end{bmatrix},\ \hat{\boldsymbol{H}} := \begin{bmatrix} \tilde{\boldsymbol{H}}_{\mathcal{B}} \\ \dfrac{\sigma_v}{\sigma_s}\boldsymbol{I}_m \end{bmatrix},\ \hat{\boldsymbol{v}} := \begin{bmatrix} \tilde{\boldsymbol{v}} \\ -\dfrac{\sigma_v}{\sigma_s}\tilde{\boldsymbol{u}}_{\mathcal{B}} \end{bmatrix}. \tag{33}$$

Then, we obtain the unimodular matrix $\boldsymbol{T}$ satisfying $\hat{\boldsymbol{H}}' = \hat{\boldsymbol{H}}\boldsymbol{T}$ by applying LR to $\hat{\boldsymbol{H}}$, and (32) can be further rewritten as

$$\hat{\boldsymbol{r}}^{\ell} = \hat{\boldsymbol{H}}'\boldsymbol{u}'_{\mathcal{B}} + \hat{\boldsymbol{v}}, \tag{34}$$

where $\boldsymbol{u}'_{\mathcal{B}} := \boldsymbol{T}^{-1}\tilde{\boldsymbol{u}}_{\mathcal{B}}$. Moreover, by using QR decomposition of $\hat{\boldsymbol{H}}' = \hat{\boldsymbol{Q}}\hat{\boldsymbol{R}}$, (34) can be finally rewritten as

$$\hat{\boldsymbol{z}}^{\ell} = \hat{\boldsymbol{R}}\boldsymbol{u}'_{\mathcal{B}} + \hat{\boldsymbol{\eta}}, \tag{35}$$

where $\hat{\boldsymbol{z}}^{\ell} := \hat{\boldsymbol{Q}}^{\mathrm{T}}\hat{\boldsymbol{r}}^{\ell}$ and $\hat{\boldsymbol{\eta}} := \hat{\boldsymbol{Q}}^{\mathrm{T}}\hat{\boldsymbol{v}}$. The estimate of $\boldsymbol{u}'_{\mathcal{B}}$ can be obtained in the same way as the conventional LR-aided MMSE-SIC in [14]. Thereby, we can get $\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell}$, i.e., the estimate of $\tilde{\boldsymbol{u}}_{\mathcal{B}}$ corresponding to $\tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell}$, by using $\tilde{\boldsymbol{u}}_{\mathcal{B}} = \boldsymbol{T}\boldsymbol{u}'_{\mathcal{B}}$.

Finally, we choose the best candidate, which maximizes the likelihood, as the detected signal. Specifically, we obtain

$$\hat{\ell} = \underset{\ell \in \{k_1, \dots, k_L\}}{\arg\min} \left\| \tilde{\boldsymbol{y}} - \tilde{\boldsymbol{H}}_{\mathcal{A}}\tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} - \tilde{\boldsymbol{H}}_{\mathcal{B}}\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell} \right\|^2 \tag{36}$$

and select $\tilde{\boldsymbol{u}}_{\mathcal{A}}^{\hat{\ell}}$ and $\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\hat{\ell}}$ as the estimates of $\tilde{\boldsymbol{s}}_{\mathcal{A}}$ and $\tilde{\boldsymbol{s}}_{\mathcal{B}}$, respectively.

4.2 Selection of C_{SLAB}

In the proposed algorithm, the selection of C_{SLAB} is one of the key issues, since it has a direct impact on the computational complexity and performance. Here, we discuss how to set C_{SLAB}, such that the complexity is reduced as much as possible while keeping the performance loss to an acceptable level.

Let $P_{e,\mathrm{SLAB}}$ be the probability that the true transmit signals $\bar{s}_{2m}, \dots, \bar{s}_{2n}$ is not included in the set of candidates obtained with slab decoding. For true $\bar{s}_{2m}, \dots, \bar{s}_{2n}$, we have

$$\bar{z}_{2m} - (\bar{r}_{2m,2m}\bar{s}_{2m} + \cdots + \bar{r}_{2m,2n}\bar{s}_{2n}) = \bar{\eta}_{2m} \tag{37}$$

from (29), thus

$$P_{e,\mathrm{SLAB}} = 1 - \Pr(-C_{\mathrm{SLAB}} \leq \bar{\eta}_{2m} \leq C_{\mathrm{SLAB}}). \tag{38}$$

Since $\bar{\boldsymbol{\eta}} = \bar{\boldsymbol{Q}}^{\mathrm{T}}\boldsymbol{v}$, $\bar{\eta}_{2m}$ is written as

$$\bar{\eta}_{2m} = \bar{q}_{1,2m}v_1 + \bar{q}_{2,2m}v_2 + \cdots + \bar{q}_{2m,2m}v_{2m}, \tag{39}$$

where $\bar{q}_{i,2m}$ $(i = 1, \ldots, 2m)$ represents the $(i, 2m)$ element of $\bar{\boldsymbol{Q}}$. Moreover, since v_i $(i = 1, \ldots, 2m)$ are Gaussian random variables with zero mean and variance $\sigma_v^2/2$ and $\bar{\boldsymbol{Q}}$ is an orthogonal matrix, $\bar{\eta}_{2m}$ is also a Gaussian random variable with zero mean and variance $\sigma_v^2/2$. Therefore, $P_{e,\mathrm{SLAB}}$ can be calculated as

$$\begin{aligned} P_{e,\mathrm{SLAB}} &= 2\int_{C_{\mathrm{SLAB}}}^{+\infty} \frac{1}{\sqrt{2\pi(\sigma_v^2/2)}} \exp\left(-\frac{x^2}{2(\sigma_v^2/2)}\right) \mathrm{d}x \\ &= \frac{2}{\sqrt{\pi}} \int_{C_{\mathrm{SLAB}}/\sigma_v}^{+\infty} \exp\left(-t^2\right) \mathrm{d}t \\ &= \mathrm{erfc}\left(C_{\mathrm{SLAB}}/\sigma_v\right), \end{aligned} \tag{40}$$

where

$$\mathrm{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{+\infty} \exp\left(-t^2\right) \mathrm{d}t \tag{41}$$

is the complementary error function. From (40), C_{SLAB} can be given as

$$C_{\mathrm{SLAB}} = \sigma_v \mathrm{erfc}^{-1}\left(P_{e,\mathrm{SLAB}}\right), \tag{42}$$

thus we can determine C_{SLAB} by setting the acceptable probability $P_{e,\mathrm{SLAB}}$ that slab decoding fails to obtain the true $\bar{s}_{2m}, \ldots, \bar{s}_{2n}$.

4.3 Selection of $\mathcal{A}$ and $\mathcal{B}$

The selection of $\mathcal{A}$ and $\mathcal{B}$ also has an impact on the computational complexity, because the number of candidates of pre-voting vectors obtained by slab decoding depends on the selection. Thus, we consider how to select $\mathcal{A}$ and $\mathcal{B}$ here, and propose a simple but effective selection criterion named maximum variance (MV) criterion.

Let $X := \bar{z}_{2m} - \left(\bar{r}_{2m,2m}\bar{S}_{2m} + \cdots + \bar{r}_{2m,2n}\bar{S}_{2n}\right)$, where $\bar{S}_{2m}, \ldots, \bar{S}_{2n}$ are i.i.d. random variables distributed uniformly on $\mathcal{S}$. The middle term in (30) for each candidate of $(\bar{u}_{2m}, \ldots, \bar{u}_{2n})$ equals to the value of X for the corresponding realization of $\left(\bar{S}_{2m}, \ldots, \bar{S}_{2n}\right)$. Thus, the ratio of the number of candidates of $(\bar{u}_{2m}, \ldots, \bar{u}_{2n})$ satisfying (30) to that of all candidates (i.e., $|\mathcal{S}|^{2n-2m+1}$) is $\Pr\left(-C_{\mathrm{SLAB}} \le X \le C_{\mathrm{SLAB}}\right)$, which should be minimized to reduce the number of candidates of pre-voting vectors obtained by slab decoding. In our approach, therefore, we select $\mathcal{A}$ and $\mathcal{B}$ so that the variance of X is as large as possible. Since

$$\mu_x := \mathrm{E}[X] = z_{2m}, \tag{43}$$

$$\sigma_x^2 := \mathrm{E}[(X - \mu_x)^2] = \left(\bar{r}_{2m,2m}^2 + \cdots + \bar{r}_{2m,2n}^2\right)\sigma_s^2/2, \tag{44}$$

for QPSK or QAM symbols, we obtain

$$\left[\hat{\mathcal{A}}, \hat{\mathcal{B}}\right] = \arg\max_{[\mathcal{A},\mathcal{B}]} \left\{\bar{r}_{2m,2m}^2 + \cdots + \bar{r}_{2m,2n}^2\right\}, \tag{45}$$

where $\bar{r}_{2m,j}$ $(j = 2m, \ldots, 2n)$ denotes the $(2m, j)$ element of the upper triangular matrix obtained by QR decomposition of $\bar{\boldsymbol{H}} = [\boldsymbol{H}_{\mathcal{B}}\ \boldsymbol{H}_{\mathcal{A}}]$. Note that MV criterion does not require LR for the evaluation, thus it has much lower complexity than MD criterion.

5. Performance Analysis

In this section, we evaluate the error probability of the proposed Slab-LR-MMSE-SIC taking a similar approach as in [3]. Let $\mathcal{U}_{\mathcal{A}} = \{\tilde{\boldsymbol{u}}_{\mathcal{A}}^{k_1}, \ldots, \tilde{\boldsymbol{u}}_{\mathcal{A}}^{k_L}\}$ and $\mathcal{U} = \{\tilde{\boldsymbol{u}}^{k_1}, \ldots, \tilde{\boldsymbol{u}}^{k_L}\}$ be the set of the candidates of $\tilde{\boldsymbol{s}}_{\mathcal{A}}$ obtained by using slab decoding and that of $\tilde{\boldsymbol{s}}$ after LR-aided MMSE-SIC, respectively. In addition, we denote $\hat{\boldsymbol{s}}$ as the final estimate of the true transmitted signal vector $\tilde{\boldsymbol{s}}$ obtained with Slab-LR-MMSE-SIC. The error probability of the proposed approach P_e is written as

$$\begin{aligned} P_e &= 1 - \Pr(\hat{\boldsymbol{s}} = \tilde{\boldsymbol{s}} \mid \tilde{\boldsymbol{s}} \in \mathcal{U}) \Pr(\tilde{\boldsymbol{s}} \in \mathcal{U}) \\ &= 1 - (1 - \Pr(\hat{\boldsymbol{s}} \neq \tilde{\boldsymbol{s}} \mid \tilde{\boldsymbol{s}} \in \mathcal{U}))(1 - \Pr(\tilde{\boldsymbol{s}} \notin \mathcal{U})) \\ &= 1 - (1 - P_{e,\mathrm{SEL}})(1 - P_{e,\mathrm{PV}}), \end{aligned} \tag{46}$$

where $P_{e,\mathrm{SEL}} = \Pr(\hat{\boldsymbol{s}} \neq \tilde{\boldsymbol{s}} \mid \tilde{\boldsymbol{s}} \in \mathcal{U})$ is the probability that the final estimate of $\tilde{\boldsymbol{s}}$ is not equal to $\tilde{\boldsymbol{s}}$ though $\mathcal{U}$ contains $\tilde{\boldsymbol{s}}$, and $P_{e,\mathrm{PV}} = \Pr(\tilde{\boldsymbol{s}} \notin \mathcal{U})$ is the probability that $\mathcal{U}$ does not contain the true transmitted signal vector. As mentioned in Sect. 4.1, the candidates of $\bar{s}_{2m}$ are not used in order to reduce the candidates of $\tilde{\boldsymbol{s}}_{\mathcal{A}} = [\bar{s}_{2m+1}, \ldots, \bar{s}_{2n}]^{\mathrm{T}}$ though they were obtained by slab decoding. Thus, the probability that the set of candidates of the pre-voting vector $\mathcal{U}_{\mathcal{A}}$ includes the true pre-voting vector $\tilde{\boldsymbol{s}}_{\mathcal{A}}$ is greater than the success probability of slab decoding, namely

$$\Pr(\tilde{\boldsymbol{s}}_{\mathcal{A}} \in \mathcal{U}_{\mathcal{A}}) \ge 1 - P_{e,\mathrm{SLAB}}. \tag{47}$$

Similarly, we also define $\tilde{\boldsymbol{s}}_{\mathcal{B}}$ as the true post-voting vector. Using (47), $P_{e,\mathrm{PV}}$ can be bounded as

$$\begin{aligned} &P_{e,\mathrm{PV}} \\ &= 1 - \Pr(\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{B}} \mid \tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{A}}) \Pr(\tilde{\boldsymbol{s}}_{\mathcal{A}} \in \mathcal{U}_{\mathcal{A}}) \\ &\le 1 - \Pr(\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{B}} \mid \tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{A}})(1 - P_{e,\mathrm{SLAB}}) \\ &= (1 - \Pr(\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{B}} \mid \tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{A}}))(1 - P_{e,\mathrm{SLAB}}) + P_{e,\mathrm{SLAB}} \\ &\le (1 - \Pr(\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{B}} \mid \tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{A}})) + P_{e,\mathrm{SLAB}}, \end{aligned} \tag{48}$$

where $1 - \Pr(\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{B}} \mid \tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{A}})$ is the probability that the post-voting vector $\tilde{\boldsymbol{s}}_{\mathcal{B}}$ is not correctly estimated in (31) for the true pre-voting vector $\tilde{\boldsymbol{s}}_{\mathcal{A}}$. As shown in [3], [19], we have

$$\begin{aligned} &1 - \Pr(\tilde{\boldsymbol{u}}_{\mathcal{B}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{B}} \mid \tilde{\boldsymbol{u}}_{\mathcal{A}}^{\ell} = \tilde{\boldsymbol{s}}_{\mathcal{A}}) \\ &\le c_{mm}\left(\frac{2}{c_\delta}\right)^m \frac{(2m-1)!}{(m-1)!}\left(\frac{1}{\sigma_v^2}\right)^{-m}, \end{aligned} \tag{49}$$

where c_{mm} is a constant depending on m, $1/2 < \delta < 1$ is a parameter in complex LLL algorithm, and

$$c_\delta = 2^{\frac{m}{2}}\left(\frac{2}{2\delta - 1}\right)^{-m(m+1)/4}. \tag{50}$$

If $\tilde{s} \in \mathcal{U}$ and the transmitted signal vector $\tilde{s}$ can be correctly obtained with ML detection among all possible candidates, Slab-LR-MMSE-SIC can also select $\tilde{s}$ among candidates in $\mathcal{U}$ by using (36), which obtains the candidate having maximum likelihood among candidates in $\mathcal{U}$. Thus, we have

$$P_{e,\mathrm{SEL}} \leq P_{e,\mathrm{ML}}, \tag{51}$$

where $P_{e,\mathrm{ML}}$ is the error probability of ML detection, which can be bounded as

$$P_{e,\mathrm{ML}} \leq c_{\mathrm{ML}} \left(\frac{1}{\sigma_v^2} \right)^{-m}, \tag{52}$$

where c_{ML} is a constant independent of σ_v^2 [20]. From (46), (48), (49), (51) and (52), therefore, the error probability of the proposed scheme P_e is bounded as

$$\begin{aligned} P_e &= P_{e,\mathrm{PV}} + P_{e,\mathrm{SEL}} - P_{e,\mathrm{PV}} P_{e,\mathrm{SEL}} \\ &\leq P_{e,\mathrm{PV}} + P_{e,\mathrm{ML}} \\ &\leq c_{mm} \left(\frac{2}{c_\delta} \right)^m \frac{(2m-1)!}{(m-1)!} \left(\frac{1}{\sigma_v^2} \right)^{-m} \\ &\qquad + P_{e,\mathrm{SLAB}} + c_{\mathrm{ML}} \left(\frac{1}{\sigma_v^2} \right)^{-m}. \end{aligned} \tag{53}$$

It should be noted that we can control $P_{e,\mathrm{SLAB}}$ as the parameter of the acceptable error probability of slab decoding. Specifically, by choosing $P_{e,\mathrm{SLAB}}$ as

$$P_{e,\mathrm{SLAB}} \propto \left(\frac{1}{\sigma_v^2} \right)^{-m}, \tag{54}$$

P_e can be bounded as

$$P_e \leq c \left(\frac{1}{\sigma_v^2} \right)^{-m}, \tag{55}$$

where c is a constant which is independent of σ_v^2, meaning that the proposed scheme can achieve a diversity order of m. Since the maximum diversity order for $n \times m$ overloaded MIMO is known to be m [3], the proposed scheme can achieve the full diversity order.

6. Simulation Results

In this section, we demonstrate the performance of the proposed Slab-LR-MMSE-SIC using computer simulations. In the simulations, $\tilde{\boldsymbol{H}}$ is assumed to be time-invariant and is composed of i.i.d. complex Gaussian random variables with zero mean and unit variance. All the results are obtained by averaging the performance for 1,000 realizations of $\tilde{\boldsymbol{H}}$. The acceptable error probability of slab decoding in the proposed Slab-LR-MMSE-SIC is set to be $P_{e,\mathrm{SLAB}} = BER_{\mathrm{ML}}/a$ at each E_b/N_0, where $a > 0$ is a constant and BER_{ML} is the BER achieved by ML detection, which is the same as that of SSD. The parameter δ in the complex LLL algorithm is set as $\delta = 3/4$.

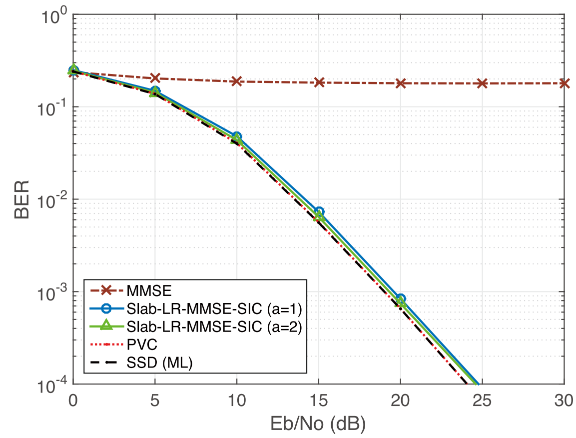

Fig. 2 BER performance ($n = 4$, $m = 2$, QPSK).

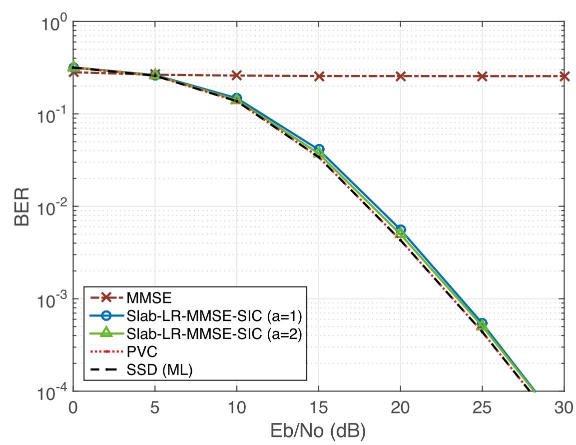

Fig. 3 BER performance ($n = 6$, $m = 2$, QPSK).

6.1 BER Performance

First, we evaluate the BER performance of Slab-LR-MMSE-SIC and conventional signal detection schemes. Figures 2, 3, and 4 show the BER performance of the proposed Slab-LR-MMSE-SIC for $n = 4$, $m = 2$ with QPSK modulation, for $n = 6$, $m = 2$ with QPSK modulation, and for $n = 4$, $m = 2$ with 16-QAM, respectively. The BERs of the conventional MMSE detection (*MMSE*), LR-aided MMSE-SIC detection with PVC (*PVC*), and slab sphere decoding (*SSD*) are also plotted in the same figures. In all the figures, we can see that the conventional LR-aided MMSE-SIC detection can achieve almost the same BER performance as the optimal ML detection. In addition, the proposed Slab-LR-MMSE-SIC can also achieve similar performance as the conventional schemes. It should be noted here that Slab-LR-MMSE-SIC with the proper parameter choice can achieve the same diversity order as ML detection, which is confirmed by the simulation results.

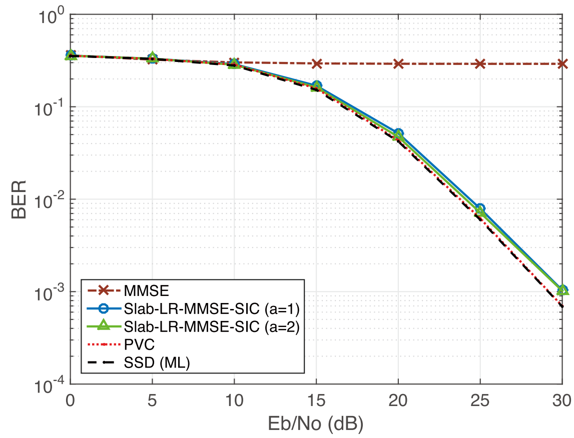

Fig. 4 BER performance (n = 4, m = 2, 16-QAM).

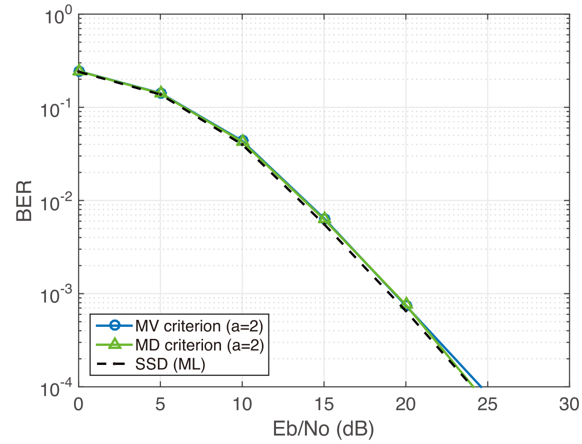

Fig. 6 BER performance (n = 4, m = 2, QPSK).

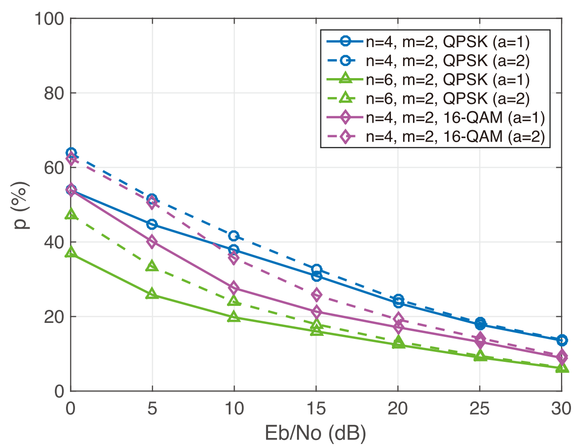

Fig. 5 Ratio of the number of pre-voting vector candidates $p = L/\left|\tilde{\mathcal{S}}\right|^{n-m}$.

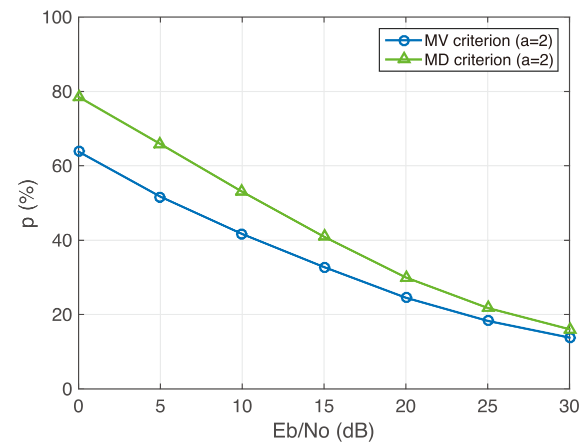

Fig. 7 Ratio of the number of pre-voting vector candidates $p = L/\left|\tilde{\mathcal{S}}\right|^{n-m}$ (n = 4, m = 2, QPSK).

6.2 Number of Candidates of Pre-Voting Vectors

Next, we evaluate the number of candidates obtained by slab decoding in Slab-LR-MMSE-SIC. Figure 5 shows the ratio of the number of candidates $p = L/\left|\tilde{\mathcal{S}}\right|^{n-m}$ in percentage, where L denotes the number of candidates of $\tilde{\mathbf{s}}_{\mathcal{A}}$ obtained by slab decoding in Slab-LR-MMSE-SIC, and $\left|\tilde{\mathcal{S}}\right|^{n-m}$ represents that in the conventional scheme with PVC. Since different values of C_{SLAB} are used for each E_b/N_0, the amount p for higher E_b/N_0 is less than that for lower E_b/N_0. We can also see that smaller a, which means larger $P_{e,\mathrm{SLAB}}$, results in larger reduction of the number of candidates though it entails a slight performance degradation as shown in Figs. 2, 3, and 4. In addition, we observe a larger reduction of the number of candidates for greater values of $n - m$ and higher modulation levels. Note that, by reducing the number of candidates for $\tilde{\mathbf{s}}_{\mathcal{A}}$, the required number of LR-aided MMSE-SIC detections for $\tilde{\mathbf{s}}_{\mathcal{B}}$ is also reduced. Therefore, Slab-LR-MMSE-SIC is able to reduce the computational complexity as compared to the conventional schemes, while achieving a near-optimal performance.

6.3 Comparison of the Selection Criteria of $\mathcal{A}$ and $\mathcal{B}$

We demonstrate the effectiveness of the proposed MV criterion against the conventional MD criterion for $n = 4$, $m = 2$ with QPSK modulation. Figure 6 shows the BER performances of Slab-LR-MMSE-SIC with MV criterion and MD criterion. We can observe that both MV criterion and MD criterion provide almost the same BER performance as the optimal ML detection, while MD criterion requires higher computational complexity than MV criterion. Figure 7 shows the ratio of the number of candidates of pre-voting vector obtained with each criterion. We can see that Slab-LR-MMSE-SIC with MV criterion has less candidates than that with MD criterion, and hence the proposed MV criterion enables further reduction of the required computational complexity.

7. Conclusion

In this paper, we have proposed the overloaded MIMO signal detection scheme with slab decoding and LR, referred as Slab-LR-MMSE-SIC. With the proposed parameter choice in slab decoding and the selection of the indexes for the pre-voting vector, Slab-LR-MMSE-SIC can significantly reduce the candidates of pre-voting vector compared to the conventional scheme, closely approaching the BER performance of optimal ML detection. In addition, we have analyzed the error probability of Slab-LR-MMSE-SIC and have clarified that the proposed scheme can achieve full diversity order with a proper parameter choice in slab decoding.

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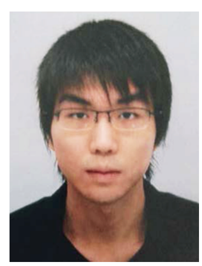

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