Introducing Dual Regularization Parameters into Regularized Channel Inversion (RCI)-Based Vector Perturbation for Modulo Loss Reduction

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***Abstract*—This paper proposes a method to reduce the symbol error caused by modulo operator for regularized channel inversion (RCI)-based vector perturbation (RCI-VP). The proposed method introduces dual regularization parameters of RCI precoding matrix. First regularization parameter α_1 is set so as to maximize the signal to interference plus noise ratio (SINR) value of each stream to find the optimal perturbation vector. The second regularization parameter α_2 is set so as to minimize the total MSE between the transmitted perturbation vector and received perturbation vector to reduce the symbol error caused by modulo operator. The simulated results confirm that the proposed method can improve the performance of RCI-VP over $i.i.d.$ MIMO channel and frequency-selective fading MIMO channel.**

***Keywords*—Vector perturbation, SINR maximization, Modulo loss, Regularization parameter, Minimum mean square error**

I. Introduction

THE technique of multiuser multiple-input multiple-output (MU-MIMO) can be utilized to improve downlink transmission rate of each user in picocell or femotocell systems. For a downlink MU-MIMO system, many spatial division multiple access (SDMA) techniques can be selected to improve the MU-MIMO channel capacity [1]. Among them, linear precoding combined with vector perturbation (VP) [2] is an algorithm to achieve MU-MIMO capacity bound using dirty paper coding (DPC) [3].

VP algorithm includes regularized channel inversion (RCI)-based VP (RCI-VP) [4] and zero-forcing (ZF)-based VP (ZF-VP). RCI-VP utilizes a parameter α for RCI precoding matrix and it is equivalent to ZF-VP if α equals zero. RCI-VP generally outperforms ZF-VP if the α value is appropriately selected. Therefore, finding an efficient regularization parameter α for RCI precoding matrix is a research topic for performance improvement.

The general objective function for finding an optimal α is to maximize the signal to interference plus noise ratio (SINR) of each stream. However, this optimal value is still an open issue and is only searched with a numerial method [2], [5]. Another objective function for optimizing α is to minimize the total mean square error (MSE) of the transmitted data and received data. To reach the aim, several methods have been proposed such as processing VP with continuous-valued perturbation vector [6] or minimizing the bit-error ratio (BER) of generalized RCI-VP system as the optimization criterion [7]. Several schemes improve the RCI-VP performance by shaping the transmitted symbols with different lattice transformation techniques [8]. Reference [9] showed that finding an optimal α to maximize the SINR value of each stream is equivalent to finding the optimum perturbation vector that minimizes the total MSE of the transmitted data and received data. But the method requires a transformed precoding matrix which needs some high-complexity matrix decomposition processes for searching the optimal perturbation vector.

In this paper, we first show that, using precoding matrix with optimized α based on SINR, the total MSE between the transmitted perturbation vector and received perturbation vector is not generally minimized. In such cases, the modulo operator at receiver sides deteriorates BER performance. In order to improve the performance of RCI-VP, we propose a method using dual regularization parameters of RCI precoding matrix. First, we find the optimal regularization parameter α_1 to maximize the SINR value of each stream by simulation for different modulation to realize the optimal perturbation vector search. Then we find the optimal regularization parameter α_2 to minimize the total MSE between the transmitted perturbation vector and received perturbation vector to reduce the symbol error generated from a modulo operator. The simulated results show that the proposed method can improve the performance of RCI-VP especially for QPSK modulation over $i.i.d.$ MIMO channel and frequency-selective fading MIMO channel.

This paper is organized as follows. The RCI-VP algorithm and QR-decomposition M-algorithm encoder (QRDM-E) [10] are briefly described in Section II. Then the conventional RCI-VP with optimized α based on SINR and the proposed method are introduced in Section III. The performance of the proposed method over flat-fading and frequency-selective fading channels is shown in Section IV. Finally Section V gives conclusions.

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$Notation$: We use upper (lower) boldface letters to denote matrices (column vectors), sometimes with subscripts to emphasize their sizes. $(.)^*$, $(.)^T$, $(.)^H$ will denote complex conjugate, transpose, conjugate transpose. $\mathbf{E}\{.\}$ and $\mathbf{Tr}\{.\}$ are the expectation operator and matrix trace operator.

II. RCI-BASED VECTOR PERTURBATION (RCI-VP) AND QRDM-ENCODING

A. RCI-based vector perturbation (RCI-VP) algorithm for MU-MIMO

A general model of downlink MU-MIMO system includes a BS with N_t transmitting antennas and K users, each with N_r receiving antennas. We assume that $N_t = KN_r$. The corresponding vector equation is

$$\mathbf{y} = \mathbf{Hu} + \mathbf{n} \tag{1}$$

where $\mathbf{y} = [y_1, \ldots, y_{N_t}]^T$ $\mathbf{u} = [u_1, \ldots, u_{N_t}]^T$, and $\mathbf{n} = [n_1, \ldots, n_{N_t}]^T$. The $N_t \times N_t$ matrix $\mathbf{H}$ has complex element $h_{i,j}$ of MIMO channel with $\mathbf{E}\{|h_{ij}|^2\} = 1$. We assume the power constraint $E\{|\mathbf{u}|^2\} = 1$ and σ^2 is the signal to noise ratio (SNR) at the receiving antenna named as SNR per stream. Therefore the noise variance matrix $E\{\mathbf{nn}^H\}$ is represented as $\frac{1}{N_t\sigma^2}\mathbf{I}_{N_t}$ and $\mathbf{I}_{N_t}$ is $N_t \times N_t$ identity matrix.

The linear RCI MU-MIMO structure is shown in Fig. 1 (a). Suppose that BS has the perfect CSI $\mathbf{H}$, the RCI spatial filter is represented as

$$\mathbf{W} = \mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}. \tag{2}$$

The transmitted data $\mathbf{x}$ is processed as

$$\mathbf{s} = \mathbf{Wx} = \mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}\mathbf{x}. \tag{3}$$

After normalized the symbol $\mathbf{s}$ as

$$\mathbf{u} = \sqrt{\frac{1}{\gamma}}\,\mathbf{s} \tag{4}$$

with $\gamma = ||\mathbf{s}||^2 = ||\mathbf{Wx}||^2$, the transmit symbol $\mathbf{u}$ is transmitted over MU-MIMO channel $\mathbf{H}$ to all users. Therefore, the received symbol $\mathbf{y}$ is represented as

$$\mathbf{y} = \sqrt{\frac{1}{\gamma}}\mathbf{HH}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}\mathbf{x} + \mathbf{n}. \tag{5}$$

After multipled by $\sqrt{\gamma}$, the received symbol $\sqrt{\gamma}\mathbf{y}$ is demodulated as $\hat{\mathbf{x}}$. The regularization parameter α is used to minimize the total MSE between the transmitted symbols $\mathbf{x}$ and received symbols $\hat{\mathbf{x}}$.

However, if $\mathbf{H}$ is a high correlated channel matrix, the normalized parameter γ becomes large therefore the SNR becomes small. To mitigate its effect, vector perturbation (VP) perturbs the transmitted symbol $\mathbf{x}$ with a perturbation vector to reduce the normalized parameter γ [2]. We use Fig. 1(b) to show its sturcture. Let us set $\hat{\mathbf{x}} = \mathbf{x} + \tau\boldsymbol{\ell}$ where τ is chosen as $2(|c|_{max} + d_{min}/2)$. Here $|c|_{max}$ is the absolute value of constellation point with the largest amplitude and d_{min} is the spacing between two adjacent constellation points. $\boldsymbol{\ell}$ is an N_t-dimensional complex perturbation vector $a + ib$, where a and b are integers. The normalized parameter γ is computed as

$$\gamma = ||\mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}(\mathbf{x} + \tau\boldsymbol{\ell})||^2 = ||\mathbf{W}(\mathbf{x} + \tau\boldsymbol{\ell})||^2. \tag{6}$$

The core design of VP is to find the optimum choice $\boldsymbol{\ell}_0$ which minimizes the γ to γ_0, that is

$$\boldsymbol{\ell}_0 = \arg\min_{\boldsymbol{\ell}'} \left|\left|\mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}(\mathbf{x} + \tau\boldsymbol{\ell}')\right|\right|^2 \tag{7}$$

with

$$\gamma_0 = \left|\left|\mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}(\mathbf{x} + \tau\boldsymbol{\ell}_0)\right|\right|^2. \tag{8}$$

If BS uses the precoding matrix $\mathbf{W}$ with regularization parameter α to pre-cancel the interference among streams, the transmitted signal after perturbation vector search as Eq. (4) is

$$\mathbf{u} = \frac{1}{\sqrt{\gamma_0}}\mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}(\mathbf{x} + \tau\boldsymbol{\ell}_0). \tag{9}$$

In such case, the purpose of RCI-VP is, in essence, the optimization to get the smallest γ to improve SNR at the receiver side.

The symbol $\mathbf{u}$ is transmitted over MU-MIMO channel $\mathbf{H}$ to all users. After multiplied by $\sqrt{\gamma_0}$, the received symbol can be represented as

$$\hat{\mathbf{y}} = \mathbf{HH}^H(\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t})^{-1}(\mathbf{x} + \tau\boldsymbol{\ell}_0) + \sqrt{\gamma_0}\mathbf{n}. \tag{10}$$

To remove the effect of the integer multiple of τ for ith stream, the receiver utilizes the modulo function as

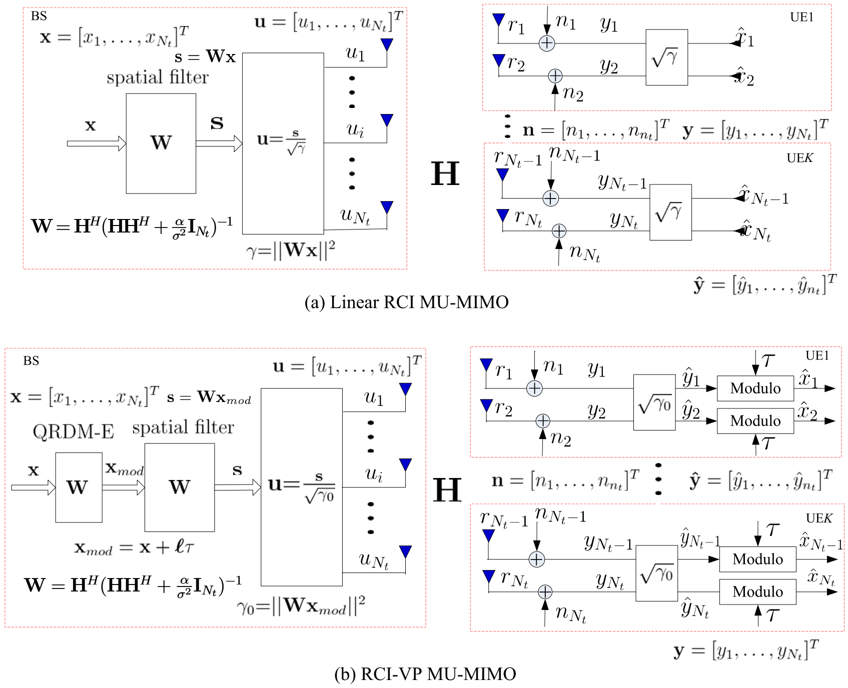
$$\hat{x}_i = \mod_\tau(\hat{y}_i) = \hat{y}_i - \left\lfloor \frac{\hat{y}_i + \tau/2}{\tau} \right\rfloor \tau \tag{11}$$

where the function $\lfloor . \rfloor$ gives the largest integer less than or equal to its argument. With the modulo function, the receiver can demodulate its own data.

B. QR-decomposition M-algorithm encoder

The perturbation vector search of Eq. (7) is a $2N_t$-dimensional integer-lattice least-squares problem which can be resolved using the sphere decoder [11]. However, the computational complexity (CC) of the sphere decoder is large and limits the application of VP. An efficient sphere decoder algorithm can be realized using the QR-decomposition M-algorithm encoder (QRDM-E) [10] which can balance the trade-off between the CC and the diversity order of VP.

QRDM-E limits the integer value a and b of $\boldsymbol{\ell}$ selected from the symmetric integer set $\mathcal{A}$ as $\mathcal{A} = \{-T, -T+1, \ldots, -1, 0, 1, \ldots, T-1, T\}$, which reduces the search complexity with a smaller value T. On the other hand, QRDM-E factorizes the matrix $\mathbf{W}$ of Eq. (7) into the product of a unitary



(a) Linear RCI MU-MIMO

(b) RCI-VP MU-MIMO

Fig. 1. The structures of linear MMSE MU-MIMO and nonlinear RCI-VP MU-MIMO.

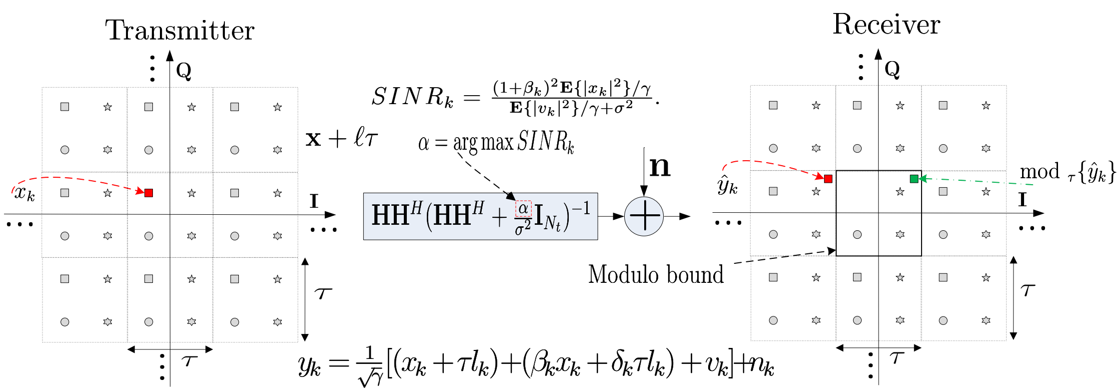


Fig. 2. The symbol mismatch caused by modulo operator on received symbol with optimization of SINR for each stream.

matrix $\mathbf{Q}$ and an upper triangular matrix $\mathbf{R}$. Thus, the search problem in Eq. (7) is simplified to

$$\boldsymbol{\ell}_0 = \arg\min_{\boldsymbol{\ell}' \in \mathcal{A}^{N_t}} ||\mathbf{QR}(\mathbf{x}+\tau\boldsymbol{\ell}')||^2 = \arg\min_{\boldsymbol{\ell}' \in \mathcal{A}^{N_t}} ||\mathbf{R}(\mathbf{x}+\tau\boldsymbol{\ell}')||^2. \quad (12)$$

The search process of Eq. (12) is realized using an M-algorithm for each stream in a successive way. The best M branches that have the least accumulative metrics to find $\ell_0(k+1)\tau$ for the $(k+1)$th stream are retained for the next stage to find $\ell_0(k)\tau$ for the kth stream. We omit the illustration for QRDM-E process and reader can find the clear explanation in [10].

III. The Proposal of RCI-VP Algorithm with Dual Regularization Parameters

A. Regularization parameter α for optimization of SINR for each stream

The regularization parameter α can be optimized to balance the inter-stream interference and noise power to maximize the SINR. The optimal value α is generally obtained by a numerical method as pointed out in References [2], [5]. It is also shown in [2] and [5] that the optimal α for maximizing SINR is generally smaller than N_t. We briefly review this process. To get the optimal α, the received signal is written as

$$\begin{aligned}\mathbf{y} &= \frac{1}{\sqrt{\gamma_0}} \frac{\mathbf{HH}^H}{\mathbf{HH}^H + \frac{\alpha}{\sigma^2}\mathbf{I}_{N_t}}(\mathbf{x}+\tau\boldsymbol{\ell}_\mathbf{0}) + \mathbf{n} \\ &= \frac{1}{\sqrt{\gamma_0}}\Big[\mathbf{I}_{N_t}(\mathbf{x}+\tau\boldsymbol{\ell}_\mathbf{0}) + \mathcal{F}(\mathbf{x}+\tau\boldsymbol{\ell}_\mathbf{0})\Big] + \mathbf{n}, \quad (13)\end{aligned}$$

where $\mathcal{F} = \{(\mathbf{I}_{N_t} + \frac{\alpha}{\sigma^2}(\mathbf{HH}^H)^{-1})^{-1} - \mathbf{I}_{N_t}\}$. The received signal for the kth stream is

$$y_k = \frac{1}{\sqrt{\gamma_0}}[(x_k + \tau\ell_0(k)) + < \mathcal{F}(\mathbf{x}+\tau\boldsymbol{\ell}_\mathbf{0}) >_k] + n_k \quad (14)$$

where the notation $< \mathbf{C} >_k$ represents the kth row of matrix $\mathbf{C}$. It is clear that $< \mathcal{F}(\mathbf{x}+\tau\boldsymbol{\ell}_\mathbf{0}) >_k$ is potentially correlated with x_k and $\ell_0(k)$. This correlation can be model as

$$y_k = \frac{1}{\sqrt{\gamma_0}}[(x_k + \tau\ell_0(k)) + (\beta_k x_k + \delta_k \tau\ell_0(k)) + v_k] + n_k \quad (15)$$

where v_k is co-channel interference (CCI) and uncorrelated with x_k and $\ell_0(k)$. Here β_k and δ_k represent the correlation coefficients of the term $< \mathcal{F}(\mathbf{x}+\tau\boldsymbol{\ell}_\mathbf{0}) >_k$ with x_k and $\ell_0(k)$. As shown in Reference [5], the SINR of the kth stream $SINR_k$ is

$$SINR_k = \frac{(1+\beta_k)^2\mathbf{E}\{|x_k|^2\}/\gamma}{\mathbf{E}\{|v_k|^2\}/\gamma_0 + (N_t\sigma^2)^{-1}}. \quad (16)$$

The regularization parameter α controls the value of γ_0, the correlation β_k and the variance of v_k. Increasing α generally decreases γ_0, then potentially increasing the $SINR_k$, but increases the variance of v_k, then potentially decreasing the $SINR_k$. Therefore the overall impact on the performance of RCI-VP is difficult to determine analytically. Therefore, it is generally obtained by a numerical method.

However, the optimization of maximizing SINR does not consider the effect of modulo operator which will increase the symbol error caused by the modulo process. Let us use Fig. 2 to show the process of symbol error on transmitting symbol x_k. After optimization of maximizing SINR, the RCI-VP utilizes the regularization parameter α to the transmit data. The receiver receives the symbol $\hat{y}_k$ which statistically has the maximum SINR. As shown in Fig. 2, the received symbol $\hat{y}_k$ is out of modulo bound and causes symbol error after the modulo operation.

B. Regularization parameter α for optimization of total MSE between the transmitted perturbated vector and received perturbated vector

To minimize the symbol error caused by modulo operator, α is to be optimized so as to minimize the total MSE between the transmitted perturbated vector $(\mathbf{x} + \boldsymbol{\ell}_\mathbf{0}\tau)$ and its received perturbated vector $\hat{\mathbf{x}}_r$ at the receiver side. After perturbation vector search, the transmit data $\mathbf{x}$ is perturbated as $\hat{\mathbf{x}} = \mathbf{x} + \tau\boldsymbol{\ell}_\mathbf{0}$. Here $\tau\boldsymbol{\ell}_\mathbf{0}$ can obtain the smallest γ_0 as shown in Eq. (8). To realize such optimization, we consider a precoding matrix $\mathbf{P}$. The received symbol $\hat{\mathbf{x}}$ is represented as

$$\hat{\mathbf{x}}_\mathbf{r} = \frac{1}{\sqrt{\gamma_P}}\mathbf{HP}\hat{\mathbf{x}} + \mathbf{n} \quad (17)$$

where γ_P equals $\mathbf{E}\{||\mathbf{P}\hat{\mathbf{x}}||^2\}$.

The optimization can be represented as

$$\{\mathbf{P}_{opt}, \gamma_{opt}\} = \arg\min_{\mathbf{P},\gamma_P} \mathbf{E}\{||\hat{\mathbf{x}}_r - \hat{\mathbf{x}}||^2\} \quad S.t.: \quad \mathbf{E}\{||\mathbf{P}\hat{\mathbf{x}}||^2\} = \gamma_P \quad (18)$$

The analytic solution for this optimization is represented as

$$\begin{aligned}\mathbf{P}_{opt} &= \mathbf{H}^H(\mathbf{HH} + \xi\mathbf{I}_{N_t})^{-1} \\ \gamma_{opt} &= ||\mathbf{P}_{opt}\hat{\mathbf{x}}||^2 \quad (19)\end{aligned}$$

where the regularization parameter $\xi = \mathbf{Tr}\{\frac{1}{\sigma^2}\mathbf{I}_{N_t}\} = \frac{N_t}{\sigma^2}$ [12]. The solution also shows that if the previous optimal regularization parameter α_1 for maximizing the SINR obtained by numerical method is identical to the regularization parameter $\xi\sigma^2$, the total MSE between the $\hat{\mathbf{x}}$ and $\hat{\mathbf{x}}_r$ is also minimized. However, as shown in References [2] and [5], the optimal α for maximizing the SINR is generally smaller than N_t and cannot realize both optimization targets.

C. Proposed method with dual regularization parameters

The proposed method, which is combined by both optimalization targets of the regularization parameters, is realized as following steps.

(1) We use numerical method to find an efficient regularization parameter α_1 which can achieve best BER performance for each different modulation based on simulated results.

(2) For perturbation vector search, the optimum choice $\boldsymbol{\ell}$ which minimizes γ is searched using precoding matrix with regularization parameter α_1 as

$$\boldsymbol{\ell} = arg \min_{\boldsymbol{\ell}' \in \mathcal{A}^{N_t}} \left|\left| \frac{\mathbf{H}^H(\mathbf{x}+\tau\boldsymbol{\ell}')}{\mathbf{HH}^H + \frac{\alpha_1}{\sigma^2}\mathbf{I}_{N_t}} \right|\right|^2. \quad (20)$$

(3) The precoding matrix $\mathbf{W}$ is set as $\mathbf{W} = \mathbf{P}_{opt} = \mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha_2}{\sigma^2}\mathbf{I}_{N_t})^{-1}$ with the minimum-mean square error (MMSE) weight to realize the total MSE optimization. Therefore, after obtaining the optimum choice $\tau\boldsymbol{\ell}$, BS sets the transmit symbol as

$$\mathbf{u} = \frac{1}{\sqrt{\gamma'}}\mathbf{W}(\mathbf{x}+\tau\boldsymbol{\ell}) = \mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha_2}{\sigma^2}\mathbf{I}_{N_t})^{-1}(\mathbf{x}+\tau\boldsymbol{\ell}) \quad (21)$$

where $\gamma' = ||(\mathbf{H}^H(\mathbf{HH}^H + \frac{\alpha_2}{\sigma^2}\mathbf{I}_{N_t})^{-1})(\mathbf{x}+\tau\boldsymbol{\ell})||^2$.

IV. Performance evaluation of proposed method over the flat-fading and correlated frequency-selective fading MIMO Channel

A. Finding α_1 by numerical method

We utilize a numerical method to find efficient value of α_1. As shown in References [2] and [5], the optimal α_1 is usually smaller than N_t. We simulate the BER performance of VP

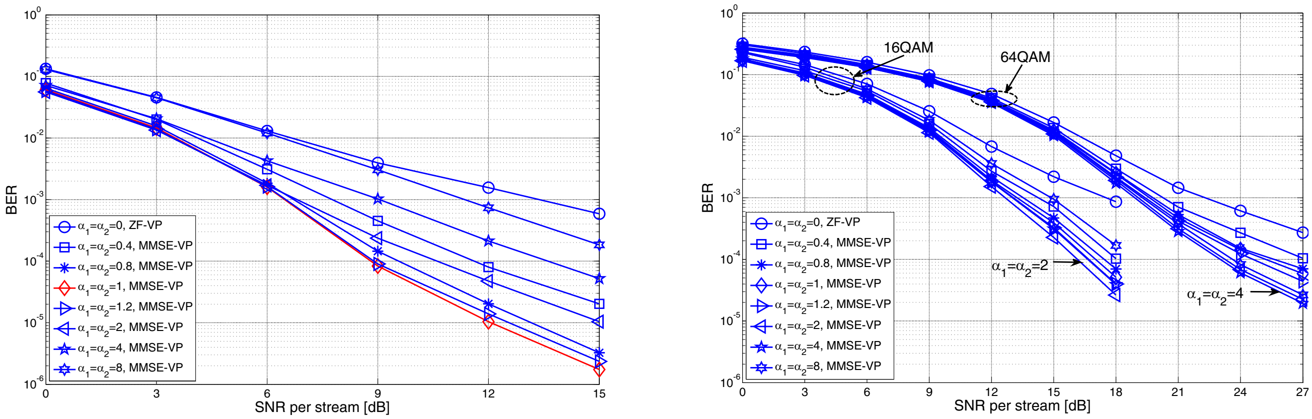


Fig. 3. The simulated BER performance of RCI-VP algorithm when $\alpha_1 = \alpha_2$ (left: QPSK modulation; right: 16QAM, 64QAM modulations)

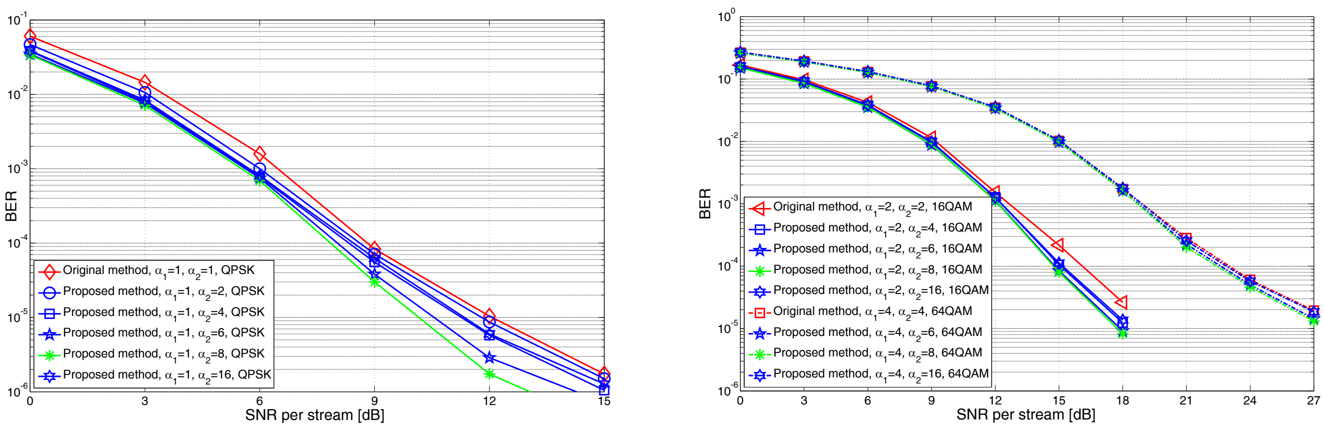


Fig. 4. The simulated BER performance RCI-VP algorithm with different value of α_2 (left: QPSK modulation; right: 16QAM, 64QAM modulations)

algorithm with different value of α_1 and α_2 over $i.i.d.$ MIMO channel. We assume $N_t = 8$ and $(T, M) = (3, 7)$ for QRDM-E algorithm. The simulated BER results are shown in Fig. 3 for QPSK, 16QAM and 64QAM modulations. According to the simulated results, $\alpha_1 = 1, 2, 4$ gives the best performance for QPSK, 16QAM and 64QAM over (8×8) $i.i.d.$ channel, respectively.

B. BER performance evaluation of proposed method over flat-fading MIMO Channel

Fig. 4 shows the simulated results of the proposed method over $i.i.d.$ MIMO channel with different modulations. We also assume $N_t = 8$ and $(T, M) = (3, 7)$ for QRDM-E algorithm. To show the impact of α_2, we choose different values to compare the BER performance. The simulated results show that the proposed method can improve the performance of RCI-VP for all modulations especially for QPSK modulation. The reason dues to that, for modulation with a large number of constellation points, the effect of modulo function has little impact on the interior constellation points than that of boundary constellation points even if the MSE of between the transmitted perturbated vector and received perturbated vector is slightly increased.

C. Spectrum efficiency (SE) evaluation of proposed method over flat and frequency-selective fading MIMO Channels

We compare the spectrum efficiency (SE) of the proposed method using dual regularization parameters with the original method using one regularization parameter based on SINR optimization. The simulation specifications are given in Table I. We use $i.i.d.$ channel, one indoor correlated channel model (A1 LOS) and one suburban macro cell channel model (C1 NLOS) as shown in Table II to evaluate SE of the proposed method and the original method. We also assume that the transmitter and the receiver have the perfect knowledge of CSI.

We first compare the proposed method using dual regularization parameters with the original method using one regularization parameter over $i.i.d.$ channel and the simulated results are given in Fig. 5. The values of α_1 and α_2 are set based on the previous simulated results. As shown in the figure, the proposed method can achieve better SE performance than that of original method especially for QPSK modulation.

The simulated results over A1 LOS channel with 1λ and 10λ spacing for BS antennas are shown in Fig. 6 and Fig. 7. The values of α_1 and α_2 are also set based on the previous simulated results over $i.i.d.$ MIMO channel. As shown in both figures, the simulated results confirm that using different

TABLE I. SIMULATION SPECIFICATIONS

Sampling rate	30.72 Msamples/s
FFT size	2048
Length of cyclic prefix	$4.7\mu s$
Number of subcarriers	1200
Number of antennas	8 (BS) 2 (UE)
Number of users (N)	4
Direction of UEs	-67.5, -22.5, 22.5 and 67.5 (Deg.)
Modulation scheme	QPSK, 16QAM, 64QAM
Channel coding	Turbo code
Coding rate	3/4
Frame size	3597 bits +3 pality bits (QPSK) 3597 bits +3 parity bits (16QAM) 5397 bits +3 parity bits (64QAM)
Interleaver	Random interleaver
Decoding algorithm	soft-output Viterbi algorithm
Number of deocoding iterations	6
Array configuration	Equally spaced linear array
Antenna spacing	1λ and 10λ of DL carrier frequency (BS) 0.5λ of DL carrier frequency (UE)
Carrier frequnecy	3.36 GHz (DL)
Spatial filtering	MMSE
Estimation of average received SNR	Perfect
Perturbated vector search	QRDM-E [10], $(T, M) = (3, 7)$

TABLE II. CHANNEL PARAMETERS FOR A1 LOS AND C1 NLOS [13]

Channel model	A1 LOS	C1 NLOS
Average delay spread [ns]	40	234
Average AoA/AoD [Deg.]	44/45	8/45
Average K-factor [dB]	5-6	-

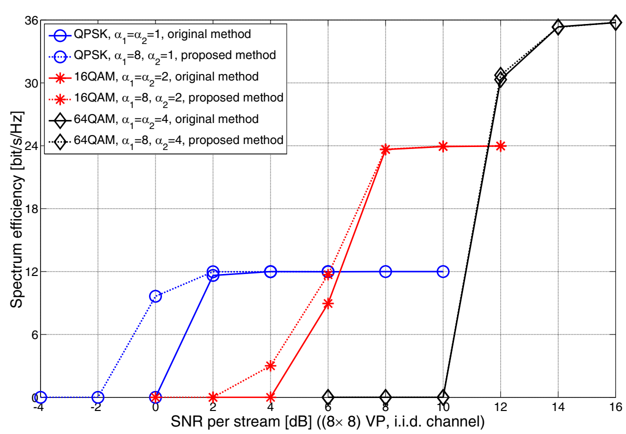


Fig. 5. The spectrum efficiency performance comparison of RCI-VP algorithm with and without dual regularization parameters over $i.i.d.$ MIMO channel.

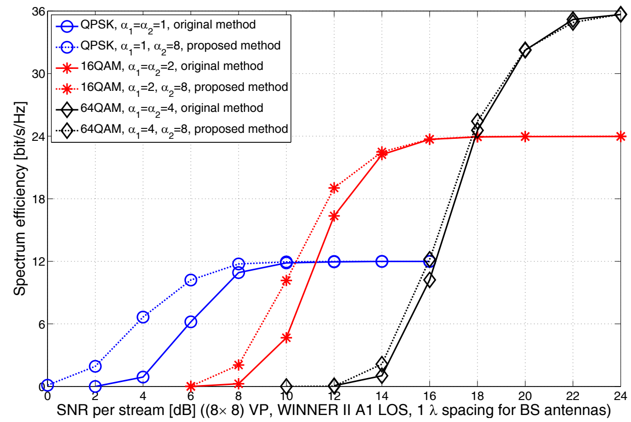


Fig. 6. The spectrum efficiency performance comparison of RCI-VP algorithm with and without dual regularization parameters over A1 LOS MIMO channel (1 λ spacing for BS antennas).

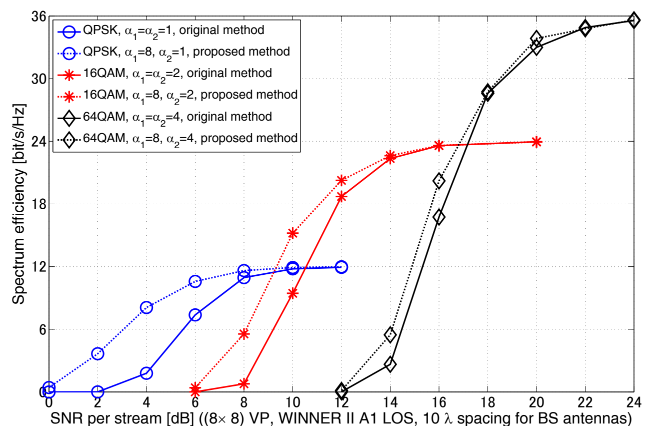


Fig. 7. The spectrum efficiency performance comparison of RCI-VP algorithm with and without dual regularization parameters over A1 LOS MIMO channel (10 λ spacing for BS antennas).

values of α_1 and α_2 can increase the SE of the RCI-VP system than that using the method based on the original SINR optimization especially for the modulation with a small number of constellation points such as QPSK modulation.

The simulated results over C1 NLOS channel with 1λ and 10λ spacing for the BS antennas are shown in Fig. 8 and Fig. 9. As shown in both figures, the simulated results confirm that using dual regularization parameters increases the SE of RCI-VP system than that using the method based on original SINR optimization especially for QPSK modulation. However, compared with Fig. 8, the SE improvement in Fig. 9 using dual regularization parameters is small because the channel is a low correlated one even if the BS antenna spacing is 1 λ.

Based on the simulated results over flat and frequency-selective fading channels, using dual regularization parameters for RCI-VP system can reduce the symbol error caused by a modulo operator compared with the system using one regularization parameter based on the criteria of SINR maximum. The proposed method will provide better SE improvement

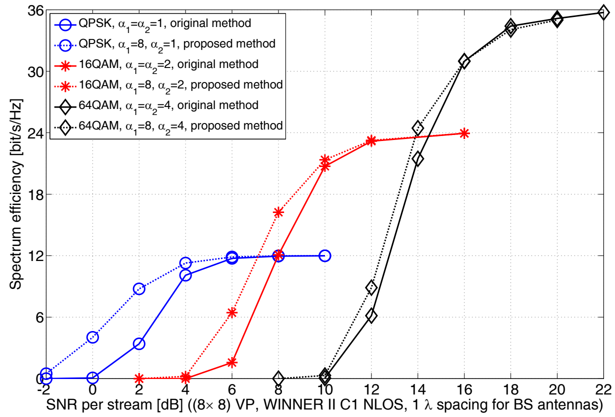


Fig. 8. The spectrum efficiency performance comparison of RCI-VP algorithm with and without dual regularization parameters over C1 NLOS MIMO channel (1 λ spacing for BS antennas).

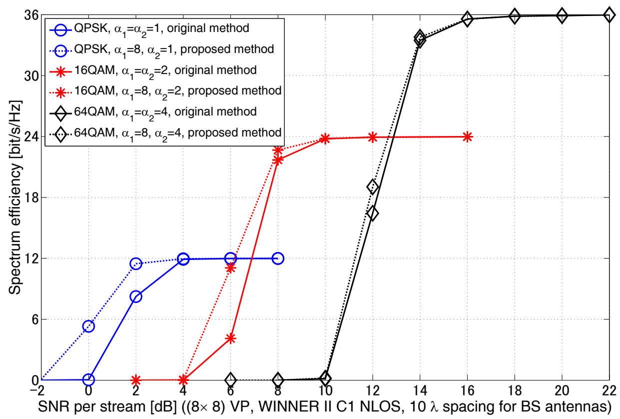


Fig. 9. The spectrum efficiency performance comparison of RCI-VP algorithm with and without dual regularization parameters over C1 NLOS MIMO channel (10 λ spacing for BS antennas).

especially over a low SNR range using the modulation with small number of constellation points.

V. Conclusions

We have proposed a method to reduce the symbol error caused by a modulo operator for RCI-VP using dual regularization parameters of RCI precoding matrix. The proposed method utilizes the RCI precoding matrix with regularization parameter α_1 which can maximize the SINR of each stream to find the optimal perturbation vector. For the RCI precoding matrix to pre-cancel the interference among the streams, the RCI-VP uses the RCI precoding matrix with regularization parameter α_2 which can minimize the total MSE between the transmitted perturbation vector and received perturbation vector. The simulated results confirm that the proposed method can improve the performance of RCI-VP especially for QPSK modulation over $i.i.d.$ MIMO channel and frequency-selective fading MIMO channel.

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