

Effective Transmit Weight Design for DPC with Maximum Beam in Multiuser MIMO OFDM Downlink

Cong LI^{†a)}, Nonmember and Yasunori IWANAMI^{†b)}, Member

SUMMARY In this paper, we consider the signal processing algorithm on each subcarrier for the downlink of Multi-User Multiple-Input Multiple-Output Orthogonal Frequency Division Multiplexing (MU-MIMO OFDM) system. A novel transmit scheme is proposed for the cancellation of Inter-User Interference (IUI) at the Base Station (BS). The improved performance of each user is obtained by optimizing the transmit scheme on each subcarrier, where the Particle Swarm Optimization (PSO) algorithm is employed to solve the constrained nonlinear optimization problem. Compared with the conventional Zero Forcing Dirty Paper Coding (ZF-DPC) having only single receive antenna at each Mobile Station (MS), the proposed scheme also applies the principle of DPC to cancel the IUI, but the MS users can be equipped with multiple receive antennas producing their increased receive SNR's. With the Channel State Information (CSI) being known at the BS and the MS, the eigenvalues for all the user channels are calculated first and then the user with the maximum eigenvalue is selected as the 1-st user. The remaining users are ordered and sequentially processed, where the transmit weights are generated from the previously selected users by the Particle Swarm Optimization (PSO) algorithm which ensures the transmit gain for each user as large as possible. The computational complexity analysis, BER performance and achievable sum-rate analysis of system verify the effectiveness of the proposed scheme.

key words: MU-MIMO OFDM, inter-user interference, particle swarm optimization, dirty paper coding

1. Introduction

Recently, Multiuser MIMO systems have attracted considerable interests because of their potential for increasing the capacity [1]–[5]. On the other hand, OFDM is a practical technology to convert a broadband frequency selective channel to parallel flat fading channels over many subcarriers, making a lot of MIMO-related algorithms for flat fading channel easy to be implemented. For the above reasons, OFDM is a strong candidate for wideband MIMO communication systems. At each subcarrier in Multiuser MIMO OFDM downlink, the BS transmits spatially multiplexed signals to multiple MS's simultaneously over the same frequency. However, the MS suffers from the IUI in the received signal. To mitigate the IUI, we can intelligently design the transmit signals for Specially Multiplexing (SM) by using linear or nonlinear precoding techniques under the condition that the CSI is known at BS and MS. Many linear precoding techniques have been employed to eliminate the IUI, such as the

Channel Inversion (CI) [4] and the Block Diagonalization (BD) [5]. In the case of CI, The Zero Forcing (ZF) transmit weights can completely remove the IUI, however, it leads to the noise enhancement at the receiver. Though the transmit weight with Minimum Mean-Squared Error (MMSE) criterion can achieve the increased sum-rate, it results in the vestigial IUI. The BD strategy is a well-known linear precoding technique, which completely cancels the IUI by using the orthogonal space theory. However, these schemes impose the condition in respect of the number of receive antennas that the number of transmit antennas at BS is larger than the total number of receive antennas of all users. In addition, as the channel correlation among users degrades the downlink capacity, the spatially multiplexed users with highly correlated channels should be avoided.

The DPC technique can not only completely suppresses the IUI but also approaches the capacity region [6]–[8], where the achievable rate is dependent on the ordering of users. In [9] the Maximum Beam (MB) transmit scheme utilizes the eigenvector corresponding to the maximum eigenvalue of desired user channel to determine the transmit weight. However, as the IUI among MS becomes serious, the authors gave this problem the solution using the imperfect block diagonalization which reduces the IUI by employing Gram-Schmidt orthonormalization on transmit weights. But this method needs to keep the balance between removing IUI and maximizing transmit gain. In [10] the authors also proposed the design method in which the near-orthogonal effective channels are successively obtained from the 1-st user to the last user by skilfully subtracting the interference components. However, the interference among users cannot be cancelled completely because of the incomplete orthogonality.

Particle Swarm Optimization (PSO), firstly proposed by Kennedy and Eberhart in 1995 [11], is developed from the swarm intelligence and based on the research of flock movement behaviour of birds flock finding foods [12]–[14]. It shows the better computational efficiency than the other algorithms such as Genetic Algorithm (GA) [15]. Recently, the PSO attracts considerable interest in Multiuser MIMO system and the PSO aided optimal Multi-User MIMO linear precoding scheme is proposed in [14], where the PSO is used to search the optimal transmit weight which makes the SINR maximum at each user. However, though the IUI among users can be completely removed by multiplying the decoder matrix, it leads to the noise enhancement and the great computational load for MS.

Manuscript received March 8, 2011.

Manuscript revised July 11, 2011.

[†]The authors are with the Department of Computer Science and Engineering, Graduate School of Engineering, Nagoya Institute of Technology, Nagoya-shi, 466-8555 Japan.

a) E-mail: chx17515@stn.nitech.ac.jp

b) E-mail: iwanami@nitech.ac.jp

DOI: 10.1587/transfun.E94.A.2710

In this paper, we proposed a novel transmit scheme for each subcarrier of Multiuser MIMO OFDM downlink, not only to obtain the optimal transmit weight but also to completely eliminate the IUI for each subcarrier of individual user. We firstly select the user with the maximum eigenvalue as the 1-st user by calculating the eigenvalues of all users. Then we obtain the possible transmit weight for the next user by using the PSO algorithm, which makes sure that the selected user has an optimal accessible SNR. The transmit weights for the remaining users are generated by the same method as the previous users. In the proposed scheme, we also utilized the DPC principle as in the conventional DPC scheme to remove the IUI at the BS, but we make it possible that the MS can be equipped with multiple antennas to increase the receive SNR, whereas the conventional DPC scheme only uses one receive antenna at each MS.

The contents of this paper are as follows. In Sect. 2, we will explain the system model of MU-MIMO. In Sect. 3, we propose the optimal transmit weight design based on the PSO algorithm for each user, and then we give the analysis of computational load and achievable sum-rate of the system. We give the simulation results in Sect. 4, in which the proposed scheme obtains the considerable sum-rate and shows the excellent BER performance compared with the conventional schemes. The conclusions are given in Sect. 5. We illustrate some of the notations as follows; vectors and matrixes are expressed by bold letters, we use $E[\cdot]$, $[\cdot]^T$ and $[\cdot]^H$ as the expectation, transpose and conjugate transpose of matrix, respectively.

2. System Model

We consider the downlink multiuser MIMO system with N_T transmit antennas and $n_R^{(k)}$ receive antennas at the k -th user, as shown in Fig. 1, where N_u is the number of multiple antenna users and we denote N_R as the total number of receive antennas. In this paper, we focus on the quasi-static flat Rayleigh (i.i.d.) fading channel model, because the wideband OFDM can convert the quasi-static frequency selective Rayleigh fading channel to the flat Rayleigh fading

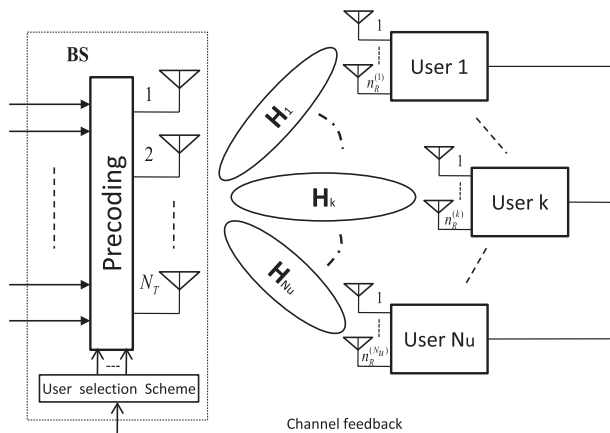


Fig. 1 Downlink model for each subcarrier of multiuser MIMO OFDM.

at each frequency index (subcarrier). On each subcarrier, we assume that the k -th channel matrix $\mathbf{H}_k \in \mathbb{C}^{n_R^{(k)} \times N_T}$ ($k = 1, 2, \dots, N_u$) is available at BS and MS. The channel matrix $\mathbf{H} \in \mathbb{C}^{N_R \times N_T}$ and the precoding matrix $\mathbf{M} \in \mathbb{C}^{N_T \times N_T}$ of system are expressed as

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}_1^T & \mathbf{H}_2^T & \dots & \mathbf{H}_{N_u}^T \end{bmatrix}^T$$

$$\mathbf{M} = \begin{bmatrix} \mathbf{M}_1^T & \mathbf{M}_2^T & \dots & \mathbf{M}_{N_u}^T \end{bmatrix}^T \tag{1}$$

The $n_R^{(k)} \times 1$ received signal at the k -th user can be written as

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{M}_k \mathbf{x}_k + \sum_{j=1, j \neq k}^{N_u} \mathbf{H}_k \mathbf{M}_j \mathbf{x}_j + \mathbf{n}_k \tag{2}$$

where \mathbf{x}_k is the transmit signal vector for the k -th user, and \mathbf{n}_k represents the additive Gaussian noise. In this paper, we only focus on one transmit stream for each user and assume that

$$E(\mathbf{s}_k \mathbf{s}_k^H) = \sigma_s^2 \mathbf{I}_{n_T^{(k)}}, E(\mathbf{n}_k^H \mathbf{n}_k) = \sigma_n^2 \mathbf{I}_{n_R^{(k)}}, E(\mathbf{s}_k \mathbf{n}_k^H) = \mathbf{0} \tag{3}$$

3. Proposed Optimal Transmit Weights Based on Particle Swarm Optimization

In this section, after a simple introduction of the MB scheme and the conventional DPC based on QR decomposition, we propose a novel transmit scheme, which employs the nonlinear optimization technique PSO to obtain the optimal transmit weights for transmitted diversity and then to cancel the IUI by the DPC technique.

3.1 Maximum Beamforming (MB)

Maximum Beamforming (MB), literally, utilizes the eigenvector corresponding to the maximal singular value of the channel matrix to obtain the maximum transmit gain. The MIMO channel matrix of k -th user can be decomposed by the Singular Value Decomposition (SVD) as

$$\mathbf{H}_k = \mathbf{U}_k \sum_k \mathbf{V}_k^H \tag{4}$$

where $\mathbf{V}_k = [\mathbf{v}_k^1 \dots \mathbf{v}_k^{N_T}]$ is an unitary matrix, and \mathbf{v}_k^1 denotes the maximal eigenvector of k -th user. It is noticed that if \mathbf{v}_k^1 is used as the transmit weight for the k -th user, we can obtain the maximum transmit gain as follows.

$$\|\mathbf{H}_k \mathbf{M}_k\|_2 = \lambda_k^{\max}, \mathbf{M}_k = \mathbf{v}_k^1 \tag{5}$$

where λ_k^{\max} denotes the maximal singular value of \mathbf{H}_k . In the case of MB scheme, the IUI is so serious that it cannot be removed because of the independence among users, especially in the situation of so many users.

3.2 Zero Forcing Dirty Paper Coding (ZF DPC)

Dirty paper coding, one of nonlinear techniques, is firstly introduced by Costa in the case of Single Input Single Output

(SISO) channel [6] and subsequently extended in the case of MIMO, where the IUI among users are preliminarily subtracted at the BS. The transmit signal can be denoted as

$$x_i = \text{mod} \left[s_i - \frac{1}{l_{i,i}} \sum_{j < i} l_{i,j} x_j \right], \quad i = 1, 2, \dots, N_T \quad (6)$$

where x_i is generated from the user information s_i and $l_{i,j}$ is the element of matrix $\mathbf{L} = \mathbf{R}^H$ obtained by the QR decomposition $\mathbf{H} = \mathbf{QR}$. However, the average transmit power is boosted and a modulo device is used to avoid this power enhancement problem [8].

Note that in (6) the first user gets no interference from the others, its signal is detected regardless of other users, while the interference for second user is only affected by the first user. It can be overcome by using the DPC scheme. The following users are processed in similar manner, and the interference among users can be eliminated and the channel matrix is transformed into the array of parallel channels for each user.

3.3 Design of Optimal Transmit Weights for DPC in MU-MIMO

The principle of conventional DPC based on QR decomposition indicates that the sufficient condition for the feasibility of DPC is the existence of lower or upper triangular matrix derived from the channel matrix. Since the IUI cannot be removed at the receiver in the case of MB, we carefully design the transmit weight for each user to transform the effective channels to the lower or upper triangular matrices. Then we can use DPC to remove the IUI completely. However, how to obtain the optimal transmit weight becomes a problem, referred to as the problem of the user order and the optimal transmit weight design.

3.3.1 Transmit Scheme for Eliminating IUI

We design the transmit weight for each user as the following steps. We make the SVD for channel matrixes of all users.

$$\mathbf{H}_k = \mathbf{U}_k \mathbf{\Lambda}_k [\mathbf{v}_k^1, \mathbf{v}_k^2, \dots, \mathbf{v}_k^{N_T}]^H, \quad (k = 1, 2, \dots, N_u; N_u \geq N_T) \quad (7)$$

In this paper, we can also use the QR decomposition of $\mathbf{H}_k(\mathbf{I} - \mathbf{H}_k^H \mathbf{H}_k) = \mathbf{0}$ to obtain the null space of matrix \mathbf{H}_k to reduce the computational complexity [16]. To achieve the optimal transmit weight for the 1-st user, we perform the following algorithm.

$$\mathbf{H}_q \mathbf{v}_q^1 = \arg \max_{\mathbf{H}_q} (\|\mathbf{H}_q \mathbf{v}_q^1\|), \quad q \in [1, N_u] \quad (8)$$

The transmit weight for the 1-st user is given by

$$\mathbf{M}_1 = \mathbf{v}_q^1, \quad o(1) = q \quad (9)$$

where $o(1)$ denotes the number of the firstly selected user in (1). Then the channel matrix of the selected user is arranged

on the first layer of the system channel matrix.

$$\mathbf{H} = [\mathbf{H}_{o(1)}^T \quad \mathbf{H}_2^T \quad \dots \quad \mathbf{H}_{N_T}^T]^T \quad (10)$$

In this way, we ensure that the 1-st user obtains the largest transmit gain. For the 2-nd user, in order to use the DPC for eliminating the IUI, we have to transform the effective channel matrix to the triangular matrix, and the following operation is performed.

$$(\mathbf{H}_{o(1)} \mathbf{M}_1)^H \mathbf{H}_{o(1)} \stackrel{\text{SVD}}{=} \mathbf{U} \mathbf{\Lambda} [\underbrace{\mathbf{v}^1, \mathbf{v}^2, \dots, \mathbf{v}^{N_T}}_{\text{Null space}}]^H \quad (11)$$

We can obtain the transmit weight for the 2-nd user from the null space in (11). However, we notice that all of these vectors in the null space can meet the condition of the availability of DPC. The transmit weight for the 2-nd user can be expressed as follows.

$$\mathbf{M}_2 = \sum_{l=1}^{N_T-1} \alpha_l \mathbf{v}^{l+1} / \left\| \sum_{l=1}^{N_T-1} \alpha_l \mathbf{v}^{l+1} \right\| \quad (12)$$

where α_l ($l = 1, 2, \dots, N_u$) is real coefficient. Then we estimate the channel of the 2-nd user corresponding to \mathbf{M}_2 in (12), which can be obtained by the following algorithm.

$$\mathbf{H}_q = \arg \max_{\mathbf{H}_q} (\|\mathbf{H}_q \mathbf{M}_2\|); \quad q \in [1, N_u], \quad q \neq o(1) \quad (13)$$

Let $o(2) = q$ and the 2-nd user is determined. Similarly, the channel matrix corresponding to the selected 2-nd user in (12) is arranged on the second layer of channel matrix in (10).

Now we consider the k -th user and its transmit weight. The same operations as the above are performed to the matrix corresponding to these $k-1$ selected users.

$$\begin{bmatrix} (\mathbf{H}_{o(1)} \mathbf{M}_1)^H \mathbf{H}_{o(1)} \\ (\mathbf{H}_{o(2)} \mathbf{M}_2)^H \mathbf{H}_{o(2)} \\ \vdots \\ (\mathbf{H}_{o(k-1)} \mathbf{M}_{k-1})^H \mathbf{H}_{o(k-1)} \end{bmatrix} \stackrel{\text{SVD}}{=} \mathbf{U} \mathbf{\Lambda} [\mathbf{v}^1, \dots, \mathbf{v}^{k-1}, \underbrace{\mathbf{v}^k, \dots, \mathbf{v}^{N_T}}_{\text{Null space}}]^H \quad (14)$$

From the null space in (14), the transmit weight for k -th user can be given by

$$\mathbf{M}_k = \sum_{l=1}^{N_T-k+1} \alpha_l \mathbf{v}^{k+l-1} / \left\| \sum_{l=1}^{N_T-k+1} \alpha_l \mathbf{v}^{k+l-1} \right\| \quad (15)$$

$$\mathbf{H}_q = \arg \max_{\mathbf{H}_q} (\|\mathbf{H}_q \mathbf{M}_k\|); \quad q \in [1, N_u] \quad q \neq o(1), o(2), \dots, o(k-1) \quad (16)$$

Similarly, the user channel obtained in (16) is arranged on the k -th layer of the system channel matrix.

Consequently, we obtain the transmit weights for all users, and the transmit signal vector can be written as

$$\mathbf{X} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N_T} \end{pmatrix} = \begin{pmatrix} s_2 - \frac{1}{\|\mathbf{H}_2 \mathbf{M}_2\|} \sum_{j < 2} \|\mathbf{H}_2 \mathbf{M}_j\| x_j \\ \vdots \\ s_{N_T} - \frac{1}{\|\mathbf{H}_{N_T} \mathbf{M}_{N_T}\|} \sum_{j < N_T} \|\mathbf{H}_{N_T} \mathbf{M}_j\| x_j \end{pmatrix} \quad (17)$$

To avoid the power enhancement problem, the same modulo device as in [17] is used in this paper.

Then we discuss the Signal to Noise Ratio (SNR) at each user terminal. If the Maximum Ratio Combining (MRC) is used to detect the receive signal, the SNR at each MS is given by

$$\langle \text{SNR} \rangle_k = \|\mathbf{H}_k \mathbf{M}_k\|^2 \cdot \|s_k\|^2 / N_k \quad (18)$$

where $\|\mathbf{H}_k \mathbf{M}_k\|$ can be considered as the transmit gain of the k -th user. In the case of $\|\mathbf{v}_k^{\max} \mathbf{M}_k\| = 1$, \mathbf{M}_k is considered as the ideal transmit weight which enables the k -th user to get the largest transmit gain λ_k^{\max} , and \mathbf{v}_k^{\max} is the vector corresponding to the maximum eigenvalue of \mathbf{H}_k . However, in fact, $\|\mathbf{v}_k^{\max} \mathbf{M}_k\|$ lies in between 0 and 1, and it depends on the coefficients α_i for combining \mathbf{M}_k , thus we assume $\alpha_i \in \mathcal{R}$ is constrained to lie in a certain lattice. Accordingly in order to obtain the optimal transmit gain, it is crucial to search the optimal combination coefficients which makes \mathbf{M}_k tend to parallel to \mathbf{v}_k^{\max} . We solve the nonlinear optimization problem by employing PSO algorithm to obtain the optimal transmit weights. In this case, if we use the DPC technology to cancel the IUI, the achievable rate can reach optimal.

3.3.2 Particle Swarm Optimization Aided Optimal Transmit Weights

In the PSO algorithm, the random flying bird flocks are referred to as particles, which represent potential solutions initialized over the whole search space randomly. An objective function is used to evaluate the goodness of positions of particles. Each particle has a fitness value which is evaluated by the objective function to be optimized, and the fitness value is evaluated at each iterative search.

For k -th user, we assume that the size of swarm and the dimension of search space are Ω_k and D_k , respectively. The position and velocity of particle i ($i = 1, 2, \dots, \Omega_k$) are denoted as $\chi_{i,k}^t = [\chi_{i1}^t \cdots \chi_{iD_k}^t]^T$ and $\zeta_{i,k}^t = [\zeta_{i1}^t \cdots \zeta_{iD_k}^t]^T$ respectively. At each iteration, the velocity and position of particle i are updated based on the following equations.

$$\begin{aligned} \zeta_{id_k}^{t+1} &= w \zeta_{id_k}^t + c_1 \varphi_1 (p_{id_k}^t - \chi_{id_k}^t) + c_2 \varphi_2 (p_{gd_k}^t - \chi_{id_k}^t) \\ \chi_{id_k}^{t+1} &= \chi_{id_k}^t + \zeta_{id_k}^{t+1}, \quad d_k = 1, 2, \dots, D_k \end{aligned} \quad (19)$$

where t is the current iteration number, $\zeta_{id_k}^t$ and $\chi_{id_k}^t$ denote the velocity and location of the particle i in the d_k -th dimensional space, respectively. $p_{id_k}^t$ is the individual best location that the particle i has achieved so far, and $p_{gd_k}^t$ is the global best location that all particles have achieved so far at

the i -th iteration. w is the inertia weight which determines to what extent the particle remains along its original course unaffected by the influence of $p_{id_k}^t$ and $p_{gd_k}^t$, and it is usually set between 0 and 1. c_1 and c_2 are acceleration constants those are set to 2. φ_1 and φ_2 are uniformly distributed random number in $[0, 1]$. This iterative search process will be repeated up to the maximal iteration number or till the termination when the criterion is satisfied.

Then we have to consider two important issues; one is the model building, that is, how to convert the optimization of transmit weights to the particle modelling, and the other is the selection of objective function. Considering the SNR in Eq. (18), our objective is to search the optimal \mathbf{M}_k , which infinitely close to the ideal transmit weight \mathbf{v}_k^{\max} for the k -th user, where \mathbf{v}_k^{\max} denotes the desired point lying in the best location. We define the angle between \mathbf{v}_k^{\max} and \mathbf{M}_k as $\theta_{\mathbf{v}_k^{\max}, \mathbf{M}_k}$ and its cosine is expressed as

$$\begin{aligned} \cos(\theta_{\mathbf{v}_k^{\max}, \mathbf{M}_k}) &= \langle \mathbf{v}_k^{\max}, \mathbf{M}_k \rangle / \|\mathbf{v}_k^{\max}\| \\ &= [\mathbf{v}_k^{\max}]^H \mathbf{M}_k / \|\mathbf{v}_k^{\max}\| \end{aligned} \quad (20)$$

where $\langle \mathbf{v}_k^{\max}, \mathbf{M}_k \rangle$ means the inner product of \mathbf{v}_k^{\max} and \mathbf{M}_k . So we consider the following expression as the objective function for k -th user at the t -th iteration.

$$\begin{cases} \alpha_l = \chi_{il} \in [\chi_{i1}, \dots, \chi_{iD_k}] \\ \mathbf{M}_k = \frac{\sum_{l=1}^{N_T-k+1} \alpha_l \mathbf{v}^{k+l-1}}{\left\| \sum_{l=1}^{N_T-k+1} \alpha_l \mathbf{v}^{k+l-1} \right\|} \\ f_{i,k}^t = \text{function}(\mathbf{v}_k^{\max}, \mathbf{M}_k) = \sin(\theta_{\mathbf{v}_k^{\max}, \mathbf{M}_k}) \\ = \sqrt{1 - \cos^2(\theta_{\mathbf{v}_k^{\max}, \mathbf{M}_k})} = \sqrt{1 - \left\| (\mathbf{v}_k^{\max})^H \mathbf{M}_k \right\|^2} \end{cases} \quad (21)$$

Here, we use the sine value of angle between the ideal weight \mathbf{v}_k^{\max} and the tentative weight \mathbf{M}_k to measure the degree of approach. During the process of search, the sine value becomes small when the tentative weight gets close to the desired weight, and the search speed and accuracy are conditioned on the size of swarm, iteration number and search dimension. In this paper, the proposed optimal transmit weights based on PSO algorithm is obtained by the following steps:

(1) BS obtains the information of the channels by the feedback from MS and computes the maximum eigenvalues λ_k^{\max} of each user and determines the first user. By Eq. (14), the dimension D_k of search space for PSO is determined for the other users, and then the swarm size Ω_k and the maximum iteration number I_{\max}^k are set for each user.

(2) PSO algorithm is used to search the optimal transmit weight for each user. For the k -th user, after setting the swarm size of Ω_k , we initialize the velocity and location for each particle as $\zeta_{i,k}^1 = [\zeta_{i1}^1, \dots, \zeta_{iD_k}^1]^T$, where $\zeta_{i,l}^1 \in [-10, 10]$ and $\chi_{i,k}^1 = [1, 1, \dots, 1] / \sqrt{N_T - k}$ respectively.

(3) Taking $\zeta_{i,k}^1$ and $\chi_{i,k}^1$ as starting point, PSO is implemented to search the optimal transmit weights. In each iteration, the temporal best locations are measured and updated by the objective function in (21), and all the particles

achieve the next optimal directions for the search. For example, in the t -th iteration, all particles use the given best locations $\mathbf{p}_{g,k}^{t-1} = [p_{g,1}^{t-1} \cdots p_{g,d_k}^{t-1} \cdots p_{g,D_k}^{t-1}]$ to update the velocity and the location by using (19). Then $\mathcal{X}_{i,k}^t$ obtained from (19) of each particle is substituted into (21) to get one cost function value of $f_{i,k}^t$. Next, $\mathcal{X}_{i,k}^t$ is updated by comparing $f_{i,k}^t$ with $p_{i,d_k}^t \in \mathbf{p}_{i,k}^t$ ($\mathbf{p}_{i,k}^t = [p_{i,1}^t \cdots p_{i,d_k}^t \cdots p_{i,D_k}^t]$) stored by each individual particle. Lastly $f_{i,k}^t$ is exchanged among all particles to obtain the global best location $\mathbf{p}_{g,k}^t$ and go into the $t+1$ -th iteration. In this paper, $\mathcal{X}_{i,k}^t$ is normalized after the update in each iteration.

(4) PSO algorithm is repeated till the maximum iteration number of I_{\max}^k . We can also set an error function of angle $\theta_{v_k^{\max}, M_k}$ to control the search.

The above operations are separately implemented at all users and the different user has the different search dimension. In other words, from the 1-st to the N_T -th user, the search dimension becomes small, which leads to the low SNR. Thus for those “bad” users, we can enlarge the swarm size or increase the iteration number to obtain the optimal weights. The increase of computational burden is acceptable in the case of low search dimension. It is known that, each user feedbacks the downlink channel information \mathbf{H}_k to the base station before the signals are transmitted, and after the optimization of transmit weights, the base station transmits the transmit weight \mathbf{M}_k to each user for detecting the received signals. However, when the PSO algorithm is employed in searching the optimal transmit weights; we should consider the influence channel estimation error on the convergence value of PSO algorithm. Here, we denote the estimated channel matrix of k -user as $\tilde{\mathbf{H}}_k = \mathbf{H}_k + \tilde{\mathbf{H}}_k$, where $h_{ij} \in \mathbf{H}_k$ is the channel coefficient and $\tilde{h}_{ij} \in \tilde{\mathbf{H}}_k$ is the channel estimation error with the mean of zero and the variance of $\sigma_{error}^2 (E[\tilde{h}_{ij}^2] = \sigma_{error}^2)$. We will briefly examine the influence of the estimation error σ_{error}^2 on the BER performance in Sect. 4.

3.3.3 Computational Load Analysis

Under the same simulation conditions, we compare the computational complexities of the conventional scheme, the proposed OW-DPC (Optimal Weight-DPC) scheme in this paper, and the schemes in [10] and [14]. At the user side, compared with other two schemes in [10] and [14], the proposed OW-DPC and the conventional DPC schemes only employ the modulo operation, but have no need to cancel the Inter-User Interference (IUI). So we only focus on the total computational complexity at the base station for each transmit vector $\mathbf{X} \in \mathbb{C}^{N_T \times 1}$. The computational complexity is counted by the number of flops. A flop is defined to be a real floating point operation, e.g., a real addition, multiplication, or division is counted as one flop. In this paper, a SVD has a complexity with the order of $\max(p^2q, pq^2, q^3)$ for the k -th user, where $p = N_T$ and $q = k-1$ [18]. The particle number $\Omega_k = 10$ and the iteration number $I_{\max}^k = 20$ are assumed. In this paper, the PSO algorithm has at least the amount of

Table 1 Computational complexity.

Φ_{C-DPC}	$(11N_R + 7)N_T^2 + (15 - 2N_R)N_T$
Φ_{OW-DPC}	$(18 + 16N_u)N_T^3 + (32\Omega_k I_{\max}^k + 4N_R + 28)N_T - 28\Omega_k I_{\max}^k - 2I_{\max}^k - 4$
Φ_L [10]	$60N_T^3 + (2304n_R^{(k)} + 2N_R + 84)N_T + 6n_R^{(k)} + 4N_R$
Φ_{OW-L} [14]	$4N_T^3 + [(8N_u + 2)\Omega_k N_u I_{\max}^k + 2N_R]N_T - N_u I_{\max}^k + 4N_R$

real computation of $[\Omega_k(10 + \Phi_f) + \Omega_k - 1] \times I_{\max}^k$ till the convergence is obtained, where Φ_f denotes the amount of computation of objective function. The total computational complexities for each transmit vector $\mathbf{X} \in \mathbb{C}^{N_T \times 1}$ are derived as Table 1.

Table 1 shows the computational complexity of the conventional DPC scheme, the proposed OW-DPC scheme in this paper, the scheme in [10], and the scheme in [14]. For example, in the case of single receive antenna, the computational complexity of those schemes are 844, 25380, 13398 and 109024 flops, respectively. It is noticed that the conventional DPC scheme consumes the least computational complexity compared with the other three schemes. However, in this paper, the complexity of the conventional DPC scheme is computed without considering of the optimal transmit weights and the order. In particular, for the optimal transmit weights and the order of the conventional DPC scheme, [21] gives the solution to find the optimal covariance structures. But the solution is still difficult because it is the nonconvex optimization problem and consumes the great computational load. It is also noticed that the scheme in [14] consumes the largest computational load because of the continuous complex vector space. For the proposed scheme in this paper, we only search the optimal coefficients in the real vector space and greatly reduce the computational load. In addition, although the scheme in [10] consumes less computational load compared to the proposed OW-DPC scheme, the residual IUI at the user side will lead to the certain loss of achievable rate and the degradation of BER performance. In the case of multiple receive antennas, it is also noticed that the proposed scheme in this paper does not consume large computational load compared with the schemes in [10] and [14]. Considering all the above together, the proposed scheme in this paper is feasible to be actually implemented.

3.3.4 Achievable Sum-Rate Analysis

Assuming that the transmit data streams are independently encoded and decoded, the sum-rate capacity of the multiuser MIMO system is simply the summation of capacity of each individual user. In this section we discuss the system achievable sum-rate of the proposed scheme.

It is well known that the DPC scheme achieves the capacity region, when the users cooperate [2], [19]. The sum achievable rate of ZF DPC can be expressed as

$$R_{DPC} = \sum_{k=1}^{N_u} \left\{ \log \mu_{DPC}^2 \right\}_+ \quad (22)$$

where μ_{DPC} solves $\sum_{k=1}^{N_u} [\mu_{DPC} - 1/l_{k,k}^2]_+ = P_T$.

In the proposed optimal weight scheme with PSO, the sum achievable rate can be expressed as

$$R_{OW-DPC} = \max_{\mathbf{M}_k, \mathbf{H}_k \mathbf{M}_j = 0, k > j} \log \left| \mathbf{I} + \frac{1}{\sigma_n^2} \mathbf{H} \mathbf{M} \mathbf{M}^H \mathbf{H}^H \right|$$

$$= \max_{\mathbf{H}_k \mathbf{M}_j = 0, k > j} \sum_{k=1}^{N_u} \log \left| \mathbf{I} + \frac{1}{\sigma_n^2} \mathbf{H}_k \mathbf{M}_k \mathbf{M}_k^H \mathbf{H}_k^H \right| \quad (23)$$

and the further simplification is expressed as

$$R_{OW-DPC} = \sum_{k=1}^{N_u} \left[\log_2 \mu_{OW-DPC} l_{k,k}^2 \right]_+ \quad (24)$$

where μ_{OW-DPC} solves $\sum_{k=1}^{N_u} [\mu_{OW-DPC} - 1/l_{k,k}^2]_+ = P_T$ and $l_{k,k} = \|\mathbf{H}_k \mathbf{M}_k\|$. From (22) and (24) it is noticed that in the case of water filling algorithm the achievable rate of system is affected by the factors of $l_{k,k}^2$ and $l_{k,k}^2$. In the proposed scheme, for the k -th user, the optimal user order and the transmit weight \mathbf{M}_k is obtained by using PSO, which makes the transmit weight of each user close to λ_k^{\max} . Accordingly we have the following relationship.

$$R_{DPC} \leq R_{OW-DPC} \leq \sum_{k=1}^{N_u} \log \left(1 + \frac{p_k}{\sigma^2} [\lambda_k^{\max}]^2 \right) \quad (25)$$

where p_k is the transmit power for the k -th user. It is known that, for a given channel matrix, unitary matrix of right multiplication do not alter the continuous product of singular values, and in the case of high SNR, for the given selected users, it is proved that the sum achievable rate of R_{DPC} independent on the user order, which is explained in the appendix, moreover, the proposal in our paper has the different continuous product of effective channel gain $l_{k,k}^2$. However, compared with the single receive antenna case in the DPC, the proposed scheme can obtain more transmit diversity and also adequate independent users with multiple receive antennas.

4. Computer Simulation

In this section, we present the simulation results demonstrating the performance of the proposed scheme. To verify the performance of the proposed scheme, first, we compare the achievable sum-rate between the proposed scheme and the other schemes, such as conventional ZF DPC based on QR decomposition, CI and BD with the water filling algorithm. Then we compare the average BER performance of each user and demonstrate the feasibility of the proposed scheme.

We consider the case of $4 \times (1, 1, 1, 1)$ contributing channels in MU-MIMO, where the average achievable rate of system is determined for the total 1000 realizations of \mathbf{H} . In this paper, we assume $\Omega_k = 10$, the convergence value can be obtained at $I_{\max}^k = 20$. The computational load also has been discussed in Sect. 3, from which it is clear that the proposed scheme is feasible when the iteration number is set to $I_{\max}^k = 20$. Figure 2 shows that the channel inversion

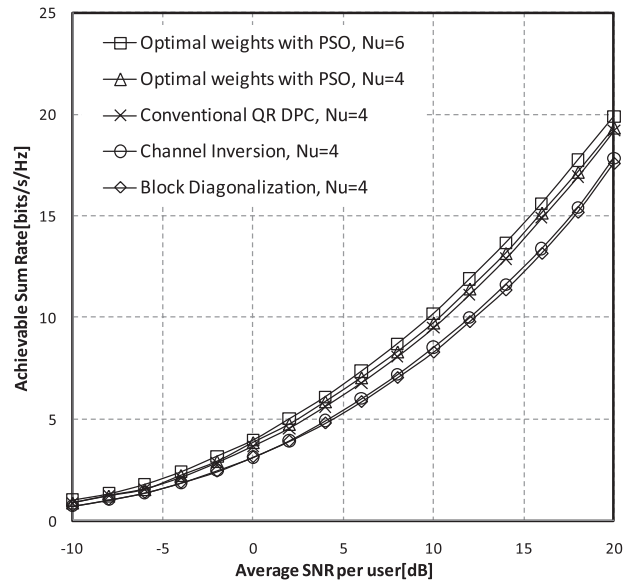


Fig. 2 Comparison of achievable sum-rate among the proposed OW-DPC (Optimal Weight with DPC), conventional QR DPC, BD and Channel Inversion.

scheme obtains the close average capacity to BD scheme by employing the water filling, but both of those two methods are inferior to the conventional DPC, which approaches the multiuser capacity more closely. The simulation results show that the proposed scheme obtains a slight advantage to the conventional DPC in the case of $N_u = 4$ and it has the same achievable rate as the conventional DPC at 20 dB. However, we can obtain more rate in the case of $N_u \geq N_T$, e.g., $N_u = 6$, because of the optimal the user ordering and diversity, while in the same conditions, the conventional DPC can not obtain diversity.

Next we show the average BER performance of proposed transmit scheme and compare it with the BD, CI and the conventional DPC schemes in case of $N_u = N_T$. Here we only consider the uniform assignment of transmit power to all users. Figure 3 shows the case of single receive antenna in the downlink of $4 \times (1, 1, 1, 1)$ MU-MIMO. The particle number $\Omega_k = 10$ and the iteration number $I_{\max}^k = 20$ are set in the PSO algorithm and QPSK is used to modulate the transmit signal in this paper. The BER performance is simulated under the same simulation condition for BD, CI (ZF&MMSE) and the conventional DPC based on the QR decomposition. Firstly, in the case of perfect CSI (solid line), we observe that, without considering the power distribution on the diagonal elements of effective channels, both BD and CI with ZF can completely eliminate the IUI on i.i.d. flat Rayleigh fading channels and these two methods show almost the same performance as the SISO case in the same Rayleigh fading channels.

As shown in Fig. 3, though the channel inversion with MMSE can not exactly cancel the IUI caused by the spatially multiplexing, it can reduce the noise enhancement between 0 and 12 dB. The conventional QR DPC, referred to as the interference dependent nonlinear precoding, can obtain

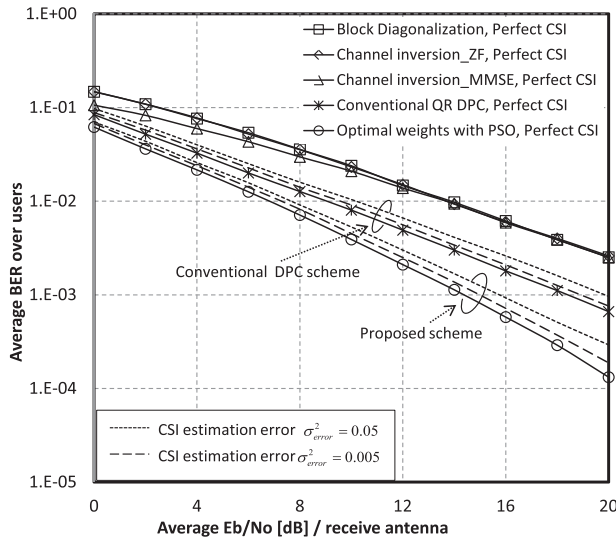


Fig. 3 Comparison of BER characteristics among the proposed OW-DPC, BD, Channel Inversion (ZF & MMSE) and conventional QR DPC.

the better performance compared with the BD and Channel Inversion scheme. In the case of conventional DPC, the QR decomposition only aims to cancel the IUI but does not involve the optimality of transmit weights. The proposed transmit scheme with optimal weights by PSO, not only suppresses the IUI completely, but also searches the optimal transmit weights achieving the transmit diversity as large as possible for each MS. Figure 3 shows the proposed scheme has obtained the better BER performance by about 4 dB than the conventional DPC at $\text{BER}=10^{-3}$. Then we discuss the influence of CSI estimation error on the proposed scheme and compare the proposed scheme with the conventional DPC. We denote the cases of CSI estimation error by dotted lines. Figure 3 shows that compared with the case of perfect CSI ($\sigma_{\text{error}}^2 = 0$), the BER performance of the proposed scheme for the estimation error σ_{error}^2 of 0.005 and 0.05 deteriorates by 0.6 dB and 2 dB at the average $\text{BER}=1.E-03$ respectively. It is also noticed that the proposed scheme is more easily affected by the CSI estimation error compared to the conventional DPC scheme. This is because some convergence error exists during the search of optimal weights with PSO algorithm. For these problems, some error detection techniques can be employed to reduce the CSI estimation error, such as Cyclic Redundancy Check (CRC) code and Automatic Repeat-Request (ARQ) schemes etc. Since the assessing the CSI estimation error is a big topic to all the MU MIMO downlink schemes, we restrict the discussion only in Fig. 3. In the following section, we assume that there is no estimation error on CSI.

Figure 4 shows the BER performance of proposed scheme with multiple receives antennas and it is compared with the conventional DPC and the SU-MIMO scheme. The conventional DPC based on QR decomposition is available to the users equipped with single receive antenna only. In the case of users with multiple receive antennas, if the conventional DPC scheme is employed to cancel the IUI, BS

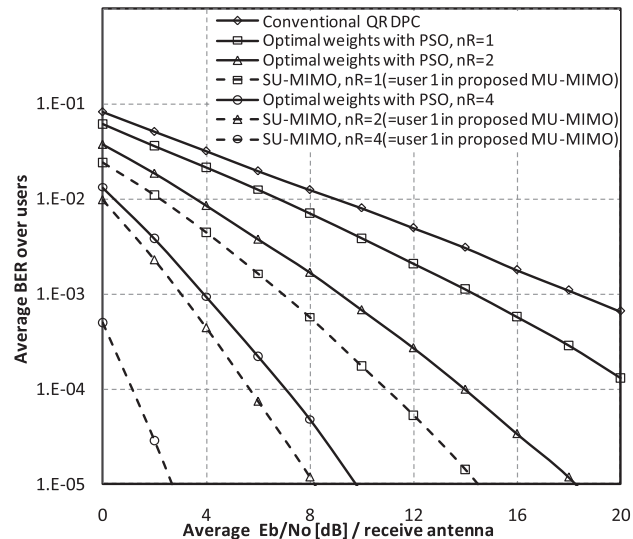


Fig. 4 Comparison of BER characteristics between the proposed OW-DPC with multiple receive antennas, the conventional QR DPC and the SU-MIMO scheme.

cannot afford to give enough diversity to users, and only small or no throughput is available for users. However, the proposed scheme can ensure the throughput for each user and achieve more transmit diversity for each user. In addition, based on the channel condition and the QoS requirement for users, the PSO search algorithm works with different swarm size of Ω_k and the iteration number of I_{max}^k to improve the transmit gains. As shown in Fig. 4, with the increase of receive antenna number, the system performance can be greatly improved. In addition, we compared the proposed MU-MIMO scheme with the SU-MIMO scheme in Fig. 4. In the SU-MIMO scheme, since the IUI does not exist, the largest transmit gain is obtained by using the Maximum Beam (MB) method, which is the same situation as the user 1 in the proposed MU-MIMO. The BER of user 1 in the proposed MU-MIMO scheme is exactly the same as the one of SU-MIMO, since the IUI for the user 1 in the proposed scheme is completely excluded at the base station. But, as for the average BER performance, the BER of proposed MU-MIMO is inferior to the one of SU-MIMO due to the degraded BER's of user 2, user 3 and user 4.

5. Conclusion

A novel scheme with optimal transmit weights for each sub-carrier of MU-MIMO OFDM downlink has been proposed, in which we employed the PSO algorithm to search the optimal transmit weights and achieved the significantly better performance than the conventional DPC, BD and Channel Inversion schemes. With the CSI being known at both of BS and MS, the BS determines the user order and the corresponding transmit weight to each user with as large transmit gain as possible. The DPC has been used not only to suppress the IUI, but also to maintain the system capacity. In the case of single receive antenna at each MS, the pro-

posed scheme approaches more closely to the capacity of MU-MIMO than the above other conventional schemes, because of the optimal user ordering and transmit weight design by using the principle of DPC and the PSO. In addition, the proposed scheme can employ the multiple receive antennas, whereas the conventional DPC based on QR decomposition is equipped with only one receive antenna at each MS. Equipping multiple receive antennas in the proposed scheme enables the user to obtain the better BER performance, especially for the user with weak receive SNR. For the PSO algorithm, the swarm size and iteration number determine the search accuracy and the required computation time. Thus, according to the requirement of each user, we can independently make the optimal search for each user. Through the comparative analysis of computational complexity, the feasibility of proposed scheme has been proved.

Acknowledgments

This study is partially supported by the Grants-in-Aid for Scientific Research 21560396 of the Japan Society for the Promotion of Science, the KDDI Foundation and the Sharp Corporation. The authors also acknowledge the helps by Dr. Eiji Okamoto and Mrs. Kazumi Ueda.

References

- [1] H.S. Quentin, B.P. Christian, A. Lee Swindlehurst, and M. Haardt, "An introduction to the multi-user MIMO downlink," *IEEE Commun. Mag.*, vol.42, no.10, pp.60–67, Oct. 2004.
- [2] I.E. Telatar, "Capacity of multi-antenna Gaussian channels," *European Trans. Tel.*, vol.10, no.6, pp.585–595, Nov./Dec. 1999.
- [3] D. Aftas, M. Bacha, J. Evans, and S. Hanly, "On the sum capacity of multi-user MIMO channels," *Proc. Intl. Symp. on Inform. Theory and its Applications*, pp.1013–1018, Oct. 2004.
- [4] T. Haustein, C. von Helmolt, E. Jorswieck, V. Jungnickel, and V. Pohl, "Performance of MIMO systems with channel inversion," *IEEE 55th VTC*, vol.1, pp.35–39, May 2002.
- [5] Q.H. Spencer, A.L. Swindlehurst, and M. Haardt, "Zero-forcing methods for downlink spatial multiplexing in multiuser MIMO channels," *IEEE Trans. Signal Process.*, vol.52, no.2, pp.461–471, Feb. 2004.
- [6] M. Costa, "Writing on dirty paper," *IEEE Trans. Inf. Theory*, vol.29, no.3, pp.439–441, May 1983.
- [7] S. Vishwanath, N. Jindal, and A. Goldsmith, "Duality, achievable rates, and sum-rate capacity of MIMO broadcast channels," *IEEE Trans. Inf. Theory*, vol.49, no.10, pp.2658–2668, Oct. 2003.
- [8] R.F.H. Fischer, *Precoding and Signal Shaping for Digital Transmission*, pp.127–151, Wiley, New York, 2002.
- [9] H. Nishimoto, S. Kato, Y. Ogawa, T. Ohgane, and T. Nishimura, "Imperfect block diagonalization for multiuser MIMO downlink," *IEEE PIMRC 2008*, pp.1–5, Sept. 2008.
- [10] J.-S. Kim and S.-H. Moon, "Linear beamforming for multiuser MIMO downlink systems with channel orthogonalization," *Global Telecommunications Conference 2009, GLOBECOM 2009*, pp.1–6, Dec. 2009.
- [11] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proc. 1995 IEEE Int. Conf. Neural Networks*, vol.4, pp.1942–1948, Perth, Australia, Nov.-Dec. 1995.
- [12] Y. Zhao and J. Zheng, "Multiuser detection employing particle swarm optimization in space-time CDMA systems," *Proc. 2005 Int. Symp. Communications and Information Technology*, vol.2, pp.940–942, Oct. 2005.
- [13] K.K. Soo, Y.M. Siu, W.S. Chan, L. Yang, and R.S. Chen, "Particle swarm optimization-based multiuser detector for CDMA communications," *IEEE Trans. Veh. Technol.*, vol.56, no.5, pp.3006–3013, Sept. 2007.
- [14] F. Shu, L. Lihua, and Z. Ping, "Optimal multi-user MIMO linear precoding based on particle swarm optimization," *ICC2008*, pp.3355–3359, May 2008.
- [15] R. Hassan and B. Cohan, "A comparison of particle swarm optimization and the genetic algorithm," *46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, Austin, TX, Genetic Algorithm, April 2005.
- [16] R. Chen, R.W. Heath, and J.G. Andrews, "Transmit selection diversity for unitary precoded multiuser spatial multiplexing systems with linear receivers," *IEEE Trans. Signal Process.*, vol.55, pp.1159–1171, March 2007.
- [17] C. Li, Y. Iwanami, and E. Okamoto, "Comparative study for Tomlinson-Harashima precoding based on MMSE criteria in multiuser MIMO downlink system," *IEEE TENCON 2009*, pp.1–6, Nov. 2009.
- [18] G.H. Golub and C.F. Van Loan, *Matrix Computation*, 3rd ed., pp.253–254, John Hopkins Univ. Press, 1996.
- [19] J. Dai and C. Chang, "An efficient greedy scheduler for zero-forcing dirty-paper coding," *IEEE Trans. Commun.*, vol.57, no.7, pp.1939–1943, July 2009.
- [20] G. Caire and S. Shamai, "On the achievable throughput of a multi-antenna Gaussian broadcast channel," *IEEE Trans. Inf. Theory*, vol.49, no.7, pp.1691–1706, July 2003.
- [21] N. Jindal, W. Rhee, S. Vishwanath, S. Jafar, and A. Goldsmith, "Sum power iterative water-filling for multi-antenna Gaussian broadcast channels," *IEEE Trans. Inf. Theory*, vol.51, no.4, pp.1570–1580, April 2005.

Appendix: Derivation of Sum-Capacity of Proposed Scheme

We use the similar method in [20] to analyze the sum-capacity between conventional DPC and proposed scheme at high SNR. For the given selected channels, we have

$$\prod_k^{N_r} l_{k,k} = \det(\mathbf{H}\mathbf{H}^H) = \det(\mathbf{H}\mathbf{M}\mathbf{M}^H\mathbf{H}^H) = \prod_k^{N_r} l'_{k,k} \quad (\text{A} \cdot 1)$$

where $l'_{k,k}$ denotes the effective coefficient of channel in the proposed scheme. We define the following arithmetic means

$$\Gamma_a = \frac{1}{N_T} \sum_{k=1}^{N_T} \frac{1}{l_{k,k}^2}, \quad \Gamma'_a = \frac{1}{N_T} \sum_{k=1}^{N_T} \frac{1}{l'^2_{k,k}}$$

and the geometric mean

$$\Gamma_g = \left(\prod_{k=1}^{N_T} 1/l_{k,k}^2 \right)^{1/N_T} = \left(\prod_{k=1}^{N_T} 1/l'^2_{k,k} \right)^{1/N_T}$$

Then we examine the existence of μ_{DPC} and μ_{OW-DPC} to satisfy $P_T < \infty$ with Eqs. (22) and (24).

$$\sum_{k=1}^{N_r} [\mu_{DPC} - 1/l_{k,k}^2]_+ = P_T \quad (\text{A} \cdot 2)$$

$$\sum_{k=1}^{N_r} [\mu_{OW-DPC} - 1/l'^2_{k,k}]_+ = P_T \quad (\text{A} \cdot 3)$$

We only need to find μ_{DPC} and μ_{OW-DPC} to satisfy (A.2) and (A.3) with $P_T < \infty$. In (A.2) we assume $\mu_{DPC} > 1/l_{k,k}^2$ and it becomes

$$\sum_{k=1}^{N_u} \mu_{DPC} - \sum_{k=1}^{N_u} 1/l_{k,k}^2 = P_T \Rightarrow \sum_{k=1}^{N_u} \mu_{DPC} = P_T + \sum_{k=1}^{N_u} 1/l_{k,k}^2 \quad (\text{A.4})$$

By letting $\mu_{DPC}^0 = P_{T_0}/N_u + M_a$, we obtain

$$\sum_{k=1}^{N_u} \mu_{DPC}^0 = \sum_{k=1}^{N_u} \left(\frac{P_{T_0}}{N_u} + \Gamma_a \right) = P_{T_0} + \sum_{k=1}^{N_u} \Gamma_a = P_{T_0} + \sum_{k=1}^{N_u} 1/l_{k,k}^2 \quad (\text{A.5})$$

Similarly, we can find $\mu_{OW-DPC}^0 = P_{T_0}/N_u + \Gamma_b$ satisfying $P_{T_0} < \infty$. So for all $P_T > P_{T_0}$, (22) can be expressed as

$$\begin{aligned} R_{DPC} &= \sum_{k=1}^{N_u} \left\{ \log \mu_{DPC} l_{k,k}^2 \right\}_+ = \sum_{k=1}^{N_u} \left\{ \log \left[(P_T/N_u + \Gamma_a) l_{k,k}^2 \right] \right\}_+ \\ &= \log \left[(P_T/N_u + \Gamma_a)^{N_u} \prod_{k=1}^{N_u} l_{k,k}^2 \right]_+ \\ &= \log \left\{ \left[(P_T/N_u + \Gamma_a) / \Gamma_g \right]^{N_u} \right\}_+ \\ &= N_u \log \left[(P_T/N_u + \Gamma_a) / \Gamma_g \right] \end{aligned} \quad (\text{A.6})$$

Similarly, (24) can be expressed as

$$R_{OW-DPC} = N_u \log \left[(P_T/N_u + \Gamma'_a) / \Gamma_g \right] \quad (\text{A.7})$$

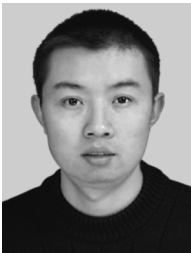
From (A.6) and (A.7), when $P_T \rightarrow \infty$ we have

$$\begin{aligned} &\lim_{P_T \rightarrow \infty} (R_{OW-DPC} - R_{DPC}) \\ &= N_u \lim_{P_T \rightarrow \infty} \left\{ \log \left[(P_T/N_u + \Gamma'_a) / (P_T/N_u + \Gamma_a) \right] \right\} = 0 \end{aligned} \quad (\text{A.8})$$

In the case of $N_u \geq N_T$, we have $l'_{k,k} \geq l_{k,k}$ because of the optimal user order by using PSO, so the proposal can obtain the more achievable rate.



Yasunori Iwanami received the B.E. and M.E. degrees in electrical engineering from Nagoya Institute of Technology in 1976 and 1978, respectively, and the Ph.D. degree in computer engineering from Tohoku University in 1981. He joined the Department of Electrical Engineering at Nagoya Institute of Technology in 1981 and is currently a Professor of Graduate school of the department of Computer Science and Engineering at Nagoya Institute of Technology. From July 1995 to April 1996 he was a guest researcher in the Department of Electrical Engineering at Queen's University, Ontario, Canada. His current research interests include bandwidth efficient coded modulation, coded digital FM, turbo equalization, space-time signal processing, mobile communication systems and various noise problems. Dr. Iwanami is a member of IEEE and SITA.



Cong Li received the B.E. degree in Electrical Engineering from Northeast Forest University, Harbin, China, in 2005 and the M.S. degree in the department of computer science and engineering at Nagoya Institute of Technology in 2010. Now he is currently pursuing the Ph.D. degree in the same department. His research interests lie in the areas of MIMO antenna system, precoding for Multiuser MIMO system, signal detection and Multiuser interference cancellation.