An Overloaded MIMO Signal Detection Scheme with Slab Decoding and Lattice Reduction

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***Abstract*—This paper proposes a reduced complexity signal detection scheme for overloaded MIMO (Multiple-Input Multiple-Output) systems. The proposed scheme firstly divides the transmitted signals into two parts, the post-voting vector containing the same number of signal elements as of receive antennas, and the pre-voting vector containing the remaining elements. Secondly, it uses slab decoding to reduce the solution candidates of the pre-voting vector and determines the post-voting vectors for each pre-voting vector candidate by lattice reduction aided MMSE (Minimum Mean Square Error)-SIC (Successive Interference Cancellation) detection. Simulation results show that the proposed scheme can achieve almost the same performance as the optimal ML (Maximum Likelihood) detection while drastically reducing the required computational complexity.**

I. Introduction

In MIMO (Multiple-Input Multiple Output) systems, a sufficient number of receive antennas may not always be available due to the limits of the size, weight, or power consumption of the receiver. Various signal detection schemes have been proposed for such MIMO systems, i.e., having less receive antennas than transmit streams, known as overloaded MIMO systems [1]-[6]. Although ML (Maximum Likelihood) detection can achieve the best BER (Bit Error Rate) performance, its complexity increases exponentially with the number of transmitted streams because it searches all possible candidates of transmitted signals. In order to reduce the decoding complexity, a method applying sphere decoding [7] to the overloaded MIMO signal detection, named SSD (Slab-Sphere Decoding), has been proposed [1]. In SSD, the transmitted signals are divided into two parts, the signals containing the same number of signal elements as of receive antennas minus one, and the remaining signals. The candidates of the latter signals are found by slab decoding and the former signals corresponding to each candidate are searched by sphere decoding. On the other hand, in order to further reduce the computational complexity, lattice reduction [8] aided MMSE (Minimum Mean Square Error)-SIC (Successive Interference Cancellation) detection with PVC (Pre-Voting Cancellation) has been proposed [2]. This scheme firstly divides the transmitted signals into two parts, the post-voting vector containing the same number of signal elements as of receive antennas, and the pre-voting vector containing the remaining elements. Secondly, it obtains the candidates of the transmitted signals by determining the post-voting vectors for each pre-voting vector candidate by lattice reduction aided MMSE-SIC detection. Finally, it selects the best candidate in terms of the likelihood as the detected signal. Thus, the complexity of this scheme increases exponentially with the difference between the number of the transmitted streams and that of receive antennas which is still problematic, especially for massive MIMO systems. Therefore, the design of efficient and low-complexity detection schemes for overloaded MIMO is an essential issue for 5G systems.

In this paper, we propose a reduced complexity overloaded MIMO signal detection scheme based on lattice reduction aided MMSE-SIC. The key idea of the proposed scheme is to reduce the solution candidates for pre-voting vectors by using slab decoding, which has been originally proposed for SSD. Thus, the proposed scheme can considerably reduce the number of required calculations for MMSE-SIC detection compared to the conventional scheme with PVC. Simulation results show that the proposed scheme can achieve almost the same performance as the optimal ML schemes while drastically reducing the computational complexity.

In the rest of the paper, we use the following notations. Superscript T and H represent transpose and Hermitian transpose, respectively. $\mathbf{I}_n$ denotes $n \times n$ identity matrix. For a complex matrix $\mathbf{A}$, $\mathrm{Re}\{\mathbf{A}\}$ and $\mathrm{Im}\{\mathbf{A}\}$ denote the real and imaginary parts of $\mathbf{A}$, respectively.

II. System Model

Fig. 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. Information bits are mapped to n symbols, converted by the serial-parallel converter, and sent from the transmit antennas. Here, $\tilde{s}_1, \ldots, \tilde{s}_n$ are the symbols sent from n transmit antennas and $\tilde{\mathbf{s}} = [\tilde{s}_1, \ldots, \tilde{s}_n]^T \in \tilde{\mathcal{S}}^n$ is the transmitted signal vector, where $\tilde{\mathcal{S}}$ denotes the set of transmitted signals and $E\left[\tilde{\mathbf{s}}\tilde{\mathbf{s}}^H\right] = \sigma_s^2 \mathbf{I}_n$. The received signal vector $\tilde{\mathbf{y}} = [\tilde{y}_1, \ldots, \tilde{y}_m]^T \in \mathbb{C}^m$ is given by

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

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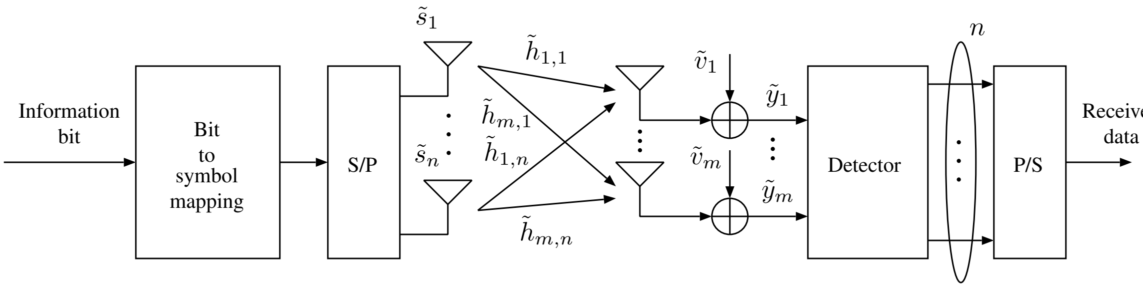

Fig. 1. System Model

where

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

represents the flat fading channel matrix and $\tilde{\mathbf{v}} = [\tilde{v}_1, \ldots, \tilde{v}_m]^T \in \mathbb{C}^m$ is a zero mean white complex Gaussian noise vector with covariance matrix $\sigma_v^2 \mathbf{I}_m$.

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

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

where

$$\mathbf{y} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{y}}\} \\ \mathrm{Im}\{\tilde{\mathbf{y}}\} \end{bmatrix} \in \mathbb{R}^M, \ \mathbf{H} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{H}}\} & -\mathrm{Im}\{\tilde{\mathbf{H}}\} \\ \mathrm{Im}\{\tilde{\mathbf{H}}\} & \mathrm{Re}\{\tilde{\mathbf{H}}\} \end{bmatrix} \in \mathbb{R}^{M \times N},$$
$$\mathbf{s} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{s}}\} \\ \mathrm{Im}\{\tilde{\mathbf{s}}\} \end{bmatrix} \in \mathcal{S}^N, \ \mathbf{v} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{v}}\} \\ \mathrm{Im}\{\tilde{\mathbf{v}}\} \end{bmatrix} \in \mathbb{R}^M, \tag{4}$$

and $M = 2m, N = 2n$. $\mathcal{S}$ denotes the set of the real and imaginary part of $\tilde{\mathcal{S}}$.

III. Conventional Signal Detection Schemes for Overloaded MIMO Systems

For overloaded MIMO systems, sphere decoding and lattice reduction aided MMSE-SIC detection are not directly applicable because the channel matrix $\mathbf{H}$ is fat. Here, we briefly review conventional methods to apply sphere decoding and lattice reduction aided MMSE-SIC detection to the overloaded MIMO systems.

A. Slab-Sphere Decoding [1]

In the same way as sphere decoding, slab-sphere decoding finds all $\mathbf{s}$ satisfying

$$\|\mathbf{y} - \mathbf{H}\mathbf{s}\|^2 \leq C^2, \tag{5}$$

where C is a constant. By using QR decomposition of $\mathbf{H}$, i.e., $\mathbf{H} = \mathbf{Q}\mathbf{R}$, (5) can be rewritten as

$$\|\mathbf{z} - \mathbf{R}\mathbf{s}\|^2 \leq C^2, \tag{6}$$

where $\mathbf{z} = \mathbf{Q}^T\mathbf{y}$. Since $M < N$, (6) can be written as

$$\left\| \begin{bmatrix} z_1 \\ \vdots \\ z_M \end{bmatrix} - \begin{bmatrix} r_{1,1} & \cdots & r_{1,M} & \cdots & r_{1,N} \\ 0 & \ddots & \vdots & \ldots & \vdots \\ 0 & 0 & r_{M,M} & \cdots & r_{M,N} \end{bmatrix} \begin{bmatrix} s_1 \\ \vdots \\ s_M \\ \vdots \\ s_N \end{bmatrix} \right\|^2 \leq C^2, \tag{7}$$

where z_i and $r_{i,j}$ represent the i-th element of $\mathbf{z}$ and element (i,j) of $\mathbf{R}$, respectively ($i = 1, \ldots, M$ and $j = 1, \ldots, N$). To find all $s_1, \ldots, s_N$ satisfying (7), we firstly focus on the M-th row of $\mathbf{z} - \mathbf{R}\mathbf{s}$ and find all $s_M, \ldots, s_N$ satisfying

$$|z_M - (r_{M,M}s_M + \cdots + r_{M,N}s_N)|^2 \leq C^2 \tag{8}$$

by slab decoding algorithm [1]. Once $s_M, \ldots, s_N$ are obtained,

$$\left\| \begin{bmatrix} w_1 \\ \vdots \\ w_{M-1} \end{bmatrix} - \begin{bmatrix} r_{1,1} & \cdots & r_{1,M-1} \\ 0 & \ddots & \vdots \\ 0 & 0 & r_{M-1,M-1} \end{bmatrix} \begin{bmatrix} s_1 \\ \vdots \\ s_{M-1} \end{bmatrix} \right\|^2 \leq C^2 - \|z_M - (r_{M,M}s_M + \cdots + r_{M,N}s_N)\|^2 \tag{9}$$

becomes the inequality for $s_1, \ldots, s_{M-1}$, where $w_i = z_i - (r_{i,M}s_M + \cdots + r_{i,N}s_N)$ ($i = 1, \ldots, M-1$). Therefore candidates of $s_1, \ldots, s_{M-1}$ for each candidate of $s_M, \ldots, s_N$ can be obtained by sphere decoding. Finally we select $\mathbf{s}$ minimizing $\|\mathbf{y} - \mathbf{H}\mathbf{s}\|^2$ over the candidate signals.

B. Lattice Reduction aided MMSE-SIC Detection with PVC [2]

Lattice reduction aided MMSE-SIC detection with PVC determines each post-voting vector corresponding to each possible pre-voting vector by lattice reduction aided MMSE-SIC detection [8]. In the signal detection with PVC, we divide the index set $\{1, \ldots, n\}$ into $\mathcal{P} = \{p_1, \ldots, p_{n-m}\} \subset \{1, \ldots, n\}$ and $\mathcal{Q} = \{q_1, \ldots, q_m\} = \{1, \ldots, n\} \setminus \mathcal{P}$. In addition, we divide the transmitted signal vector $\tilde{\mathbf{s}}$ into $\tilde{\mathbf{s}}_{\mathcal{P}} = [\tilde{s}_{p_1}, \ldots, \tilde{s}_{p_{n-m}}]^T$(pre-voting vector) and $\tilde{\mathbf{s}}_{\mathcal{Q}} = [\tilde{s}_{q_1}, \ldots, \tilde{s}_{q_m}]^T$(post-voting vector). Similarly, channel matrix

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$\tilde{\mathbf{H}} = [\tilde{\mathbf{h}}_1, \ldots, \tilde{\mathbf{h}}_n]$ is divided into $\tilde{\mathbf{H}}_{\mathcal{P}} = [\tilde{\mathbf{h}}_{p_1}, \ldots, \tilde{\mathbf{h}}_{p_{n-m}}]$ and $\tilde{\mathbf{H}}_{\mathcal{Q}} = [\tilde{\mathbf{h}}_{q_1}, \ldots, \tilde{\mathbf{h}}_{q_m}]$, where $\tilde{\mathbf{h}}_j$ denotes the j-th column vector of $\tilde{\mathbf{H}}$ $(j = 1, \ldots, n)$. By the above splitting, (1) can be rewritten as

$$\tilde{\mathbf{y}} = \tilde{\mathbf{H}}_{\mathcal{P}}\tilde{\mathbf{s}}_{\mathcal{P}} + \tilde{\mathbf{H}}_{\mathcal{Q}}\tilde{\mathbf{s}}_{\mathcal{Q}} + \tilde{\mathbf{v}}. \quad (10)$$

Moreover, we can obtain the real model equivalent to (10)

$$\mathbf{y} = \mathbf{H}_{\mathcal{P}}\mathbf{s}_{\mathcal{P}} + \mathbf{H}_{\mathcal{Q}}\mathbf{s}_{\mathcal{Q}} + \mathbf{v}, \quad (11)$$

where

$$\mathbf{H}_{\mathcal{P}} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{H}}_{\mathcal{P}}\} & -\mathrm{Im}\{\tilde{\mathbf{H}}_{\mathcal{P}}\} \\ \mathrm{Im}\{\tilde{\mathbf{H}}_{\mathcal{P}}\} & \mathrm{Re}\{\tilde{\mathbf{H}}_{\mathcal{P}}\} \end{bmatrix}, \mathbf{s}_{\mathcal{P}} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{s}}_{\mathcal{P}}\} \\ \mathrm{Im}\{\tilde{\mathbf{s}}_{\mathcal{P}}\} \end{bmatrix},$$
$$\mathbf{H}_{\mathcal{Q}} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{H}}_{\mathcal{Q}}\} & -\mathrm{Im}\{\tilde{\mathbf{H}}_{\mathcal{Q}}\} \\ \mathrm{Im}\{\tilde{\mathbf{H}}_{\mathcal{Q}}\} & \mathrm{Re}\{\tilde{\mathbf{H}}_{\mathcal{Q}}\} \end{bmatrix}, \mathbf{s}_{\mathcal{Q}} = \begin{bmatrix} \mathrm{Re}\{\tilde{\mathbf{s}}_{\mathcal{Q}}\} \\ \mathrm{Im}\{\tilde{\mathbf{s}}_{\mathcal{Q}}\} \end{bmatrix}. \quad (12)$$

The signal detection with PVC determines signals based on (11). Let $\mathbf{s}_{\mathcal{P}}^1, \ldots, \mathbf{s}_{\mathcal{P}}^K$ be all possible candidates of $\mathbf{s}_{\mathcal{P}}$, where $K = |\mathcal{S}|^{N-M}$ and $|\mathcal{S}|$ is the number of elements in $\mathcal{S}$. Assuming $\mathbf{s}_{\mathcal{P}} = \mathbf{s}_{\mathcal{P}}^k$ $(k = 1, \ldots, K)$,

$$\mathbf{r}^k = \mathbf{H}_{\mathcal{Q}}\mathbf{s}_{\mathcal{Q}} + \mathbf{v} \quad (13)$$

can be obtained from (11), where $\mathbf{r}^k = \mathbf{y} - \mathbf{H}_{\mathcal{P}}\mathbf{s}_{\mathcal{P}}^k$. Since $\mathbf{H}_{\mathcal{Q}}$ is $M \times M$ square matrix, (13) can be regarded as the model of MIMO systems where the number of receive antennas is equal to that of transmit antennas. Therefore, $\mathbf{s}_{\mathcal{Q}}^k$, the estimate of $\mathbf{s}_{\mathcal{Q}}$ can be obtained by applying lattice reduction aided MMSE-SIC detection to (13). We calculate $\mathbf{s}_{\mathcal{P}}^k$ and $\mathbf{s}_{\mathcal{Q}}^k$ for all $k = 1, \ldots, K$ in this way and get

$$\hat{k} = \underset{k \in \{1,\ldots,K\}}{\arg\min} \|\mathbf{y} - \mathbf{H}_{\mathcal{P}}\mathbf{s}_{\mathcal{P}}^k - \mathbf{H}_{\mathcal{Q}}\mathbf{s}_{\mathcal{Q}}^k\|^2. \quad (14)$$

$\mathbf{s}_{\mathcal{P}}^{\hat{k}}$ and $\mathbf{s}_{\mathcal{Q}}^{\hat{k}}$ are the estimated values of $\mathbf{s}_{\mathcal{P}}$ and $\mathbf{s}_{\mathcal{Q}}$.

Note that $\mathcal{P}$ and $\mathcal{Q}$ are determined as follows in [2]. MD (Max-min Diagonal) criterion [9]

$$\mathcal{Q}_{\mathrm{MD}} = \arg\max_{\mathcal{Q}} \left\{ \min_{i \in \{1,\ldots,M\}} \left| r_{i,i}^{\mathcal{Q}} \right|^2 \right\} \quad (15)$$

is used to get a better performance of lattice reduction aided MMSE-SIC detection, where $r_{i,i}^{\mathcal{Q}}$ denotes the element (i, i) of the upper triangular matrix by QR decomposition of the matrix obtained by applying lattice reduction to $[\mathbf{H}_{\mathcal{Q}}^T \ (\sigma_v/\sigma_s)\mathbf{I}_M]^T$.

IV. Proposed Signal Detection Scheme

Since lattice reduction aided MMSE-SIC detection with PVC searches all pre-voting vectors $\mathbf{s}_{\mathcal{P}}$, the complexity increases exponentially with $n - m$, namely the difference between the number of transmit antennas and receive antennas. The proposed scheme reduces the required complexity by reducing the candidates of $\mathbf{s}_{\mathcal{P}}$ by slab decoding.

Firstly, sets $\mathcal{P}, \mathcal{Q}$ are determined by MD criterion (15) as in the case with lattice reduction aided MMSE-SIC detection with PVC.

Secondly, we obtain the candidates of pre-voting vector $\mathbf{s}_{\mathcal{P}}$ by slab decoding. To implement slab decoding algorithm, we consider the model

$$\mathbf{y} = \bar{\mathbf{H}}\bar{\mathbf{s}} + \mathbf{v}, \quad (16)$$

where $\bar{\mathbf{H}} = [\mathbf{H}_{\mathcal{Q}} \ \mathbf{H}_{\mathcal{P}}]$ and

$$\bar{\mathbf{s}} = \begin{bmatrix} \bar{s}_1 \\ \vdots \\ \bar{s}_M \\ \hline \bar{s}_{M+1} \\ \vdots \\ \bar{s}_N \end{bmatrix} = \begin{bmatrix} \mathbf{s}_{\mathcal{Q}} \\ \hline \mathbf{s}_{\mathcal{P}} \end{bmatrix}. \quad (17)$$

By using QR decomposition $\bar{\mathbf{H}} = \bar{\mathbf{Q}}\bar{\mathbf{R}}$, we can rewrite (16) as

$$\bar{\mathbf{z}} = \bar{\mathbf{R}}\bar{\mathbf{s}} + \bar{\boldsymbol{\eta}}, \quad (18)$$

where $\bar{\mathbf{z}} = \bar{\mathbf{Q}}^T\mathbf{y}, \bar{\boldsymbol{\eta}} = \bar{\mathbf{Q}}^T\mathbf{v}$. The M-th row of (18) can be written as

$$\bar{z}_M = \bar{r}_{M,M}\bar{s}_M + \cdots + \bar{r}_{M,N}\bar{s}_N + \bar{\eta}_M. \quad (19)$$

Therefore, the absolute value of $\bar{z}_M - (\bar{r}_{M,M}\bar{s}_M + \cdots + \bar{r}_{M,N}\bar{s}_N)$ corresponding to the true transmitted signals of $\bar{s}_M, \ldots, \bar{s}_N$ tends to be smaller than that for the other values of $\bar{s}_M, \ldots, \bar{s}_N$. Thus, by slab decoding we find all $\bar{s}_M, \bar{s}_{M+1}, \ldots, \bar{s}_N$ satisfying

$$|\bar{z}_M - (\bar{r}_{M,M}\bar{s}_M + \cdots + \bar{r}_{M,N}\bar{s}_N)|^2 \leq C, \quad (20)$$

where C is a constant. Here, it should be noted that, since $\mathbf{s}_{\mathcal{P}} = [\bar{s}_{M+1}, \cdots, \bar{s}_N]^T$, slab decoding gives the candidates for not only $\mathbf{s}_{\mathcal{P}}$ but also $\bar{s}_M$. However, we utilize the candidates of $\mathbf{s}_{\mathcal{P}}$ only, and $\bar{s}_M$ will be detected as one of the elements of the post-voting vector using lattice reduction aided MMSE-SIC later. Let L denote the number of candidates of $\mathbf{s}_{\mathcal{P}}$ obtained by slab decoding, and we define the candidates as $\mathbf{s}_{\mathcal{P}}^1, \ldots, \mathbf{s}_{\mathcal{P}}^L$.

Next, we obtain the post-voting vectors $\mathbf{s}_{\mathcal{Q}}^1, \ldots, \mathbf{s}_{\mathcal{Q}}^L$ corresponding to $\mathbf{s}_{\mathcal{P}}^1, \ldots, \mathbf{s}_{\mathcal{P}}^L$ by lattice reduction aided MMSE-SIC detection. Assuming $\mathbf{s}_{\mathcal{P}} = \mathbf{s}_{\mathcal{P}}^\ell$ $(\ell = 1, \ldots, L)$, (11) can be rewritten as

$$\mathbf{r}^\ell = \mathbf{H}_{\mathcal{Q}}\mathbf{s}_{\mathcal{Q}} + \mathbf{v}, \quad (21)$$

where $\mathbf{r}^\ell = \mathbf{y} - \mathbf{H}_{\mathcal{P}}\mathbf{s}_{\mathcal{P}}^\ell$. By applying lattice reduction aided MMSE-SIC detection to (21), we obtain $\mathbf{s}_{\mathcal{Q}}^\ell$ corresponding to $\mathbf{s}_{\mathcal{P}}^\ell$. Firstly, we get the model equivalent to (21)

$$\hat{\mathbf{r}}^\ell = \hat{\mathbf{H}}_{\mathcal{Q}}\mathbf{s}_{\mathcal{Q}} + \hat{\mathbf{v}}_{\mathcal{Q}}, \quad (22)$$

where

$$\hat{\mathbf{r}}^\ell = \begin{bmatrix} \mathbf{r}^\ell \\ \mathbf{0}_M \end{bmatrix}, \hat{\mathbf{H}}_{\mathcal{Q}} = \begin{bmatrix} \mathbf{H}_{\mathcal{Q}} \\ \frac{\sigma_v}{\sigma_s}\mathbf{I}_M \end{bmatrix}, \hat{\mathbf{v}}_{\mathcal{Q}} = \begin{bmatrix} \mathbf{v} \\ -\frac{\sigma_v}{\sigma_s}\mathbf{s}_{\mathcal{Q}} \end{bmatrix}. \quad (23)$$

Secondly, we obtain the unimodular matrix $\mathbf{T}_{\mathcal{Q}}$ satisfying $\hat{\mathbf{H}}'_{\mathcal{Q}} = \hat{\mathbf{H}}_{\mathcal{Q}}\mathbf{T}_{\mathcal{Q}}$ by applying lattice reduction to $\hat{\mathbf{H}}_{\mathcal{Q}}$. Eq. (22) can be rewritten as

$$\hat{\mathbf{r}}^\ell = \hat{\mathbf{H}}'_{\mathcal{Q}}\mathbf{s}'_{\mathcal{Q}} + \hat{\mathbf{v}}_{\mathcal{Q}}, \quad (24)$$

where $\mathbf{s}'_{\mathcal{Q}} = \mathbf{T}_{\mathcal{Q}}^{-1}\mathbf{s}_{\mathcal{Q}}$. By using QR decomposition $\hat{\mathbf{H}}'_{\mathcal{Q}} = \hat{\mathbf{Q}}'\hat{\mathbf{R}}'$, (24) can be rewritten as

$$\hat{\mathbf{z}}^\ell = \hat{\mathbf{R}}'\mathbf{s}'_{\mathcal{Q}} + \hat{\boldsymbol{\eta}}_{\mathcal{Q}}, \quad (25)$$

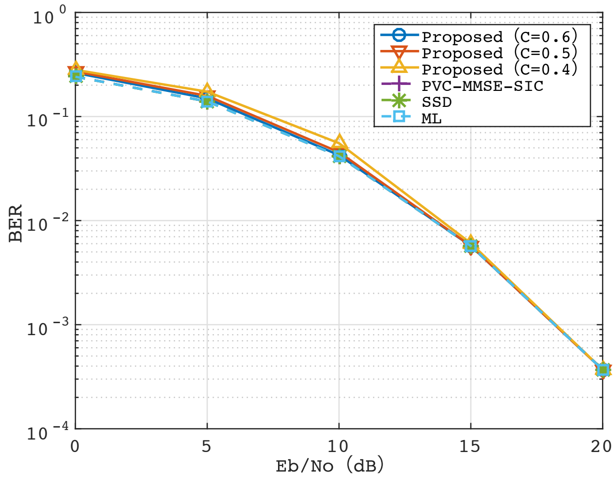

Fig. 2. BER performance ($n = 4, m = 2$, QPSK)

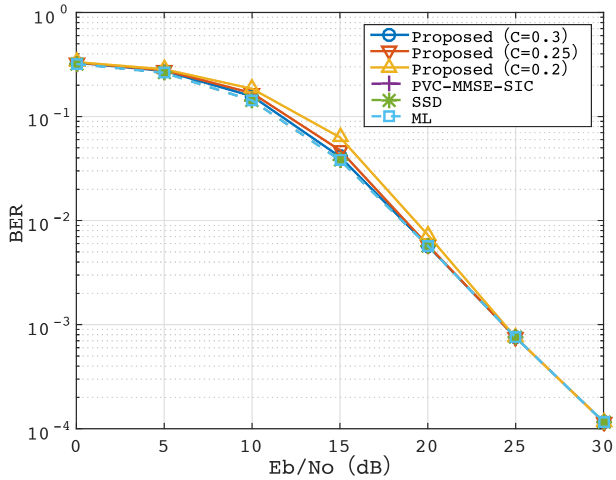

Fig. 3. BER performance ($n = 6, m = 2$, QPSK)

where $\hat{\mathbf{z}}^\ell = (\hat{\mathbf{Q}}')^T \hat{\mathbf{r}}^\ell, \hat{\boldsymbol{\eta}}_\mathcal{Q} = (\hat{\mathbf{Q}}')^T \hat{\mathbf{v}}_\mathcal{Q}$

When applying MMSE-SIC detection to (25), we cannot obtain the estimate of $\mathbf{s}'_\mathcal{Q}$ by an unconstrained quantization because the true value of $\mathbf{s}'_\mathcal{Q}$ depends on $\mathbf{T}_\mathcal{Q}$ and $\mathbf{H}$. Then as in [10], we translate the model so that each element of the transmitted signal vector is an integer. For example, when $\mathcal{S} = \{1/2, -1/2\}$, we consider

$$\mathbf{s}_{\mathcal{Q},\mathbb{Z}} = \mathbf{s}_\mathcal{Q} + \begin{bmatrix} \frac{1}{2} \\ \vdots \\ \frac{1}{2} \end{bmatrix} \in \mathbb{Z}^{N-M} \tag{26}$$

and rewrite (25) as

$$\hat{\mathbf{z}}^\ell = \hat{\mathbf{R}}' \left(\mathbf{s}'_{\mathcal{Q},\mathbb{Z}} - \mathbf{T}_\mathcal{Q}^{-1} \begin{bmatrix} \frac{1}{2} \\ \vdots \\ \frac{1}{2} \end{bmatrix} \right) + \hat{\boldsymbol{\eta}}_\mathcal{Q}, \tag{27}$$

namely

$$\hat{\mathbf{z}}^\ell + \hat{\mathbf{R}}' \mathbf{T}_\mathcal{Q}^{-1} \begin{bmatrix} \frac{1}{2} \\ \vdots \\ \frac{1}{2} \end{bmatrix} = \hat{\mathbf{R}}' \mathbf{s}'_{\mathcal{Q},\mathbb{Z}} + \hat{\boldsymbol{\eta}}_\mathcal{Q}, \tag{28}$$

where $\mathbf{s}'_{\mathcal{Q},\mathbb{Z}} = \mathbf{T}_\mathcal{Q}^{-1} \mathbf{s}_{\mathcal{Q},\mathbb{Z}}$. $\mathbf{s}'_{\mathcal{Q},\mathbb{Z}}$ is an integer vector regardless of the value of $\mathbf{H}$ because $\mathbf{T}_\mathcal{Q}$ is a unimodular matrix and $\mathbf{s}_{\mathcal{Q},\mathbb{Z}}$ is a integer vector. Therefore we can obtain the estimate of $\mathbf{s}'_{\mathcal{Q},\mathbb{Z}}$ by a unconstrained quantization. $\mathbf{s}^\ell_\mathcal{Q}$ can be obtained by using (26) and $\mathbf{s}'_{\mathcal{Q},\mathbb{Z}} = \mathbf{T}_\mathcal{Q}^{-1} \mathbf{s}_{\mathcal{Q},\mathbb{Z}}$.

Finally, we select the best candidate in terms of likelihood as the detected signal. We obtain

$$\hat{\ell} = \underset{\ell \in \{1,\ldots,L\}}{\arg\min} \|\mathbf{y} - \mathbf{H}_\mathcal{P} \mathbf{s}^\ell_\mathcal{P} - \mathbf{H}_\mathcal{Q} \mathbf{s}^\ell_\mathcal{Q}\|^2 \tag{29}$$

and select $\mathbf{s}^{\hat{\ell}}_\mathcal{P}$ and $\mathbf{s}^{\hat{\ell}}_\mathcal{Q}$ as the estimates of $\mathbf{s}_\mathcal{P}$ and $\mathbf{s}_\mathcal{Q}$, respectively.

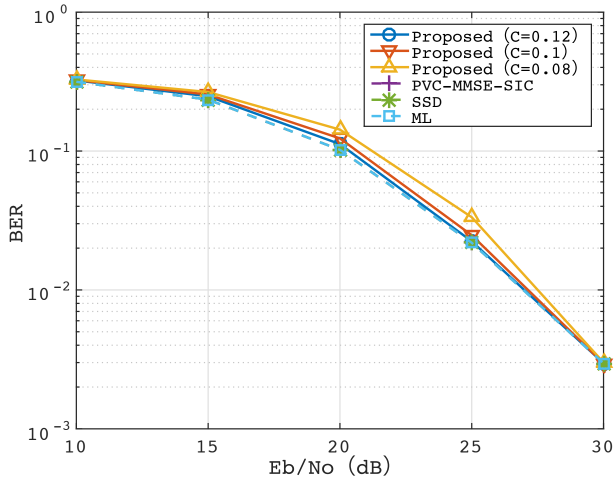

Fig. 4. BER performance ($n = 4, m = 2$, 16-QAM)

V. Simulation Results

In this section, we evaluate the BER performance of the proposed scheme as well as the number of possible solution candidates obtained by slab decoding in the proposed scheme to give an idea of the complexity reduction achieved by the proposed scheme. $\tilde{\mathbf{H}}$ is time-invariant and composed by i.i.d. complex Gaussian random variables with zero mean and unit variance. The BER performance is averaged over a thousand transmit transmitted signal vectors, each passing through a hundred independent channel realizations $\tilde{\mathbf{H}}$. As the algorithm for lattice reduction, LLL (Lenstra-Lenstra-Lovász) algorithm [11] is used in the same way as in [8].

Figures 2, 3, and 4 show the BER performance of the proposed scheme with different values of C 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 optimal ML detection (ML), the conventional

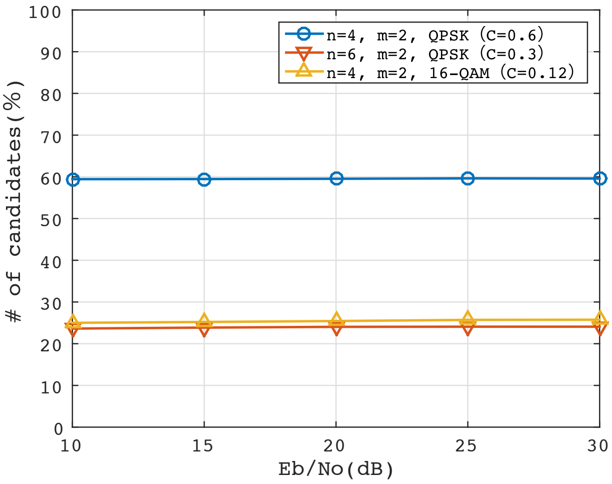

Fig. 5. Number of candidates (%)

lattice reduction aided MMSE-SIC detection (PVC-MMSE-SIC), and slab-sphere decoding (SSD) are also plotted in the same figures. In all the figures, we can see that the conventional lattice reduction aided MMSE-SIC detection almost achieves the same BER performance as the optimal ML detection. It should be noted here that the proposed scheme with rather small values of C also can achieve a similar BER performance as the optimal ML detection in all the three figures, while the proposed scheme with a large value of C results in exactly the same scheme as the conventional lattice reduction aided MMSE-SIC.

Next, Fig. 5 plots the amount $L/|\mathcal{S}|^{N-M}$ in percentage, where L denotes the number of candidates of $\mathbf{s}_{\mathcal{P}}$ obtained by slab decoding in the proposed scheme, and $|\mathcal{S}|^{N-M}$ represents that in the conventional scheme with PVC. We observe that the larger the difference $n-m$ and the higher the modulation level, the more effective the proposed scheme, as it enables a larger reduction of the number of candidates. In fact, the larger $n-m$ and the modulation level, the higher the ratio of erroneous vector elements and hence of candidate vectors for $\mathbf{s}_{\mathcal{P}}$ that can be eliminated. By reducing the candidates for $\mathbf{s}_{\mathcal{P}}$, the required calculation of lattice reduction aided MMSE-SIC detection for $\mathbf{s}_{\mathcal{Q}}$ is also reduced. Therefore, the proposed scheme is able to reduce the computational complexity as compared to the conventional schemes, while achieving a performance close to optimal.

VI. Conclusion

In this paper, we have proposed the reduced complexity signal detection scheme for overloaded MIMO systems. While the conventional scheme with PVC searches over all pre-voting vectors, the proposed scheme reduces their number by making use of slab decoding. Simulation results have shown that the proposed scheme achieves a BER performance that is close to optimal while largely reducing the required computational complexity.

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