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PAPER

Low Complexity Soft Input Decoding in an Iterative Linear Receiver for Overloaded MIMO

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SUMMARY This paper proposes a low complexity soft input decoding in an iterative linear receiver for overloaded MIMO. The proposed soft input decoding applies two types of lattice reduction-aided linear filters to estimate log-likelihood ratio (LLR) in order to reduce the computational complexity. A lattice reduction-aided linear with whitening filter is introduced for the LLR estimation in the proposed decoding. The equivalent noise caused by the linear filter is mitigated with the decoder output stream and the LLR is re-estimated after the equivalent noise mitigation. Furthermore, LLR clipping is introduced in the proposed decoding to avoid the performance degradation due to the incorrect LLRs. The performance of the proposed decoding is evaluated by computer simulation. The proposed decoding achieves about 2 dB better BER performance than soft decoding with the exhaustive search algorithm, so called the MLD, at the BER of 10^{-4}, even though the complexity of the proposed decoding is $\frac{1}{10}$ as small as that of soft decoding with the exhaustive search.

key words: *MIMO, overloaded, linear detection, iterative decoding, soft-input-soft-output (SISO)*

1. Introduction

High speed wireless communication has been demanded for access networks such as cellular networks and wireless local area networks (WLANs). The fifth generation cellular system is going to provide us with communication links that offer about 100 times higher speeds than the fourth generation system [1]. For such high speed wireless communications, a lot of techniques have been investigated, e.g., adaptive modulation and coding (AMC), orthogonal frequency division multiplexing (OFDM), multiple-input-multiple-output (MIMO). Especially, MIMO spatial multiplexing has been intensively investigated because it can increase the link capacity in proportion to the number of antennas on a receiver and a transmitter without additional frequency band [2]–[4]. Many techniques have been proposed to exploit the potential of MIMO spatial multiplexing. Minimum mean square error (MMSE) spatial filters, serial interference cancellers (SICs), complexity reduced maximum likelihood detection (MLD) with QR decomposition and $M-$algorithm (QRM-MLD) [5], and so on, have been proposed for the receiver. To improve the transmission performance, the Turbo principle [6], [7] has been considered for MIMO receivers [8]–[13]. For instance, the Turbo equalization, a representative of those techniques, has been investigated because of its high transmission performance.

Non-orthogonal signal transmission systems that simultaneously send more signal streams than the degree of freedom have been proposed for further high speed signal transmission. For instance, low density signature (LDS) and sparse code multiple access (SCMA) have been proposed that employ sparse codes for spectrum spreading [14]–[16]. The faster than Nyquist (FTN), which loads more subcarriers in a band than OFDM, is also regarded as a type of non-orthogonal transmission schemes, and its performance has been evaluated [17]. Overloaded MIMO can be also classified into non-orthogonal signal transmission. Several receiver configurations have been proposed for overloaded MIMO [18], [19]. Linear detectors such as MMSE spatial filters, SICs and QRM-MLD are useless because of their poor performance due to lack of the freedom in overloaded MIMO systems. Non-linear detectors, e.g. the MLD, have been considered. For instance, joint decoding has been proposed to achieve the optimum performance in overloaded MIMO systems with error correction coding [20]. Because non-linear detection executes exhaustive search, non-linear detection imposes a prohibitively high computational load on receivers. Therefore, reduced complexity detection techniques have been proposed [21]–[23]. Iterative soft input decoding for those receivers has been proposed [24], [25]. Since those receivers still have some non-linear signal processing, the complexity of the receivers grows exponentially as the number of the signal streams increases. For further complexity reduction, linear signal detectors have also been considered even for overloaded MIMO [26]. Although the receiver proposed in [26] achieves superior performance, hard input decoding is utilized, because lattice reduction is applied for linear detectors to achieve superior performance even in overloaded MIMO systems. Though soft input decoding is known to achieve better performance, prohibitive high complexity is needed to convert received signals into soft signals, because only exhaustive search has been known to be useful for the soft signal conversion in overloaded MIMO systems.

This paper proposes a low complexity soft input decoding in an iterative linear receiver for overloaded MIMO. The proposed soft input decoding applies linear filters to convert the received signals into log likelihood ratios (LLRs) as soft signals for reducing the complexity of the signal conversion. Lattice reduction is applied to the linear filters for attaining

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near optimum performance. However, some of the linear filters are obliged to detect the signals in the channel with strong interference. Because the interference can be regarded as colored noise, noise whitening based on cholesky factorization is introduced in the proposed decoding. The noise cancellation proposed in [26] is also used because it can improve the SNR of the linear filter output signals. Moreover, we propose iterative decoding where the signal processing chain from the LLR estimation, the decoding and, the noise cancellation fed with the decoder output stream is iterated in order to improve the reliability of the LLRs. In addition, we propose to clip the amplitude of the LLRs prior to the channel decoding for avoiding incorrect LLR violating the proposed decoding.

A system model of overload MIMO is described in the next section. The proposed decoding is explained in Sect. 3, and Sect. 4 evaluates the performance of the proposed decoding. The conclusion is remarked in Sect. 5.

Throughout this paper, $(\mathbf{A})^{-1}$, $\{\mathbf{A}\}_m$ and superscript T denote an inverse matrix, an mth column vector of a matrix $\mathbf{A}$, and transpose of a matrix or a vector, respectively. $\mathrm{E}[\beta]$, $\Re[\alpha]$, and $\Im[\alpha]$ represent the ensemble average of a variable β, a real part and an imaginary part of a complex number α.

2. System Model

We assume that a transmitter with N_T antennas sends signals to a receiver with N_R antennas. However, the number of the transmit antennas N_T is bigger than that of the receive antennas N_R, which channel is so called "Overloaded MIMO". The information bit stream is firstly fed to a channel encoder, and the output bit stream is provided to Quaternary phase shift keying (QPSK) modulators via an interleaver. The modulation signals from one of the modulators are provided to an IFFT processor in order to convert the input signals into the time domain. The modulator, the IFFT processor and the antennas are comprised of a transmit signal chain connected to one of the antennas. Let $x_{\mathrm{c},n}(k) \in \mathbb{C}$ denote the nth signal from the ith modulator, the transmission signal vector $\mathbf{X}_{\mathrm{c},n} \in \mathbb{C}^{N_\mathrm{T}\times 1}$ consisting of the nth signals from all the modulators can be defined as $\mathbf{X}_{\mathrm{c},n} = \left(x_{\mathrm{c},n}(1) \cdots x_{\mathrm{c},n}(N_\mathrm{T})\right)^\mathrm{T}$. The transmission signal vector at the k time instant $\mathbf{S}_k \in \mathbb{C}^{N_\mathrm{T}\times 1}$ can be defined as,

$$\mathbf{S}_k = \frac{1}{\sqrt{N_\mathrm{F}}} \sum_{n=0}^{N_\mathrm{F}-1} \mathbf{X}_{\mathrm{c},n} \mathrm{e}^{\mathrm{j}2\pi \frac{kn}{N_\mathrm{F}}}, \tag{1}$$

where $\mathrm{j} \in \mathbb{C}$, $\mathrm{e} \in \mathbb{R}$, and $N_\mathrm{F} \in \mathbb{Z}$ represent the imaginary unit, and the Napier's constant, and the number of the FFT points, i.e., the number of the subcarriers. The transmission signal vector travels a multipath fading channel, and is received at the N_R receive antennas. Let $\mathbf{Y}_{\mathrm{c},k} \in \mathbb{C}^{N_\mathrm{R}\times 1}$ denote the received signal vector at the k time instant, the vector can be written as follows.

$$\mathbf{Y}_{\mathrm{c},k} = \sum_{l=0}^{N_\mathrm{P}-1} \mathbf{H}_{\mathrm{c},l} \mathbf{S}_{k-l} + \mathbf{N}_{\mathrm{c},k} \tag{2}$$

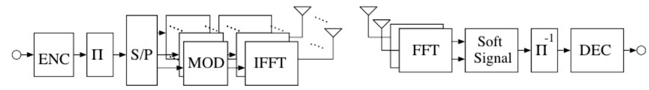

Fig. 1 System model.

In (2), $N_\mathrm{P} \in \mathbb{Z}$, $\mathbf{H}_{\mathrm{c},l} \in \mathbb{C}^{N_\mathrm{R}\times N_\mathrm{T}}$ and $\mathbf{N}_{\mathrm{c},k} \in \mathbb{C}^{N_\mathrm{R}\times 1}$ represent the number of the paths in the channel, the channel matrix of the lth delayed path and the additive white Gaussian noise vector. If the received signal vector is provided to the FFT processor, a frequency domain vector $\mathbf{Y}_{\mathrm{c},n} \in \mathbb{C}^{N_\mathrm{R}\times 1}$ on the nth subcarriers can be obtained as,

$$\mathbf{Y}_{\mathrm{c},n} = \frac{1}{\sqrt{N_\mathrm{F}}} \sum_{k=0}^{N_\mathrm{F}-1} \mathbf{Y}_{\mathrm{c},k} \mathrm{e}^{-\mathrm{j}2\pi \frac{kn}{N_\mathrm{F}}} = \mathbf{H}_{\mathrm{c},n}\mathbf{X}_{\mathrm{c},n} + \mathbf{N}_{\mathrm{c},n} \tag{3}$$

$$\mathbf{H}_{\mathrm{c},n} = \sum_{l=0}^{N_\mathrm{P}-1} \mathbf{H}_{\mathrm{c},l} \mathrm{e}^{-\mathrm{j}2\pi \frac{ln}{N_\mathrm{F}}}.$$

$\mathbf{H}_{\mathrm{c},n} \in \mathbb{C}^{N_\mathrm{R}\times N_\mathrm{T}}$ and $\mathbf{N}_{\mathrm{c},n} \in \mathbb{C}^{N_\mathrm{R}\times 1}$ denote a channel matrix and the AWGN vector on the nth subcarrier [27]. All the frequency domain vectors $\mathbf{Y}_{\mathrm{c},n} \in \mathbb{C}^{N_\mathrm{R}\times 1}$ $n = 1 \cdots N_\mathrm{F}$ are fed to our proposed detector and the output signals from the detector is provided to a channel decoder. The transmission system is shown in Fig. 1 as a system model.

The transmission signal vector $\mathbf{X}_{\mathrm{c},n}$, the received signal vector $\mathbf{Y}_{\mathrm{c},n}$, and the AWGN vector are transformed into real vectors in our proposed soft detector. The real transmission signal vector $\mathbf{X}_n \in \mathbb{R}^{2N_\mathrm{T}\times 1}$, the real received signal vector $\mathbf{Y}_n \in \mathbb{R}^{2N_\mathrm{R}\times 1}$ and the real AWGN vector $\mathbf{N}_n \in \mathbb{R}^{2N_\mathrm{R}\times 1}$ on the nth subcarriers are defined as $\mathbf{X}_n = \left(\Re[\mathbf{X}_{\mathrm{c},n}]^\mathrm{T}\ \Im[\mathbf{X}_{\mathrm{c},n}]^\mathrm{T}\right)^\mathrm{T}$, $\mathbf{Y}_n = \left(\Re[\mathbf{Y}_{\mathrm{c},n}]^\mathrm{T}\ \Im[\mathbf{Y}_{\mathrm{c},n}]^\mathrm{T}\right)^\mathrm{T}$, and $\mathbf{N}_n = \left(\Re[\mathbf{N}_{\mathrm{c},n}]^\mathrm{T}\ \Im[\mathbf{N}_{\mathrm{c},n}]^\mathrm{T}\right)^\mathrm{T}$, respectively. In addition, the real channel matrix on the nth subcarriers $\mathbf{H}_n \in \mathbb{R}^{2N_\mathrm{R}\times 2N_\mathrm{T}}$ is also defined as,

$$\mathbf{H}_n = \begin{pmatrix} \Re[\mathbf{H}_{\mathrm{c},n}] & -\Im[\mathbf{H}_{\mathrm{c},n}] \\ \Im[\mathbf{H}_{\mathrm{c},n}] & \Re[\mathbf{H}_{\mathrm{c},n}] \end{pmatrix}. \tag{4}$$

Even if those vectors and the matrix are expressed in real numbers, the system model can be expressed in a similar manner as (3), which is written as follows.

$$\mathbf{Y}_n = \mathbf{H}_n\mathbf{X}_n + \mathbf{N}_n \tag{5}$$

Next section describes our proposed low complexity soft input decoding with the signal vectors $\mathbf{Y}_n$ $n = 1 \cdots N_\mathrm{F}$.

3. Low Complexity Iterative Decoding

3.1 Lattice Reduction-Aided LLR Estimation

As is well known, *a posteriori* LLR can be dealt as a soft input signal. Let $x(k) \in \mathbb{R}$ denote the kth transmission signal included in the transmission signal vector on the nth subcarrier, $\mathbf{X}_n$, if we assume that every signal takes ± 1 with equal probability, *a posteriori* LLR of the signal $x(k)$, $\gamma(x(k)) \in \mathbb{R}$, can be approximately written as follows.

$$\begin{aligned}\gamma(x(k)) &= \log \frac{\mathrm{P}(x(k)=1|\mathbf{Y}_n)}{\mathrm{P}(x(k)=-1|\mathbf{Y}_n)} \\ &\approx \log \frac{\sum_{x(k)=1} \mathrm{P}(\mathbf{Y}_n|c_0 \cdots c_{2N_\mathrm{T}-1})}{\sum_{x(k)=-1} \mathrm{P}(\mathbf{Y}_n|c_0 \cdots c_{2N_\mathrm{T}-1})} \\ &\approx \max_{x(k)=1} \left[\log \mathrm{P}(\mathbf{Y}_n|c_0 \cdots c_{2N_\mathrm{T}-1})\right] \\ &\quad - \max_{x(k)=-1} \left[\log \mathrm{P}(\mathbf{Y}_n|c_0 \cdots c_{2N_\mathrm{T}-1})\right] \\ &= -\frac{1}{\sigma^2}\left(\min_{x(k)=1} \left|\mathbf{Y}_n - \mathbf{H}_n\bar{\mathbf{X}}_n\right|^2 - \min_{x(k)=-1} \left|\mathbf{Y}_n - \mathbf{H}_n\bar{\mathbf{X}}_n\right|^2\right)\end{aligned} \tag{6}$$

σ^2 and $\mathrm{P}(a|b)$ in (6) represent a variance of the AWGN and a conditional probability that an event a happens when an event b occurred. In addition, $\max_{\alpha}[\beta]$ indicates a function that outputs the maximum value of β under a constraint of α. $\min_{\alpha}[\beta]$ also outputs the minimum value of β under a constraint of α. In the most right hand side of (6), the minimum values with respect to the transmission signal vector $\mathbf{X}_n$ under a constraint of $x(k) = \pm 1$ have to be searched. The optimum vectors to satisfy the minimization problems can be found by the exhaustive search, which almost requires twice as much complexity as the MLD. In principle, complexity of the exhaustive search grows exponentially as the number of the transmit antennas increases. Such a high complexity signal processing is needed for every bit, which means that the LLR calculation requires about $4N_\mathrm{T}$ times as much complexity of the MLD. Prohibitive higher complexity can not be imposed on receivers. Therefore, the LLR estimation that requires such high complexity can not be implemented in wireless communication systems.

For complexity reduction of the LLR estimation, we introduce the following assumption that detectors can find the similar vector as the exhaustive search if the performance of those detectors comes close to that of the exhaustive search. In a word, the assumption is that the optimum estimation vector is almost unique in spite of configuration of detectors, if those detectors achieve similar performance. On this assumption, we apply a linear detector to estimate a transmission signal vector $\bar{\mathbf{X}}_n$ instead of the exhaustive search. On the other hand, the same signal processing is carried out in every subcarrier except for the channel decoding, the suffix n indicating the number of the subcarrier is hereafter dropped. Let $\mathrm{LF}^{(0)}[\mathbf{Y}]$ indicate a function of a linear filter where the vector $\mathbf{Y}$ is an input signal vector, the assumption can be written as follows.

$$\begin{aligned}\bar{\mathbf{X}} &= \arg\min_{\mathbf{X}} \left[|\mathbf{Y} - \mathbf{H}\mathbf{X}|^2\right] \\ &\approx \mathrm{LF}^{(0)}[\mathbf{Y}]\end{aligned} \tag{7}$$

To make the linear filter achieve better performance in overloaded MIMO systems, the lattice reduction is applied to the following extended channel matrix in which an diagonal matrix is added under the channel matrix $\mathbf{H}$ [26].

$$\begin{pmatrix} \mathbf{H} \\ \frac{\sigma}{\sigma_\mathrm{d}}\mathbf{I}_{2N_\mathrm{T}\times 2N_\mathrm{T}} \end{pmatrix}\mathbf{T} = (\mathbf{Q}_1\ \mathbf{Q}_2)\begin{pmatrix} \mathbf{R}_1 \\ \mathbf{O}_{2N_\mathrm{R}\times 2N_\mathrm{T}} \end{pmatrix} \tag{8}$$

σ_d, $\mathbf{I}_{2N_\mathrm{T}\times 2N_\mathrm{T}} \in \mathbb{R}^{2N_\mathrm{T}\times 2N_\mathrm{T}}$ and $\mathbf{T} \in \mathbb{R}^{2N_\mathrm{T}\times 2N_\mathrm{T}}$ in (8) represent a standard deviation of the transmission signals, i.e., $\sigma_\mathrm{d} = \sqrt{\mathrm{E}\left[|x(k)|^2\right]}$, the $2N_\mathrm{T} \times 2N_\mathrm{T}$-dimensional identity matrix and a unimodular matrix. As is shown in (8), the extended channel matrix with the unimodular matrix is QR-decomposed into a unitary matrix $(\mathbf{Q}_1\ \mathbf{Q}_2) \in \mathbb{R}^{2(N_\mathrm{T}+N_\mathrm{R})\times 2(N_\mathrm{T}+N_\mathrm{R})}$ and a right upper triangular matrix $\left(\mathbf{R}_1^\mathrm{T}\ \mathbf{O}_{2N_\mathrm{T}\times 2N_\mathrm{R}}\right)^\mathrm{T} \in \mathbb{R}^{2N_\mathrm{T}\times 2(N_\mathrm{T}+N_\mathrm{R})}$, where $\mathbf{Q}_1 \in \mathbb{R}^{2(N_\mathrm{T}+N_\mathrm{R})\times 2N_\mathrm{T}}$, $\mathbf{Q}_2 \in \mathbb{R}^{2(N_\mathrm{T}+N_\mathrm{R})\times 2N_\mathrm{R}}$, and $\mathbf{R}_1 \in \mathbb{R}^{2N_\mathrm{T}\times 2N_\mathrm{T}}$ denote the right submatrix and the left submatrix of the unitary matrix, and a square right upper triangular matrix. In addition, $\mathbf{O}_{2N_\mathrm{R}\times 2N_\mathrm{T}}$ represents the $2N_\mathrm{R}\times 2N_\mathrm{T}$-dimensional null matrix. The transmission signals can be be detected with an SIC by making use of the right upper triangular matrix given by the QR-decomposition. Let an extended received signal matrix $\underline{\mathbf{Y}}^{(0)} \in \mathbb{R}^{2(N_\mathrm{T}+N_\mathrm{R})\times 1}$ be defined as $\underline{\mathbf{Y}}^{(0)} = \left(\mathbf{Y}^\mathrm{T}\ \mathbf{O}_{2N_\mathrm{T}}^\mathrm{T}\right)^\mathrm{T}$ where $\mathbf{O}_{2N_\mathrm{T}} \in \mathbb{R}^{2N_\mathrm{T}\times 1}$ represents the $2N_\mathrm{T}$-dimensional null vector, the signal detection can be written as follows.

$$\bar{z}^{(0)}(m) = \left\lfloor \frac{\mathbf{Q}_{1,m}^\mathrm{T}\underline{\mathbf{Y}}^{(0)} - \sum_{i=2N_\mathrm{T}}^{m-1} r_1(m,i)\bar{z}(i)}{r_1(m,m)} \right\rceil \qquad m = 2N_\mathrm{T}, \cdots, 1 \tag{9}$$

In (9), $\bar{z}(m) \in \mathbb{R}$ $\quad m = 1 \cdots 2N_\mathrm{T}$, $\mathbf{Q}_{1,m} \in \mathbb{R}^{2(N_\mathrm{T}+N_\mathrm{R})\times 1}$ and $r_1(m,n) \in \mathbb{R}$ denote an SIC output signals, the mth column of the matrix $\mathbf{Q}_1$ and the (m,n)-entry of the square right upper triangular matrix $\mathbf{R}_1$. In addition, $\lfloor \bullet \rceil$ denotes the function that outputs a possible nearest integer of the input signal. This detection can be regarded as an SIC assisted with the lattice reduction. The output signals are written in a vector format, i.e., $\bar{\mathbf{Z}}^{(0)} = \left(\bar{z}^{(0)}(1) \cdots \bar{z}^{(0)}(2N_\mathrm{T})\right)^\mathrm{T} \in \mathbb{R}^{2N_\mathrm{T}\times 1}$. Finally, the output vector of the linear function $\mathrm{LF}^{(0)}[\mathbf{Y}]$ can be obtained as,

$$\mathrm{LF}^{(0)}[\mathbf{Y}] = \mathbf{T}\bar{\mathbf{Z}}^{(0)} \quad . \tag{10}$$

As is shown above, the transmission signal vector $\mathbf{X}$ is estimated without any exhaustive search. Hence, the complexity of the linear filter is much less than that of the exhaustive search.

One of the two terms in the most right hand side of (6) has only been estimated with the linear filter, even though the two terms are necessary. Hence, we propose a linear filtering technique for estimating the other term in the next section.

3.2 Complementary Vector Estimation

Let the channel matrix be expressed with the column vectors as $\mathbf{H} = (\mathbf{H}_1 \cdots \mathbf{H}_{2N_\mathrm{T}})$, a complementary matrix $\tilde{\mathbf{H}}_k \in \mathbb{R}^{2N_\mathrm{R}\times(2N_\mathrm{T}-1)}$ is defined with all the column vectors except the kth column as $\tilde{\mathbf{H}}_k = (\mathbf{H}_1 \cdots \mathbf{H}_{k-1}\ \mathbf{H}_{k+1} \cdots \mathbf{H}_{2N_\mathrm{T}})$. Similarly, a complementary vector $\tilde{\mathbf{X}}_k \in \mathbb{R}^{(2N_\mathrm{T}-1)\times 1}$ is also defined with all the entries of the transmission vector except the kth entry as $\tilde{\mathbf{X}}_k = (x(1) \cdots x(k-1)\ x(k+1) \cdots x(2N_\mathrm{T}))^\mathrm{T}$. The linear detector defined in the previous section is assumed to estimate the transmission signal vector with $x(k) = d_k^{(0)}$ where $d_k^{(0)}$ takes ±1, i.e., $d_k^{(0)} = \pm 1$ for one of the term in (6). Let a signal $\ddot{d}_k^{(0)} \in \mathbb{Z}$ be defined as $\ddot{d}_k^{(0)} = -1 \times d_k^{(0)}$, the other term in (6) can be rewritten as,

$$\min_{x(k)=\ddot{d}_k^{(0)}} \left[|\mathbf{Y} - \mathbf{H}\mathbf{X}|^2\right] = \min \left[\left|\mathbf{Y} - \tilde{\mathbf{H}}_k \tilde{\mathbf{X}}_k - \mathbf{H}_k \ddot{d}_k^{(0)}\right|^2\right]. \quad (11)$$

Let a complementary received signal vector $\tilde{\mathbf{Y}}_k^{(0)} \in \mathbb{R}^{2N_\mathrm{R}\times 1}$ be defined as,

$$\tilde{\mathbf{Y}}_k^{(0)} = \mathbf{Y} - \mathbf{H}_k \ddot{d}_k^{(0)}. \quad (12)$$

As is done in (7), the minimization in the right hand side of (11) can be transformed to the estimation of the complementary vector $\tilde{\mathbf{X}}_k$.

$$\begin{aligned}\bar{\tilde{\mathbf{X}}}_k^{(0)} &= \arg\min_{\tilde{\mathbf{X}}_k} \left[\left|\tilde{\mathbf{Y}}_k^{(0)} - \tilde{\mathbf{H}}_k \tilde{\mathbf{X}}_k\right|^2\right] \\ &= \mathrm{LF}_\mathrm{k}^{(0)} \left[\tilde{\mathbf{Y}}_k^{(0)}\right] \end{aligned} \quad (13)$$

We introduce a liner filter to estimate the complementary vector $\tilde{\mathbf{X}}_k$ as follows. We can expect that the SIC explained in the previous section is able to estimate the transmission signal vector $\mathbf{X}$ with high accuracy, which means that the probability that d_k equals to the transmission signal is high. In a word, $\ddot{d}_k$ is different from the transmission signal with high probability, which causes $\mathbf{H}_k \ddot{d}_k^{(0)}$ to play a role of interference in (12). If the signal d_k is transmitted as the signal $x(k)$, actually, the vector $\tilde{\mathbf{Y}}_k$ can be written as follows.

$$\begin{aligned}\tilde{\mathbf{Y}}_k &\fallingdotseq \tilde{\mathbf{H}}_k \tilde{\mathbf{X}}_k + 2\mathbf{H}_k d_k + \mathbf{N} \\ &\fallingdotseq \tilde{\mathbf{H}}_k \tilde{\mathbf{X}}_k + \tilde{\mathbf{N}}_k, \end{aligned} \quad (14)$$

where $\tilde{\mathbf{N}}_k \in \mathbb{R}^{2N_\mathrm{R}\times 1}$ represents the equivalent noise vector defined as,

$$\tilde{\mathbf{N}}_k = 2\mathbf{H}_k \ddot{d}_k + \mathbf{N}. \quad (15)$$

As is indicated in (15), the interference signal $2\mathbf{H}_k \ddot{d}_k$ is mixed with the AWGN in the equivalent noise vector. The equivalent noise vector is not classified into the Gaussian noise, and the correlation matrix of the equivalent noise vector can be decomposed as follows.

$$\frac{1}{\sigma^2}\mathrm{E}\left[\tilde{\mathbf{N}}_k \tilde{\mathbf{N}}_k^\mathrm{T}\right] = \frac{\sigma_d^2}{\sigma^2}\mathbf{H}_k \mathbf{H}_k^\mathrm{T} + \mathbf{I}_{2N_\mathrm{R}\times 2N_\mathrm{R}} = \mathbf{L}_k \mathbf{L}_K^\mathrm{T} \quad (16)$$

In (16), $\mathbf{I}_{2N_\mathrm{R}\times 2N_\mathrm{R}} \in \mathbb{R}^{2N_\mathrm{R}\times 2N_\mathrm{R}}$ and $\mathbf{L}_k \in \mathbb{R}^{2N_\mathrm{R}\times 2N_\mathrm{R}}$ represent the $2N_\mathrm{R} \times 2N_\mathrm{R}$-dimensional identity matrix and a lower triangular matrix. The decomposition into the lower triangular matrix can be uniquely performed by the Cholesky factorization. Because colored noise such as the equivalent noise degrades the estimation performance of linear filters, whitening is applied to the vector $\underline{\tilde{\mathbf{Y}}}_k^{(0)}$ where $\underline{\tilde{\mathbf{Y}}}_k^{(0)}$ represents an extended signal vector defined as $\underline{\tilde{\mathbf{Y}}}_k^{(0)} = \left(\left(\tilde{\mathbf{Y}}_k^{(0)}\right)^\mathrm{T}\ \mathbf{O}_{2N_\mathrm{T}-1}^\mathrm{T}\right)^\mathrm{T}$.

$$\begin{aligned}\underline{\hat{\mathbf{Y}}}_k^{(0)} &= \begin{pmatrix} \mathbf{L}_k^{-1} & \mathbf{O}_{2N_\mathrm{R}\times(2N_\mathrm{T}-1)} \\ \mathbf{O}_{2N_\mathrm{T}-1\times 2N_\mathrm{R}} & \mathbf{I}_{(2N_\mathrm{T}-1)\times(2N_\mathrm{T}-1)} \end{pmatrix} \underline{\tilde{\mathbf{Y}}}_k^{(0)} \\ &= \begin{pmatrix} \mathbf{L}_k^{-1}\tilde{\mathbf{H}}_k \\ \frac{\sigma}{\sigma_\mathrm{d}}\mathbf{I} \end{pmatrix} \tilde{\mathbf{X}}_k + \begin{pmatrix} \mathbf{L}_k^{-1}\tilde{\mathbf{N}}_k \\ -\frac{\sigma}{\sigma_\mathrm{d}}\tilde{\mathbf{X}}_k \end{pmatrix} \end{aligned} \quad (17)$$

$\hat{\mathbf{Y}}_k^{(0)} \in \mathbb{R}^{(2N_\mathrm{T}+2N_\mathrm{R}-1)\times 1}$ denotes a whitening filter output vector. If the equation in (17) is regarded as a system model where the vector $\tilde{\mathbf{X}}_k$ is transmitted in the extended channel with the whitening, the vector $\tilde{\mathbf{X}}_k$ can be estimated by the linear filter similar as that explained in the previous section. The lattice reduction is applied to the channel matrix in the system model in (17) as follows.

$$\begin{pmatrix} \mathbf{L}_k^{-1}\tilde{\mathbf{H}}_k \\ \frac{\sigma}{\sigma_\mathrm{d}}\mathbf{I}_{(2N_\mathrm{T}-1)\times(2N_\mathrm{T}-1)} \end{pmatrix} \tilde{\mathbf{T}}_k = \begin{pmatrix} \tilde{\mathbf{Q}}_{1,k} & \tilde{\mathbf{Q}}_{2,k} \end{pmatrix} \begin{pmatrix} \tilde{\mathbf{R}}_{1,k} \\ \mathbf{O}_{2N_\mathrm{R}\times(2N_\mathrm{T}-1)} \end{pmatrix} \quad (18)$$

In (18), $\tilde{\mathbf{T}}_k \in \mathbb{R}^{(2N_\mathrm{T}-1)\times(2N_\mathrm{T}-1)}$, $\left(\tilde{\mathbf{Q}}_{1,k}\ \tilde{\mathbf{Q}}_{2,k}\right) \in \mathbb{R}^{(2N_\mathrm{T}+2N_\mathrm{R}-1)\times(2N_\mathrm{T}+2N_\mathrm{R}-1)}$ and $\left(\tilde{\mathbf{R}}_{1,k}^\mathrm{T}\ \mathbf{O}_{(2N_\mathrm{T}-1)\times 2N_\mathrm{R}}\right)^\mathrm{T} \in \mathbb{R}^{(2N_\mathrm{T}+2N_\mathrm{R}-1)\times(2N_\mathrm{T}-1)}$ denote a unimodular matrix, a unitary matrix and an upper triangular matrix where $\tilde{\mathbf{Q}}_{1,k} \in \mathbb{R}^{(2N_\mathrm{R}+2N_\mathrm{T}-1)\times(2N_\mathrm{T}-1)}$, $\tilde{\mathbf{Q}}_{2,k} \in \mathbb{R}^{(2N_\mathrm{R}+2N_\mathrm{T}-1)\times 2N_\mathrm{R}}$, and $\tilde{\mathbf{R}}_{1,k} \in \mathbb{R}^{(2N_\mathrm{T}-1)\times(2N_\mathrm{T}-1)}$ represent the right submatrix and the left submatrix of the unitary matrix, and a square right upper triangular matrix. The entries of the vector $\tilde{\mathbf{X}}_k$ can also be estimated with an SIC in the similar manner to that proposed in the previous section.

$$\bar{z}_k^{(0)}(m) = \left\lfloor \frac{\tilde{\mathbf{Q}}_{1,k,m}^\mathrm{T}\underline{\hat{\mathbf{Y}}}_k^{(0)} - \sum_{i=2N_\mathrm{T}-1}^{m-1} \tilde{r}_{1,k}(m,i)\bar{z}_k(i)}{\tilde{r}_{1,k}(m,m)} \right\rfloor$$
$$m = 2N_\mathrm{T}-1, \cdots, 1 \quad (19)$$

In (19), $\bar{z}_k^{(0)}(m) \in \mathbb{R}$ $m = 1 \cdots 2N_\mathrm{T}-1$, $\tilde{\mathbf{Q}}_{1,k,m} \in \mathbb{R}^{2(N_\mathrm{T}+N_\mathrm{R}-1)\times 1}$ and $\tilde{r}_{1,k}(m,i) \in \mathbb{R}$ denote an SIC output signals, the mth column of the matrix $\tilde{\mathbf{Q}}_1$ and the (m,n)-entry of the square right upper triangular matrix $\tilde{\mathbf{R}}_{1,k}$. Let $\tilde{\mathbf{Z}}_k^{(0)} \in \mathbb{R}^{(2N_\mathrm{T}-1)\times 1}$ be defined as $\tilde{\mathbf{Z}}_k^{(0)} = \left(\bar{z}_k^{(0)}(1) \cdots \bar{z}_k^{(0)}(2N_\mathrm{T}-1)\right)^\mathrm{T}$, the linear filter for the signal $x(k)$ is written as,

$$\mathrm{LF}_k^{(0)}\left[\tilde{\mathbf{Y}}_k\right] = \tilde{\mathbf{T}}_k \tilde{\mathbf{Z}}_k^{(0)}. \quad (20)$$

When the linear filter output vector $\bar{\tilde{\mathbf{X}}}_k^{(0)}$ is expressed as $\bar{\tilde{\mathbf{X}}}_k^{(0)} = \left(\bar{\tilde{x}}_k^{(0)}(1) \cdots \bar{\tilde{x}}_k^{(0)}(2N_\mathrm{T}-1)\right)$, the $2N_\mathrm{R}$-dimensional complementary vector $\bar{\mathbf{X}}^{(0)} \in \mathbb{R}^{2N_\mathrm{T}\times 1}$ can be formed as $\bar{\mathbf{X}}_k^{(0)} = \left(\bar{\tilde{x}}_k^{(0)}(1) \cdots \bar{\tilde{x}}_k^{(0)}(k-1)\ \ddot{d}_k^{(0)}\ \bar{\tilde{x}}_k^{(0)}(k) \cdots \bar{\tilde{x}}_k^{(0)}(2N_\mathrm{T}-1)\right)$. The complementary vector $\bar{\mathbf{X}}_k^{(0)}$ is provided to the LLR estimation as well as $\bar{\mathbf{X}}^{(0)}$.

$$\gamma^{(0)}(x(k)) \approx -\frac{d_k^{(0)}}{\sigma^2}\left(\left|\mathbf{Y} - \mathbf{H}\bar{\mathbf{X}}^{(0)}\right|^2 - \left|\mathbf{Y} - \mathbf{H}\bar{\mathbf{X}}_k^{(0)}\right|^2\right) \quad (21)$$

As is shown in (21), the LLR can be estimated without any exhaustive search.

As is shown in (17), the whitening filter output vector includes the transmission signals as a part of the equivalent noise vector, which may degrade the LLR estimation performance. Next section proposes a technique to improve the

LLR estimation performance.

3.3 Iterative LLR Estimation

As is drawn in Fig. 1, the LLR is provided to the channel decoder that outputs the soft signal stream. The output signal streams is used to improve the reliability of the LLR, and the improved LLR is fed to the decoder again. In a word, the decoding and the LLR estimation can be iterated, which could improve the LLR estimation and the channel decoding. In the iterative decoding, the signal stream is converted to the estimated transmission signal vectors $\mathbf{X}_{\mathrm{s}}^{(n_{\mathrm{s}})} \in \mathbb{R}^{2N_{\mathrm{T}}\times 1}$ via the interleaver where $n_{\mathrm{s}} \in \mathbb{Z}$ represents the number of the iterations of the decoding. As is suggested by [26], the equivalent noise† included in the system defined in (17) can be mitigated by adding the estimated transmission signal vector multiplied with a coefficient $\frac{\sigma}{\sigma_{\mathrm{d}}}$ as,

$$\underline{\mathbf{Y}}^{(n_{\mathrm{s}})} = \underline{\mathbf{Y}}^{(0)} + \frac{\sigma}{\sigma_{\mathrm{d}}} \begin{pmatrix} \mathbf{O}_{2N_{\mathrm{R}}} \\ \mathbf{X}_{\mathrm{s}}^{(n_{\mathrm{s}})} \end{pmatrix}. \quad (22)$$

The output vector $\underline{\mathbf{Y}}^{(n_{\mathrm{s}})} \in \mathbb{R}^{2(N_{\mathrm{T}}+N_{\mathrm{R}})\times 1}$ is fed to the LLR estimation where the vector is substituted for $\underline{\mathbf{Y}}^{(0)}$ in (9). Let $\bar{\mathbf{Z}}^{(n_{\mathrm{s}})} \in \mathbb{R}^{2N_{\mathrm{T}}\times 1}$ denote an output vector from the SIC when the vector $\underline{\mathbf{Y}}^{(n_{\mathrm{s}})}$ is given as an input vector, the output vector from the linear vector, $\bar{\mathbf{X}}^{(n_{\mathrm{s}})} \in \mathbb{R}^{2N_{\mathrm{T}}\times 1}$, is described as,

$$\bar{\mathbf{X}}^{(n_{\mathrm{s}})} = \mathrm{LF}^{(n_{\mathrm{s}})}\left[\mathbf{Y}\right] = \mathbf{T}\bar{\mathbf{Z}}^{(n_{\mathrm{s}})} \quad (23)$$

$\mathrm{LF}^{(n_{\mathrm{s}})}$ means the linear filter at n_{s}th decoding. As is previously explained, the output vector of the linear filter is provided to the LLR re-estimation based on (21).

On the other hand, the complementary vector $\tilde{\mathbf{X}}_k^{(n_{\mathrm{s}})}$ is also needed for the LLR re-estimation. Let the kth entry of the vector $\bar{\mathbf{X}}^{(n_{\mathrm{s}})}$ be $d_k^{(n_{\mathrm{s}})}$, the complementary received signal vector $\tilde{\mathbf{Y}}_k^{(n_{\mathrm{s}})}$ is obtained by substituting $\ddot{d}_k^{(n_{\mathrm{s}})}$ for $\ddot{d}_k^{(0)}$ in (12). Let the estimated transmission signal vector $\bar{\mathbf{X}}_{\mathrm{s}}^{(n_{\mathrm{s}})}$ be defined as. $\bar{\mathbf{X}}_{\mathrm{s}}^{(n_{\mathrm{s}})} = \left(\bar{x}_{\mathrm{s}}^{(n_{\mathrm{s}})}(1) \cdots \bar{x}_{\mathrm{s}}^{(n_{\mathrm{s}})}(2N_{\mathrm{T}})\right)$, an estimated complementary transmission signal vector $\tilde{\mathbf{X}}_{\mathrm{s},k}^{(n_{\mathrm{s}})} \in \mathbb{R}^{(2N_{\mathrm{T}}-1)\times 1}$ can be also defined as $\tilde{\mathbf{X}}_{\mathrm{s},k}^{(n_{\mathrm{s}})} = \left(\bar{x}_{\mathrm{s}}^{(n_{\mathrm{s}})}(1) \cdots \bar{x}_{\mathrm{s}}^{(n_{\mathrm{s}})}(k-1)\ \bar{x}_{\mathrm{s}}^{(n_{\mathrm{s}})}(k+1) \cdots \bar{x}_{\mathrm{s}}^{(n_{\mathrm{s}})}(2N_{\mathrm{T}})\right)$. The equivalent noise in the complementary received signal vector is also mitigated in the similar manner as (22).

$$\underline{\mathbf{Y}}_k^{(n_{\mathrm{s}})} = \begin{pmatrix} \tilde{\mathbf{Y}}_k^{(n_{\mathrm{s}})} \\ \mathbf{O}_{2N_{\mathrm{T}}-1} \end{pmatrix} + \frac{\sigma}{\sigma_{\mathrm{d}}} \begin{pmatrix} \mathbf{O}_{2N_{\mathrm{R}}} \\ \tilde{\mathbf{X}}_{\mathrm{s},k}^{(n_{\mathrm{s}})} \end{pmatrix} \quad (24)$$

The output signal vector from the noise canceller for the complementary received signal vector, $\underline{\mathbf{Y}}_k^{(n_{\mathrm{s}})} \in \mathbb{R}^{(2N_{\mathrm{T}}+2N_{\mathrm{R}}-1)\times 1}$, is provided for the LLR re-estimation where $\underline{\mathbf{Y}}_k^{(n_{\mathrm{s}})}$ is substituted for $\hat{\underline{\mathbf{Y}}}_k^{(0)}$ in (19). The linear filter output vector $\bar{\tilde{\mathbf{X}}}_k^{(n_{\mathrm{s}})} \in \mathbb{R}^{(2N_{\mathrm{T}}-1)\times 1}$ can be defined with the vector $\tilde{\mathbf{Z}}_k^{(n_{\mathrm{s}})}$ output from the SIC defined in (19) as,

$$\bar{\tilde{\mathbf{X}}}_k^{(n_{\mathrm{s}})} = \mathrm{LF}_k^{(n_{\mathrm{s}})}\left[\tilde{\mathbf{Y}}_k^{(n_{\mathrm{s}})}\right] = \tilde{\mathbf{T}}_k \tilde{\mathbf{Z}}_k^{(n_{\mathrm{s}})}. \quad (25)$$

The linear filter output vector is also provided for the LLR re-estimation based on (21).

3.4 LLR Clipping

As is explained in the previous section, our proposed decoder assumes that the linear filter described in Sect. 3.1 estimates the correct transmission signal vector. Actually, the assumption is not always held true when E_{b}/N_0 is not high enough. This causes the proposed LLR estimation to produce incorrect LLR with large amplitude, which violates the following decoding. Because the estimated vector $\mathbf{X}$ is the solution of (7), the first term in the right hand side of (21) is the smallest, even if the estimated signal $d_k^{(n_{\mathrm{s}})}$ included in the vector $\mathbf{X}$ is incorrect. Besides, because the linear filter defined in (13) is designed to estimate the vector in the channel with the strong noise defined in (14) and (15), the filter detects the incorrect vectors with high probability even if $\ddot{d}_k^{(0)}$ is correct, which causes the second term in the right hand side of (21) much bigger than the first term. As a result, a big incorrect LLR is fed to the decoder as the soft input signal. The incorrect LLR violates error correction of the decoder. We apply the following clipping technique to mitigate the violence††.

$$\gamma\left(x(k)\right) = \begin{cases} 2N_{\mathrm{R}}\sigma^2 & \left(\gamma\left(x(k)\right) > 2N_{\mathrm{R}}\sigma^2\right) \\ -2N_{\mathrm{R}}\sigma^2 & \left(\gamma\left(x(k)\right) < -2N_{\mathrm{R}}\sigma^2\right) \end{cases} \quad (26)$$

The proposed iterative soft input decoding is summarized as follows.

(a) initialization of the index n_{s}; $n_{\mathrm{s}} = 0$
(b) the transmission signal vector estimation $\bar{\mathbf{X}}^{(n_{\mathrm{s}})}$ with the extended received signal vector $\underline{\mathbf{Y}}^{(n_{\mathrm{s}})}$ shown in (10)
(c) the complementary vector estimation for all the bits included in the transmission signal vector $\bar{\tilde{\mathbf{X}}}^{(n_{\mathrm{s}})}$ as shown in (20)
(d) the LLRs estimation using the vectors $\bar{\mathbf{X}}^{(n_{\mathrm{s}})}$ and $\bar{\mathbf{X}}_k^{(n_{\mathrm{s}})}$ based on (21)
(e) the LLR clipping
(f) the channel decoding with the LLRs and its output soft signal stream
(g) $n_{\mathrm{s}} = n_{\mathrm{s}} + 1$
(h) the noise cancellation for the received signal vector and all the complementary received signal vectors as explained by (22) and (24)
(i) go back to (b)

4. Simulation

The performance of the proposed decoding is evaluated by

†The system model can be modeled by $\underline{\mathbf{Y}}^{(0)} = \begin{pmatrix} \mathbf{H} \\ \frac{\sigma}{\sigma_{\mathrm{d}}}\mathbf{I}_{2N_{\mathrm{T}}\times 2N_{\mathrm{T}}} \end{pmatrix}\mathbf{X} + \begin{pmatrix} \mathbf{N} \\ -\frac{\sigma}{\sigma_{\mathrm{d}}}\mathbf{X} \end{pmatrix}$. The second term in the right hand side of the above equation is called "the equivalent noise". The transmission signal vector in the equivalent noise can be removed by the noise cancellation defined in (22).

††The clipping technique is found to work well through computer simulation. It is one of our future works to prove the optimality of the technique.

Table 1 Parameters in computer simulation.

(N_T, N_R)	(6, 2)
Modulation	QPSK/OFDM
Number of subcarriers	128
Channel model	3-path Rayleigh fading
Channel estimation	Perfect
δ in LLL	0.9
Error correction coding	Convolutional code ($R = 1/2$, $K = 3$)
Decoding	Soft input soft output Viterbi algorithm

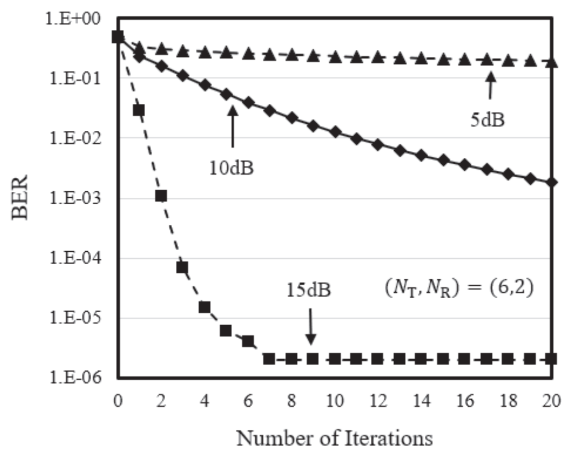

Fig. 2 Convergence property.

computer simulation in a 6×2 MIMO channel where 6 independent streams are simultaneously transmitted to a receiver with 2 antennas without any precoding. Overloading ratio is 3. 3-path Rayleigh fading based on the Jakes' model [28] is applied as a channel model between all the transmit and the receive antenna pairs. The number of subcarriers is 128. The Lenstra–Lenstra–Lovász (LLL) algorithm is used for the lattice reduction [29]. The convolutional code is employed as channel coding. The channel estimation is perfect†. The simulation parameters are listed in Table 1.

4.1 Convergence Property

The performance with respect to the number of the iterations is evaluated in Fig. 2. The horizontal and the vertical axes mean the number of the iterations and the average bit error rate (BER). The performances in the channel with the E_b/N_0 of 5 dB, 10 dB, and 15 dB are drawn in the figure. As is shown in the figure, the BER performance is improved as the number of the iterations increases, although the performance gain given by the iteration greatly depends on the E_b/N_0. The performance converges at the 8th iterators when the E_b/N_0 is 15 dB, while it takes more than 20 iterations to converge when the E_b/N_0 is 10 dB. As the number of the iterations is increased, complexity of the decoding rises. To balance the complexity and the performance, the number of the iterations is hereafter set to 15.

†The channel state estimation error causes the transmission performance degradation in not only the proposed decoding but also in the MLD. It is one of our future works to evaluate how much performance is degraded by the estimation error.

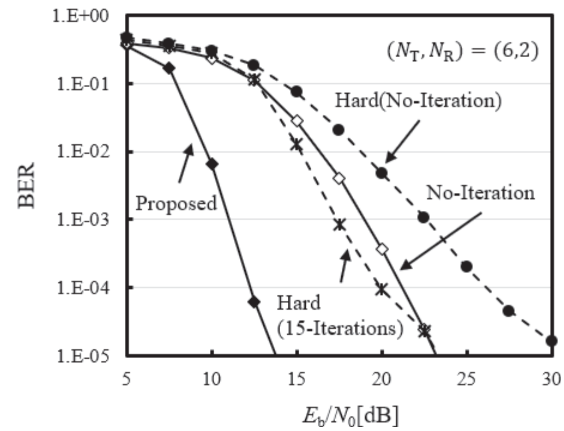

Fig. 3 Comparison with hard input decoding.

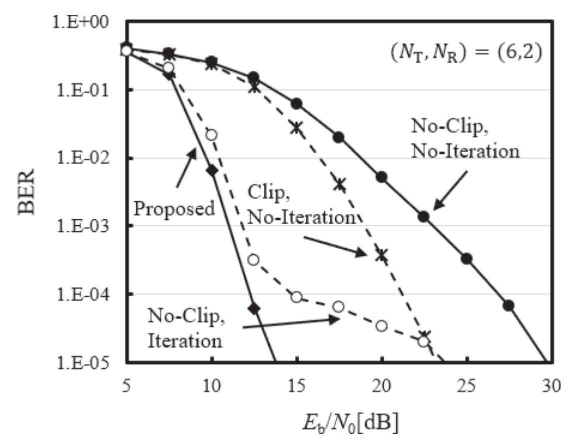

Fig. 4 Performance on proposed clipping.

4.2 Performance Gain from Hard Input Decoding

The performance of the proposed decoding is compared with that of hard iterative decoding in Fig. 3. We apply the iterative receiver proposed in [26] as the hard input decoding. The number of the iterations is set to 15 in both the hard input decoding and the soft input decoding. In the figure, the horizontal axis means the E_b/N_0 and the vertical axis is the BER. In the figure, the performances without the iteration are added as references. The soft input decoding achieves about 4 dB better performance than the hard input decoding at the BER of 10^{-4} when no iteration is executed. If the decoding is iterated 15 times, the performance gap between the soft input decoding and the hard input decoding is increased to about 7 dB at the BER of 10^{-4}. In a word, the soft input decoding attains higher gains than the hard input decoding.

4.3 Performance Gain by Clipping

Figure 4 shows the performance gain given by the proposed clipping. In the figure, the performance without the iterative LLR estimation is also added. The proposed clipping attains

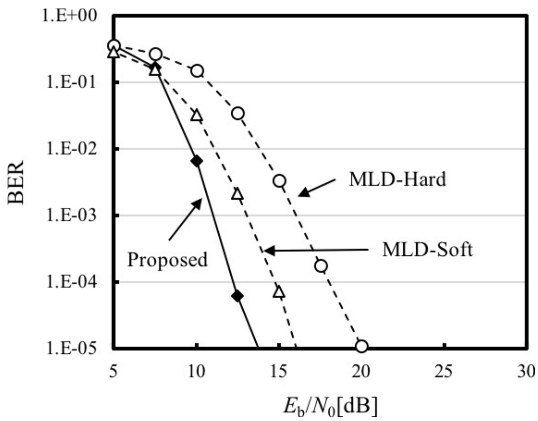

Fig. 5 Comparison with MLD.

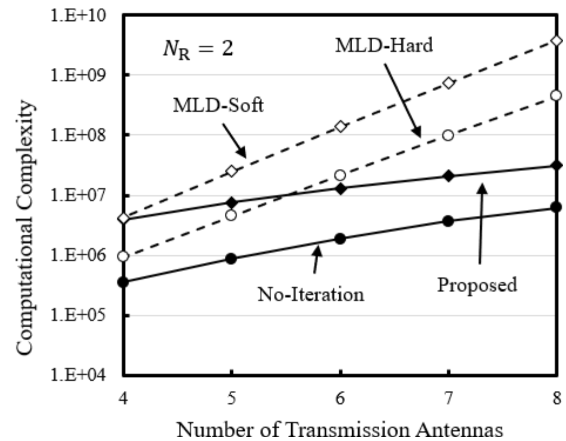

Fig. 6 Complexity.

a gain of about 4 dB at the BER of 10^{-3} even without the iteration. If the decoding is iterated 15 times, although the BER performance gain at the BER of 10^{-3} reduces to about 1 dB, the proposed clipping improves the BER in the region of the E_b/N_0 higher than 15 dB. The clipping achieves a gain of about 10 dB at the BER of 10^{-5}.

4.4 Comparison with MLD

The performance of the proposed decoding is compared with that of the soft input decoding with the exhaustive search in Fig. 5. In the figure, the soft input decoding with the exhaustive search is referred as "MLD". In addition, the hard input decoding with the exhaustive search is added as a reference. The soft input decoding and the hard input decoding with the exhaustive search are referred as "MLD-soft" and "MLD-hard" in the figure, respectively. The hard signal vector detected by the exhaustive search is provided to the decoder in the hard input decoding with the exhaustive search. Although the soft input decoding with the exhaustive search is known to achieve the optimum performance, the proposed decoding outperforms the soft input decoding with the exhaustive search. The proposed decoding achieves about 2 dB better BER performance than the soft input decoding with the exhaustive search. The proposed decoding utilizes the decoder output signal streams to mitigate the noise, which helps the proposed decoding to outperform the soft input decoding with the exhaustive search.

4.5 Complexity

Figure 6 compares the complexity of the proposed decoding with that of the decoding with the exhaustive search. In the figure, the horizontal axis means the number of transmit antennas and the vertical axis is the number of multiplications to detect one packet. Because no precoding is employed, the number of the transmit antennas is equal to that of the streams. The number of the iteration in the proposed decoding is also set to 15, and the packet length is a 100-symbol duration. While the complexity of the decoding with the exhaustive search grows exponentially with respect to the number of the transmit antennas, the complexity of the proposed decoding only gradually rises as the number of the transmit antennas is increased[†]. Even though the complexity of the proposed decoding will be greater than that of the MLD-Soft if the number of the transmit antennas is less than 4, the complexity of the MLD easily overtakes that of the proposed decoding as the number of the transmit antennas is increasing from 4 to 8. When 6 independent streams are simultaneously transmitted from the transmit antennas, the complexity of the proposed decoding is $\frac{1}{10}$ as small as that of the MLD-soft, even though the proposed decoding achieve better BER performance than the MLD-soft.

5. Conclusion

This paper has proposed a low complexity soft input decoding in an iterative linear receiver for overloaded MIMO. The proposed soft input decoding applies two types of lattice reduction-aided SICs to estimate the LLR in order to reduce the computational complexity. While one type of the SIC detects the signals in overloaded MIMO channels, the other type of the SIC has to detect the signals in overloaded MIMO channels with strong interference. This proposed detector introduces the noise whitening filter implemented with the Cholesky factorization into the latter SIC for mitigating the performance degradation due to the strong interference. The noise reduction is introduced to mitigate an equivalent noise caused by those filters and to improve the reliability of the LLRs. Moreover, the decoding is iterated, whenever the LLRs are re-estimated after the noise mitigation. However, a

[†]Although the complexity of the proposed decoding can not be formulated exactly because the LLL algorithm, one of heuristic algorithms to implement the lattice reduction, is applied, the complexity can be roughly estimated as follows. Let N_I and N_S denote the number of the iterations in the decoding and the number of the symbols in a stream, basically, the complexity of the signal decoding is proportional to $N_I N_T N_R N_F N_S$ in the proposed decoding, whereas that of the soft MLD is roughly in proportion to $N_I N_T^2 N_R N_F N_S 4^{N_T}$. Therefore, the complexity of the MLD grows higher than that of the proposed decoding as the number of the antennas increases.

clipping technique is introduced to avoid incorrect the LLRs violating the decoding.

The performance of the proposed decoding is evaluated by computer simulation in a 6×2 overloaded MIMO system. The proposed soft decoding with the 15 times iterations achieves 7 dB better BER performance than no-iterative hard input decoding at the BER of 10^{-4}, and is about 2 dB superior to the soft decoding with the exhaustive search, although the soft decoding with the exhaustive search is known to be the optimum. Even though the performance of the proposed decoding is superb, the complexity of the proposed decoding is $\frac{1}{10}$ as small as that of the soft decoding with the exhaustive search.

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