

A Low Complexity Non-linear Iterative Receiver for Overloaded MIMO-OFDM Systems

Shuhei MAKABE, Satoshi DENNO, Yafei HOU

Graduate School of Natural Science and Technology, Okayama University
Tsushima-Naka 3-1-1, Kita, Okayama, Okayama, 700-8530 Japan
email ples7qow@s.okayama-u.ac.jp

Abstract—This paper proposes a low complexity receiver that outperforms the MLD in overloaded MIMO-OFDM systems. The proposed receiver applies iterative noise cancellation to improve the transmission performance. A low complexity LLR calculation technique is introduced in the proposed receiver. The proposed low complexity iterative non-linear receiver achieves better transmission performance than the MLD with smaller calculational complexity. The performance of the proposed techniques is verified by computer simulation in a 6×3 overloaded MIMO channel. When the reception process is only iterative 2times, the proposed iterative non-linear receiver attains a gain of 0.8dB at the BER of 10^{-6} . The computational complexity is evaluated in terms of the number of additions. The proposed receiver achieves such superior performance with the complexity which is about half as much as conventional soft input decoding with the MLD.

I. INTRODUCTION

Communication speed has been increasing to a few Gbps in wireless communication systems such as the fifth generation cellular systems and IEEE802.11 wireless local area networks. The next generation cellular system will provide users with faster communication links than the fifth generation system. Lots of techniques have been utilized to implement such high speed wireless communication systems, for example, orthogonal frequency division multiplexing (OFDM), adaptive modulation and coding (AMC), adaptive resource allocation, and multiple input multiple output (MIMO) spatial multiplexing [1]- [3]. Among them, MIMO spatial multiplexing is still being considered to such high speed signal transmission in the next generation cellular system, MIMO spatial multiplexing is recognized to have the potential to increase the transmission speed furthermore. In addition, another approach has been considered to raise the transmission speed, e.g., non-orthogonal multiple access (NOMA), faster than nyquist (FTN), and overloaded MIMO [4]- [9]. All of them load much more signals in the system than usual to enhance the transmission speed. NOMA has been identified as a technique in the fifth generation cellular standard. The other two techniques are also regarded as promising techniques. Overloaded MIMO spatial multiplexing can increase the number of the spatially multiplexed signal stream than conventional MIMO spatial multiplexing, which implements a higher signal transmission. Because the number of the spatially multiplexed signal streams exceeds the degree of freedom of the receiver, non-linear receivers such as the

maximum likelihood detection (MLD) has been mainly applied [10]- [13].

This paper proposes a low complexity receiver that outperforms the MLD in overloaded MIMO-OFDM systems. The proposed receiver applies an iterative noise cancellation to improve the transmission performance. A low complexity log-likelihood ratio (LLR) calculation technique is introduced in the proposed receiver. The proposed low complexity iterative non-linear receiver achieves better from transmission performance than the MLD with smaller calculational complexity.

This paper is organized as follows. The next section describes a system model, and the proposed low complexity iterative non-linear receiver is explained in the section 3. The performance of the proposed receiver is confirmed in the section 4, and conclusion is remarked in the final section.

II. SYSTEM MODEL

It is assumed that the transmitter is equipped with N_T antennas and the receiver with N_R antennas. We are considering an overloaded MIMO-OFDM system in which the number of transmit antennas is larger than the number of receive antennas, $N_T > N_R$. A convolutional coder is used. The encoder output sequence is fed to a quaternary phase shift keying (QPSK) modulator via an interleaver. The QPSK modulator output signals are converted to the time domain with the inverse discrete Fourier transform (IDFT). The signals in the time domain are called as OFDM symbols. The OFDM symbols are emitted to the air via the N_T antennas without any precoding. The transmitted signals are traveling in the multipath fading channels, and received with the N_R at the receiver. The receiver signals are fed to the discrete Fourier transform (DFT) after removing the cycle prefix. The signal received at the antenna is fed to as dedicated DFT processor to perform the DFT independently. Let $\mathbf{Y}_m \in \mathbb{C}^{N_R}$ denote a received signal vector that contains the m th output signals from the DFTs, the received signal vector \mathbf{Y}_m can be written as

$$\mathbf{Y}_m = \mathbf{H}_m \mathbf{X}_m + \mathbf{N}_m \quad (1)$$

$\mathbf{X}_m \in \mathbb{C}^{N_T}$, $\mathbf{N}_m \in \mathbb{C}^{N_R}$, and $\mathbf{H}_m \in \mathbb{C}^{N_R \times N_T}$ denote the modulation signal vector, an additive white Gaussian noise

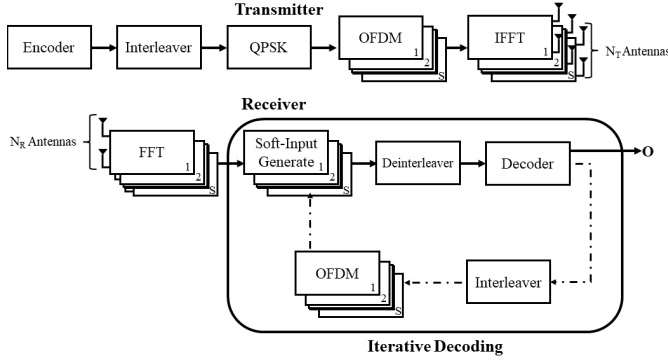


Fig. 1. System model

vector, and a channel matrix in the m th subcarrier, which is defined as,

$$\mathbf{H}_m = \begin{pmatrix} H_m(1,1) & \cdots & H_m(1,N_T) \\ \vdots & \ddots & \vdots \\ H_m(N_R,1) & \cdots & H_m(N_R,N_T) \end{pmatrix} \quad (2)$$

$$H_m(i,k) = \sum_{n=0}^{L_p-1} h_m(i,k) e^{-j2\pi \frac{nm}{N_s}} \quad (3)$$

In the above equations, $H_m(i,k) \in \mathbb{C}$, $h_m(i,k) \in \mathbb{C}$, and $N_s \in \mathbb{N}$ represent a frequency response on the m th subcarrier from the k th transmit antenna to the i th receive antenna, m th path gain of the channel response between those antennas, and the number of the DFT points. The received signal vector is provided to the proposed non-linear iterative receiver, which is explained in the next section.

III. ITERATIVE NON-LINEAR RECEIVER

A. Noise reduction by soft output signal

The proposed receiver applies a soft input decoding where the LLR of the transmission bit is fed as a soft signal. The channel matrix \mathbf{X}_m is decomposed into a unitary matrix and an upper triangular matrix for reducing the computational complexity of the LLR calculation, which is explained in the following section.

$$\begin{pmatrix} \mathbf{H}_m \\ \frac{\sigma}{\sigma_d} \mathbf{I} \end{pmatrix} = \bar{\mathbf{H}}_m = \mathbf{Q}_m \mathbf{R}_m \quad (4)$$

In (4), $\bar{\mathbf{H}}_m \in \mathbb{C}^{(N_R+N_T) \times N_T}$, $\mathbf{Q}_m \in \mathbb{C}^{(N_R+N_T) \times N_T}$, $\mathbf{R}_m \in \mathbb{C}^{N_T \times N_T}$, $\mathbf{I}_{N_T} \in \mathbb{R}^{N_T \times N_T}$, $\sigma \in \mathbb{R}$ and $\sigma_d \in \mathbb{R}$ denote an extended channel matrix a unitary matrix, an upper triangular matrix, the identity matrix, a standard deviation of the AWGN, and an amplitude of the modulation signal [14]. The receiver signal vector \mathbf{Y}_m is transformed with the unitary matrix \mathbf{Q}_m before the LLR calculation. On the other hand, though the QR decomposition defined in (4) is obtained from the viewpoint of the minimum mean square error (MMSE) criterion, the QR decomposition introduces additional noise into the transmission system. The proposed receiver cancels the additional noise with the decoder output signals for the performance improvement.

For further performance enhancement, the noise cancellation is iterated in the proposed receiver.

Let $\mathbf{Y}_m^{(t)}$ represent a received signal vector at the t th noise cancellation stage. The received signal vector at the t th cancellation stage is defined as,

$$\mathbf{Y}_m^{(t)} = \begin{cases} \begin{pmatrix} \mathbf{Y}_m \\ \mathbf{0}_{N_T} \end{pmatrix} & (t = 0) \\ \begin{pmatrix} \mathbf{Y}_m \\ \mathbf{0}_{N_T} \end{pmatrix} + \begin{pmatrix} \mathbf{0}_{N_R} \\ \frac{\sigma}{\sigma_d} \dot{\mathbf{X}}_m^{(t)} \end{pmatrix} & (t > 0) \end{cases} \quad (5)$$

In (5), $\dot{\mathbf{X}}_m^{(t)} \in \mathbb{C}^{N_T}$ and $\mathbf{0}_K \in \mathbb{R}^K$ a modulation signal vector made by the decoder output signals and the K -dimensioned null vector. Whenever the noise cancellation is iterated, the LLR is recalculated with the vector $\mathbf{Y}_m^{(t)}$. As is described above $\mathbf{Y}_m^{(t)}$ is transformed with the unitary vector \mathbf{Q}_m . Let $\mathbf{S}_m^{(t)}$ represents a transformed received signal, i.e., $\mathbf{S}_m^{(t)} = \mathbf{Q}_m \mathbf{Y}_m^{(t)}$, the LLR of the bit sent on the real part of the QPSK modulation signal $x_m(k) \in \mathbb{C}$ is defined as

$$\zeta_m^{(t)}(\Re[x_m(k)]) = -\frac{1}{2\sigma_m^2} \left(\min_{\Re[x_m(k)]=1} \left| \mathbf{S}_m^{(t)} - \mathbf{R}_m \mathbf{X}_m \right|^2 - \min_{\Re[x_m(k)]=-1} \left| \mathbf{S}_m^{(t)} - \mathbf{R}_m \mathbf{X}_m \right|^2 \right) \quad (6)$$

In (6), $\Re[\cdot]$ and $\Im[\cdot]$ denote the real and imaginary part of the complex number in large bracket, respectively. $x_m(k)$ and $2\sigma_m^2 \in \mathbb{R}$ denote the k th element of the modulation signal vector variance of the noise, which is defined as follows.

$$\begin{aligned} 2\sigma_m^2 &= \mathbb{E} \left[\left| \mathbf{Q}_m^H \begin{pmatrix} \mathbf{N}_m \\ \frac{\sigma}{\sigma_d} (\dot{\mathbf{X}}_m^{(t)} - \mathbf{X}_m) \end{pmatrix} \right|^2 \right] \\ &= \text{Tr} \left[\mathbf{Q}_m \mathbf{Q}_m^H \mathbf{A}_m \right] \end{aligned} \quad (7)$$

, where $\mathbf{A}_m \in \mathbb{R}^{(N_T+N_R) \times (N_T+N_R)}$ denotes a diagonal matrix defined in the following equation.

$$a_m(i,j) = \begin{cases} 0 & (i \neq j) \\ 2 \left(\frac{\sigma}{\sigma_d} \right)^2 & (i = j < N_T) \\ 2 - \Re[\dot{x}_m^{(t)}(i)]^2 - \Im[\dot{x}_m^{(t)}(i)]^2 & (i = j \geq N_T) \end{cases} \quad (8)$$

$a_m(i,j)$, $\mathbb{E}[\alpha]$ and $\text{Tr}[\beta]$ represent an (i,j) element of the matrix \mathbf{A}_m , the ensemble average of a variable α , and a trace of a square matrix β .

The calculation of $\dot{\mathbf{X}}_m^{(t)}$ is explained next. The LLR series ζ_m^t obtained from equation (6) is integrated on all subcarriers, deinterleaved to restore the original order, and input to the Viterbi decoder. When iterative decoding is applied, the Viterbi decoder outputs a soft output series $\mathbf{u} = [u(1), \dots, u(2N)]$ from the following formula each time iterative decoding is performed (N is the number of transmitted information bits).

$$u(2i+k) = \frac{e^{\rho(2i+k)} - 1}{e^{\rho(2i+k)} + 1} (i=0,1,\dots,N|k=0,1) \quad (9)$$

$$\begin{aligned} \rho(2i+k) = & - \min_{c(2i+k)=1} (\alpha(i) + \beta(i) + \gamma(i)) \\ & + \min_{c(2i+k)=-1} (\alpha(i) + \beta(i) + \gamma(i)) \end{aligned} \quad (10)$$

$\rho(2i+k)$ in equation (10) is the LLR of the value taken by the code $c(2i+k)$. The code $c(2i+k)$ is the output obtained from a convolutional coder with a coding rate of 1/2. α, β and γ in equation (10) represent the forward path metric, branch metric, and backward path metric in Viterbi decoding, respectively. The soft output sequence \mathbf{u} obtained from the decoder is interleaved and assigned to each subcarrier to form the estimated signal vector $\hat{\mathbf{X}}_1^{(t)}, \dots, \hat{\mathbf{X}}_{N_S}^{(t)} \in \mathbb{C}^{N_T}$. This $\hat{\mathbf{X}}_m^{(t)}$ is added to the orthogonalized received signal vector as in equation (5). The above results indicate that iterative decoding can reduce the influence of noise components, and therefore, better transmission characteristics can be obtained than with the conventional soft-decision maximum-likelihood decoding method.

B. Low complexity of soft decision signal

As described in (3), the LLR calculation needs two brute force searches for only one bit. The calculation cost grows exponentially as the number of the signal streams N_T or that of bits conveyed by a modulation signal increases. Let K represent the number of bits, the LLR calculation is proportioned to $KN_T 2^{KN_T}$. The cost is about KN_T times as much as that of the MLD. This section introduces a low complexity LLR calculation technique. Since the channel matrix \mathbf{H}_m is QR-decomposed as shown in (4), some signals are only associated with limited number of bits less than K bits. When the number of bits decreases, in principle, the computational cost of the brute force search is decreased. the technique introduced in the section makes use of the fact to reduce the computational cost of the LLR calculation. The proposed technique defines a sub set of the redeclined signal vector. If the sub set is defined as $\{\mathbf{S}_{m,0}^{(t)}, \dots, \mathbf{S}_{m,N_T-M}^{(t)}\}$ where $\mathbf{S}_{m,i}^{(t)} \in \mathbb{C}^{M+i}$ denotes a sub vector defined as $\mathbf{S}_{m,i} = \{s^{(t)}(N_T - M - i + 1) \dots s^{(t)}(N_T)\}^T$. The vector $\mathbf{S}_{m,i}^{(t)}$ can be written as,

$$\mathbf{S}_{m,i}^{(t)} = \mathbf{R}_{m,i} \mathbf{X}_{m,i} + \mathbf{N}_{m,i}^{(t)} \quad (11)$$

In the above equation, $\mathbf{R}_{m,i} \in \mathbb{C}^{(M+i) \times (M+i)}$, $\mathbf{X}_{m,i} \in \mathbb{C}^{M+i}$, and $\mathbf{N}_{m,i}^{(t)} \in \mathbb{C}^{M+i}$ represent sub vectors of the modulation signal vector $\mathbf{X}_{m,i}$ and the AWGN vector $\mathbf{N}_{m,i}^{(t)}$, which are defined as $\mathbf{X}_{m,i} = (x_m(N_T - M - i + 1) \dots x_m(N_T))^T$ and $\mathbf{N}_{m,i}^{(t)} = (n_m^{(t)}(N_T - M - i + 1) \dots n_m^{(t)}(N_T))^T$. $x_m(i) \in \mathbb{C}$ and $n_m^{(t)}(i) \in \mathbb{C}$ denote on i th entries of the modulation signal vector $\mathbf{X}_{m,i}$ and the AWGN vector $\mathbf{N}_{m,i}^{(t)}$, respectively. When

i is small enough, for example $i = 2$, the vector $\mathbf{S}_{m,i}^{(t)}$ is associated with four bits. Therefore, if the LLR of some of the 4bits is calculation based on (11), the LLR computation cost can be reduced. Because the LLRs of those bits have been calculated, even when i is incremented, the complexity of the brute force search can be reduced. When a part of the LLR is denoted as $L_m^{(t)}(i) \in \mathbb{R}$, $L_m^{(t)}(i)$ can be defined as,

$$\begin{aligned} L_m^{(t)}(i) &= \left| \mathbf{S}_{m,i}^{(t)} - \mathbf{R}_{m,i} \mathbf{X}_{m,i} \right|^2 \\ &= \sum_{l=i}^M \left| s_m^{(t)}(N_T - M + l) \right. \\ &\quad - \sum_{k=N_T-M+l}^{N_T-i} r_m(N_T - M + l, k) x_m(k) \\ &\quad \left. - \sum_{k'=N_T-i+1}^{N_T} r_m(N_T - M + l, k') x_m^{(t)}(k') \right|^2. \end{aligned} \quad (12)$$

If we introduce a log-likelihood $\xi_m^{(t)}(\Re[x_m(k)] = l)$ that is the smallest under constraint of $\Re[x_m(k)] = l$, the log-likelihood $\xi_m^{(t)}(\Re[x_m(k)] = l)$ can be defined as,

$$\xi_m^{(t)}(\Re[x_m(k)] = l) = \min_{x_m^{(t)}(k)=l} L_m^{(t)}(i). \quad (13)$$

With the log-likelihoods, the log-likelihood ratio $\zeta_m^{(t)}(\Re[x_m(k)])$ can be written as,

$$\begin{aligned} \zeta_m^{(t)}(\Re[x_m(k)]) &= \frac{1}{2\sigma_m^2} \left(\xi_m^{(t)}(\Re[x_m(k)] = 1) \right. \\ &\quad \left. - \xi_m^{(t)}(\Re[x_m(k)] = -1) \right). \end{aligned} \quad (14)$$

In (12)~(14), $\hat{x}_m(k') \in \mathbb{C}$ represents the estimated signals made of the bits estimated in the previous LLR calculations. When M is set to T , the above LLR calculation gets identical to the original LLR. As M is decreased, the computational complexity of the LLR calculation is reduced, which could cause to degrade the decoding performance. As is described, the receiving process including the decoding is iterated for the noise cancellation in the proposed receiver. As the receiving process is iterated, the computational complexity increases linearly. To mitigate the increase in the computational complexity, we propose a per iteration stage M -value setting, where a different M value is used at each iteration stage. The M values at the n th iteration stage is defined as M_n . When the receiving process is iterated t times, the set of M -values is described as (M_0, M_1, \dots, M_t) in this paper. Fig. 2 shows the state transitions of $\mathbf{X}_{m,i}$, with the value of i in the horizontal line and the states of $\mathbf{X}_{m,i}$ in the vertical line. For convenience, BPSK is applied to this figure instead of QPSK. The state is determined by the value of $x_m(N_T - M - i + 1) \sim x_m(N_T - i)$, and the total number of states is 4^M when QPSK is applied. In Fig. 2, the solid lines represent branches that survived the selection operation in each state, and the dashed lines represent branches that were truncated. The selection operation is based on the size of $L_m^{(t)}(i)$, and this operation results in 4^M types

of $\mathbf{X}_{m,i}$ for each i used in the LLR calculation.

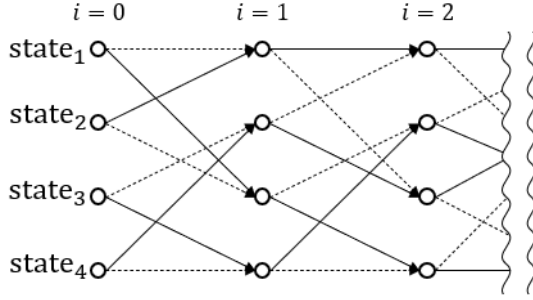


Fig. 2. State transition

IV. SIMULATION

The performance of the proposed techniques is evaluated by computer simulation in an overloaded 6×3 MIMO channel, i.e., $(N_T, N_R) = (6, 3)$. Because the number of the transmit antennas is equal to that of the spatially multiplexed signal streams, the overloading ratio is 2. Multi-path fading is applied as a channel model, and the channel matrix is assumed to be estimated perfectly. The rate half convolutional code with constraint length of 3 is applied. The simulation parameters are listed in TABLE I.

TABLE I
PARAMETERS IN COMPUTER SIMULATION

Channel model	4-path fading
Number of subcarriers	64
Modulation	QPSK
Code rate	1/2
Constraint length	3
Interleaver	Block interleaver
N_T	6
N_R	3

A. BER

Fig. 3 and Fig. 4 show the BER performance of the proposed receiver. In Fig. 3 and Fig. 4, the number of iterations is 0 and 2, respectively. The” $(M_0, M_1, M_2) = (4, 4, 6)$ ” in the figure represents the BER performance of the proposed receiver when $M = 4$ for the first decoding, $M = 5$ for the first iteration, and $M = 6$ for the second iteration. In the figures, the soft decoding without any iteration and complexity reduction technique is added as one of conventional techniques. The application of the low complexity decoding with $M = 4$ and 5 degrades the transmission performance by about 0.5dB and 0.3dB of the BER of 10^{-6} , respectively. If the decoding is not iterated, with M of 6 is reduced to the conventional receiver. The BER performance with $M = 6$ is exactly the same to the conventional receiver in Fig.3. When the decoding is iterated, the performance of the proposed receiver is getting better than that of the conventional receiver as shown in Fig.4. However, the performance gain depends on the complexity reduced decoding. While the proposed receiver with $(M_0, M_1, M_2) = (4, 4, 6)$ in the low complexity decoding attains just a gain of 0.4dB of the BER of 10^{-6} , $(M_0, M_1, M_2) = (4, 4, 5)$

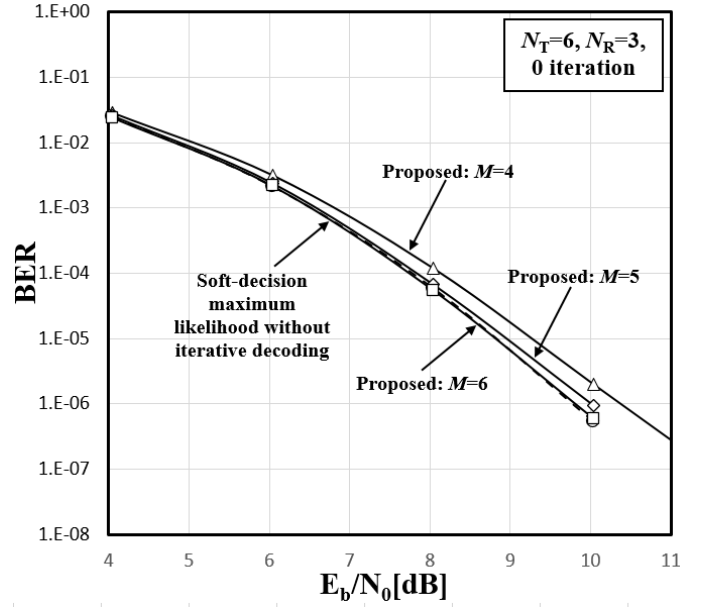


Fig. 3. BER of the proposed method in 6×3 MIMO(0 iteration)

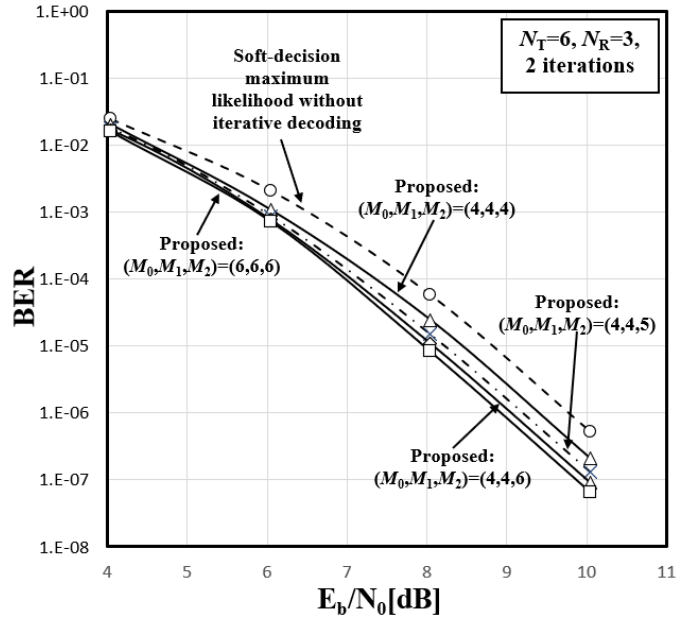


Fig. 4. BER of the proposed method in 6×3 MIMO(2 iteration) and $(M_0, M_1, M_2) = (4, 4, 6)$ enable the proposed receiver to achieve gains of 0.6dB and 0.8dB at the same BER. The proposed receiver with $(M_0, M_1, M_2) = (4, 4, 6)$ is only 0.1dB inferior to that with $(M_0, M_1, M_2) = (6, 6, 6)$, i.e., that without complexity reduction in the decoding.

Fig. 5 shows the gain obtained using the proposed method over the conventional method at BER of 10^{-6} with respect to the receiver antennas N_R . The number of the transmit antennas is set to 6, and the decoding is iterated twice in the figure. The performance gain of the proposed receiver

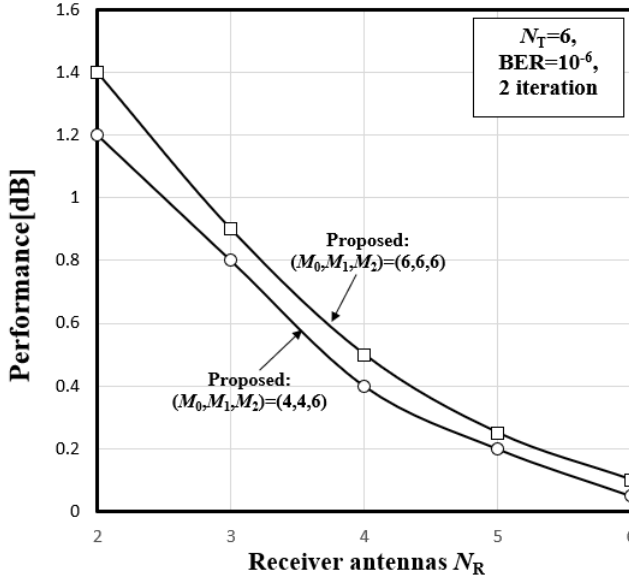


Fig. 5. Gains obtained by the proposed method

with $(M_0, M_1, M_2) = (4, 4, 6)$ is drawn in the figure, where that without any low complexity decoding, $(M_0, M_1, M_2) = (6, 6, 6)$ is added. As is shown, higher performance gain can be achieved as the number of the receive antennas is decreased in spite of the decoding schemes. In other words, the proposed receiver attains higher gain as the over loading ratio is raised. When the overloading ratio is 1, i.e., $N_R = 6$, the proposed iterative receiver attains a gain of only less than 0.2dB. On the other hand, if the number of the received antennas is reduced to 2, the gain is increased to 1.4dB at most. Even if the proposed low complexity decoding is applied to the proposed receiver, a gain of 1.4dB is attained.

B. Computational complexity

The computational complexity of the proposed iterative receiver with the low complexity decoding is evaluated in terms of the number of additions. Though the number of multiplies is usually used as a metric of the complexity, the number of multiplies is not appropriate for evaluating the complexity of the proposed receiver, because the number of the complexity is independent of the iteration. Fig. 6 shows the computational complexity with respect to the parameter of the low complexity decoding M_n , where the decoding is iterated twice. In the figure, the vertical axis and the horizontal axis are the number of additions per packet and M_2 -value. The complexity with $(M_0, M_1) = (4, 4)$ is compared with that with $(M_0, M_1) = (6, 6)$. When $(M_0, M_1) = (4, 4)$ is used, the computational complexity with $(M_0, M_1) = (4, 4)$ is about one-seventh as much as the other in spite of the M_2 values. Even when M_0 is equal to 6, the performance gap is kept approximately. If we see the transmission performance shown in Fig. 4 where the transmission performance with $(M_0, M_1, M_2) = (4, 4, 6)$ is about the same to that with $(M_0, M_1, M_2) = (6, 6, 6)$, we can conclude that the proposed low complexity decoding can successfully reduce the computational complexity without any

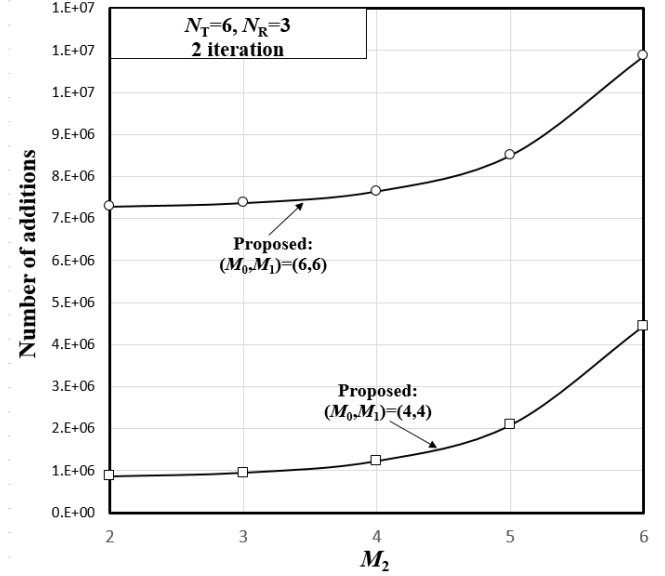


Fig. 6. Number of additions

transmission performance degradation, if the parameters are carefully selected.

V. CONCLUSION

This paper proposes a low complexity iterative non-linear receiver for overloaded MIMO-OFDM systems. The proposed receiver applies iterative noise cancellation to improve the transmission performance. A low complexity LLR calculation technique is introduced in the proposed receiver. The proposed low complexity iterative non-linear receiver achieves better transmission performance than the MLD with smaller calculational complexity. The performance of the proposed techniques is verified by computer simulation in a 6×3 overloaded MIMO channel. When iterative decoding is applied, the proposed techniques attain a gain about 0.8 dB with low complexity $(M_0, M_1, M_2) = (4, 6, 6)$ and a gain about 0.9 dB without low complexity decoding at BER of 10^{-6} . Additionally, the larger the overload factor, the greater the gain obtained from iterative decoding. Even when M_0 is equal to 6, the performance gap is kept approximately. If we see the transmission performance shown in Fig. 4 where the transmission performance with $(M_0, M_1, M_2) = (4, 4, 6)$ is about the same to that with $(M_0, M_1, M_2) = (6, 6, 6)$, we can conclude that the proposed low complexity decoding can successfully reduce the computational complexity without any transmission performance degradation, if the parameters are carefully selected.

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