Low Complexity Linear MMSE detector with Recursive Update Algorithm for Iterative Detection-Decoding MIMO OFDM system

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Abstract—Iterative turbo processing between detection and decoding shows near-capacity performance on a multiple-antenna system. Combining iterative processing with optimum front-end detection is particularly challenging because the front-end maximum a posteriori (MAP) algorithm has a computational complexity that is exponential in the throughput. Sub-optimum detector such as the soft interference cancellation linear minimum mean square error (SIC-LMMSE) detector with near front-end MAP performance has been proposed. The asymptotic computational complexity of SIC-LMMSE remains \(O(n_t^2 n_r + n_t n_r^2 \Gamma(\beta) + n_t M_c 2^{M_c/2})\) per detection-decoding cycle where \(n_t\) is number of transmit antenna, \(n_r\) is number of receive antenna, and \(M_c\) is modulation size. A lower complexity detector is the hard interference cancellation LMMSE (HIC-LMMSE) detector. HIC-LMMSE has asymptotic complexity of \(O(n_t^2 n_r + n_t M_c 2^{M_c/2})\) but suffers extra performance degradation. In this paper, we introduce a low complexity front-end detection algorithm that not only achieves asymptotic computational complexity of \(O(n_t^2 n_r + n_t n_r^2 \Gamma(\beta) + 1) + n_t M_c 2^{M_c/2}\) where \(\Gamma(\beta)\) is a function with discrete output \([-1, 2, 3, ..., n_t]\). Simulation results demonstrate that the proposed low complexity detection algorithm offers exactly same performance as its full complexity counterpart in an iterative receiver while being computational more efficient.

I. INTRODUCTION

Ever since Berrou and Glavieux published their landmark paper on iterative decoding between two parallel concatenated convolutional codes (turbo-codes) [1], [2], it has been generally accepted that iterative (turbo) processing techniques have great value. As pointed out in [3] the “Turbo Principle” not only can be used with traditional concatenated channel coding schemes, but also generally applies to many detection-decoding algorithms. Of late, multiple-input multiple-output (MIMO) systems receive tremendous amount of attention due to the information theoretic studies done by Telatar, Foschini and Gans [4], [5]. To approach channel capacity in a computationally efficient manner, it seems quite natural to apply the “Iterative(Turbo) Paradigm” to MIMO systems. Therefore, many of iterative detection-decoding algorithms have successfully been generalized to MIMO environment [6]–[8], especially multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) systems [9].

The complexity of optimum front-end MIMO detection motivates the search for a low complexity suboptimal detector. In fact, the optimal front-end MAP detector has complexity that grows exponentially with the modulation size and the number of antennas. To address complexity issues, suboptimal detectors/decoders such as: soft interference cancellation linear minimum mean square error (SIC-LMMSE) detector [6], [9], [10], hard interference cancellation LMMSE (HIC-LMMSE) detector [8], [11] and “list” sphere decoder [12] are proposed in the literature. However, the asymptotic computational complexity of this SIC-LMMSE detector is \(O(n_t^2 n_r + n_t n_r^2 + n_t M_c 2^{M_c/2})\) per detection-decoding cycle (i.e. turbo iteration) [8], [13], where \(n_t\) is number of transmit antenna, \(n_r\) is number of receive antenna and \(M_c\) is modulation size. Despite the SIC-LMMSE detector having a linear growth in the number of transmit antennas, it’s computational complexity remains high even with moderate number of \(n_t\), \(n_r\), and \(M_c\). Further reduced complexity detection such as the HIC-LMMSE detector is also advocated in [8], [11]. HIC-LMMSE has asymptotic computational complexity of \(O(n_t^2 n_r + n_t M_c 2^{M_c/2})\) at the price of performance degradation.

By reformulating a matrix inversion step in SIC-LMMSE detection algorithm into Recursive Update Algorithm (RUA), SIC-LMMSE detector is transformed into a structure more suitable for iterative detection and decoding receiver. In particular, SIC-LMMSE detector with RUA allocates its computational power depending on the level of the \(a\) priori information provided by outer channel decoder. As number of turbo iteration increases, \(a\) priori information becomes more and more reliable. Thus, asymptotic complexity of \(O(n_t^2 n_r + n_t n_r^2 \Gamma(\beta) + 1 + n_t M_c 2^{M_c/2})\) is achieved without any performance degradation, where \(\Gamma(\beta)\) is a function with discrete output \([-1, 2, 3, ..., n_t]\).

The remainder of the paper is organized as follows: Section II presents the system model and introduces our notation. Section III introduces the SIC-LMMSE with RUA detector. Section IV presents several numerical examples for different number of receive and transmit antennas on standard wireless local area network (WLAN) channel model. Section V concludes the paper.

II. SYSTEM MODEL

A. Transmitter

We consider a multiple-input multiple-output orthogonal frequency division multiplexing (MIMO-OFDM) system with \(n_t\) transmit and \(n_r\) receive antennas. The transmission scheme
is detailed in the upper half of Fig. 1. Let vector $b$ be source information bits entering the rate $R_c$ LDPC channel encoder. We denote $e$ the vector of encoded bits; which is not only grouped into blocks of $M_c$ bits where $M_c$ is number of bits per constellation symbol, but also multiplexed to $n_t$ sub-streams. We will consider a linear model at the $k$th frequency subcarrier in which received vector $y(k) = [y_1(k), \ldots, y_{n_r}(k)]^T \in \mathbb{C}^{n_r \times 1}$ depends on transmitted vector $x(k) = [x_1(k), \ldots, x_{n_t}(k)]^T \in \mathbb{C}^{n_t \times 1}$ via

$$y(k) = H(k)x(k) + n(k) \quad (1)$$

where $H(k) \in \mathbb{C}^{n_r \times n_t}$ is complex channel matrix, known perfectly by receiver, $n(k) \in \mathbb{C}^{n_r \times 1}$ is a vector of independent zero-mean complex Gaussian noise entries with variance $\sigma^2 = N_0/2$ per each real component and $k = 1, 2, \ldots, K$ where $K$ refers to total number of frequency subcarriers. We assume the average symbol energy $E_s \equiv \mathbb{E}[|x_i(k)|^2] = 1$ where $i = 1, 2, \ldots, n_t$ and symbols are equally likely chosen from a complex constellation $\mathcal{X}$ with cardinality $|\mathcal{X}| = 2^{M_c}$. The spectral efficiency $R$ is then defined as $R = n_tM_cR_c$ bits per channel use (BPCU). We also define the signal-to-noise ratio (SNR) as $E_b/N_0$, where $E_b$ is the energy per transmitted information bit per receive antenna. Notice that each receive antenna collects total energy of $n_tE_s$ which carries $n_tM_cR_c$ information bits, therefore $E_b$ can be expressed as $E_b = E_s/(M_cR_c)$.

We assume that the data model (1) is used repeatedly for each frequency subcarrier $k$ to transmit a continuous stream of information bits. During each application of data model (1), the channel matrix $H(k)$ is a “snapshot” of the frequency response of MIMO propagation channel between all transmit and receive antennas. More specifically, $H(k)$ is fully described as

$$H(k) = [h_1(k) \quad h_2(k) \quad \ldots \quad h_{n_t}(k)] \quad (2)$$

where $h_i(k) = [h_{1,i}(k), h_{2,i}(k), \ldots, h_{n_r,i}(k)]^T$ and $h_{j,i}(k)$ represents the complex channel coefficient from transmit antenna $i$ to receive antenna $j$, $j = 1, 2, \ldots, n_r$, at $k$th frequency subcarrier.

B. Iterative Receiver Structure

The iterative receiver structure is depicted in the lower half of Fig. 1. The MIMO detector takes the channel observation $y(k)$ and a priori log-likelihood ratio (LLR) $L_A(c_l)$ to compute the extrinsic information $L_E(c_l)$ for each of $n_tM_c$ bits per received vector $y(k)$. With $c_l = +1$ representing a binary one and $c_l = -1$ representing a binary zero, we define $L_A(c_l)$ from outer channel decoder as

$$L_A(c_l) \equiv \log \frac{P[c_l = +1]}{P[c_l = -1]} \quad (3)$$

where $l = 1, \ldots, n_tM_c$. Moreover, $L_A(c_l)$ can also be viewed as the extrinsic information learned at the outer channel decoder. The a posteriori LLR $L_D(c_l|y(k))$ for bit $c_l$, conditioned on received vector $y(k)$ is similarly defined as

$$L_D(c_l|y(k)) \equiv \log \frac{P[c_l = +1|y(k)]}{P[c_l = -1|y(k)]} \quad (4)$$

where $P[c_l = m|y(k)]$, $m = \pm 1$, is the a posteriori probability (APP) of bit $c_l$. Using Bayes’ theorem, (4) can be rewritten as

$$L_D(c_l|y(k)) = \log \frac{P[y(k)|c_l = +1]}{P[y(k)|c_l = -1]} + \log \frac{P[c_l = +1]}{P[c_l = -1]}$$

$$= L_E(c_l) + L_A(c_l) \quad (5)$$

where the first term in (5), denoted as $L_E(c_l)$, is the extrinsic information delivered by MIMO detector, based on the received vector $y(k)$ and prior information about the coded bits $L_A(c_l)$. “New” (extrinsic) information learned at the detection
stage can easily be separated from a posteriori LLR $L_D(c_i)$ by subtracting off the a priori LLR $L_A(c_i)$. That is,
\[ L_E(c_i) = L_D(c_i(y(k))) - L_A(c_i). \] (6)

In view of (6), extrinsic information $L_E(c_i)$ is then fed into outer channel decoder as a priori information on the coded bit $c_i$.

III. SIC-LMMSE DETECTOR WITH RUA

As a priori LLR becomes available, we form symbol mean $\bar{x}_i(k), i=1,2,\ldots,n_t$, as
\[ \bar{x}_i(k) = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} x P[x_i(k) = x], \] (7)
where $\mathcal{X}$ is the complex constellation set and $P[x_i(k) = x]$ refers to a priori symbol probability. Assuming bits within symbol $x$ are statistical independent and let $x_j$ represents the $l$th bit of symbol $x$ (i.e. $x_j = +1$ means $l$th bit of symbol $x$ is binary one), where $l = 1,2,\ldots,M_c$, then $P[x_i(k) = x]$ can be computed as
\[ P[x_i(k) = x] = \prod_{l=1}^{M_c} \frac{1}{1+e^{-x_l L_A(c_l)}}. \] (8)

For $t$th transmit antenna, interference from rest of $n_t-1$ antennas is “parallel” cancelled to obtain
\[ y_i(k) = y(k) - \sum_{n=1,n \neq i}^{n_t} \bar{x}_n(k)h_n(k) \]
\[ = x_i(k)h_i(k) + \sum_{n=1,n \neq i}^{n_t} (x_n(k) - \bar{x}_n(k))h_n(k) + n(k). \] (9)

The LMMSE filter $w_i(k)$ is chosen to minimize the mean-square error (MSE) between the transmit symbol $x_i(k)$ and the filter output $\hat{x}_i(k)$. Equivalently, LMMSE filtering is precisely stated in the following optimization problem:

\[ \text{minimize } E[(x_i(k) - \hat{x}_i(k))^2] \]
\[ \text{subject to } \hat{x}_i(k) = w_i(k)^\dagger y_i(k), \] (10)

where $(\cdot)^\dagger$ denotes conjugate-transpose. Hence, the optimal LMMSE filter coefficient $w_i(k)$ is obtained by solving (10). It can be shown that the optimal solution [6], [8]–[10] is given by,
\[ w_i(k) = \left( \frac{N_0}{E_s} I_{n_r} + H(k) \Delta_i(k) H(k)^\dagger \right)^{-1} h_i(k), \] (11)

where the covariance matrix $\Delta_i(k)$ is
\[ \Delta_i(k) = \text{diag}\left[ \frac{\sigma^2_{x_1(k)}}{E_s}, \ldots, \frac{\sigma^2_{x_{i-1}(k)}}{E_s}, 1, \frac{\sigma^2_{x_{i+1}(k)}}{E_s}, \ldots, \frac{\sigma^2_{x_{n_t}(k)}}{E_s} \right]. \] (12)

and $\sigma^2_{x_i(k)}, n = 1,2,\ldots,n_t$ with $n \neq i$, is the transmit symbol variance and generally can be computed as,
\[ \sigma^2_{x_i(k)} = \sum_{x \in \mathcal{X}} \mathbb{E}[x - \bar{x}_i(k)]^2 P[x_i(k) = x]. \] (13)

In view of (11), the LMMSE filter adapts its filter coefficients according to the quality of soft interference cancelled symbols through covariance matrix $\Delta_i(k)$. Depending on the level of a priori LLR $L_A(c_i)$, actual value of symbol variance $\sigma^2_{x_i(k)}$ can range from zero to $E_s$. Hence, small symbol variance $\sigma^2_{x_i(k)}$ indicates that symbol mean, $\bar{x}_i(k)$, approaches the true transmit symbol $x_i(k)$ and soft interference cancellation perform in (9) is near perfect.

There is an interesting way to perform matrix inversion via a recursive update algorithm (RUA). As (11) suggests, finding the optimal LMMSE filter coefficient $w_i(k)$ often involves solving a system of equations which is also the most “expensive" step in the algorithm in terms of complexity. Efficient methods such as QR decomposition and Cholesky factorization [14] are used in practice for solving such system of equations, but still at the cost of cubic complexity [14]. One naive way to “solve" the system of equations would be inverting a $n_r \times n_r$ matrix of
\[ P_i(k) = \left( \frac{N_0}{E_s} I_{n_r} + H(k) \Delta_i(k) H(k)^\dagger \right)^{-1}, \] (14)

and compute $w_i(k) = P_i(k)h_i(k)$. In what follows, we will propose an algorithm to construct $P_i(k)$ directly via recursive update. A similar idea can also be found in [10] for multiuser detection. We define the following matrices
\[ P_i^{(n_t-1)}(k) = \left( I_{n_r} + \frac{E_s}{N_0} \sum_{n=1}^{n_t-1} \frac{\sigma^2_{x_n(k)}}{E_s} h_n h_n^\dagger \right)^{-1}, \] (15)
\[ P_i^{(n_t)}(k) = \left( I_{n_r} + \frac{E_s}{N_0} \sum_{n=1}^{n_t} \frac{\sigma^2_{x_n(k)}}{E_s} h_n h_n^\dagger \right)^{-1}. \] (16)

We then can rewrite the term $H(k) \Delta_i(k) H(k)^\dagger$ in (14) as sum of vector outer products
\[ H(k) \Delta_i(k) H(k)^\dagger = \sum_{n=1}^{n_t} \frac{\sigma^2_{x_n(k)}}{E_s} h_n h_n^\dagger. \] (17)

In view of (17), we can re-express (14) as
\[ P_i(k) = \frac{E_s}{N_0} \left( I_{n_r} + \frac{E_s}{N_0} \sum_{n=1}^{n_t} \frac{\sigma^2_{x_n(k)}}{E_s} h_n h_n^\dagger \right)^{-1}, \] (18)

The recursive update relation hinges on rewriting $P_i^{(n_t)}(k)$ as shown in (19). To arrive at (19), we had applied the “degenerate" matrix inversion lemma [14]. As (19) suggests, we have found a recursive update relation between $P_i^{(n_t-1)}(k)$ and $P_i^{(n_t)}(k)$. Therefore, we can directly construct $P_i(k)$ by RUA which is outlined in Table I.
\[
P^{(n_t)}_i(k) = P^{(n_t-1)}_i(k) - \frac{\sigma^2 s_n(k)}{N_0} \frac{1}{1 + \frac{\sigma^2 s_n(k)}{N_0} \| \bar{h}_n \|^2} \left( P^{(n_t-1)}_i(k) \bar{h}_n \right) \left( P^{(n_t-1)}_i(k) \bar{h}_n \right)^\dagger \tag{19}
\]

### TABLE I

**Recursive Update Algorithm**

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Initialization: ( P^{(0)}<em>i(k) = \mathbf{I}</em>{n_r} ).</td>
</tr>
<tr>
<td>2.</td>
<td>Updating ( P_i^{(n)}(k) ) from ( P_i^{(n-1)}(k) ) as shown in (19).</td>
</tr>
<tr>
<td>3.</td>
<td>( P_i(k) = \frac{\sigma^2}{N_0} P_i^{(n)}(k) ).</td>
</tr>
</tbody>
</table>

Because of this recursive algorithm the detection problem on the MIMO channel can be transformed into a structure more suitable for iterative detection and decoding receiver. Conventionally, SIC-LMMSE detector forms its optimum LMMSE filter coefficient \( \mathbf{w}_i(k) \) by solving system of equations without incorporating a priori information. Thus, fixed amount of computational resources are allocated uniformly through out the iterative detection-decoding process. Different from SIC-LMMSE detector, SIC-LMMSE detector with RUA obtains \( \mathbf{w}_i(k) \) by directly constructing \( P_i(k) \) which is made explicitly a function of a priori information. Without a priori information, RUA is still a cubic complexity algorithm to form \( P_i(k) \). But, once a priori information becomes available, \( P_i^{(n)}(k) \) is only updated from the previous iteration \( P_i^{(n-1)}(k) \) in (19) when \( \sigma^2 s_n(k)/N_0 \gg 0, n \neq i \), where \( \sigma^2 s_n(k) \) is computed from a priori LLR. Hence, SIC-LMMSE detector with RUA enables a more flexible allocation of computing power depending on the level of a priori information.

The RUA is mainly a function of “effective” signal-to-noise ratio, \( \text{SNR}_e(n) \),

\[
\text{SNR}_e(n) = \frac{\sigma^2 s_n(k)}{N_0}, n \neq i, \tag{20}
\]

which also appears in (19). Depending on the number of turbo iterations and \( E_b/N_0 \), the actual value of \( \text{SNR}_e(n) \) is varying. If \( \text{SNR}_e(n) < \beta \), where \( \beta \) is the threshold, the RUA skips the updating step as in (19) and achieves a lower complexity. In particular, since a priori LLR becomes more and more reliable as the number of turbo iteration increases, the “estimated” symbol mean \( \bar{x}_i(k) \) becomes more likely to be the true transmit symbol while the “estimated” symbol variance \( \sigma^2 s_n(k), n \neq i \) is approximating zero. When \( \sigma^2 s_n(k) = 0, n \neq i \), (i.e. perfect cancellation), RUA achieves further complexity reduction since it costs nothing to iterate from \( P_i^{(n-1)}(k) \) to \( P_i^{(n)}(k) \) with \( n \neq i \) as clearly shown in (19). Thus, \( P_i(k) \) is formed exactly one iteration at \( n = i \) which in effect forms MRC filter with the corresponding column vector \( \bar{h}_n \) of channel matrix.

The explicit parameterization of threshold \( \beta \) in SIC-LMMSE detector with RUA enables a trade-off between achieving a lower complexity and better performance. Smaller the value selected for \( \beta \) (i.e. \( \beta = 0 \)), less likely that \( P_i(k) \) will be formed in exactly one iteration, which implies more computational complexity. On the other hand, a larger value of \( \beta \) (i.e. \( \beta = 1 \)) will be more likely to form \( P_i(k) \) in exactly one iteration (i.e. HIC-LMMSE detection).

The output of LMMSE filter is,

\[
\hat{x}_i(k) = \mu_i(k)x_i(k) + z_i(k), \tag{21}
\]

where

\[
\mu_i(k) = \mathbf{w}_i(k)^\dagger \bar{h}_i(k), \tag{22}
\]

and \( z_i(k) \) is the ISI-plus-noise term. As shown in [15], we approximate \( \hat{x}_i(k) \) the output of LMMSE filter as complex Gaussian distributed given \( x_i(k) \). That is,

\[
P[\hat{x}_i(k)|x_i(k) = x] \sim N_c(\mu_i(k)x, \eta^2(k))
\]

\[
= \frac{1}{\pi \eta^2(k)} e^{-\frac{1}{\eta^2(k)}|\hat{x}_i(k) - \mu_i(k)x|^2}, \tag{23}
\]

where \( x \in \mathcal{X} \) and the variance \( \eta^2(k) \) is given by,

\[
\eta_0^2(k) = (\mu_i(k) - \mu_0^2(k))E_x. \tag{24}
\]

Having (8) and (23) in mind, the a posteriori LLR \( L_D(c_i|\hat{x}_i(k)) \), \( i = 1, 2, \ldots, M_c \), is computed for each detection symbol estimate \( \hat{x}_i(k) \) (i.e. \( i = 1, 2, \ldots, n_t \)) per transmit antenna within \( \mathbf{x}(k) \), where \( \mathbf{x}(k) = [\hat{x}_1(k), \ldots, \hat{x}_{n_t}(k)]^T \) via,

\[
L_D(c_i|\hat{x}_i(k)) = \log \frac{\sum_{x \in \mathcal{X}_i^+} P[\hat{x}_i(k)|x_i(k) = x] P[x_i(k) = x]}{\sum_{x \in \mathcal{X}_i^+} P[\hat{x}_i(k)|x_i(k) = x] P[x_i(k) = x]}, \tag{25}
\]

where \( \mathcal{X}_i^+ \) is the set of \( 2^{M_c} \) actual constellation symbols \( x \) which the \( i \)th bit is \( +1 \) (i.e. \( x_i = +1 \)). With (25), SIC-LMMSE detector computes the extrinsic LLR \( L_E(c_i) \) as,

\[
L_E(c_i) = L_D(c_i|\hat{x}_i(k)) - L_A(c_i). \tag{26}
\]

Replacing original matrix inversion with RUA in SIC-LMMSE detector will allow a more efficient computation of detection symbol estimate as number of turbo iteration increases. When a priori information feedback from outer channel decoder becomes very reliable, SIC-LMMSE detector with RUA forms its detection estimate \( \hat{x}_i(k) \) via MRC filter which is same as HIC-LMMSE detector. On the other hand, unlike HIC-LMMSE detector which always uses MRC filter, SIC-LMMSE detector with RUA also utilizes “unreliable” a priori information to form \( \hat{x}_i(k) \) as clearly shown in (19).

Table II gives a detailed outline of SIC-LMMSE detector with RUA. At the first turbo iteration, SIC-LMMSE detector with RUA share the same computational complexity as SIC-LMMSE detection algorithm which is \( \mathcal{O}(n_t^2 n_r + n_r^3) \).

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TABLE II
SIC-LMMSE DETECTION ALGORITHM WITH RUA

<table>
<thead>
<tr>
<th>β</th>
<th>SIC-LMMSE detector with RUA</th>
<th>SIC-LMMSE detector with RUA</th>
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<tbody>
<tr>
<td>0</td>
<td>3−turbo, SIC−LMMSE detector</td>
<td>3−turbo, SIC−LMMSE detector</td>
</tr>
<tr>
<td>1.0e−1</td>
<td>3−turbo, SIC−LMMSE detector</td>
<td>3−turbo, SIC−LMMSE detector</td>
</tr>
<tr>
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<tr>
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<tr>
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<td>3−turbo, SIC−LMMSE detector</td>
<td>3−turbo, SIC−LMMSE detector</td>
</tr>
</tbody>
</table>

For each packet transmission, we perform 4 turbo iterations. The SIC-LMMSE detector with RUA is expected to achieve lower complexity but suffers potential performance degradation. Hence, SIC-LMMSE detector with RUA allows a more flexible trade-off between performance and complexity. As Fig. 3 suggests, we observe no noticeable performance degradation up to \( \beta = 0.1 \) with 3 turbo iterations. At higher values of \( \beta \), RUA achieves a more lower complexity but at the price of performance degradation.

Fig. 4 compares complexity by evaluating the ratio \( \rho \), which is defined as,

\[
\rho = \frac{C_{\text{SIC-LMMSE with RUA}}}{C_{\text{HIC-LMMSE}}}
\]
between SIC-LMMSE detector with RUA and HIC-LMMSE detector. To measure the complexity of either detection algorithm, we observe that $C_{\text{SIC-LMMSE}}$ with RUA (i.e. also true for $C_{\text{HIC-LMMSE}}$) is inversely proportional to number of MRC performed during each packet detection. As shown in Fig. 4, $C_{\text{SIC-LMMSE}}$ with RUA is approaching $C_{\text{HIC-LMMSE}}$ as $\beta$ increases. At $\beta = 0.1$, SIC-LMMSE detector with RUA achieves almost the same complexity of HIC-LMMSE detector but sacrifices no performance degradation as compared to full complexity SIC-LMMSE detector with RUA at $\beta = 0$ as shown in Fig. 3.

Fig. 5 presents a PER performance comparison between HIC-LMMSE detector and SIC-LMMSE detector with RUA at $\beta = 0.1$. HIC-LMMSE detection algorithm converges at 4 turbo iterations. At 1% PER with 4 turbo iterations, we observe that SIC-LMMSE detector with RUA outperforms HIC-LMMSE detector by 1 dB.

V. CONCLUSION

We have presented a computational more efficient front-end detection algorithm for iterative detection and decoding MIMO system, namely SIC-LMMSE detector with RUA. By reformulating the matrix inversion step in conventional LMMSE filtering process into RUA, this allows a more flexible allocation of computational power and more suitable for iterative processing receiver. Moreover, a complexity analysis demonstrates that the proposed system achieves about the same complexity as HIC-LMMSE detector proposed in the past, but also has better PER performance.

REFERENCES


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