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Approximate maximum a posteriori detection for multiple-input–multiple-output systems with bit-level lattice reduction-aided detectors and successive interference cancellation

Lin Bai[1], Qiaoyu Li[1], Wei Bai[2], Jinho Choi[3]

[1]School of Electronic and Information Engineering, Beihang University, Beijing, People's Republic of China
[2]Department of Electrical and Computer Engineering, University of Maryland, College Park, MA, USA
[3]School of Information and Communications, Gwangju Institute of Science and Technology (GIST), Gwangju, Korea
E-mail: l.bai@buaa.edu.cn

Abstract: For iterative detection and decoding (IDD) in multiple-input–multiple-output (MIMO) systems, although the maximum a posteriori (MAP) detector can achieve an optimal performance, because of its prohibitively high computational complexity, various low-complexity approximate MAP detectors are studied. Among the existing MIMO detectors for the non-IDD receivers, lattice reduction (LR)-aided detectors can provide a near maximum-likelihood (ML) detector's performance with reasonably low complexity, and they could be modified to be used in the IDD receivers. In this study, the authors propose a bit-level LR-aided MIMO detector whose performance can approach that of the MAP detector, where a priori information is taken into account for soft-decisions. Furthermore, the proposed method can be extended to large dimensional MIMO systems by channel matrix decomposition and successive interference cancellation, by which a significant complexity reduction can be achieved. Through simulations and complexity analysis, it is shown that a near-optimal performance is obtained by the authors proposed low-complexity bit-level LR-aided detector for the IDD in the MIMO systems.

1 Introduction

In wireless communications, multiple transmit and receive antennas can be employed, which results in multiple-input–multiple-output (MIMO) systems, to increase the channel capacity linearly with the minimum number of transmit and receive antennas [1, 2]. This results in the data rate that also increases linearly with the number of antennas, which is referred to as spatial multiplexing (SM) gain. To effectively exploit the SM gain in the MIMO systems, the vertical Bell Labs layered space-time (V-BLAST) architectures have been proposed in [3–5]. The maximum-likelihood (ML) detection can offer the best performance with a full receive diversity gain in the V-BLAST. However, because of its high computational complexity when an exhaustive search is used, successive interference cancellation (SIC) that has low complexity is considered for the MIMO detection. The performance of the SIC detection is inferior to that of the ML detection, because a full receive diversity gain cannot be obtained.

To achieve a data rate close to the channel capacity, bit interleaved coded modulation (BICM) [6] can be adopted over the MIMO channels, which results in the MIMO-BICM systems. In the MIMO-BICM systems, coded bit sequences are generated from a channel encoder and split into multiple streams after bit interleaving and transmitted through multiple antennas. Since the conventional V-BLAST receivers [4] assume that the received signals are uncoded signals, the detection performance is not satisfactory for the MIMO-BICM systems as coded systems. With a soft-input–soft-output (SISO) channel decoder, a MIMO detector that can accommodate extrinsic information from a SISO channel decoder would be desirable for iterative detection and decoding (IDD) based on the turbo principle [7]. For the MIMO detection, the maximum a posteriori (MAP) probability detection can be used to generate the log-likelihood ratio (LLR) for each coded bit from the a posteriori probability (APP). However, because of the complexity growing exponentially with the number of transmit antennas, suboptimal but low-complexity approximate MAP detectors would be practical for implementation.

Various approximate MAP detection methods have been studied in [8–23]. In [8–11], list-sphere decoding (LSD) detectors are proposed to provide the LLRs of coded bits by finding candidates for a list via iterative tree search (ITS) techniques. However, the complexity of the LSD varies depending on the channel realisations or the signal-to-noise ratio (SNR), which makes efficient implementations difficult. Suboptimal ITS detectors with fixed complexity have been investigated in [12–16], but their performance is not satisfactory as the search dimension has been reduced during list generation. To avoid random complexity, semi-definite relaxation (SDR) [17] and Monte Carlo Markov chain (MCMC) sampling [18–20] can be considered for the IDD in the MIMO systems, where the SDR has less random complexity, whereas the MCMC has fixed complexity. However, in order to achieve near optimal performance, the average complexity of the SDR and the MCMC could even be higher than that of the LSD approaches.

Approximate MAP detection can also be considered by using parallel soft (interference) cancellation (SC) together with minimum-mean-square error (MMSE) filtering to avoid list generation [21]. Although the MMSE-SC detector has fixed and relatively low complexity, its performance is not close to an ideal one because of the Gaussian approximation for the residual noise and the interference and the detection dimension reduction. To improve the performance of the MMSE-SC detector, various techniques have been considered, for example, applying additional successive processing [22], or exploiting the trade-off between complexity and performance [23].

By obtaining a near orthogonal lattice basis reduced from the original channel matrix with low complexity in the non-IDD MIMO systems, LR-based detectors are proposed [24–26] to improve the performance of the linear and the SIC detectors. Since the diversity order obtained by the LR-based detectors is the same as that obtained by the ML detector [27, 28], the LR-based hard detection provides a near ML performance in the non-IDD uncoded systems. With list generation, two LR-based soft-output detectors are proposed in [29, 30]. Unfortunately, they suffer from high computational complexity for a large number of antennas and severe performance degradation, respectively. In [31], an LR-based detector is first employed for the IDD to provide near MAP performance with reasonable trade-off between performance and complexity, where a fixed-length list of candidates is generated to obtain the soft information of each bit. However, since there is no a priori information (API) taken into account to generate the lists in [31], the performance may not be improved with consecutive iterations. Moreover, as the candidates are not generated in the LR domain in [31], the performance gain provided by the LR cannot be fully exploited.

In this paper, in order to achieve a near optimal performance with reasonable complexity by using LR-aided detection algorithms for the IDD in the MIMO-BICM systems, we propose a bit-level LR-aided approximate MAP detector, where the LR-aided MMSE detectors are derived for each coded bit individually incorporating with the API. A list of candidates is also generated from a hard decision by a bit-level manner to obtain a better soft-decision. To reduce the complexity further in the large dimensional MIMO systems, we then investigate the channel matrix decomposition algorithms to break the MIMO detection problem into several sub-detection problems, where SIC is carried out to reduce the complexity. From the complexity comparison and the simulation results, we can confirm that a near optimal performance can be achieved with reasonable complexity by our proposed LR-aided detectors.

The rest of this paper is organised as follows. In Section 2, we describe the model of the MIMO-BICM system and MAP detection within the IDD. Then, the structure of the LR-aided MIMO detectors for the uncoded systems is briefly reviewed in Section 3. In Section 4, we derive our bit-level LR-aided detection method within the IDD, and extend the proposed approach to large dimensional systems by considering the channel matrix decomposition with the complexity analysis. The simulation results are presented in Sections 5 and 6 concludes the paper.

Notation: Uppercase and lowercase boldface letters are used for the matrices and the vectors, respectively. $\boldsymbol{A}^{\mathrm{T}}$ and $\boldsymbol{A}^{\mathrm{H}}$ denote the transpose and the Hermitian transpose of $\boldsymbol{A}$, respectively. $\boldsymbol{I}$ represents the identity matrix. The statistical expectation is denoted by $\mathbb{E}[\cdot]$ and $\mathrm{Var}(\cdot)$ stands for the variance. $\mathcal{CN}(\boldsymbol{a}, \boldsymbol{R})$ represents the distribution of the circularly symmetric complex Gaussian (CSCG) random vectors with mean vector $\boldsymbol{a}$ and covariance matrix $\boldsymbol{R}$. The covariance matrix of a random vector $\boldsymbol{x}$ is given by

$$\mathbf{Cov}(\boldsymbol{x}) = \mathbb{E}\big[(\boldsymbol{x} - \mathbb{E}[\boldsymbol{x}])(\boldsymbol{x} - \mathbb{E}[\boldsymbol{x}])^{\mathrm{H}}\big]$$

In addition, for a set$\mathcal{S}$, $|\mathcal{S}|$ stands for the cardinality of $\mathcal{S}$.

2 MIMO-BICM systems and MAP detection

In this section, the structures of the MIMO-BICM transmitter and the IDD receiver with MAP detection are presented. Throughout this paper, we assume that the perfect CSI is available at a receiver.

Suppose that a transmitter and a receiver are equipped with N_{t} transmit and N_{r} receive antennas, respectively. Thus, the received signal vector is given by

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{s} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{H}$ and $\boldsymbol{s} = [s_1, s_2, \ldots, s_{N_{\mathrm{t}}}]^{\mathrm{T}}$ are the $N_{\mathrm{r}} \times N_{\mathrm{t}}$ channel matrix and the $N_{\mathrm{t}} \times 1$ transmitted signal vector, respectively. The $N_{\mathrm{r}} \times 1$ noise vector $\boldsymbol{n}$ is assumed to be a CSCG random vector, that is, $\boldsymbol{n} \sim \mathcal{CN}(0, N_0\boldsymbol{I})$. It is assumed that each transmitted symbol s_k is drawn from a quadrature amplitude modulation (QAM) alphabet $\mathcal{S}$, where $|\mathcal{S}| = 2^L = M$. The transmission power for each transmit antenna is normalised as $\frac{1}{|\mathcal{S}|}\sum_{s_k \in \mathcal{S}} |\mathcal{S}_k^2| = 1$.

The structures of a MIMO-BICM transmitter and an IDD receiver over a MIMO channel are presented in Fig. 1. In the transmitter, a random bit interleaver is employed, while a rate-R_{c} convolutional code is used for channel coding. Note that the other channel codes can be used and a best mapping rule for a given modulation and a channel code can be found [32]. For the modulation, a coded interleaved bit sequence $\{b_{k,1}, b_{k,2}, \ldots, b_k\}$ is individually modulated to the M-ray transmitted signal s_k and sent through the kth antenna, where $b_{k,l}$ denotes the lth bit of s_k. Owing to the interleaver, the s_k's and the $b'_{k,l}$s are assumed to be independent. In the IDD receiver, for the first iteration, a soft-decision of each coded bit is generated by the MIMO detector, which is then fed to the channel decoder as input. Then, the soft-decisions of the coded bits from the channel decoder, which are assumed to be the API, are exploited by the MIMO detector to generate the (improved) soft-decisions of the coded bits in successive iterations.

Consequently, extrinsic information is exchanged between the MIMO detector and the channel decoder through the iterations based on the turbo principle [7]. After several iterations, the extrinsic information becomes more reliable and better performance can be achieved by the IDD receiver.

Within the IDD receiver, the soft information of the coded bits $b_{k,l}$ to the decoder can be generated as the exact LLR by

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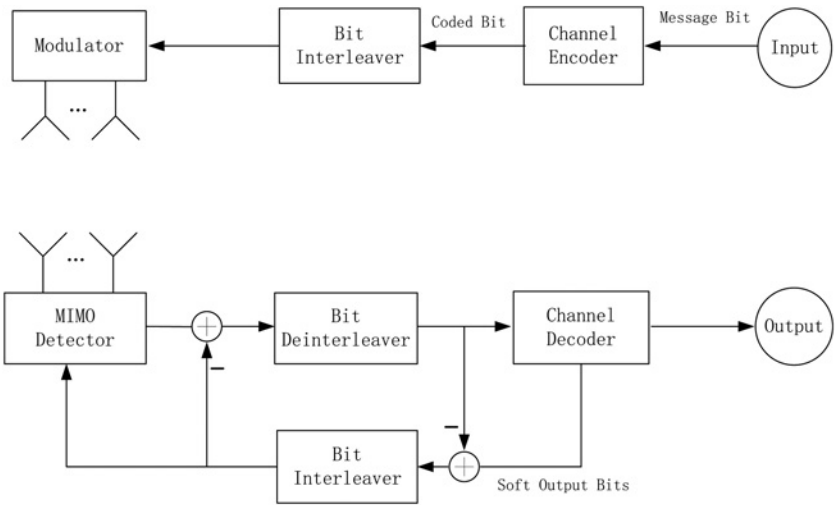

Fig. 1 *Structure of a MIMO-BICM transmitter and an IDD receiver over a MIMO channel*

the MAP detector, which is given by

$$\begin{aligned}\text{LLR}\ (b_{k,l}) &= \log\frac{\Pr(b_{k,\,l}=+1|\boldsymbol{y})}{\Pr(b_{k,\,l}=-1|\boldsymbol{y})} - L_{\text{api}}(b_{k,\,l}) \\ &= \log\frac{\sum_{s\in\mathcal{S}_{k,l,+}}\Pr(\boldsymbol{s}|\boldsymbol{y})}{\sum_{s\in\mathcal{S}_{k,l,-}}\Pr(\boldsymbol{s}|\boldsymbol{y})} - L_{\text{api}}(b_{k,\,l})\end{aligned} \tag{2}$$

where

$$\mathcal{S}_{k,l,\pm} = \{\boldsymbol{s}|\boldsymbol{s}\in\mathcal{S}^{N_t},\ b_{k,\,l}=\pm 1\}$$

and

$$L_{\text{api}}(b_{k,\,l}) = \log\frac{\Pr(b_{k,\,l}=+1)}{\Pr(b_{k,\,l}=-1)} \tag{3}$$

Here, $\Pr(b_{k,\,l}=\pm 1)$ stands for the a priori probability of $b_{k,l}$ provided by the channel decoder. In the first iteration, $L_{\text{api}}(b_{k,l})=0$, $\forall k\in N_t$, $\forall l\in L$, as no API is available from the channel decoder. As the noise vector $\boldsymbol{n}$ is assumed to be a CSCG random vector, by using the Bayes' rule, (2) is rewritten as (see (4))

where $\Pr(\boldsymbol{s})$ represents the a priori probability of $\boldsymbol{s}$ given by the channel decoder. With the max-log approximation [8], (4) can be approximated as (see (5))

As shown in (4) and (5), the complexity of the MAP detector to find the LLR grows exponentially with N_t and L since $|\mathcal{S}_{k,l,\pm}| = 2^{N_t L-1}$. Therefore, in order to reduce the complexity, the subsets of $\mathcal{S}_{k,l,\pm}$ should be considered to approximate the LLR as (see (6))

where $\mathcal{C}_{k,l,+}\subset\mathcal{S}_{k,l,+}$ and $\mathcal{C}_{k,l,-}\subset\mathcal{S}_{k,l,-}$. It is noteworthy that the list length (i.e. the number of candidate vectors within $\mathcal{C}_{k,l,\pm}$) plays a key role in the tradeoff between the performance and the complexity. If the candidate list is too

$$\text{LLR}\ (b_{k,l}) = \log\frac{\sum_{s\in\mathcal{S}_{k,l,+}}\exp\left(-(1/N_0)\|\boldsymbol{y}-\boldsymbol{Hs}\|^2\right)\Pr(\boldsymbol{s})}{\sum_{s\in\mathcal{S}_{k,l,-}}\exp\left(-(1/N_0)\|\boldsymbol{y}-\boldsymbol{Hs}\|^2\right)\Pr(\boldsymbol{s})} - L_{\text{api}}(b_{k,\,l}) \tag{4}$$

$$\begin{aligned}\text{LLR}\ (b_{k,\,l}) \simeq{}& \frac{1}{2}\max_{s\in\mathcal{S}_{k,l,+}}\left\{-\frac{2}{N_0}\|\boldsymbol{y}-\boldsymbol{Hs}\|^2 + \sum_{k=1}^{N_t}\sum_{l=1}^{L} b_{k,l}L_{\text{api}}(b_{k,l})\right\} \\ &-\frac{1}{2}\max_{s\in\mathcal{S}_{k,l,-}}\left\{-\frac{2}{N_0}\|\boldsymbol{y}-\boldsymbol{Hs}\|^2 + \sum_{k=1}^{N_t}\sum_{l=1}^{L} b_{k,l}L_{\text{api}}(b_{k,l})\right\} - L_{\text{api}}(b_{k,l})\end{aligned} \tag{5}$$

$$\begin{aligned}\text{LLR}\ (b_{k,\,l}) \simeq{}& \frac{1}{2}\max_{s\in\mathcal{C}_{k,l,+}}\left\{-\frac{2}{N_0}\|\boldsymbol{y}-\boldsymbol{Hs}\|^2 + \sum_{k=1}^{N_t}\sum_{l=1}^{L} b_{k,l}L_{\text{api}}(b_{k,l})\right\} \\ &-\frac{1}{2}\max_{s\in\mathcal{C}_{k,l,-}}\left\{-\frac{2}{N_0}\|\boldsymbol{y}-\boldsymbol{Hs}\|^2 + \sum_{k=1}^{N_t}\sum_{l=1}^{L} b_{k,l}L_{\text{api}}(b_{k,l})\right\} - L_{\text{api}}(b_{k,l})\end{aligned} \tag{6}$$

long, the complexity may be prohibitively high, although near optimal performance can be achieved. Otherwise, a low complexity can be achieved at the expense of degraded performance.

3 LR-aided MIMO detection

To improve the performance of the linear detectors, an LR is considered that can reduce the original channel basis into a near orthogonal basis that has the same lattice as the original channel basis.

Before performing the lattice basis reduction, the transmitted QAM symbols need to be shifted and scaled to the consecutive complex integer ring as

$$\tilde{\boldsymbol{s}} = \alpha \boldsymbol{s} + \beta 1_{N_t} \quad (7)$$

where $1/\alpha$ is the minimum distance between the symbols of the QAM constellation, $\beta = ((1+j)/2)$, and 1_{N_t} stands for an $N_t \times 1$ vector with all one elements. Note $\tilde{\mathcal{S}} = \{\tilde{s} | \tilde{s} = \alpha s + \beta, s \in \mathcal{S}\}$. Thus, (1) is rewritten as

$$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{H}}\tilde{\boldsymbol{s}} + \boldsymbol{n} \quad (8)$$

where $\tilde{\boldsymbol{y}} = \boldsymbol{y} + (\beta/\alpha)\boldsymbol{H}1_{N_t}$ and $\tilde{\boldsymbol{H}} = (1/\alpha)\boldsymbol{H}$.

The lattice basis reduction is to find a near orthogonal basis that spans the same lattice as that spanned by $\tilde{\boldsymbol{H}}$. A reduced basis can be expressed as $\boldsymbol{G} = \tilde{\boldsymbol{H}}\boldsymbol{T}$, where $\boldsymbol{T}$ should be unimodular (i.e. with integer elements and $|\det(\boldsymbol{T})| = 1$). The received signal can be further written as

$$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{H}}\boldsymbol{T}\boldsymbol{T}^{-1}\tilde{\boldsymbol{s}} + \boldsymbol{n} = \boldsymbol{G}\boldsymbol{u} + \boldsymbol{n} \quad (9)$$

Within an LR-aided detector, the detection is carried out over the following signal set

$$\left\{\boldsymbol{u} | \boldsymbol{u} = \boldsymbol{T}^{-1}\tilde{\boldsymbol{s}}, \tilde{\boldsymbol{s}} \in \tilde{\mathcal{S}}^{N_t}\right\} \quad (10)$$

namely the LR domain. Several algorithms have been proposed for the lattice basis reduction. Among them, the Lenstra–Lenstra–Lovász (LLL) algorithm [33] has been studied extensively as the complexity increases at a polynomial order of N_t. Although the LLL algorithm is initially derived for the real-valued matrices in [33], it is possible to extend to derive the complex-valued LLL (CLLL) algorithm for the complex-valued matrices [28]. Therefore the CLLL algorithm is adopted for the MIMO detection in this paper.

The LR-aided linear detectors [34] find an estimate of $\boldsymbol{u}$ as

$$\hat{\boldsymbol{u}} = \lfloor \boldsymbol{W}\boldsymbol{y} \rceil \quad (11)$$

where the linear filter weights $\boldsymbol{W} = (\boldsymbol{G}^H\boldsymbol{G})^{-1}\boldsymbol{G}^H$ and $\boldsymbol{W} = (\boldsymbol{G}^H\boldsymbol{G} + N_0\boldsymbol{T}^H\boldsymbol{T})^{-1}\boldsymbol{G}^H$ are used for the LR-aided ZF and the LR-aided MMSE detection, respectively. Here, $\lfloor . \rceil$ represents the rounding operation. Then, the estimation of $\boldsymbol{s}$ is obtained from $\hat{\boldsymbol{u}}$ as $\hat{\boldsymbol{s}} = \boldsymbol{T}\hat{\boldsymbol{u}}$.

Although the LR-aided linear detectors in the uncoded systems can have a full receive diversity gain as the ML detector [27, 28], their performance may not be close to that of the approximate MAP detectors in the IDD, because no extrinsic information is taken into account. In the next section, we modify the LR-aided detectors for the IDD.

4 LR-aided MIMO detection within the IDD

In this section, in order to approximate the max-log LLR for each coded bit, a bit-level soft LR-aided detector exploiting API is derived for approximate MAP detection. Then, a list of candidates is generated based on the shortest Euclidean distance from the original LR-aided decision. Moreover, to reduce the computational complexity of the proposed approach in large MIMO systems (i.e. systems with large numbers of N_t and N_r), the channel matrix decomposition is considered with the SIC. Note that as the QR decomposition is considered for the LR-based detection, the proposed approach can only be used in the underloaded systems (i.e. $N_t \leq N_r$).

4.1 Bit-level LR-aided MIMO detection within the IDD

To find the soft-decisions for a certain coded bit, we need to split a single alphabet into two sub-alphabets (a sub-alphabet consisting of the symbols whose certain bit is +1 and the other is −1). The LR-aided linear detectors can provide good performance by separately estimating the two dominant candidates in (6). Note that the proposed LR-aided detector needs to accommodate the API provided by the channel decoder in the IDD.

Denote by $\mathcal{S}$ and $\tilde{\mathcal{S}}$ the QAM symbol alphabet and the symbol alphabet after shifting and scaling, respectively. For $b_{k,l}$, let

$$\mathcal{S}_{k,l,\pm} = \left\{\boldsymbol{s} | \boldsymbol{s} \in \mathcal{S}^{N_t}, b_{k,l} = \pm 1\right\} \quad (12)$$

$$\tilde{\mathcal{S}}_{k,l,\pm} = \left\{\tilde{\boldsymbol{s}} | \tilde{\boldsymbol{s}} \in \tilde{\mathcal{S}}^{N_t}, b_{k,l} = \pm 1\right\} \quad (13)$$

and

$$\mathcal{U}_{k,l,\pm} = \left\{\boldsymbol{u} | \boldsymbol{u} = \boldsymbol{T}^{-1}\tilde{\boldsymbol{s}}, \tilde{\boldsymbol{s}} \in \tilde{\mathcal{S}}^{N_t}, b_{k,l} = \pm 1\right\} \quad (14)$$

where $\mathcal{U}_{k,l,\pm}$ is the LR sub-domain corresponding to $\tilde{\mathcal{S}}_{k,l,\pm}$.

Now let us consider the estimation for $\boldsymbol{u}_{k,l,\pm}$, which is given by

$$\hat{\boldsymbol{u}}_{k,l,\pm} = \boldsymbol{W}_{k,l,\pm}(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m}) + \boldsymbol{m}_{k,l,\pm} \quad (15)$$

where $\boldsymbol{W}_{k,l,\pm}$ is to be derived by using the MMSE criterion such that

$$\boldsymbol{W}_{k,l,\pm} = \underset{\boldsymbol{W}_{k,l,\pm} \in \mathbb{C}^{N_t \times N_r}}{\operatorname{argmax}} \mathbb{E}\left\|\hat{\boldsymbol{u}}_{k,l,\pm} - \boldsymbol{u}_{k,l,\pm}\right\|^2 \quad (16)$$

and

$$\boldsymbol{m} = \mathbb{E}\{\boldsymbol{u}\} = \mathbb{E}\left\{\boldsymbol{T}^{-1}\tilde{\boldsymbol{s}}\right\} = \boldsymbol{T}^{-1}\mathbb{E}\{\tilde{\boldsymbol{s}}\} \quad (17)$$

$$\boldsymbol{m}_{k,l,\pm} = \mathbb{E}\left\{\boldsymbol{u}_{k,l,\pm}\right\} = \mathbb{E}\left\{\boldsymbol{T}^{-1}\tilde{\boldsymbol{s}}_{k,l,\pm}\right\} = \boldsymbol{T}^{-1}\mathbb{E}\left\{\tilde{\boldsymbol{s}}_{k,l,\pm}\right\} \quad (18)$$

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Then, we have (see (19))

Let (see (20))

Noting that $\tilde{\boldsymbol{y}} = \boldsymbol{G}\boldsymbol{u} + \boldsymbol{n}$ and $\mathbb{E}\{\boldsymbol{n}\} = 0$, the solution of $(\partial/(\partial \boldsymbol{W}_{k,l,\pm}))f(\boldsymbol{W}_{k,l,\pm}) = 0$ becomes

$$\boldsymbol{W}_{k,l,\pm} = \boldsymbol{V}_{k,l,\pm}\boldsymbol{G}^{\mathrm{H}}(\boldsymbol{G}\boldsymbol{V}\boldsymbol{G}^{\mathrm{H}} + N_0\boldsymbol{I})^{-1} \tag{21}$$

where

$$\boldsymbol{V} = \mathrm{Cov}\{\boldsymbol{u}\} = \boldsymbol{T}^{-1}\mathrm{Cov}\{\tilde{\boldsymbol{s}}\}\boldsymbol{T}^{-\mathrm{H}} \tag{22}$$

and

$$\boldsymbol{V}_{k,l,\pm} = \mathrm{Cov}\{\boldsymbol{u}_{k,l,\pm}\} = \boldsymbol{T}^{-1}\mathrm{Cov}\{\tilde{\boldsymbol{s}}_{k,l,\pm}\}\boldsymbol{T}^{-\mathrm{H}} \tag{23}$$

denote the covariance matrices of $\boldsymbol{u}$ and $\boldsymbol{u}_{k,l,\pm}$, respectively.

In the LR-aided MIMO detection for the uncoded systems, quantisation is an important step. However, since the quantisation error may also lead to performance degradation for the IDD, we need a list of candidates that are close to a hard-decision to overcome this problem. Moreover, among various quantisation schemes, rounding to the nearest integer vector is the simplest and conventional means. However, with the soft estimation $\hat{\boldsymbol{u}}_{k,l,\pm}$, after such a simple rounding operation and mapping back to $\mathcal{S}_{k,l,\pm}$, the resulting signal vector may not be the desired candidate according to (5).

In this paper, we present another quantisation scheme, where we search over $\mathcal{U}_{k,l,\pm}$ instead of the whole LR domain, for a list. Let

$$q^{(i)}_{k,l,\pm} = \left\| \hat{\boldsymbol{u}}_{k,l,\pm} - \boldsymbol{u}^{(i)}_{k,l,\pm} \right\| \tag{24}$$

where $i = 1, 2, \ldots, |\mathcal{U}_{k,l,\pm}|$ and $\boldsymbol{u}_{k,l,\pm} \in \mathcal{U}_{k,l,\pm}$. Without loss of generality, we assume that

$$q^{(1)}_{k,l,\pm} \le q^{(2)}_{k,l,\pm} \le \cdots \le q^{(|\mathcal{U}_{k,l,\pm}|)}_{k,l,\pm} \tag{25}$$

Therefore $\boldsymbol{u}^{(i)}_{k,l,\pm}$ denotes the ith closest vector to $\hat{\boldsymbol{u}}_{k,l,\pm}$ in $\mathcal{U}_{k,l,\pm}$, and a list with length J corresponding to $\boldsymbol{u}_{k,l,\pm}$ as

$$\mathcal{U}^{J}_{k,l,\pm} = \left\{\boldsymbol{u}^{(1)}_{k,l,\pm}, \ldots, \boldsymbol{u}^{(J)}_{k,l,\pm}\right\} \tag{26}$$

can be used to approximate the LLR for the $b_{k,l}$ in (6).

In this paper, the proposed approach is referred to as the bit-level LR-aided (bit-LR) approach.

4.2 Detection in large dimensional systems with channel decomposition

As investigated in [33], since the LLL algorithm requires a polynomial complexity, the complexity increases relatively rapidly with the dimension of basis, N_{t}. Therefore the LR-aided detection may still have relatively high computational complexity for large dimensional MIMO systems.

In this subsection, we show how the proposed bitLR-aided detection can be applied to large dimensional MIMO systems within the IDD by decomposing a large dimensional system into multiple small MIMO systems by using the SIC. In addition, list generation helps to mitigate the error propagation because of the SIC.

To factorise the large dimensional system into smaller ones, QR decomposition is considered as $\tilde{\boldsymbol{H}} = \boldsymbol{Q}_1\boldsymbol{R}_1$, where $\boldsymbol{Q}_1$ and $\boldsymbol{R}_1$ are the unitary and the upper triangular, respectively. Thus, the received signal vector in (8) is rewritten as

$$\begin{aligned}\tilde{\boldsymbol{y}}_{\mathrm{ex}} &= \boldsymbol{Q}_1^{\mathrm{H}}\tilde{\boldsymbol{y}} \\ &= \boldsymbol{R}_1\tilde{\boldsymbol{s}} + \boldsymbol{Q}_1^{\mathrm{H}}\boldsymbol{n}\end{aligned} \tag{27}$$

Since the statistical properties of $\boldsymbol{Q}_1^{\mathrm{H}}\boldsymbol{n}$ are identical to those of $\boldsymbol{n}$, $\boldsymbol{Q}_1^{\mathrm{H}}\boldsymbol{n}$ can be written as $\boldsymbol{n}$ for the sake of simplicity. Then, (27) can be decomposed as

$$\begin{bmatrix}\boldsymbol{y}_1\\ \boldsymbol{y}_2\end{bmatrix} = \begin{bmatrix}\boldsymbol{A}_1 & \boldsymbol{A}_2\\ 0 & \boldsymbol{B}\end{bmatrix}\begin{bmatrix}\boldsymbol{s}_1\\ \boldsymbol{s}_2\end{bmatrix} + \begin{bmatrix}\boldsymbol{n}_1\\ \boldsymbol{n}_2\end{bmatrix} \tag{28}$$

where $\boldsymbol{y}_i$, $\boldsymbol{s}_i$ and $\boldsymbol{n}_i$ ($i = 1, 2$) denote the $N_i \times 1$ subvectors of $\tilde{\boldsymbol{y}}_{\mathrm{ex}}$, $\tilde{\boldsymbol{s}}$ and $\boldsymbol{n}$, respectively. It is noteworthy that $N = N_1 + N_2$. From (28), we can see that

$$\begin{cases}\boldsymbol{y}_2 = \boldsymbol{B}\boldsymbol{s}_2 + \boldsymbol{n}_2;\\ \boldsymbol{y}_1 = \boldsymbol{A}_1\boldsymbol{s}_1 + \boldsymbol{A}_2\boldsymbol{s}_2 + \boldsymbol{n}_1\end{cases} \tag{29a, b}$$

where two smaller dimensional MIMO sub-detection problems are solved to detect $\boldsymbol{s}_2$ and $\boldsymbol{s}_1$ successively.

In the proposed LR-aided detection, the detection of $\boldsymbol{s}_2$ is directly carried out first by using the bit-level LR-aided detector as there is no interference from $\boldsymbol{s}_1$. Then, a list of bit-level vectors of $\boldsymbol{s}_2$ is generated. In detecting $\boldsymbol{s}_1$, the candidate vectors in the list are used for the SIC to mitigate

$$\begin{aligned}\boldsymbol{W}_{k,l,\pm} &= \underset{\boldsymbol{W}_{k,l,\pm}\in\mathbb{C}^{N_{\mathrm{t}}\times N_{\mathrm{r}}}}{\mathrm{argmax}}\ \mathbb{E}\left\{\left\|\hat{\boldsymbol{u}}_{k,l,\pm} - \boldsymbol{u}_{k,l,\pm}\right\|^2\right\}\\ &= \underset{\boldsymbol{W}_{k,l,\pm}\in\mathbb{C}^{N_{\mathrm{t}}\times N_{\mathrm{r}}}}{\mathrm{argmax}}\ \mathbb{E}\left\{\left\|\boldsymbol{W}_{k,l,\pm}(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m}) + \boldsymbol{m}_{k,l,\pm} - \boldsymbol{u}_{k,l,\pm}\right\|^2\right\}\\ &= \underset{\boldsymbol{W}_{k,l,\pm}\in\mathbb{C}^{N_{\mathrm{t}}\times N_{\mathrm{r}}}}{\mathrm{argmax}}\ \mathbb{E}\{(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m})^{\boldsymbol{H}}\mathrm{W}^{\boldsymbol{H}}_{k,l,\pm}\boldsymbol{W}_{k,l,\pm}(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m})\\ &\quad + (\boldsymbol{m}_{k,l,\pm} - \boldsymbol{u}_{k,l,\pm})^{\boldsymbol{H}}\boldsymbol{W}_{k,l,\pm}(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m}) + (\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m})^{\boldsymbol{H}}\boldsymbol{W}^{\boldsymbol{H}}_{k,l,\pm}(\boldsymbol{m}_{k,l,\pm} - \boldsymbol{u}_{k,l,\pm})\}\end{aligned} \tag{19}$$

$$\begin{aligned}f(\boldsymbol{W}_{k,l,\pm}) = \mathbb{E}\{&(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m})^{\boldsymbol{H}}\boldsymbol{W}^{\boldsymbol{H}}_{k,l,\pm}\boldsymbol{W}_{k,l,\pm}(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m})\\ &+ (\boldsymbol{m}_{k,l,\pm} - \boldsymbol{u}_{k,l,\pm})^{\boldsymbol{H}}\boldsymbol{W}_{k,l,\pm}(\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m}) + (\tilde{\boldsymbol{y}} - \boldsymbol{G}\boldsymbol{m})^{\boldsymbol{H}}\boldsymbol{W}^{\boldsymbol{H}}_{k,l,\pm}(\boldsymbol{m}_{k,l,\pm} - \boldsymbol{u}_{k,l,\pm})\}\end{aligned} \tag{20}$$

the interference from s_2. It is noteworthy that the s_2 is detected at bit-level, whereas the s_1 is not.

The proposed bit-level LR-detection for the large dimensional systems is summarised as follows.

(1) According to (29a), there is no interference from s_1 in detecting s_2. Thus, with the received signal vector y_2, the bit-level LR-detection is performed for each bit in s_2 as

$$\hat{\boldsymbol{u}}_{2,k,l,\pm} = \boldsymbol{W}_{2,k,l,\pm}(\boldsymbol{y}_2 - \boldsymbol{G}_2\boldsymbol{m}_{2,k,l,\pm}) + \boldsymbol{m}_{2,k,l,\pm} \tag{30}$$

where $\boldsymbol{G}_2 = \boldsymbol{B}\boldsymbol{T}_2$, and $\boldsymbol{T}_2 = \text{CLLL(B)}$. The LR-MMSE filter weight is

$$\boldsymbol{W}_{2,k,l,\pm} = \boldsymbol{V}_{2,k,l,\pm}\boldsymbol{G}_2^{\text{H}}(\boldsymbol{G}_2^{\text{H}}\boldsymbol{V}_2\boldsymbol{G}_2 + N_0\boldsymbol{I}_{N_2})^{-1}$$

The mean vector and the covariance matrix of $\boldsymbol{u}_{2,k,l,\pm}$ are denoted by $\boldsymbol{m}_{2,k,l,\pm}$ and $\boldsymbol{V}_{2,k,l,\pm}$, respectively, and $\boldsymbol{u}_{2,k,l,\pm}$ is corresponding to $\tilde{\boldsymbol{s}}_{2,k,l,\pm}$, which is obtained from $\boldsymbol{s}_{2,k,l,\pm}$ after the shifting and the scaling operations.
(2) (List generation) By searching over $\mathcal{U}_{2,k,l,\pm} = \left\{\boldsymbol{u}_2 | \boldsymbol{u}_2 = \boldsymbol{T}_2^{-1}\tilde{\boldsymbol{s}}_2,\ \tilde{\boldsymbol{s}}_2 \in \tilde{\mathcal{S}}^{N_2},\ b_{k,l} = \pm 1\right\}$, a list of candidate vectors for each bit in the LR domain is generated as $\mathcal{U}_{2,k,l,\pm}^{J_2} = \left\{\boldsymbol{u}_{2,k,l,\pm}^{(1)}, \ldots, \boldsymbol{u}_{2,k,l,\pm}^{(J_2)}\right\}$, which is the set of the J_2 closest vectors to $\hat{\boldsymbol{u}}_{2,k,l,\pm}$. Denote by $\mathcal{S}_{2,k,l,\pm}^{J_2} = \left\{\boldsymbol{s}_{2,k,l,\pm}^{(1)}, \ldots, \boldsymbol{s}_{2,k,l,\pm}^{(J_2)}\right\}$ the list of candidates of $\boldsymbol{s}_{2,k,l,\pm}$, which is converted from $\mathcal{U}_{2,k,l,\pm}^{J_2}$ (the list of candidates in the LR domain).
(3) With (29b), the bit-level LR-aided detection of $\boldsymbol{s}_1$ is carried out after the SIC of the candidates in $\mathcal{S}_{2,k,l,\pm}^{J_2}$ as

$$\hat{\boldsymbol{u}}_1^{(j_2)} = \boldsymbol{W}_1(\boldsymbol{y}_1 - \boldsymbol{A}_2\boldsymbol{s}_{2,k,l,\pm}^{(j_2)} - \boldsymbol{G}_1\boldsymbol{m}_1) + \boldsymbol{m}_1 \tag{31}$$

where $\boldsymbol{G}_1 = \boldsymbol{A}_1\boldsymbol{T}_1$, $\boldsymbol{T}_1 = \text{CLLL}(\text{A}_1)$ and $j_2 = 1, 2, \ldots, J_2$, which means that the SIC needs to be performed J_2 times so that the J_2 estimates of $\boldsymbol{u}_1$ are obtained. The LR-MMSE filter weight is $\boldsymbol{W}_1 = \boldsymbol{V}_1\boldsymbol{G}^{\text{H}}(\boldsymbol{G}_1^{\text{H}}\boldsymbol{V}_1\boldsymbol{G}_1 + N_0\boldsymbol{I}_{N_1})^{-1}$. The mean vector and the covariance matrix of $\boldsymbol{u}_1$ are denoted by $\boldsymbol{m}_1$ and $\boldsymbol{V}_1$, respectively, and $\boldsymbol{u}_1$ corresponds to $\tilde{\boldsymbol{s}}_1$, which is obtained from $\boldsymbol{s}_1$ after the shifting and the scaling operations.
(4) (List generation) By searching over $\mathcal{U}_{2,k,l,\pm} = \left\{\boldsymbol{u}_1 | \boldsymbol{u}_1 = \boldsymbol{T}_1^{-1}\tilde{\boldsymbol{s}}_1,\ \tilde{\boldsymbol{s}}_1 \in \tilde{\mathcal{S}}^{N_1}\right\}$, is generated as $\mathcal{U}_1^{J_1} = \left\{\boldsymbol{u}_1^{(1)}, \ldots, \boldsymbol{u}_1^{(J_1)}\right\}$, which denotes the J_1 closest vectors to $\hat{\boldsymbol{u}}_1$.
(5) Find $\mathcal{S}_1^{J_1} = \left\{\boldsymbol{s}_1^{(1)}, \ldots, \boldsymbol{s}_1^{(J_1)}\right\}$, the list of candidates of $\boldsymbol{s}_1$, which is converted from $\mathcal{U}_1^{J_1}$ (the list of candidates in the LR domain).
(6) A list of the candidates of $\boldsymbol{s}$ is generated by combining $\mathcal{S}_1^{J_1}$ and $\mathcal{S}_2^{J_2}$ as

$$\boldsymbol{s}_{N_2,k,l,\pm}^{(j)} = \begin{bmatrix} \boldsymbol{s}_1^{(j_1)} \\ \boldsymbol{s}_{2,k,l,\pm}^{(j_2)} \end{bmatrix} \tag{32}$$

where $j_1 = 1, 2, \ldots, J_1$, $j_2 = 1, 2, \ldots, J_2$ and $j = 1, 2, \ldots, J_1J_2$. Note that in the detection and the list generation of $\boldsymbol{s}_1$, bit-level detection is not performed.
(7) By using the list of candidates of $\boldsymbol{s}_{N_2,k,l,\pm}^{(j)}$ and the max-log approximation in (6), we can approximate the LLRs of the bits in $\boldsymbol{s}_2$.
(8) Similarly, we can obtain the approximate LLRs of the bits in $\boldsymbol{s}_1$. To perform the bit-level detection of $\boldsymbol{s}_1$, symbol reordering and column swapping are needed. Reorder $\tilde{\boldsymbol{s}}$ as $\tilde{\boldsymbol{s}}' = \begin{bmatrix} \boldsymbol{s}_2 \\ \boldsymbol{s}_1 \end{bmatrix}$, and swap the first N_1th columns and the last N_2th columns of $\tilde{\boldsymbol{H}}$ as $\tilde{\boldsymbol{H}}'$, then the system model in (8) becomes

$$\tilde{\boldsymbol{y}} = \tilde{\boldsymbol{H}}'\tilde{\boldsymbol{s}}' + \boldsymbol{n} \tag{33}$$

For $\tilde{\boldsymbol{H}}'$, it is QR factorised as $\tilde{\boldsymbol{H}}' = \boldsymbol{Q}_2\boldsymbol{R}_2$, thus (33) is rewritten as

$$\begin{aligned} \tilde{\boldsymbol{y}}'_{\text{ex}} &= \boldsymbol{Q}_2^{\text{H}}\tilde{\boldsymbol{y}} \\ &= \boldsymbol{R}_2\tilde{\boldsymbol{s}}' + \boldsymbol{Q}_2^{\text{H}}\boldsymbol{n} \end{aligned} \tag{34}$$

Also, $\boldsymbol{Q}_2\boldsymbol{n}$ can be regarded as $\boldsymbol{n}$ because of their same statistical properties. Similar to (28), (34) can be rewritten as

$$\begin{bmatrix} \boldsymbol{y}'_1 \\ \boldsymbol{y}'_2 \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}'_1 & \boldsymbol{A}'_2 \\ 0 & \boldsymbol{B}' \end{bmatrix} \begin{bmatrix} \boldsymbol{s}_2 \\ \boldsymbol{s}_1 \end{bmatrix} + \begin{bmatrix} \boldsymbol{n}_1 \\ \boldsymbol{n}_2 \end{bmatrix} \tag{35}$$

Consequently, the LLRs of each coded bit can be obtained by repeating steps (1) through (8).

4.3 Complexity analysis

In this subsection, the Bit-LR detectors with and without channel matrix decomposition and the SIC are analysed in terms of the complexity order [In this paper, the complexity order is dominated by complex multiplications.]. Let $N_t = N_r$ for convenience. The complexity of the proposed Bit-LR detection is mainly dominated by two aspects, where the former is related to the CLLL algorithm for the lattice basis reduction and the latter is to find the LR-aided MMSE soft-decisions. Since the complexity order of the CLLL algorithm is well-known as approximately $O(N_t^4 \log N_t)$ for each channel realisation [35], we only focus on the complexity of the latter.

As for the second part, recall the MMSE filter expression in (21) as

$$\begin{aligned} \boldsymbol{W}_{k,l,\pm} &= \boldsymbol{T}^{-1}\text{Cov}\{\tilde{\boldsymbol{s}}_{k,l,\pm}\} \\ &\quad \times \boldsymbol{T}^{-\text{H}}\boldsymbol{G}^{\text{H}}(\boldsymbol{G}^{\text{H}}\boldsymbol{T}^{-1}\text{Cov}\{\tilde{\boldsymbol{s}}\}\boldsymbol{T}^{-\text{H}}\boldsymbol{G} + \text{N}_0\boldsymbol{I})^{-1} \end{aligned} \tag{36}$$

It is noteworthy that only $\text{Cov}\{\tilde{\boldsymbol{s}}_{k,l,\pm}\}$ is different for each coded bit. Therefore the complexity order of computing $\boldsymbol{T}^{-1}\text{Cov}\{\tilde{\boldsymbol{s}}_{k,\text{l},\pm}\}$ for N_tM bits is $O(MN_t^4)$, and the complexity order of the rest of the computation in (36) is $O(8N_t^3)$. For the large systems of $MN_t \gg 8$, the overall complexity order of finding the LR-MMSE filters is $O(MN_t^4)$, whereas for the systems of $MN_t \simeq 8$, the overall complexity order of obtaining the LR-MMSE filters is $O((MN_t + 8)N_t^3)$.

Now we consider the complexity of the approach exploiting the channel matrix decomposition and the SIC. We decompose the detection problem into an $N_1 \times N_1$ sub-detection problem and an $N_2 \times N_2$ sub-detection problem, where $N_1 + N_2 = N_t$. Thus, the computational complexity order of the $N_2 \times N_2$ system is $O((MN_2 + 8)N_2^3)$, and the order of the $N_1 \times N_1$ system is $O(9J_2N_1^3)$, as the J_2

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SIC operations are required. Consequently, the overall complexity order of the Bit-LR with the channel matrix decomposition and the SIC is $O((MN_2 + 8)N_2^3 + 9J_2N_1^3)$, which could be much less than its counterpart without the SIC given the appropriate decisions of J_2.

Although the complexity is reduced as the detection dimension is reduced by the proposed detection approach in the large systems, the channel matrix decomposition results in a suboptimal performance, because the joint detection is replaced with the SIC in the lower dimensions. However, through the simulations, we can see that the performance degradation is marginal, as the list generation is considered to mitigate the error propagation.

5 Simulation results

In this section, simulation results are presented to see the performance of the proposed approach. For the simulations, 4-QAM with Gray mapping is employed for signalling. For the BICM, a rate-1/2 convolutional code with the generator polynomial (13, 15) in octal and a random bit interleaver are used. The length of a message bit sequence is set to $2^{10} = 1024$, which results in a length of 2^{11} coded bit sequence. In the LR-aided detection, the CLLL algorithm is employed with the reduction parameter $\delta = 0.75$. In addition, we have

$$\frac{E_b}{N_0} = \frac{1}{N_0 R_c \log_2 M} \tag{37}$$

as the signal-to-noise ratio (SNR), where R_c represents the code rate.

For the performance comparison, the detection schemes including the LSD in [8], the MCMC in [19] and the MMSE-SC [21] are also considered, while the genie-aided list (GAL) detector is used to refer to the matched filter bound (MFB). For the LSD, the detectors with list length $N_{cand} = 64$ are used for a 4×4 system, whereas the list length $N_{cand} = 128$, $N_{cand} = 256$, $N_{cand} = 512$ and $N_{cand} = 1024$ are considered for the 8×8 system. Moreover, for the MCMC, efficient parallel implementations with 6 parallel Gibbs samplers, where each sampler is equipped with 6 samples (i.e., a 6×6 MCMC detector), and a 10×10 detector in [20] are employed for the 4×4 and the 8×8 systems, respectively. In the GAL detector, an approximate LLR for the soft solution is obtained as follows

$$\begin{aligned} \text{LLR}\,(b_{k,l}) &\simeq \log\frac{\Pr(\boldsymbol{s}_{k,l,+}|\boldsymbol{y})}{\Pr(\boldsymbol{s}_{k,l,-}|\boldsymbol{y})} - L_{\text{api}}(b_{k,\,l}) \\ &= -\frac{1}{N_0}(\|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{s}_{k,l,+}\|^2 - \|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{s}_{k,l,-}\|^2) \end{aligned} \tag{38}$$

where

$$[\mathrm{s}_{k,l,\pm}]_{k',l'} = \begin{cases} \pm 1, & \text{if } k = k' \text{ and } l = l'; \\ [\mathrm{s}]_{k',l'}, & \text{otherwise} \end{cases}$$

Thus, this approximation is the best one that can be obtained by a list-sphere decoder for the MIMO detection. In addition, the LLR provided by the GAL detector is actually based on the knowledge of the transmitted signals, where the co-antenna interference is perfectly cancelled, which implies that it achieves the match filter bound. Note that the list of the GAL detector is actually fixed and $\boldsymbol{s}_{k,l,\pm}$ is irrelevant with API. Therefore no iteration or API is required by the GAL detector.

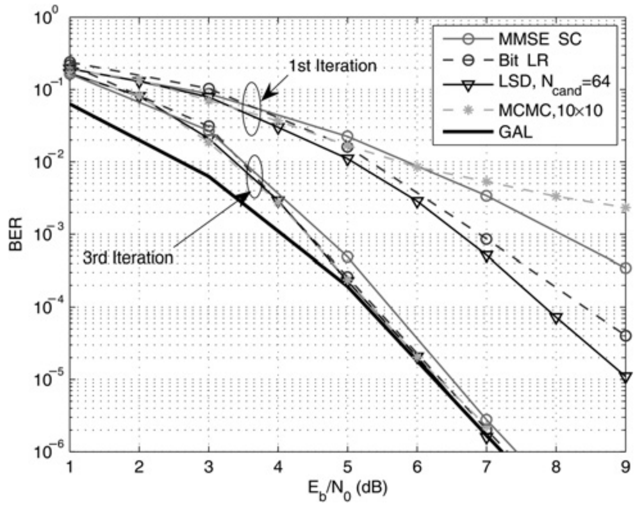

Fig. 2 *BER performance of the Bit-LR detection of the 4 × 4 MIMO system*

With $N_t = N_r = 4$, the bit error rate (BER) performances of the various IDD receivers are presented in Fig. 2. For the proposed Bit-LR approach, a candidate list with length $J = 6$ is generated. It is observed that no significant performance gain is achieved with more than three iterations. With the three iterations, we can observe that our proposed Bit-LR method, MCMC and LSD approach the optimal performance, whereas there exists a noticeable performance gap between the MMSE-SC and the GAL detectors. It is noteworthy that our Bit-LR approach also allows a parallel implementation.

In Fig. 3, we present the BER performance of different IDD receivers for an 8×8 MIMO system. For the Bit-LR, the 8×8 system is decomposed into two 4×4 systems which are detected sequentially. The two list lengths are $J_1 = 4$ and $J_2 = 7$, which results in a list length for each bit as $J_1J_2 = 28$ that is much less than a full length of 65 536. It is shown that after four iterations, our Bit-LR approach, as well as the LSD with long list length and the MCMC, can still achieve near-optimal performance with just a few candidates, while

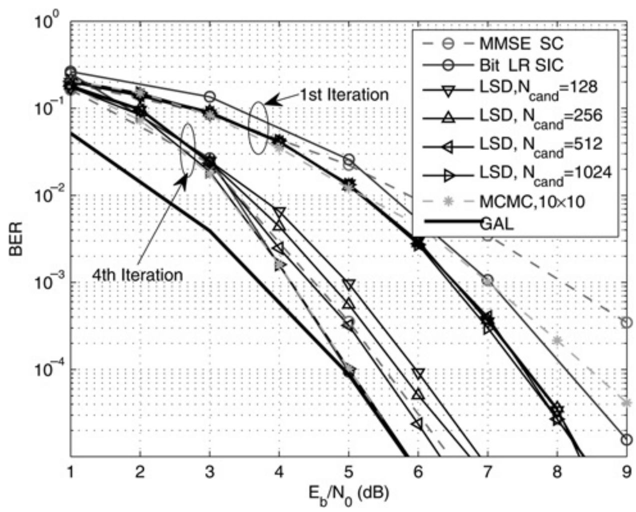

Fig. 3 *BER performance of the Bit-LR detection of the 8 × 8 MIMO system*

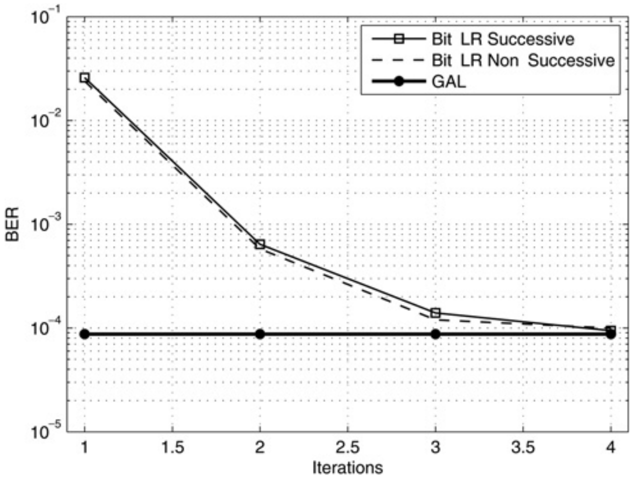

Fig. 4 *BER performance of the Bit-LR detection of the 8 × 8 MIMO system with and without the SIC*

they outperform the MMSE-SC detector obviously. It is noteworthy that the LSD with short list lengths can only provide degraded performance.

To see the complexity reduction obtained from the SIC in the proposed approach, the performance comparison at $E_b/N_0 =$ 5 dB for the Bit-LR with and without the channel matrix decomposition is considered in Fig. 3, where $N_t = N_r = 8$ and $N_1 = N_2 = 4$. The list lengths for the system with and without the SIC are still $J_1 = 4$, $J_2 = 7$ and $J = 28$. Bit-LR successive and Bit-LR non-successive denote the approaches with and without the SIC, respectively. It is shown that the BER gap between these two approaches is marginal at each iteration. However, the complexity of detection with the SIC is much lower than its counterpart. In particular, for the system in Fig. 4, the complexity order of the Bit-LR detector with the channel matrix decomposition is approximately one third of that without employing the channel matrix decomposition and the SIC. Consequently, the complexity can be reduced remarkably with marginal performance degradation by the proposed Bit-LR detector with the SIC in the large dimensional MIMO systems.

Moreover, in Fig. 5, we compare the complexity of different MIMO detection algorithms for the 8 × 8 MIMO systems in terms of the average number of floating point operations (FLOPs). To see the difference between the fixed and the variable complexity costs of various approaches, we use the empirical cumulative distribution function (CDF) of the FLOPs per channel use. We consider four iterations as the performance improvement by further iterations is not observed. As expected, we can observe a significant complexity reduction by the Bit-LR with the SIC compared with that of the Bit-LR without the SIC. Although the MCMC detectors are also able to provide good approximate LLRs, the complexity required by them is still prohibitively high. On the contrary, the complexity of the Bit-LR detector is comparable with that of the MMSE-SC detector. Note that the computational complexity of the LSD detectors is generally variable and the worst case complexity is still prohibitively high, while the proposed approach requires a fixed complexity (i.e. independent of the channel realisations or the SNR) except for the LLL algorithm, which becomes clearly an advantage over the LSD detectors.

We also present the CDF of the FLOPs of the LLL algorithm in Fig. 5. Although the complexity of the LLL algorithm is random, its worst case complexity is still not the dominant part of the proposed approach. Note that the specific domination is related to the time-selective regime. Nevertheless, even for a single signal vector, the domination is still less than 20% as shown in Fig. 5.

In Fig. 6, we analyse the convergence behaviour of various detection approaches. The convergence behaviour of the IDD can be analysed by the extrinsic information transfer (EXIT) chart, which was originally proposed for the convergence analysis of the iterative decoders [36]. Suppose that the mutual information between the transmitted bit $b_{k,l}$ and the extrinsic information $L_A(b_{k,l})$ from the SISO decoder is given by $I_{in} = I(L_A(b_{k,l}); b_{k,l})$. We also define the mutual information between the transmitted bit $b_{k,l}$ and the extrinsic information $L_E(b_{k,l})$ fed to the SISO decoder as $I_{out} = I(L_E(b_{k,l}); b_{k,l})$. Then, the transfer function of the detector in the IDD for the given SNR connecting I_{out} with I_{in} can be found as $I_{out} = f(I_{in}, E_b/N_0)$, $0 \le I_{in}$, $I_{out} \le 1$. Let $b = b_{k,l}$ and $L_A = L_A(b_{k,l})$ for convenience.

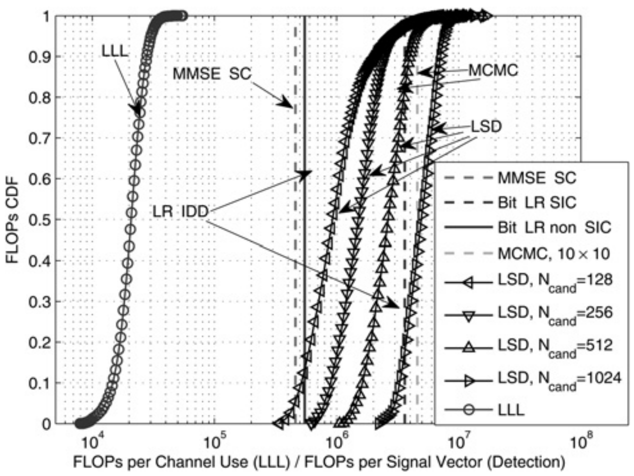

Fig. 5 *CDF of the FLOPs per signal vector for the detection and the per channel use for the LLL algorithm for the 8 × 8 system at E_b/N_0 = 5 dB*

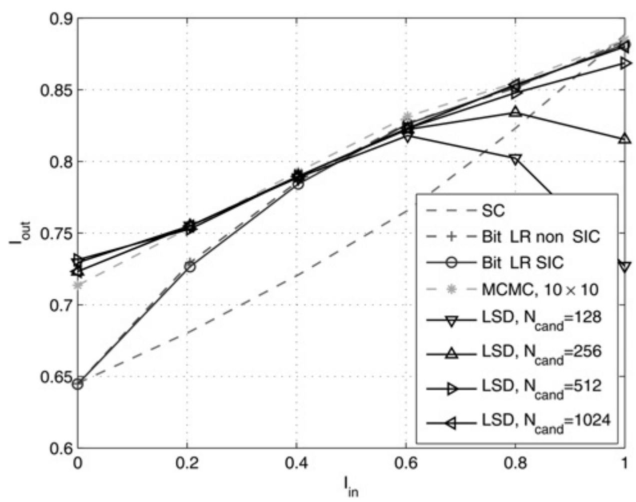

Fig. 6 *EXIT chart of different detection approaches for the 8 × 8 system at E_b/N_0 = 6 dB*

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The mutual information I_{in} for equally likely binary input bits can be given by

$$\begin{aligned} I_{in} &= H(b) - H(L_A|b) \\ &= H(b) - H(L_A; b) + H(L_A) \\ &= \frac{1}{2}\sum_{b\in\{\pm1\}}\int_{-\infty}^{\infty} f_{L_A|b}(l_A|b)\log_2 f_{L_A|b}(l_A|b)\,\mathrm{d}l_A \\ &\quad - \int_{-\infty}^{\infty} f_{L_A}(l_A)\log_2 f_{L_A}(l_A)\,\mathrm{d}l_A \end{aligned} \tag{39}$$

where

$$f_{L_A}(l_A) = \frac{1}{2}\sum\nolimits_{b\in\{\pm1\}} f_{L_A|b}(l_A|b)$$

Letting $L_E = L_E(b_{k,\,l})$, we have

$$\begin{aligned} I_{out} &= \frac{1}{2}\sum_{b\in\{\pm1\}}\int_{-\infty}^{\infty} f_{L_E|b}(l_A|b)\log_2 f_{L_E|b}(l_E|b)\,\mathrm{d}l_E \\ &\quad - \int_{-\infty}^{\infty} f_{L_E}(l_E)\log_2 f_{L_E}(l_E)\,\mathrm{d}l_E \end{aligned} \tag{40}$$

The EXIT function $I_{out} = f(I_{in}, E_b/N_0)$ can be obtained empirically through the simulations.

In general, the higher an EXIT curve, the better performance the detector can achieve, which is independent of the choice of the channel codes. Note that the curve region corresponding to the larger values of I_{in} is related to the performance of the later iterations, whereas the region corresponding to the smaller values of I_{out} is related to that of the earlier iterations in the IDD. As shown in Fig. 5, where the EXIT curves of various IDD detectors are presented with an 8×8 system at $E_b/N_0 = 6$ dB, it is interesting to see that the proposed methods may not provide satisfactory performance early iterations, because the EXIT curve at the region corresponding to small I_{in} of the proposed method is relatively low compared with that of the MAP detector. This results from less reliable API obtained in the early iterations. However, within a few iterations, the performance of the proposed method approaches that of the MCMC and the LSD with the long list length.

Interestingly, we can observe that the performance of the LSD depends on the list length. In particular, the convergence performance (after a few iterations) is highly affected by the list length. In particular, we can see that the performance is rather degraded when I_{in} is close to 1 when the list length is not sufficiently long. This performance degradation results from the LLR clipping required by the LSD detectors [8], which causes numerical instability when the list length is short [17]. On the contrary, since the LLR clipping is not requested by the proposed LR-IDD-2 detector, which performs bit-wise detection, no numerical instability exists even with a short list length. As shown in Fig. 6, we can see that the convergence behaviour of the proposed low-complexity Bit-LR detector could approach that of the MCMC detectors, because their EXIT curves are similar to each other when I_{in} is close to 1.

6 Conclusion

In this paper, bit-level LR-aided approximate MAP detectors for the IDD in the MIMO systems were studied, where the LR-MMSE filters incorporating with the API have been derived for each coded bit individually, and the lists of the candidate vectors are generated based on the LR-aided soft-decision for a better performance. To reduce the complexity further in the large dimensional MIMO systems, the channel matrix decomposition and the SIC together with the list generation have been employed. From the simulation results, we observed that the performance is marginally degraded, while the complexity was significantly reduced. Through the simulations and the complexity analysis for the IDD both in the small and the large dimensional MIMO systems, we also confirmed that the proposed methods have better performance than the conventional MMSE-SC detector with comparable complexity. For future studies, we may consider the joint channel estimation and the IDD using the LR-based detectors, where the channel estimates and the lattice basis reduction need to be jointly performed.

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8 References

1 Foschini, G.J., Gans, M.J.: 'On limits of wireless communications in a fading environment when using multiple antennas', *Wirel. Personal Commun.*, 1998, **6**, pp. 311–335
2 Telatar, I.E.: 'Capacity of multi-antenna Gaussian channels', *Eur. Trans. Telecommun.*, 1999, **10**, (6), pp. 585–595
3 Wolniansky, P.W., Foschini, G.J., Golden, G.D., Valenzuela, R.A.: 'V-BLAST: an architecture for realizing very high data rates over the rich-scattering wireless channel'. Proc. IEEE ISSSE '98, 1998, pp. 295–300
4 Foschini, G.J., Golden, G.D., Valenzuela, R.A., Wolniansky, P.W.: 'Simplified processing for high spectral efficiency wireless communication employing multi-element arrays', *IEEE J. Sel. Areas Commun.*, 1999, **17**, (4), pp. 1841–1853
5 Golden, G.D., Foschini, C.J., Valenzuela, R.A., Wolniansky, P.W.: 'Detection algorithm and initial laboratory results using V-BLAST space-time communication architecture', *Electron. Lett.*, 1999, **35**, (1), pp. 14–16
6 Caire, G., Taricco, G., Biglieri, E.: 'Bit-interleaved coded modulation', *IEEE Trans. Inf. Theory*, 1998, **44**, (3), pp. 927–946
7 Hagenauer, J., Offer, E., Papke, L.: 'Iterative decoding of binary block and convolutional codes', *IEEE Trans. Inf. Theory*, 1996, **42**, (2), pp. 429–445
8 Hochwald, B., Brink, S.t.: 'Achieving near-capacity on a multiple-antenna channel', *IEEE Trans. Commun.*, 2003, **51**, (3), pp. 389–399
9 Vikalo, H., Hassibi, B., Kailath, T.: 'Iterative decoding for MIMO channels via modified sphere decoding', *IEEE Trans. Wirel. Commun.*, 2004, **3**, (6), pp. 2299–2311
10 Choi, J., Hong, Y., Yuan, J.: 'An approximate MAP based iterative receiver for MIMO channels using a modified sphere detection', *IEEE Trans. Wirel. Commun.*, 2006, **5**, (8), pp. 2199–2126
11 Papa, G., Ciuonzo, D., Romano, G., Salvo Rossi, P.: 'Soft-input soft-output king decoder for coded MIMO wireless communications'. Proc. IEEE Int. Symp. on Wireless Communication Systems (ISWCS), Aachen, Germany, November 2011, pp. 1:760–763
12 de Jong, Y.-L.C., Wilink, T.J.: 'Iterative tree search detection for MIMO wireless systems', *IEEE Trans. Commun.*, 2005, **53**, (6), pp. 930–935

13 Choi, J.W., Shim, B., Nelson, J.K., Singer, A.C.: 'Efficient soft-input soft-output MIMO detection via improved M-algorithm'. Proc. IEEE Int. Conf. Commun., Cape Town, South Africa, May 2010, pp. 1–5

14 Studer, C., Bólcskei, H.: 'Soft-input soft-output single tree-search sphere decoding', *IEEE Trans. Inf. Theory*, 2010, **56**, (10), pp. 4827–4842

15 Lee, J., Shim, B., Kang, I.: 'Soft-input soft-output list sphere detection with a probabilistic radius tightening', *IEEE Trans. Wirel. Commun.*, 2012, **11**, (8), pp. 2848–2857

16 Prasad, N., Kalbat, K.Y., Wang, X.: 'Optimally efficient max-log APP demodulation in MIMO systems', *IEEE J. Sel. Top. Signal Process.*, 2011, **5**, (8), pp. 1400–1414

17 Nekuii, M., Kisialiou, M., Davidson, T.-N., Luo, Z.-Q.: 'Efficient soft-output demodulation of MIMO QPSK via semidefinte relaxation', *IEEE J. Sel. Top. Signal Process.*, 2011, **5**, (8), pp. 1426–1437

18 Dong, B., Wang, X., Doucet, A.: 'A new class of MIMO demodulation algorithms', *IEEE Trans. Signal Process.*, 2003, **41**, (11), pp. 2752–2763

19 Farhang-Boroujeny, B., Zhu, H., Shi, Z.: 'Markov chain Monte Carlo algorithms for CDMA and MIMO communication systems', *IEEE Trans. Signal Process.*, 2006, **54**, (5), pp. 1896–1909

20 Laraway, S., Farhang-Boroujeny, B.: 'Implementation of a markov chain monte carlo based multiuser/MIMO detector', *IEEE Trans. Circuits Syst. I, Regul. Pap.*, 2009, **56**, (1), pp. 246–255

21 Wang, X., Poor, H.V.: 'Iterative (turbo) soft interference cancellation and decoding for coded CDMA', *IEEE Trans. Commun.*, 1999, **47**, (7), pp. 1046–1061

22 Choi, J.W., Singer, A.C., Lee, J., Cho, N.I.: 'Imporved linear soft-input soft-output detection via soft feedback successive interference cancellation', *IEEE Trans. Commun.*, 2010, **58**, (3), pp. 986–996

23 Choi, J.: 'Approximate MAP detection with ordering and successive processing for iterative detection and decoding in MIMO systems', *IEEE J. Sel. Top. Signal Process.*, 2011, **5**, (8), pp. 1415–1425

24 Yao, H., Wornell, G.W.: 'Lattice-reduction-aided detectors for MIMO communication systems'. Proc. IEEE Globecom '02, 2002, vol. 1, pp. 424–428

25 Wübben, D., Böhnke, R., Kühn, V., Kammeyer, K.-D.: 'Near-maximum-likelihood detection of MIMO system using MMSE-based lattice-reduction'. Proc. IEEE Int. Conf. on Communications, June 2004, vol. 2, pp. 798–802

26 Choi, J., Nguyen, H.X.: 'SIC based detection with list and lattice reduction for MIMO channels', *IEEE Trans. Veh. Tech.*, 2009, **58**, (7), pp. 3786–3790

27 Choi, J.: 'Optimal combining and detection' (Cambridge University Press, 2010)

28 Ma, X., Zhang, W.: 'Performance analysis for MIMO systems with linear equalization', *IEEE Trans. Commun.*, 2008, **56**, (2), pp. 309–318

29 Silvola, P., Hooli, K., Juntti, M.: 'Suboptimal soft-output MAP detector with lattice reduction', *IEEE Signal Process. Lett.*, 2006, **13**, (6), pp. 321–324

30 Milliner, D., Barry, J.R.: 'A lattice-reduction-aided soft detector for multiple-input multiple-output channels'. Proc. IEEE Globecom '06, November 2006, pp. 1–5

31 Zhang, W., Ma, X.: 'Low-complexity soft-output decoding with lattice-reduction-aided detectors', *IEEE Trans. Commun.*, 2010, **58**, (9), pp. 2621–2629

32 Chindapol, A., Ritcey, J.A.: 'Design, analysis, and performance evaluation for BICM-ID with square QAM constellations in Rayleigh fading channels', *IEEE J. Select. Areas Commun.*, 2001, **19**, pp. 944–957

33 Lenstra, A.K., Lenstra, H.W., Lovász, L.: 'Factoring polynomials with rational coefficients', *Math. Annalen*, 1982, **261**, pp. 515–534

34 Wübben, D., Böhnke, R., Kühn, V., Kammeryer, K.D.: 'Near-maximum-likelihood detection of MIMO systems using MMSE-based lattice reduction'. Proc. IEEE Int. Conf. Commun., Paris, France, June 2004, pp. 798–802

35 Gan, Y.H., Ling, C., Mow, W.H.: 'Complex lattice reduction algorithm for low-complexity full-diversity MIMO detection', *IEEE Trans. Signal Process.*, 2009, **57**, (7), pp. 2701–2710

36 ten Brink, S.: 'Convergence behavior of iteratively decoded parallel concatenated codes', *IEEE Trans. Commun.*, 2001, **49**, (10), pp. 1727–1737

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