

Likelihood-Based Metric for Gibbs Sampling Turbo MIMO Detection

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SUMMARY In a multiple-input multiple-output (MIMO) system, maximum likelihood detection (MLD) is the best demodulation scheme if no *a priori* information is available. However, the complexity of MLD increases exponentially with the number of signal streams. Therefore, various demodulation schemes with less complexity have been proposed and some of those schemes show performance close to that of MLD. One kind of those schemes uses a Gibbs sampling (GS) algorithm. GS MIMO detection that combines feedback from turbo decoding has been proposed. In this scheme, the accuracy of GS MIMO detection is improved by feeding back loglikelihood ratios (LLRs) from a turbo decoder. In this paper, GS MIMO detection using only feedback LLRs from a turbo decoder is proposed. Through extrinsic information transfer (EXIT) chart analysis, it is shown that the EXIT curves with and without metrics calculated from received signals overlap as the feedback LLR values increase. Therefore, the proposed scheme calculates the metrics from received signals only for the first GS MIMO detection and the selection probabilities of GS MIMO detection in the following iterations are calculated based only on the LLRs from turbo decoders. Numerical results obtained through computer simulation show that the performance of proposed GS turbo MIMO detection is worse than that of conventional GS turbo MIMO detection when the number of GS iterations is small. However the performance improves as the number of GS iterations increases. When the number of GS iterations is 30 or more, the bit error rate (BER) performance of the proposed scheme is equivalent to that of the conventional scheme. Therefore, the proposed scheme can reduce the computational complexity of selection probability calculation in GS turbo MIMO detection.

key words: 5G, massive MIMO, turbo detection, Gibbs sampling

1. Introduction

Recently, with the spread of mobile communication devices such as mobile phones, larger capacity and higher throughput are demanded in wireless systems. Better wireless platforms for new mobile applications will emerge with the 5th generation mobile communication (5G) systems [1]. One of the key technologies in 5G is massive multi-input multi-output (MIMO); it employs dozens or hundreds of antenna elements in a base station [2]–[4]. Increasing the number of antenna elements can provide significant improvements in various aspects such as frequency and energy efficiency, communication reliability, and expanded service range.

In a MIMO system, maximum likelihood detection (MLD) achieves the best demodulation performance if no *a priori* information is available. However, the demodulation complexity of MLD increases exponentially with the

number of signal streams. Therefore, various demodulation schemes with less complexity have been proposed and some of those schemes show performance close to that of the MLD. One kind of those schemes uses a Gibbs sampling (GS) algorithm [5]. It has been shown that the complexity of GS algorithm is smaller than that of QR decomposition with M-algorithm (QRM)-MLD if the number of signal streams is more than 45. Thus, this algorithm is suitable for the uplink with the massive MIMO base station [6]. Furthermore, various GS MIMO detection schemes such as mixed GS [5], exchange GS [7], and GS with maximum ratio combining (MRC) [8] have been proposed to improve the convergence speed of the GS algorithm. GS MIMO detection that combines feedbacks from turbo decoding has also been proposed in [9]. In this scheme, the accuracy of GS MIMO detection is improved with feedback log-likelihood ratios (LLRs) from a turbo decoder. However, through extrinsic information transfer (EXIT) chart analysis, it is shown that the output LLR values from GS MIMO detection with just the feedback LLRs are almost the same as that with received signals if the LLR values are large enough. The complexity of metric calculation increases as the number of received antennas grows and it occupies the significant part of GS MIMO detection complexity [10]. Therefore, in this paper, GS MIMO detection that uses only feedback LLRs from turbo decoding for selection probability calculation is proposed. The proposed scheme calculates the metrics from received signals only for the first GS MIMO detection and selection probabilities of GS MIMO detection in the following iterations are calculated based only on the LLRs from turbo decoders.

The organization of this paper is as follows. The system model is described in Sect. 2. Section 3 presents numerical results obtained through computer simulation, and our conclusions are given in Sect. 4.

2. System Model

2.1 Gibbs Sampling MIMO Detection with Maximum Ratio Combining

In this paper the uplink communication of a cellular system in which multiple terminals are supported by a base station with many antenna elements is assumed. In a transmitter systematic parallel concatenated convolutional code, which uses two eight-state encoders and one internal interleaver as the turbo encoder, is adopted [11]. With the input of N_s bits, the turbo encoder generates three length- N_s streams. At the

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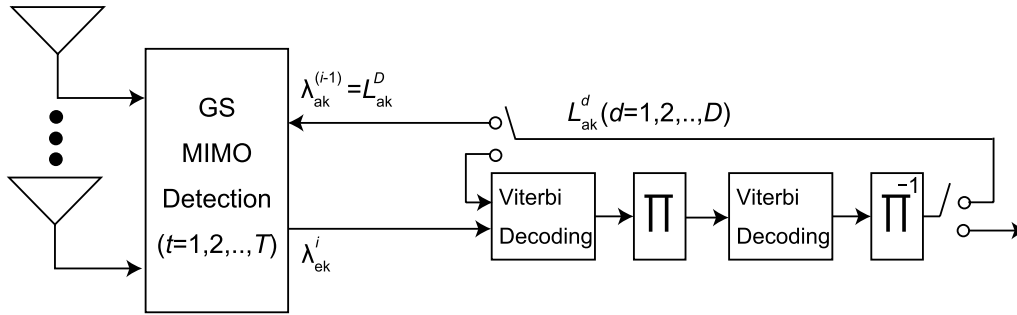


Fig. 1 Block diagram of receiver.

end of each stream, four tail bits for trellis termination are appended. The systematics bit stream in the beginning, followed by the two rearranged parity bit streams are interlaced in a bit-by-bit fashion. A single bit stream with the length of $(Ns + 4)/r$, where r is the code rate, is then output. The outputs are then mapped to M QAM symbols through Gray coding where $\log_2 M$ is the numbers of bits per symbol.

The block diagram of the GS turbo MIMO receiver is shown in Fig. 1. It is supposed to be implemented in a base station and to demodulate uplink signals from user terminals. The received signals are input to the GS MIMO detection block and the output LLRs from the decoder are feedbacked to the GS MIMO detection block, where $\lambda_{ak}^{(i-1)}$ is the LLR for the k th coded bit after the $(i-1)$ th decoding process. After T iterations of GS MIMO detection, the output LLRs are put into the turbo decoder, where λ_{ek}^i is the LLR for the k th coded bit calculated after the GS MIMO detection. In each turbo decoding process two sets of Viterbi decoding, interleaving, and deinterleaving are iterated D times, and the resultant LLRs are again feedbacked to the GS MIMO detection block, where L_{ak}^D is the output LLR for the k th coded bit after D times of decoding iterations and input to the GS MIMO detection block as $\lambda_{ak}^{(i)}$. This whole process is repeated $i = I$ times.

Suppose that N_T signal streams are received by a massive MIMO base station with N_R received antennas. A received signal vector is expressed as follows;

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n}, \quad (1)$$

where \mathbf{y} is the $N_R \times 1$ received signal vector, \mathbf{s} is the $N_T \times 1$ symbol vector, \mathbf{n} is the $N_R \times 1$ noise vector, and \mathbf{H} is the $N_R \times N_T$ channel matrix whose (n_r, n_t) th element, $H_{n_r n_t}$, is the channel response between the n_t th transmit antenna and the n_r th receive antenna.

The iteration of the mixed GS MIMO detection is applied to the real part as well as the imaginary part of each signal stream consecutively [5]. The transmit symbol candidate of the n_t th signal stream at the $(t + 1)$ th iteration is selected according to the following selection probability [5].

$$p(\hat{s}_{n_t} | s_1^{(t+1)}, \dots, s_{n_t-1}^{(t+1)}, s_{n_t+1}^{(t)}, \dots, s_{N_T}^{(t)}, \mathbf{y}, \mathbf{H}) \sim (1 - Q)\phi(\alpha, \hat{\mathbf{s}}^{n_t}) + Q\phi(\infty, \hat{\mathbf{s}}^{n_t}), \quad (2)$$

where

$$\phi(\alpha, \hat{\mathbf{s}}^{n_t}) = \exp\left(-\frac{\|\mathbf{y} - \mathbf{H}\hat{\mathbf{s}}^{n_t}\|^2}{\alpha^2 \sigma^2}\right), \quad (3)$$

Q is the mixing probability of a random sampling mode. Furthermore, the candidate symbol vector for the sampling of the n_t th signal stream at the $(t + 1)$ th iteration is

$$\hat{\mathbf{s}}^{n_t} = [s_1^{(t+1)}, \dots, s_{n_t-1}^{(t+1)}, \hat{s}_{n_t}, s_{n_t+1}^{(t)}, \dots, s_{N_T}^{(t)}]^T, \quad (4)$$

where \hat{s}_{n_t} is the transmit symbol candidate of the n_t th signal stream, $s_{n_t}^{(t)}$ is the transmit symbol from the n_t th antenna at the t th iteration, α is the temperature parameter and adjusts the selection probability of the transmit symbol candidate, and σ^2 is the variance of the noise. The first and second terms of the right hand side of Eq. (3) correspond to the selection probabilities of the Gibbs sampling and random sampling modes, respectively, as $\alpha = \infty$ implies that the selection probabilities of all the candidates are the same and they are equal to $\exp(0)$. With the probability of Q , the real or imaginary part of $s_{n_t}^{(t+1)}$ is randomly determined regardless of the selection probability and in [5] it is shown that Q should be set to $1/(2N_T)$.

Mixed GS MIMO detection with MRC has also been proposed to reduce the computational complexity in each iteration [8]. In this scheme, the amount of calculation can be reduced with multiplying the MRC coefficients by the received signal vector and the channel matrix. The selection probability of $\hat{\mathbf{s}}^{n_t}$ in this scheme is given as follows;

$$\phi(\alpha, \hat{\mathbf{s}}^{n_t}) = \exp\left(-\frac{|\mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}^{n_t}|^2}{\alpha^2 \|\mathbf{H}_{n_t}^H\|^2 \sigma^2}\right), \quad (5)$$

where \mathbf{H}_{n_t} is the n_t th column vector of \mathbf{H} . Since the size of the numerator in the argument of the exponential function turns to one after the multiplication of \mathbf{H}_{n_t} , the complexity of this scheme reduces [6].

For the implementation of the mixed GS MIMO detection algorithms, the selection probability given in Eq. (5) needs the calculation of the exponential function. Though it may be realized by a look-up table, the look-up table requires a large amount of memory. Thus, the transmit symbol candidate is selected with the following probability.

$$p(\hat{s}_{n_t} | s_1^{(t+1)}, \dots, s_{n_t-1}^{(t+1)}, s_{n_t+1}^{(t)}, \dots, s_{N_T}^{(t)}, \mathbf{y}, \mathbf{H}) \sim (1 - Q)\phi_M(\alpha, \hat{\mathbf{s}}^{n_t}) + Q\phi_M(\infty, \hat{\mathbf{s}}^{n_t}), \quad (6)$$

where the first and second terms of the right hand side of

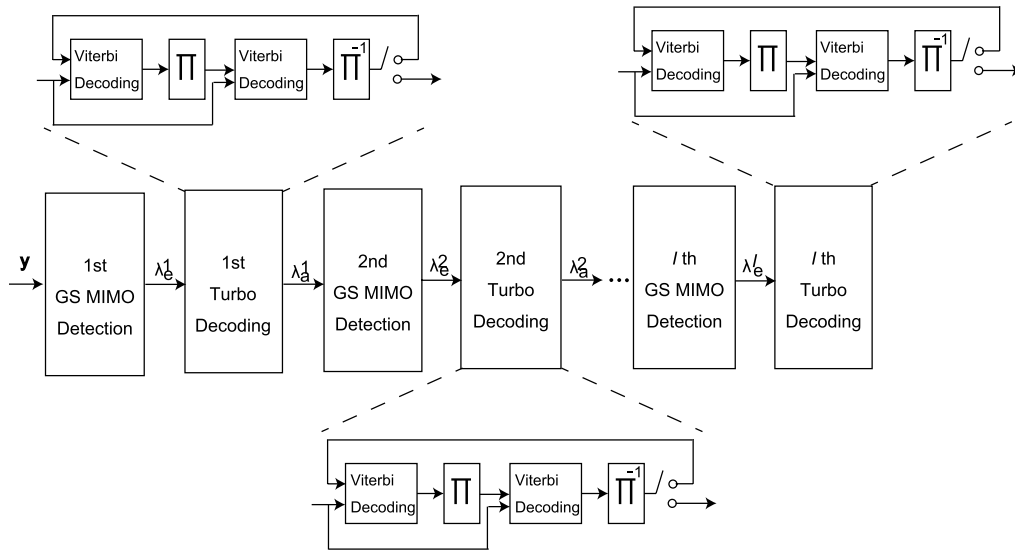


Fig. 2 GS turbo MIMO detection process.

Eq. (6) correspond to the selection probabilities of the Gibbs sampling and random sampling modes, respectively, and the exponential function is replaced by the following function [8].

$$\phi_M(\alpha, \hat{\mathbf{s}}^{n_i}) = f_\gamma \left(\frac{|\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \hat{\mathbf{s}}^{n_i}|^2}{\alpha^2 \|\mathbf{H}_{n_i}^H\|^2 \sigma^2} \right), \quad (7)$$

where $f_\gamma(d)$ is the metric function that is based on a simple fraction as

$$f_\gamma(\gamma_k) = \frac{1}{\gamma_k^3 + 1}, \quad (8)$$

where γ_k is the metric for the candidate transmit symbol vector and it is calculated as

$$\gamma_k = \frac{|\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \hat{\mathbf{s}}^{n_i}|^2}{\alpha^2 \|\mathbf{H}_{n_i}^H\|^2 \sigma^2}. \quad (9)$$

After the GS MIMO detection, a candidate transmit symbol vector, $\hat{\mathbf{s}}$, is obtained. The LLR is calculated for all the coded bits that are mapped to the transmit symbol vector. Suppose that $\hat{\mathbf{s}}_{k+}$ and $\hat{\mathbf{s}}_{k-}$ consists of the same coded bits except the k th one while their k th coded bit is differentiated as “+1” or “-1” in $\hat{\mathbf{s}}_{k+}$ or $\hat{\mathbf{s}}_{k-}$. The LLR for the k th coded bit is approximated as

$$\lambda_{ek}^i \approx \frac{1}{2\sigma^2} (|\mathbf{y} - \mathbf{H} \hat{\mathbf{s}}_{k-}|^2 - |\mathbf{y} - \mathbf{H} \hat{\mathbf{s}}_{k+}|^2) + \lambda_{ak}^{(i-1)}. \quad (10)$$

where λ_{ek}^i denotes the LLR for the k th coded bit calculated from the i th GS detection, $\lambda_{ak}^{(i-1)}$ is the *a priori* input LLR for the k th coded bit feedbacked from the $(i-1)$ th turbo decoding process. When $i = 1$, $\lambda_{ak}^0 = 0$.

2.2 Conventional Gibbs Sampling Turbo MIMO Detection

In [9], the GS using an *a priori* input LLR from a turbo

decoder is proposed to improve a convergence speed. The GS turbo MIMO detection process is presented in Fig. 2. GS and turbo decoding are iterated multiple times. In the turbo decoder, the number of turbo decoding iterations at each decoding process is set to D and the total number of decoding iterations through the detection is denoted as I .

After the i th GS MIMO detection process, the metric for the k th element of the candidate transmit symbol is given as

$$\gamma_k^i = \ln \frac{P(\hat{\mathbf{s}}_{k+} | \mathbf{y}, \lambda_{ak}^{(i-1)})}{P(\hat{\mathbf{s}}_{k-} | \mathbf{y}, \lambda_{ak}^{(i-1)})}, \quad (11)$$

where $\lambda_{ak}^{(i-1)}$ denotes the *a priori* input LLR for the k th transmit coded bit feedbacked from the $(i-1)$ th turbo decoding process to the GS MIMO detector. If MRC is applied in GS MIMO detection, Eq. (11) turns to the following.

$$\gamma_{ck}^i \approx \frac{1}{2\|\mathbf{H}_{n_i}^H\|^2 \sigma^2} (|\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \hat{\mathbf{s}}_{k-}|^2 - |\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \hat{\mathbf{s}}_{k+}|^2) + \lambda_{ak}^{(i-1)}. \quad (12)$$

For the first GS MIMO detection, $\lambda_{ak}^0 = 0$.

2.3 Proposed Gibbs Sampling Turbo MIMO Detection

The same as the conventional scheme, at the first turbo decoding, λ_{ak}^0 is set to zero in the proposed GS turbo MIMO detection. After the first GS MIMO detection, the metric is given as

$$\gamma_{pk}^1 = \frac{1}{2\|\mathbf{H}_{n_i}^H\|^2 \sigma^2} (|\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \hat{\mathbf{s}}_{k-}|^2 - |\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \hat{\mathbf{s}}_{k+}|^2) \quad (13)$$

where $\hat{\mathbf{s}}_{k+}$ and $\hat{\mathbf{s}}_{k-}$ are the same as those in Eq. (10) and they are the pseudo transmit symbol vectors that consist of the

same coded bits with the candidate transmit symbol vector except the k th one while their k th coded bit is differentiated as “+1” or “-1” in $\hat{\mathbf{s}}_{k+}$ or $\hat{\mathbf{s}}_{k-}$.

As shown in the EXIT charts in the following section, the LLR curves with and without the metric based on the received signals,

$$(|\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \mathbf{s}_{k-}|^2 - |\mathbf{H}_{n_i}^H \mathbf{y} - \mathbf{H}_{n_i}^H \mathbf{H} \mathbf{s}_{k+}|^2), \quad (14)$$

approaches as the input LLR values increase. Thus, in the proposed scheme, the metric for the k th element at the $i \geq 2$ is substituted as

$$\gamma_{pk}^i = \lambda_{ak}^{(i-1)}. \quad (15)$$

By applying Eq. (15), the metric calculation based on the received signals in the GS algorithm can be omitted and the computational complexity of GS MIMO detection reduces.

3. Numerical Results

3.1 Simulation Conditions

Simulation conditions are shown in Table 1. A turbo code with eight-state state memory is applied as the error-correction code and the code rate is set to 1/3. The size of an interleaver is set to 4800. The number of detection and decoding iterations, I , is eight and the number of decoding iterations is $D = 1$. The reason for feedbacking the LLRs to the GS MIMO detection block after each turbo decoding process is that the GS MIMO detection process preserves the temporal transmit candidate symbol vector and a larger number of GS iterations at the beginning of global iterations provides larger mutual information to the turbo decoder as explained in the following section. The transmit signals are modulated with QPSK. Both the numbers of the transmit antennas and the receive antennas are set to 16. For MIMO detection, the mixed GS with MRC is applied. The parameters, α and Q , are set to 1.5 and $1/2N_T$. The number of GS iterations is $T = 10, 50$, and 100 for 16×16 MIMO. As a channel model, the elements of \mathbf{H} are assumed as independent and identically distributed (i.i.d.) Rayleigh fading.

Table 1 Simulation conditions.

Coding scheme	Turbo code
Code rate (r)	1/3
Interleaver size	4800
Modulation	QPSK
Number of transmit antennas (N_T)	16
Number of receive antennas (N_R)	16
MIMO detection	Mixed GS with MRC
Temperature parameter (α)	1.5
Mixing probability (Q)	$1/(2N_T)$
Number of GS iterations (T_{gs})	10, 50, 100
Number of decoding iterations (D)	1
Number of detection and decoding iterations (I)	8
Channel model	i.i.d. Rayleigh fading
Channel estimation	Ideal

Channel estimation is assumed to be ideal.

3.2 Numerical Results

3.2.1 EXIT Chart

EXIT curves for the GS MIMO detector and the turbo decoder are shown in Figs. 3–8. $I(\lambda)$ in the figures implies the mutual information calculated from the LLRs, $\{\lambda\}$. The EXIT curves for turbo decoding shows the relationship between the mutual information calculated by the LLRs input to the turbo decoder and that calculated by the LLRs output from the turbo decoder after a specified number of turbo decoding iterations. The EXIT curves for MIMO detection represents the relationship between the mutual information calculated by the LLRs for all the bits that consists the N_T received symbols and that calculated by the LLRs generated by Eq. (10). They are inverted against the diagonal. E_b/N_0 is set to 3 dB and 5 dB. The number of GS iterations is 10, 50, or 100. As the number of GS iterations increases, the EXIT curves of the GS MIMO detection improve.

The output LLR values from the conventional GS MIMO detection are larger than those from the proposed scheme when the input LLR values are small because the

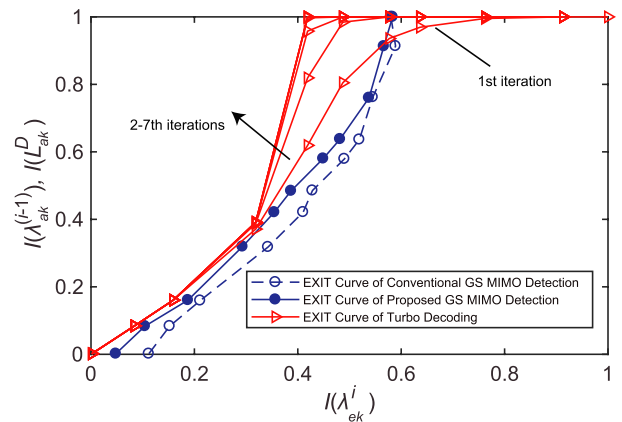


Fig. 3 EXIT chart ($E_b/N_0=3$ dB, Number of GS iterations=10).

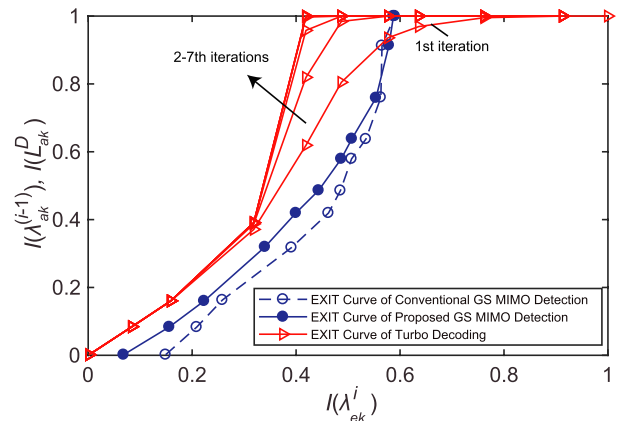


Fig. 4 EXIT chart ($E_b/N_0=3$ dB, Number of GS iterations=50).

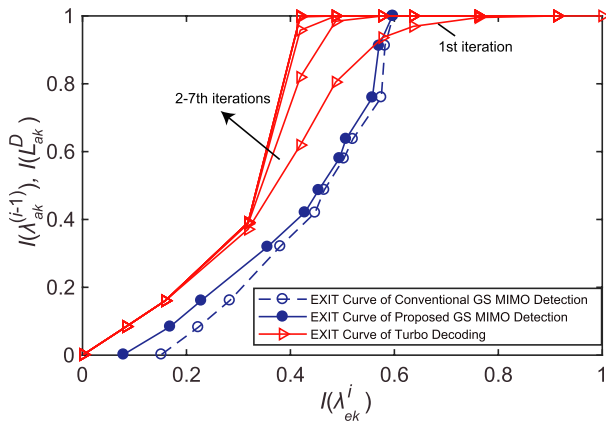


Fig. 5 EXIT chart ($E_b/N_0=3$ dB, Number of GS iterations=100).

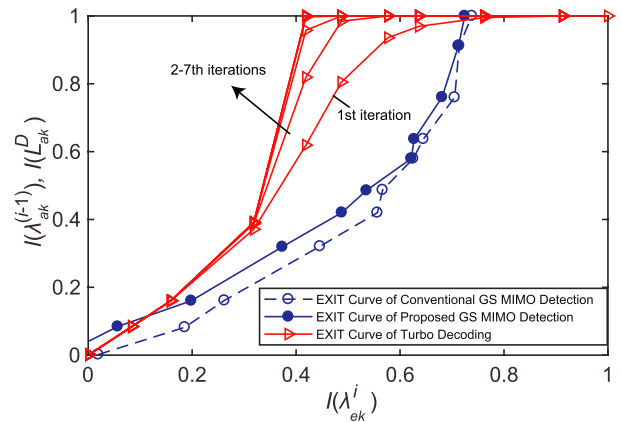


Fig. 8 EXIT chart ($E_b/N_0=5$ dB, Number of GS iterations=100).

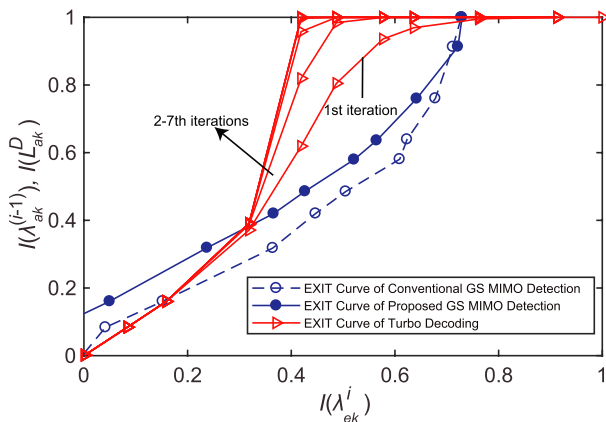


Fig. 6 (EXIT chart $E_b/N_0=5$ dB, Number of GS iterations=10).

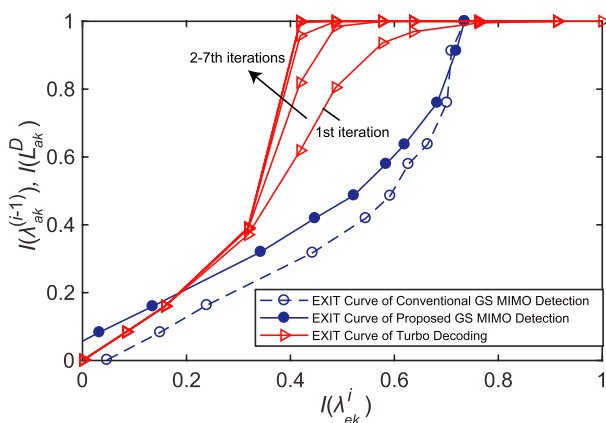


Fig. 7 EXIT chart ($E_b/N_0=5$ dB, Number of GS iterations=50).

feedbacked LLRs are smaller. This tendency is more significant as E_b/N_0 increases. However, as the number of GS iterations increases and the input LLR values grow, the curves of the proposed scheme approach those of the conventional scheme. On the other hand, the EXIT curves improve in the larger input mutual information region as the number of turbo decoding iterations increases.

The output mutual information from the MIMO detec-

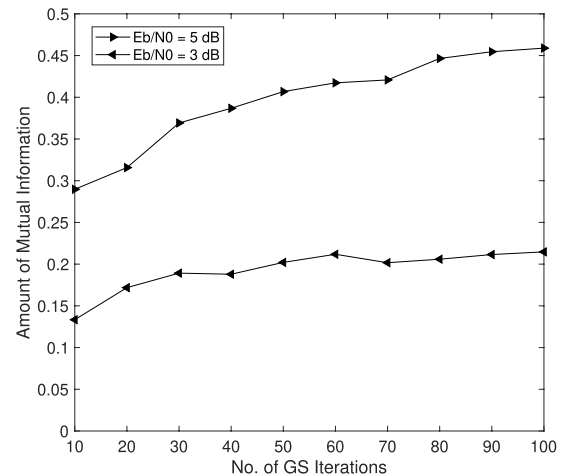


Fig. 9 Amount of mutual information after first detection and decoding iteration vs. number of GS MIMO detection iterations.

tor is jointly determined by the LLRs calculated from the received signals as well as the LLRs feedback from the decoder. If those values are different, the GS MIMO detection algorithm works improperly as the selection probabilities calculated from Eq. (12) or Eq. (15) are biased. Therefore, the output mutual information diminishes in the smaller input mutual information region for $E_b/N_0 = 5$ dB as compared with that for $E_b/N_0 = 3$ dB.

3.2.2 BER Performance with 16×16 MIMO

The amount of mutual information calculated by the LLRs output from the turbo decoder after the first decoding iteration, i.e. no feedback from the decoder to the detector, versus the number of GS MIMO detection iterations is shown in Fig. 9. The amount of mutual information is more than about 0.29 and 0.13 for $E_b/N_0 = 3$ dB and $E_b/N_0 = 5$ dB, respectively, and improves more after the first iteration since GS MIMO detection preserves the candidate transmit symbol vector for the next global iteration. Thus, the following detection and decoding iterations increase the amount of mutual information even though the detector curve and the

decoder curve are crossed in the EXIT chart for $E_b/N_0 = 5$ dB.

The bit error rate (BER) performance curves versus E_b/N_0 for $N_T = N_R = 16$ are shown in Figs. 10–12. The interleaver size is 4800, the number of GS iterations is set to 10, 50, or 100 and the total number of decoding iterations is set as $I = 2, 5$, or 8. When the number of GS iterations is small, the conventional GS turbo MIMO detection scheme shows better performance than the proposed GS turbo MIMO detection. However, the number of GS itera-

tions increases, the proposed scheme achieves the equivalent performance as compared to the conventional scheme. This is expected from the EXIT charts since the EXIT curves of the proposed GS MIMO detection approach those of the conventional GS MIMO detection in the larger mutual information region as shown in the previous section.

3.2.3 Computational Complexity

The number of multiplication operations for the conventional and proposed GS turbo MIMO detection schemes are shown in Table 2. It is assumed that all the elements of the initial candidate symbol vector are set to zero and M is the modulation order. Furthermore, it is also assumed that $\mathbf{H}_{n_t}^H \mathbf{H}$ and $\|\mathbf{H}_{n_t}^H\|^2$ are preliminarily calculated after channel estimation before MIMO detection and the numbers of multiplication operations for those equations are excluded from the table. The complexity comparison of the conventional and proposed GS turbo MIMO detection schemes are presented in Fig. 13. It is clear that the proposed scheme reduces the number of multiplication operations by a factor of about 0.7 for any numbers of GS iterations.

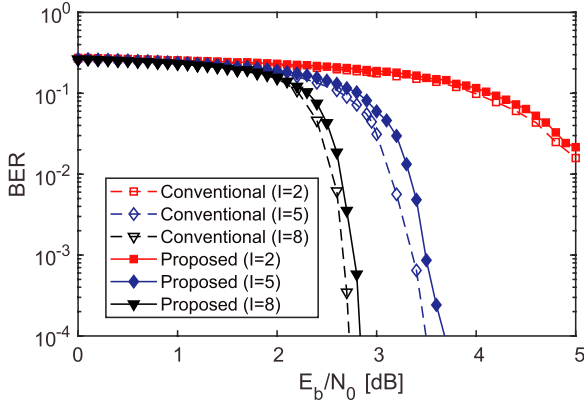


Fig. 10 BER vs. E_b/N_0 (Number of GS iterations=10).

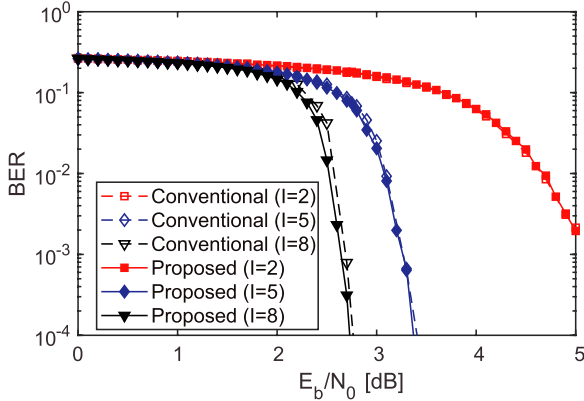


Fig. 11 BER vs. E_b/N_0 (Number of GS iterations=50).

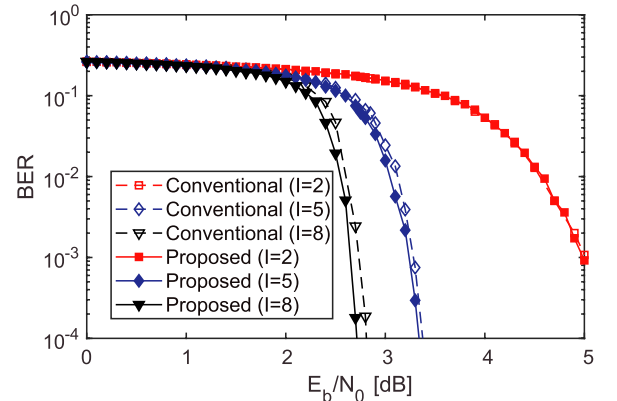


Fig. 12 BER vs. E_b/N_0 (Number of GS iterations=100).

Table 2 Numbers of required multiplication operations.

	Conventional		Proposed	
Initial calculation	$\mathbf{H}_{n_t}^H \mathbf{y}$:	$4N_T N_R$	$\mathbf{H}_{n_t}^H \mathbf{y}$:	$4N_T N_R$
Metric calculation for updating candidate transmit symbol vector (first iteration)	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	$2(2(\sqrt{M}-1)N_T T$	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	$2(2(\sqrt{M}-1)N_T T$
	$\times 1/\alpha^2 \ \mathbf{H}_{n_t}^H\ ^2 \sigma^2$:	$(2(\sqrt{M}-1)N_T T$	$\times 1/\alpha^2 \ \mathbf{H}_{n_t}^H\ ^2 \sigma^2$:	$(2(\sqrt{M}-1)N_T T$
	$f_\gamma(\gamma_{ck}^i)$	$2(\gamma-1)(\sqrt{M}-1)N_T T$	$f_\gamma(\gamma_{pk}^i)$	$2(\gamma-1)(\sqrt{M}-1)N_T T$
Metric calculation for updating candidate transmit symbol vector (following iterations)	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	$2(2(\gamma+1)(\sqrt{M}-1)N_T I T$	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	0
	$\times 1/\alpha^2 \ \mathbf{H}_{n_t}^H\ ^2 \sigma^2$:	$(2(\sqrt{M}-1)N_T I T$	$\times 1/\alpha^2 \ \mathbf{H}_{n_t}^H\ ^2 \sigma^2$:	$(2(\sqrt{M}-1)N_T I T$
	$f_\gamma(\gamma_{ck}^i)$	$2(\gamma-1)(\sqrt{M}-1)N_T I T$	$f_\gamma(\gamma_{pk}^i)$	$2(\gamma-1)(\sqrt{M}-1)N_T I T$
Updating transmit symbol candidate	random number \times metric :	$2((\sqrt{M}-1)\sqrt{M}+1)$	random number \times metric :	$2((\sqrt{M}-1)\sqrt{M}+1)$
Metric calculation for candidate transmit symbol vector	$\ \mathbf{y} - \mathbf{H} \hat{\mathbf{s}}\ ^2$:	$2N_R I T$	$\ \mathbf{y} - \mathbf{H} \hat{\mathbf{s}}\ ^2$:	$2N_R I T$
Approximated LLR calculation	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	$2(2(\sqrt{M}-1)N_T I$	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	$2(2(\gamma+1)(\sqrt{M}-1)N_T I$
	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	$2(2(\sqrt{M}-1)N_T I$	$ \mathbf{H}_{n_t}^H \mathbf{y} - \mathbf{H}_{n_t}^H \mathbf{H} \hat{\mathbf{s}}_{n_t}^{n_t} ^2$:	$2(2(\gamma+1)(\sqrt{M}-1)N_T I$
	$\times 1/\alpha^2 \ \mathbf{H}_{n_t}^H\ ^2 \sigma^2$:	$(2(\sqrt{M}-1)N_T I$	$\times 1/\alpha^2 \ \mathbf{H}_{n_t}^H\ ^2 \sigma^2$:	$(2(\sqrt{M}-1)N_T I$

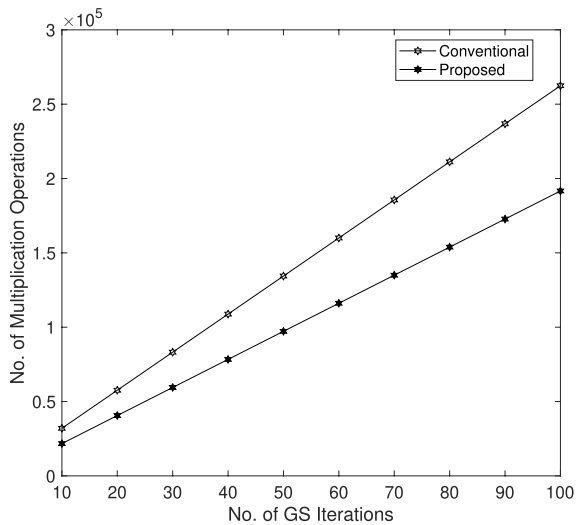


Fig. 13 Number of multiplication operations vs. number of GS iterations.

4. Conclusions

In this paper, Gibbs sampling turbo MIMO detection that uses the feedback LLRs from turbo decoding for selection probability calculation has been proposed. In this proposed scheme, the metric is calculated with the received signals only at the first GS MIMO detection because the EXIT curves with and without metric calculated from received signals approaches as the feedback LLR values increase. Comparing to that with the conventional scheme, the proposed scheme can reduce the complexity of selection probability calculation in the GS MIMO detection. Numerical results obtained through computer simulation shows that the proposed GS turbo MIMO detection matches the performance of the conventional scheme when the number of GS iterations increases.

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Appendix:

For comparison, the performance of the GS MIMO detection without feedback followed by typical turbo decoding is presented in this appendix. The total number of GS iterations is unified to that of the conventional GS turbo MIMO detection.

BER performance versus E_b/N_0 of GS MIMO detection without feedback from the turbo decoder are shown

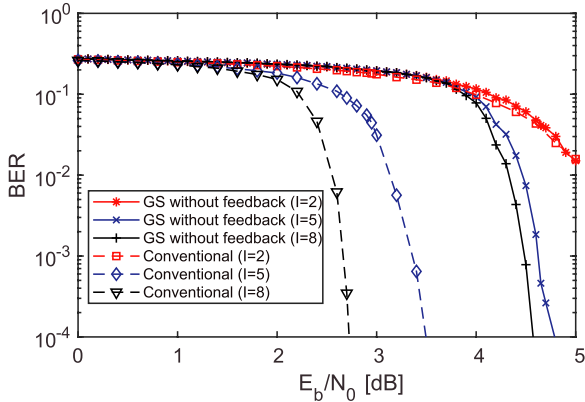


Fig. A.1 BER vs. E_b/N_0 (Number of total GS iterations= $10I$).

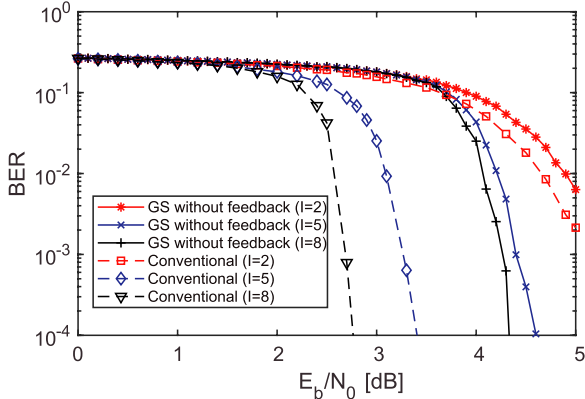


Fig. A.2 BER vs. E_b/N_0 (Number of GS total iterations= $50I$).

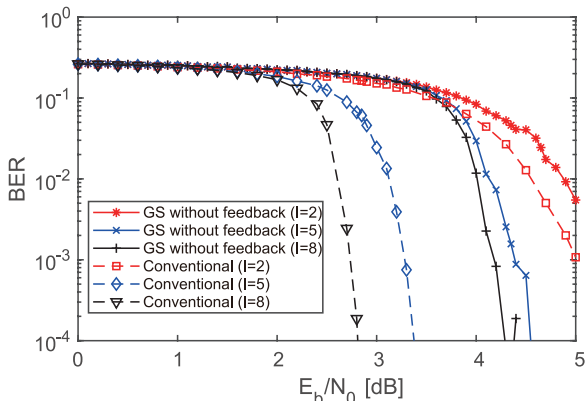


Fig. A.3 BER vs. E_b/N_0 (Number of GS total iterations= $100I$).

in Figs. A.1–A.3. In these figures, “GS without feedback” implies the GS MIMO detection followed by turbo detection, and “Conventional” denotes the conventional GS turbo MIMO detection using feedback from turbo detection. In all figures, the BER characteristics without feedback are worse than that of the conventional GS turbo MIMO detection. The reason is that the amount of mutual information improvement is saturated after a certain number of GS MIMO detection iterations as shown in Fig. 9. From these numerical results, to improve BER performance, the global iterations between GS MIMO detection and turbo decoding is necessary.



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