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THE IC-BASED DETECTION ALGORITHM IN THE UPLINK LARGE-SCALE MIMO SYSTEM

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Abstract. *Based on the fact that the linear detector (LD) is easy to implement and it can collect good diversity in the uplink large-scale multiple-input multiple-output (LS-MIMO) system, the existing detection algorithms aim to find iteration ways to approximate the inverse operation in the LD whose complexity is high. In this letter, we propose the interference cancellation (IC) based detection algorithm in the uplink LS-MIMO system. Different from the existing detection algorithms in the uplink LS-MIMO system, the IC scheme is firstly utilized, and it can provide better bit error rate (BER) performance than the linear detector. Moreover, as we divide the channel matrix into two subspaces in our algorithm, the computational complexity of our detection algorithm will be smaller than the existing detection algorithms.*

Keywords: Uplink large-scale MIMO system, Signal detection, Interference cancellation, Subspace

1. **Introduction.** It is a trend to use large number of antennas to develop high spectral efficiency and energy efficiency. It has been shown that it can provide potential opportunity to increase the spectrum and energy efficiency by using a very large number of antennas [1, 2, 3]. However, with the increasing number of antennas, one challenging problem in the large-scale MIMO system is the complex detection algorithm [4].

In the uplink LS-MIMO system, most detection algorithms in the small-scale MIMO systems will become too complex [5], and they are not applicable, e.g., the sphere decoding [6, 7] can provide efficient BER performance while it has exponential complexity. Recently, the minimum mean square error (MMSE) linear detector is shown to achieve high BER performance; however, the cubic complexity of the linear MMSE detector is still high in the LS-MIMO system. To avoid the inverse operation, some iteration methods were used to approximate the inverse operation. The Newmann serious iteration [8] is firstly applied in this situation. It converts the matrix inversion into a series of matrix-vector multiplications. However, only marginal reduction in complexity can be achieved. Then the successive over-relaxation (SOR) iteration method [9, 10] is used to improve the performance. Both the experiments and the theoretical analysis show that the SOR method can reduce the complexity in one magnitude while it has similar BER performance as the linear MMSE detector.

In this paper, we propose a novel detection algorithm in the uplink LS-MIMO system. We first partition the model into two parts, and then we iteratively detect the two parts of the symbol. It has been shown that the computational complexity relies on the size of the detection symbol, and then dividing into two parts is beneficial to the computational complexity. In the detection algorithm, the IC scheme is utilized to improve the BER performance of our algorithm. The IC scheme can reduce the undesired interference and it is an effective way to improve the system performance [11]. The simulation results show that the IC-based detection algorithm can exhibit smaller BER performance and smaller computational complexity than the previous algorithm.

The rest of this paper is organized as follows. Section 2 gives the description of uplink LS-MIMO system and introduces the iterative detection algorithm briefly. In Section 3, the IC-based detection algorithm is developed to improve the performance of the detection in the uplink LS-MIMO system. In Section 4, the simulation results are provided. Finally, the concluding remark is given in Section 5.

2. **Preliminaries.** Consider an uplink LS-MIMO system employing N antennas at the base station (BS) and it simultaneously serves K single antenna UEs [1, 12]. Usually the number of transmit antennas is much smaller than the number of the receive antennas, e.g., $N = 128$ and $K = 16$ have been considered in [12]. The system model is represented as

$$\mathbf{r}^c = \mathbf{H}^c\mathbf{s}^c + \mathbf{w}^c, \tag{1}$$

where $\mathbf{r}^c \in \mathbb{C}^N$ is the received complex signal, and $\mathbf{H}^c \in \mathbb{C}^{N\times K}$ is the channel matrix. The entries of $\mathbf{H}^c$ are represented as independent and identically distributed complex Gaussian variables which are drawn from $\mathcal{CN}(0,1)$. $\mathbf{s}^c \in \mathbb{C}^K$ is the transmitted signal, which is drawn from the MQAM (quadrature amplitude modulation with M being the constellation size) constellation. The real and imaginary parts of $\mathbf{s}^c$ are drawn from the set Φ, where $\Phi = \left\{2m+1-\sqrt{M}, m = 0, 1, \ldots, \sqrt{M}-1\right\}$. $\mathbf{w}^c \in \mathbb{C}^N$ is the Gaussian noise with zero mean and covariance matrix $\sigma^2\mathbf{I}$.

In (1), the signal-to-noise ratio (SNR) is defined as [1]

$$SNR = \frac{K\sigma^2_{\mathbf{s}^c}}{\sigma^2_{\mathbf{w}^c}} = \frac{2K(M-1)}{3\sigma^2},$$

where $\sigma^2_{\mathbf{s}^c}$ and $\sigma^2_{\mathbf{w}^c}$ are the power of the transmitted signal $\mathbf{s}^c$ and the noise $\mathbf{w}^c$.

In fact, (1) can be converted to the following real model [13]

$$\mathbf{r} = \mathbf{H}\mathbf{s} + \mathbf{w}, \tag{2}$$

where $\mathbf{r} = \left[\Re(\mathbf{r}^c)^T, \Im(\mathbf{r}^c)^T\right]^T$, $\mathbf{s} = \left[\Re(\mathbf{s}^c)^T, \Im(\mathbf{s}^c)^T\right]^T$, $\mathbf{w} = \left[\Re(\mathbf{w}^c)^T, \Im(\mathbf{w}^c)^T\right]^T$ and

$$\mathbf{H} = \begin{pmatrix} \Re(\mathbf{H}^c) & -\Im(\mathbf{H}^c) \\ \Im(\mathbf{H}^c) & \Re(\mathbf{H}^c) \end{pmatrix}.$$

Then we can show that $\mathbf{r} \in \mathbb{R}^{2N}$, $\mathbf{w} \in \mathbb{R}^{2N}$, $\mathbf{s} \in \mathbb{R}^{2K}$ and $\mathbf{H} \in \mathbb{R}^{2N\times 2K}$.

It has been shown that the MMSE LD has good performance in the uplink LS-MIMO systems [9, 10], and the estimation is represented as

$$\hat{\mathbf{s}} = \left(\mathbf{H}^T\mathbf{H} + \frac{1}{\rho}\mathbf{I}\right)^{-1}\mathbf{H}^T\mathbf{r} = \mathbf{W}\mathbf{b}, \tag{3}$$

where $\rho = \sigma^2_{\mathbf{s}^c}/\sigma^2_{\mathbf{w}^c} = \frac{2(M-1)}{3\sigma^2}$, $\mathbf{W} = \left(\mathbf{H}^T\mathbf{H} + \frac{1}{\rho}\mathbf{I}\right)^{-1}$ and $\mathbf{b} = \mathbf{H}^T\mathbf{r}$. As the transmitted signal is drawn from the QAM (quadrature amplitude modulation) constellation, then we need to quantize $\hat{\mathbf{s}}$ into the constellation Φ as $Q(\hat{\mathbf{s}})$ finally.

As calculating the inverse of $\mathbf{H}^T\mathbf{H} + \frac{1}{\rho}\mathbf{I}$ in (3) is computationally complicated, then the iterative methods are applied to alleviating the high complexity of the inverse operation in

(3). Recently, the SOR algorithm, one efficient iterative method, is used to approximate the inverse, and it can represent good performance in detection in uplink LS-MIMO systems. We will show the process of the SOR method below.

As $\mathbf{W}$ is symmetric, then the SOR algorithm writes

$$\mathbf{W} = \mathbf{D} + \mathbf{L} + \mathbf{L}^T, \tag{4}$$

where $\mathbf{D}$ is the diagonal of $\mathbf{W}$, and $\mathbf{L}$ is strictly lower triangular part of $\mathbf{W}$. In the $j+1$th iteration of the SOR detection algorithm, the detected symbol is calculated as

$$\hat{\mathbf{s}}^{(j+1)} = \left(\mathbf{L} + \frac{1}{\omega}\mathbf{D}\right)^{-1} \left[\left(\frac{1}{\omega} - 1\right)\mathbf{D} - \mathbf{L}^T\hat{\mathbf{s}}^{(j)} + \mathbf{b}\right], \tag{5}$$

where $\hat{\mathbf{s}}^{(0)}$ is obtained by the matched filter (MF) detector. In general ω is set to be 1, and we choose $\omega = 1$ in the following.

Taking the characterizes of the $\mathbf{D}$ and $\mathbf{L}$ into consideration, then from (5), the lth component of the symbol $\mathbf{s}$ can be calculated as [10]

$$\hat{s}_l^{(j+1)} = \frac{1}{W_{l,l}}\left(b_l - \sum_{k<l} W_{l,k}\hat{s}_k^{(j+1)} - \sum_{k>l} W_{l,k}\hat{s}_k^{(j)}\right), \tag{6}$$

where $W_{l,k}$ is the lth row and kth column element of $\mathbf{W}$, and $\hat{s}_k^{(j)}$ is the kth element of $\hat{\mathbf{s}}^{(j)}$. Using (6), we can find that the computational complexity of the SOR algorithm in each iteration is $O\left(K^2\right)$. Assume that the total number of the iterations is i, and then the complexity will be $O\left(iK^2\right)$. In the next section, we will show one improved detection algorithm based on the IC scheme.

3. The IC-Based Detection Algorithm.

3.1. The description of the IC-based algorithm. First, we divide the channel matrix into two subspaces as follows,

$$\mathbf{r} = [\mathbf{H}_1\ \mathbf{H}_2]\left[\mathbf{s}_1^T\ \mathbf{s}_2^T\right]^T + \mathbf{w} = \mathbf{H}_1\mathbf{s}_1 + \mathbf{H}_2\mathbf{s}_2 + \mathbf{w}, \tag{7}$$

where $\mathbf{H}_1 \in \mathbb{R}^{2N\times n}$, $\mathbf{H}_2 \in \mathbb{R}^{2N\times(2K-n)}$, $\mathbf{s}_1 \in \Omega^n$, and $\mathbf{s}_2 \in \Omega^{2K-n}$ for fixed $n \in 1, \ldots, 2K$.

Then considering (3), we first aim to detect $\mathbf{s}_1$ while regarding $\mathbf{H}_2\mathbf{s}_2 + \mathbf{w}$ as the interference. However, $\mathbf{H}_2\mathbf{s}_2 + \mathbf{w}$ is a Gaussian variable with zero mean and the covariance matrix $\mathbf{H}_2^T\mathbf{H}_2 + \frac{N_0}{2}\mathbf{I}$, and using the exact MMSE equalizer will be computationally complex.

To reduce the complexity, the IC scheme is used here. In order to detect the symbol $\mathbf{s}_1$, we need to get the estimation of $\mathbf{s}_2$. It has been shown that the error propagation is the important factor affecting the IC scheme. If the estimation of the symbol $\mathbf{s}_2$ does not have small error probability, then the IC scheme will not be efficient. Thanks to the characteristics of the uplink LS-MIMO system, the IC scheme performs well. This is because, the MF detector has small error probability in the uplink LS-MIMO system, and the MF detector is very easy to implement. Then considering (1), set $\Delta_{\mathbf{s}_2} = \mathbf{s}_2 - Q\left(\hat{\mathbf{s}}_2^{(0)}\right)$ where $Q(\cdot)$ is the quantization operation and $\hat{\mathbf{s}}_2^{(0)}$ is obtained by $\hat{\mathbf{s}}^{(0)}$ which is defined above, and then we have

$$\mathbf{r} - \mathbf{H}_2 Q\left(\hat{\mathbf{s}}_2^{(0)}\right) = \mathbf{H}_1\mathbf{s}_1 + \mathbf{H}_2\Delta_{\mathbf{s}_2} + \mathbf{w}. \tag{8}$$

Considering (8), if the error probability of $\mathbf{s}_2$ is P_2, then P_2 is small and the power of $\mathbf{H}_2\Delta_{\mathbf{s}_2}$ will be $\mathbb{E}\left(\|\mathbf{H}_2\Delta_{\mathbf{s}_2}\|^2\right) \le P_2\mathbf{Tr}\left(\mathbf{H}_2^T\mathbf{H}_2\right)\max\left(\Delta_{s_2}^2\right)$, where $\mathbb{E}(\cdot)$ denotes the mean, and $\mathbf{Tr}(\cdot)$ denotes the trace of the matrix. As P_2 is small, then the power of the interference $\mathbf{H}_2\Delta_{\mathbf{s}_2}$ is not large when compared with power of the signal $\mathbf{H}_1\mathbf{s}_1$, and the error propagation caused by $\mathbf{H}_2\Delta_{\mathbf{s}_2}$ will be small, and then the IC scheme will perform well. Moreover, as $\mathbf{H}_1 \in \mathbb{R}^{2N\times n}$, then from [14], the MMSE detector will collect the diversity of $2N-n+1$ which is larger than $2N-2K+1$, the diversity of the MMSE LD for (2).

As the estimation error of $\mathbf{s}_2$ is not large, here for simplicity, we assume that there is no error in the estimation of $\mathbf{s}_2$ which means $\Delta_{\mathbf{s}_2}=0$, then using the MMSE LD to (8), we can get the estimation of $\mathbf{s}_1$ as

$$\begin{aligned}\hat{\mathbf{s}}_1^{(1)} &= \left(\mathbf{H}_1^T\mathbf{H}_1 + \frac{1}{\rho}\mathbf{I}\right)^{-1}\mathbf{H}_1^T\left(\mathbf{r} - \mathbf{H}_2 Q\left(\hat{\mathbf{s}}_2^{(0)}\right)\right)\\ &= \left(\mathbf{H}_1^T\mathbf{H}_1 + \frac{1}{\rho}\mathbf{I}\right)^{-1}\left(\mathbf{b}_1 - \mathbf{M}_2 Q\left(\hat{\mathbf{s}}_2^{(0)}\right)\right), \end{aligned}\tag{9}$$

where $\mathbf{b}_1 = \mathbf{H}_1^T\mathbf{r}$ and $\mathbf{M}_2 = \mathbf{H}_1^T\mathbf{H}_2$ can be easily obtained by $\mathbf{b}$ and $\mathbf{W}$ respectively, and $\hat{\mathbf{s}}_2^{(0)}$ can be obtained by $\hat{\mathbf{s}}^{(0)}$. After we get the estimation of $\mathbf{s}_1$, quantize it to the constellation set Φ and substitute it into (2), then we can detect $\mathbf{s}_2$ regarding $\mathbf{s}_1$ as the noise. Note that the estimation error of $\mathbf{s}_1$ is small, then we assume it is detected correctly, and then we can get the estimation of $\mathbf{s}_2$ as

$$\hat{\mathbf{s}}_2^{(1)} = \left(\mathbf{H}_2^T\mathbf{H}_2 + \frac{1}{\rho}\mathbf{I}\right)^{-1}\left(\mathbf{b}_2 - \mathbf{M}_1 Q\left(\hat{\mathbf{s}}_1^{(1)}\right)\right), \tag{10}$$

where $\mathbf{b}_2 = \mathbf{H}_2^T\mathbf{r}$, $\mathbf{M}_1 = \mathbf{H}_2^T\mathbf{H}_1$.

Then we perform the above process iteratively, we can get

$$\hat{\mathbf{s}}_1^{(j+1)} = \left(\mathbf{H}_1^T\mathbf{H}_1 + \frac{1}{\rho}\mathbf{I}\right)^{-1}\left(\mathbf{c}_1 - \mathbf{M}_2\sum_{k=1}^{j}\boldsymbol{\Delta}_2^{(k)}\right), \tag{11}$$

$$\hat{\mathbf{s}}_2^{(j+1)} = \left(\mathbf{H}_2^T\mathbf{H}_2 + \frac{1}{\rho}\mathbf{I}\right)^{-1}\left(\mathbf{c}_2 - \mathbf{M}_1\sum_{k=1}^{j}\boldsymbol{\Delta}_1^{(k)}\right), \tag{12}$$

where $\mathbf{c}_1 = \mathbf{b}_1 - \mathbf{M}_2\hat{\mathbf{s}}_2^{(0)}$, $\mathbf{c}_2 = \mathbf{b}_2 - \mathbf{M}_1\hat{\mathbf{s}}_1^{(1)}$, $\boldsymbol{\Delta}_2^{(j)} = Q\left(\hat{\mathbf{s}}_2^{(j-1)}\right) - Q\left(\hat{\mathbf{s}}_2^{(j-2)}\right)$, $\boldsymbol{\Delta}_1^{(j)} = Q\left(\hat{\mathbf{s}}_1^{(j)}\right) - Q\left(\hat{\mathbf{s}}_1^{(j-1)}\right)$. In fact, many entries in $\boldsymbol{\Delta}_1^{(j)}$ and $\boldsymbol{\Delta}_2^{(j)}$ are zeros, and the complexity of calculating $\mathbf{M}_2\boldsymbol{\Delta}_2^{(k)}$ and $\mathbf{M}_1\boldsymbol{\Delta}_1^{(k)}$ is small. In particular, when j becomes large, $\boldsymbol{\Delta}_2^{(k)}$ and $\boldsymbol{\Delta}_1^{(k)}$ will be zero.

Considering (11) and (12), as the inverse operation is computationally expensive in the LS-MIMO systems, then we use the SOR iteration method to approximate the inverse operation, It has been shown that both of $\mathbf{H}_1^T\mathbf{H}_1 + \frac{1}{\rho}\mathbf{I}$ and $\mathbf{H}_2^T\mathbf{H}_2 + \frac{1}{\rho}\mathbf{I}$ are symmetric positive definite, and it is easy to prove that the SOR method converges to the results in (11) and (12).

Note that in (11) and (12), it needs several SOR iterations to approximate the inverse operation traditionally, and it will be computationally complex. Here we show that if the iteration number is chosen to be 1, the above proposed algorithm also works well. Set $\mathbf{F} = \mathbf{H}_1^T\mathbf{H}_1 + \frac{1}{\rho}\mathbf{I}$, $\mathbf{G} = \mathbf{H}_2^T\mathbf{H}_2 + \frac{1}{\rho}\mathbf{I}$, and write

$$\mathbf{F} = \mathbf{D}_1 + \mathbf{L}_1 + \mathbf{L}_1^T, \quad \mathbf{G} = \mathbf{D}_2 + \mathbf{L}_2 + \mathbf{L}_2^T,$$

where $\mathbf{D}_1$ and $\mathbf{D}_2$ are the diagonal of $\mathbf{F}$ and $\mathbf{G}$ respectively, and $\mathbf{L}_1$ and $\mathbf{L}_2$ are strictly lower triangular parts of $\mathbf{F}$ and $\mathbf{G}$ respectively. Then (11) and (12) can be written as

$$\hat{\mathbf{s}}_1^{(j+1)} = (\mathbf{L}_1 + \mathbf{D}_1)^{-1}\left(-\mathbf{L}_1^T\hat{\mathbf{s}}_1^{(j)} + \mathbf{f}^{(j)}\right), \tag{13}$$

$$\hat{\mathbf{s}}_2^{(j+1)} = (\mathbf{L}_1 + \mathbf{D}_1)^{-1} \left(-\mathbf{L}_2^T \hat{\mathbf{s}}_2^{(j)} + \mathbf{g}^{(j)} \right), \tag{14}$$

where $\mathbf{f}^{(j)} = \mathbf{c}_1 - \mathbf{M}_2 \sum_{k=1}^{j} \boldsymbol{\Delta}_2^{(k)}$ and $\mathbf{g}^{(j)} = \mathbf{c}_1 - \mathbf{M}_1 \sum_{k=1}^{j} \boldsymbol{\Delta}_1^{(k)}$. Then similar to (6), each element of $\hat{\mathbf{s}}_1^{(j+1)}$ and $\hat{\mathbf{s}}_2^{(j+1)}$ can be obtained as

$$\hat{s}_{1,m}^{(j+1)} = \frac{1}{F_{m,m}} \left(f_m - \sum_{k<m} F_{m,k} \hat{s}_{1,m}^{(j+1)} - \sum_{k>m} F_{m,k} \hat{s}_{1,m}^{(j)} \right), \tag{15}$$

$$\hat{s}_{2,m}^{(j+1)} = \frac{1}{G_{m,m}} \left(g_m - \sum_{k<m} G_{m,k} \hat{s}_{2,m}^{(j+1)} - \sum_{k>m} G_{m,k} \hat{s}_{2,m}^{(j)} \right), \tag{16}$$

where $\hat{s}_{1,m}^{(j)}$ and $\hat{s}_{2,m}^{(j)}$ are the mth elements of $\hat{\mathbf{s}}_1^{(j)}$ and $\hat{\mathbf{s}}_2^{(j)}$ respectively.

Note that in the jth iteration of our IC-Based algorithm, $\mathbf{f}^{(j)} = \mathbf{c}_1 - \mathbf{M}_2 \sum_{k=1}^{j} \boldsymbol{\Delta}_2^{(k)}$. Then

$$\begin{aligned} \hat{\mathbf{s}}_1^{(j)} &= (\mathbf{L}_1 + \mathbf{D}_1)^{-1} \left(-\mathbf{L}_1^T \hat{\mathbf{s}}_1^{(j-1)} + \mathbf{f}^{(j-1)} - \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j)} \right) \\ &= \left(- (\mathbf{L}_1 + \mathbf{D}_1)^{-1} \mathbf{L}_1^T \hat{\mathbf{s}}_1^{(j-1)} + (\mathbf{L}_1 + \mathbf{D}_1)^{-1} \mathbf{f}^{(j-1)} \right) \\ &\quad + \left(- (\mathbf{L}_1 + \mathbf{D}_1)^{-1} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j)} \right). \end{aligned} \tag{17}$$

Set $\mathbf{B} = (\mathbf{L}_1 + \mathbf{D}_1)^{-1}$, $\mathbf{C} = - (\mathbf{L}_1 + \mathbf{D}_1)^{-1} \mathbf{L}_1^T$, and we can get

$$\mathbf{s}_1^{(k-1)} = \left(\mathbf{C} \hat{\mathbf{s}}_1^{(k-2)} + \mathbf{B} \mathbf{f}^{(k-2)} \right) - \left(\mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(k-1)} \right) \quad (k \geq 2),$$

and then substituting it into (17), we have

$$\begin{aligned} \hat{\mathbf{s}}_1^{(j)} &= \mathbf{C} \hat{\mathbf{s}}_1^{(j-1)} + \mathbf{B} \mathbf{f}^{(j-1)} - \mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j)} \\ &= \mathbf{C} \left(\left(\mathbf{C} \hat{\mathbf{s}}_1^{(j-2)} + \mathbf{B} \mathbf{f}^{(j-2)} \right) - \left(\mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j-1)} \right) \right) + \mathbf{B} \mathbf{f}^{(j-2)} - \mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j-1)} - \mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j)} \\ &= \left(\mathbf{C}^2 \hat{\mathbf{s}}_1^{(j-2)} + \mathbf{C} \mathbf{B} \mathbf{f}^{(j-2)} + \mathbf{B} \mathbf{f}^{(j-2)} \right) - \left(\mathbf{C} \mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j-1)} + \mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j-1)} \right) - \left(\mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(j)} \right) \\ &= \cdots = \left(\mathbf{C}^j \hat{\mathbf{s}}_1^{(0)} + \sum_{k=1}^{j} \mathbf{C}^{k-1} \mathbf{B} \mathbf{c}_1 \right) - \sum_{i=1}^{j} \left(\sum_{k=i}^{j} \mathbf{C}^{j-k} \mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(i)} \right). \end{aligned} \tag{18}$$

Considering (18), when the number of iterations i is large, the term $\boldsymbol{\Delta}_{i-1}$ will be 0. Moreover, the first term $\left(\mathbf{C}^j \hat{\mathbf{s}}_1^{(0)} + \sum_{k=1}^{j} \mathbf{C}^{k-1} \mathbf{B} \mathbf{c}_1 \right)$ will converge to $\left(\mathbf{H}_1^T \mathbf{H}_1 + \frac{1}{\rho} \mathbf{I} \right)^{-1} \mathbf{c}_1$, the front term $\sum_{k=i}^{j} \mathbf{C}^{j-k} \mathbf{B} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(i)}$ in (18) will converge to $\left(\mathbf{H}_1^T \mathbf{H}_1 + \frac{1}{\rho} \mathbf{I} \right)^{-1} \mathbf{M}_2 \boldsymbol{\Delta}_2^{(i)}$ in (11), and the behind term in both (18) and (11) will be 0. Then (18) will converge to the inverse operations (11). Similarly, $\mathbf{s}_2$ in (16) also will converge to the inverse operation in (11) and (12).

3.2. **The complexity analysis of the IC-based algorithm.** Note that our IC-based algorithm is iterative. In each iteration, we need to use the SOR iteration algorithm to detect the symbols $\mathbf{s}_1$ and $\mathbf{s}_2$ respectively. If the size of the symbol $\mathbf{s}_1$ ($\mathbf{s}_2$) is x, then the computational complexity in each iteration of the SOR method in detecting $\mathbf{s}_1$ ($\mathbf{s}_2$) in (15) or (16) will be x^2+x where the computational complexity is calculated in terms of required number of multiplications [8]. Here as ω in (5) is chosen to be 1, then the complexity is a little different from the complexity when $\omega \neq 1$ which is $x^2 + 2x$. Considering (15) and (16), as the size of $\mathbf{s}_1$ and $\mathbf{s}_2$ is $2K - n$ and n respectively, then the complexity in detecting $\mathbf{s}_1$ and $\mathbf{s}_2$ in each iteration of our algorithm is

$$(2K - n)^2 + (2K - n) + n^2 + n. \tag{19}$$

Moreover, when detecting $\mathbf{s}_1$ and $\mathbf{s}_2$ in each iteration, we need to update the estimation of $\mathbf{s}_2$ and $\mathbf{s}_1$, which should calculate $\mathbf{M}_2\boldsymbol{\Delta}_2^{(k)}$ and $\mathbf{M}_1\boldsymbol{\Delta}_1^{(k)}$ in (11) and (12). This complexity is random. It is uncorrelated with the size n. So to get the smallest computational complexity, we need to minimize (19), and the complexity minimized when $x = K$. Then we set $x = K$ below.

4. **Simulations.** To validate the performance of the proposed IC-based detection algorithm, we provide the BER simulation results compared with the recently proposed SOR algorithm [10] and the MMSE algorithm in this section. The BER performance of the classical MMSE algorithm with exact matrix inversion is shown as the benchmark for comparison. We consider the uplink LS-MIMO systems with $N \times K = 128 \times 16$. The modulation scheme of 16QAM and 64QAM is adopted. The BER is shown as a function of the SNR. Figure 1 compares the proposed IC-based algorithm with the SOR and MMSE algorithms in the 16QAM modulation, while Figure 2 compares these algorithms in the 64QAM modulation. i denotes the iteration number.

From these two figures, we find that the proposed IC-based detection algorithm can exhibit better BER performance than the SOR methods when the iteration number is chosen to be the same in both the 16QAM and 64QAM modulations. Moreover, these two figures can also show that our detection algorithm converges to the BER which is smaller than the MMSE detector, and this is attributed to the IC scheme. While with the increasing of the iteration number i, the previous SOR iteration algorithm converges to the BER of the MMSE detector.

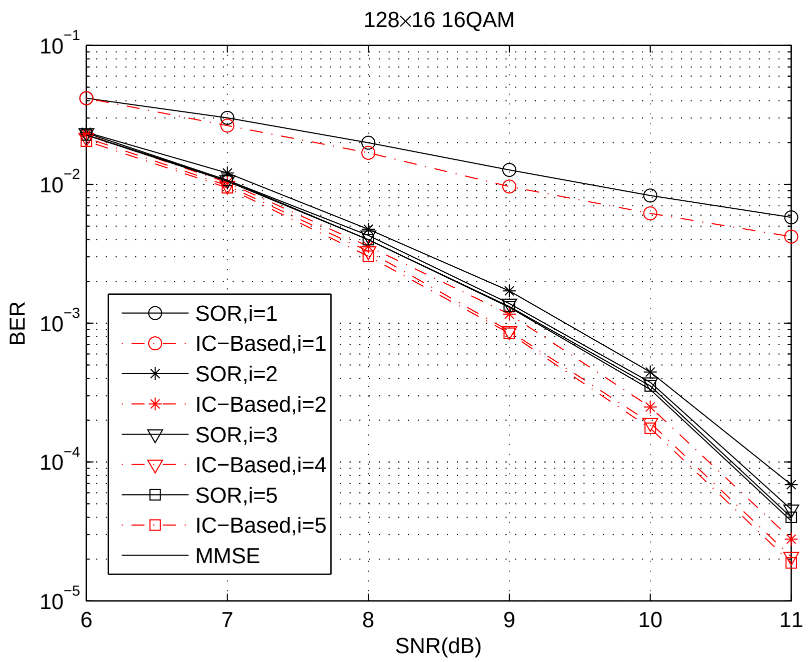

FIGURE 1. The comparison of the BER of different algorithms in 128×16 system with 16QAM

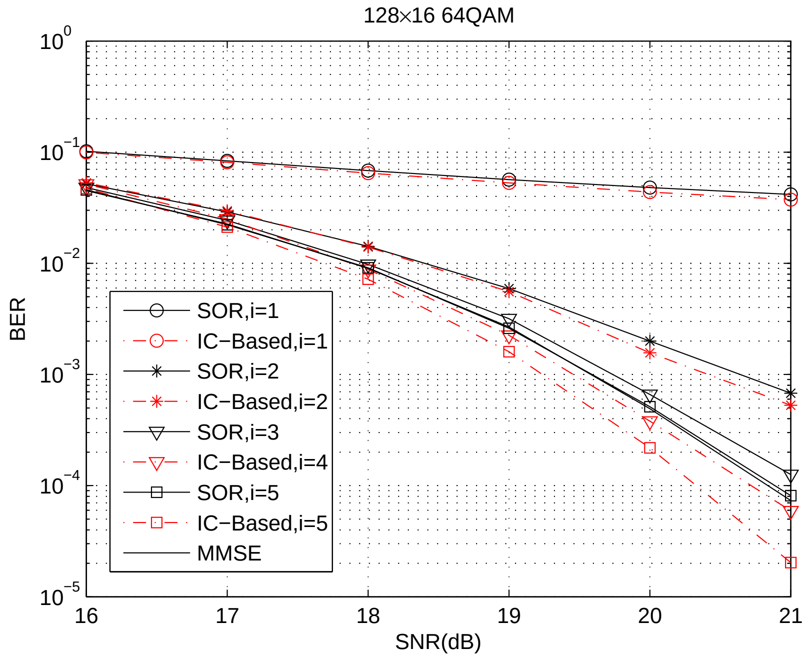

FIGURE 2. The comparison of the BER of different algorithms in 128×16 system with 64QAM

TABLE 1. Computational complexity

	SOR ($\omega = 1$) [10]	IC-Based 16 (64) QAM
$i = 1$	$4K^2 + 2K$	$4(4)K^2 + 2K$
$i = 2$	$8K^2 + 4K$	$6.15(6.52)K^2 + 4K$
$i = 3$	$12K^2 + 6K$	$8.17(8.56)K^2 + 6K$
$i = 4$	$16K^2 + 8K$	$10.18(10.57)K^2 + 8K$
$i = 5$	$20K^2 + 10K$	$12.18(12.57)K^2 + 10K$

Now we analyze the computational complexity below. Note that our IC-based algorithm is iterative. In each iteration, we need to use the SOR iteration algorithm to detect $\mathbf{s}_1$ and $\mathbf{s}_2$ whose sizes are both smaller than the size of the symbol $\mathbf{s}$.

Table 1 compares the complexity of the conventional SOR algorithm [10] with the proposed IC-based detection algorithm in both the 16QAM and 64QAM. As we know, the complexity of the SOR algorithm remains unchanged when the modulation is different. Here as ω in (5) is chosen to be 1, then the complexity of the SOR algorithm is a little different from the complexity when $\omega \neq 1$ which is $4iK^2 + 4iK$ in [10]. However, as the IC-based algorithm needs to update the symbol in each iteration, the complexity is different when the modulation is changed. The complexity of the IC-based algorithm under 16QAM is simulated in 10dB, while the complexity under 64QAM is simulated in 20dB which is shown in the bracket. Note that the complexity of the classical MMSE algorithm is $O(K^3)$, and both the conventional SOR algorithm and our proposed IC-based detection algorithm can reduce the complexity from $O(K^3)$ to $O(K^2)$. From Table 1, we can find that the overall complexity of the IC-based detection algorithm is smaller than the SOR algorithm, which means complexity reduction can be achieved, and it is very attractive in the LS-MIMO systems.

5. **Conclusion.** In this paper, we proposed the IC-based detection algorithm in the uplink LS-MIMO system. The proposed algorithm utilized the interference cancellation scheme which performed well in the uplink LS-MIMO system. In the proposed algorithm, we divided the detection problem into two sub-problems which can help us reduce the complexity. Moreover, the IC scheme was beneficial to the BER performance. The simulation results validated that our proposed detection algorithm can provide better BER performance with smaller complexity when compared with the previous iteration methods. It would be interesting to propose efficient iterative detection algorithms in the downlink LS-MIMO system, which will be studied in our future works.

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