Distributed Precoder Design for Inter-cell Interference Suppressing in Multi-cell MU-MIMO Systems

Desheng Wang, Yifan Yang, Guangxi Zhu
Department of Electronics and Information Engineering
Huazhong University of Science and Technology
Wuhan, Hubei, China
dswang@mail.hust.edu.cn

Xiaojiang Du
Department of Computer and Information Sciences
Temple University
Philadelphia, PA, USA
dxj@ieee.org

Abstract—**In this paper, we design a distributed precoder algorithm for inter-cell interference (ICI) suppressing and maximizing the average throughput of a multi-cell multi-user multi-input multi-output (MU-MIMO) system. As the problem of finding the optimal precoder is non-convex and non-trivial, it is important to find low-complexity solutions. Motivated by the recent results in the distributed signal-to-leakage-plus-noise ratio (SLNR) model, we propose an optimized precoder design algorithm that is based on modified SLNR and can achieve pareto-optimal average system throughput. Existing algorithms assume equal power allocation strategy, which cannot be adapted to multiple users with different channel conditions. Our goal is to design a distributed method that jointly optimizes the SLNR-based precoder and transmitting powers. Simulation results show that the proposed distributed transmission scheme can significantly increase the average cell throughput and improve resource efficiency while effectively reducing system overhead.**

Keywords—precoder; SLNR; power allocation; pareto-optimal; multi-cell MU-MIMO system

I. INTRODUCTION

Due to the spectrum resources scarcity, the next generation cellular networks have to use a denser distribution of base stations (BSs) with a high frequency reuse factor. However, the system throughput is still limited by interferences. For multi-cell multi-user multi-input multi-output (MU-MIMO) systems, the inter-cell interference (ICI) needs to be eliminated for further improvement in cell throughput.

So far, a closed-form solution [1][2][3] for the interference channel capacity domain has not been obtained. It has been proved that adopting joint dirty paper coding (DPC) [4] technique can cancel the interference and achieve the theoretical capacity of a multi-cell MU-MIMO downlink system. However, it is difficult to satisfy the requirements for precise time and phase synchronization in real-time communication systems. Besides, interference coordination methods -[8] (such as zero-forcing (ZF) and game theory based algorithms) can also eliminate ICI, which is achieved via coordination among multiple BSs by sharing the global channel state information (CSI). However, the information exchange and feedback significantly increases the system overhead. In order to effectively increase system throughput and further reduce the complexity of cooperative transmission, a distributed model based on SLNR [9][10][11][12][13] (signal-to-leakage-plus-noise ratio) is introduced for transmitter precoding. This technique is combined with joint processing (JP) and applied to single cell and multi-user MIMO downlink systems in [9][10]. The distributed solution of SLNR model has been proposed in [11][12][13]. The SLNR model is a compromise between egoistic and altruistic precoder game strategy, it has been proved to be able to effectively eliminate ICI, and thus achieve the pareto-optimal cell throughput. However, the existing algorithms have a common disadvantage: equal downlink transmitting power is assumed for each active user, which becomes a limiting factor for performance enhancement. In actual systems, channel conditions for each user vary a lot such that equal transmitting power cannot be adapted to different channel conditions, which reduces the power efficiency and eventually restricts the cell throughput. Therefore, an appropriate and practical power allocation scheme is required.

In the past several years, MIMO gradually becomes a mainstream technique in wireless communication systems. MIMO channels have significant higher diversity gain, array gain and multiplexing gain than MISO channels. In the multi-cell case, MU-MIMO technique is also widely used. In this paper, we study how to design distributed algorithms for multi-cell MU-MIMO systems.

In our work, we design a joint distributed precoder with power allocation algorithm that can effectively eliminate ICI in MU-MIMO systems. We briefly summarize our contribution below.

In this paper, we study the joint precoder design and power allocation algorithm. We adopt a distributed SLNR model based on only local CSI for each cell's optimization. We investigate the optimal power allocation strategy, which could fully utilize system resources and increase cell throughput. Specifically, for each cell, (1) we construct the joint optimization model of precoder and power allocation; (2) we derive the Lagrangian problem under the sum-transmitting power constraint; (3) we find the Lagrange extreme point and the corresponding transmitting power by matrix analysis[14] and orthogonal decomposition [15][16][17]. After that, the precoder can be obtained by schur decomposition [18][19][20] from the SLNR model with optimal power allocations.

Simulation results show that the proposed algorithm can effectively suppress ICI, increase average cell throughput, while reducing system overhead. For different interference factors, total transmitting powers, and the number of transmitting antennas, the proposed algorithms always have significant improvements on cell throughput, which enables better QoS support for users.

The rest of paper is organized as follows. Section II describes the system model. In Section III, we formulate the joint optimization problem for precoder design and power allocation, and we obtain a close-form solution. We design an optimal power-precoder algorithm based on the solution. We discuss the simulation results in Section IV, and draw our conclusions in Section V.

II. SYSTEM MODEL

We consider a downlink multi-cell MU-MIMO wireless system with M cells. A BS with N_T transmitting antennas is allocated in the center of each cell, where U active users with N_R receiving antennas are random distributed. The receiving signal $y_{m,u}$ of the u-th user in the m-th cell can be expressed as [10][12],

$$\begin{aligned} y_{m,u} &= \sqrt{\alpha_{m,u}}\mathbf{M}_{m,u}\mathbf{H}_{m,u}\mathbf{V}_{m,u}s_{m,u} \\ &+\mathbf{M}_{m,u}\mathbf{H}_{m,u}\sum_{j=1,j\neq u}^{U}\sqrt{\alpha_{m,j}}\mathbf{V}_{m,j}s_{m,j} \\ &+\mathbf{M}_{m,u}\sum_{n=1,n\neq m}^{M}\sum_{k=1}^{U}\sqrt{\alpha_{n,k}}\mathbf{H}_{n\to m,u}\mathbf{V}_{n,k}\mathbf{s}_{n,k}+\mathbf{M}_{m,u}\mathbf{n}_{m,u} \\ &= y_{m,u}^{sig}+y_{m,u}^{intra\text{-}int}+y_{m,u}^{inter\text{-}int}+z_{m,u} \end{aligned} \quad (1)$$

where $\mathbf{H}_{m,u}\in\mathbb{C}^{N_R\times N_T}$ denotes the channel gain from the m-th BS to the u-th user in this cell, the element of which is normally distributed as $\mathcal{CN}(\mathbf{0},1)$, and $\mathbf{H}_{n\to m,u}$ represents the channel gain from the n-th BS to the u-th user in the m-th cell, and its elements are normally distributed as $\mathcal{CN}(\mathbf{0},\eta^2)$, where $0\le\eta\le 1$ is the interference factor. $s_{m,u}$ denotes the transmitting signal for this user with unit power, and $\mathbf{s}_m=(s_{m,1},\cdots,s_{m,U})$ is the signals transmitted by the m-th BS. $\alpha_{m,u}$ denotes the downlink transmitting power for the u-th user in the m-th cell, the sum-power constraint for this cell is $\sum_{u=1}^{U}\alpha_{m,u}\le P_m$. $\mathbf{M}_{m,u}\in\mathbb{C}^{1\times N_R}$ denotes the receiver combination matrix at the referring user, while $\mathbf{V}_{m,u}\in\mathbb{C}^{N_T\times 1}$ represents the precoder of the m-th BS towards the u-th user with unit norm, and the semi-unitary matrix $\mathbf{V}_m=(\mathbf{V}_{m,1},\cdots,\mathbf{V}_{m,U})$ denotes the precoder for the m-th BS, $\mathbf{n}_{m,u}\in\mathbb{C}^{N_R\times 1}$ denotes the AWGN noise at the u-th user in the m-th cell, and $z_{m,u}\sim\mathcal{CN}(\mathbf{0},N_0)$ is the noise after combinations.

In (1), the signal $\mathbf{y}_{m,u}$ consists of four parts, the first part $\mathbf{y}_{m,u}^{sig}$ denotes the effective signal for the u-th user in the m-th cell. The second part $y_{m,u}^{intra\text{-}int}$ represents the intra-cell interference signal received by this user, which can be eliminated by OFDMA(Orthogonal Frequency Division Multiple Access) [5]-[8] and zero-forcing methods [5]-[8]. The third part $y_{m,u}^{inter\text{-}int}$ denotes the inter-cell interference signal which is the focus of our study since the strong ICI is the primary limiting factor of the system performance. The fourth part $z_{m,u}$ is the noise.

III. THE OPTIMAL DISTRIBUTED POWER-PRECODER ALGORITHM

In this section, we present a distributed precoder design and a power allocation algorithm for multi-cell MIMO systems, where a joint optimization of precoder and power control is fully considered. We also derive the distributed pareto-optimal closed-form solution. The following notations are used: operator $\|\cdot\|$ denotes the l_2-norm, $Tr(\cdot)$ denotes the trace of a matrix, and the superscript $(\cdot)^H$ denotes the conjugate transpose.

A. Formulation of the Jointly Optimization Problem

First, we obtain a distributed SLNR model for each user, which represents a compromise between the extreme egoistic and altruistic game strategies. Then, we add the power control part to improve power efficiency and system throughput.

As discussed in section II, before filtering, the effective signal for the u-th user in the m-th cell can be expressed as,

$$\mathbf{y}_{m,u}^{sig}=\mathbf{H}_{m,u}\mathbf{V}_{m,u}\sqrt{\alpha_{m,u}}s_{m,u}\,. \quad (2)$$

Similarly, the interference leakage signal originated from this user is,

$$\mathbf{y}_{m,u}^{leak}=\bar{\mathbf{H}}_{m,u}\mathbf{V}_{m,u}\sqrt{\alpha_{m,u}}s_{m,u}\,, \quad (3)$$

where $\bar{\mathbf{H}}_{m,u}=\{\mathbf{H}_{m\to i,j},(i,j)\neq(m,u)\}$ denotes the leakage channel from the m-th BS to the other $MU-1$ users in the system (except the u-th serving user).

Then, the SLNR for the u-th user in the m-th cell can be represented as,

$$\begin{aligned}\zeta_{m,u}&=\frac{\left\|\mathbf{y}_{m,u}^{sig}\right\|^2}{\left\|\mathbf{y}_{m,u}^{leak}\right\|^2+\left\|\mathbf{z}_{m,u}\right\|^2}\\ &=\frac{\alpha_{m,u}\mathbf{V}_{m,u}^H\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}\mathbf{V}_{m,u}}{\mathbf{V}_{m,u}^H\left(\alpha_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+N_RN_0\mathbf{I}_{N_T}\right)\mathbf{V}_{m,u}}\end{aligned}\,. \quad (4)$$

Combined with the sum-power constraint for the m-th cell, the 2-dimension (2-D) optimization problem can be formulated as,

$$\begin{aligned}&\underset{\mathbf{q}_{m,u},\alpha_{m,u}}{\text{maxmize}} \quad \zeta_{m,u}=\frac{\alpha_{m,u}\mathbf{V}_{m,u}^H\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}\mathbf{V}_{m,u}}{\mathbf{V}_{m,u}^H\left(\alpha_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+N_RN_0\mathbf{I}_{N_T}\right)\mathbf{V}_{m,u}}\,,\\ &\text{s.t.} \quad \left\|\mathbf{V}_{m,u}\right\|=1, \quad \sum_{u=1}^{U}\alpha_{m,u}\le P_m\end{aligned} \quad (5)$$

where the SLNR metric is maximized for each user under the power control constraint.

B. Power Control

To simply the 2-D optimization problem in (5), a Lagrange multiplier λ is used to modify the SLNR model regarding the power constraint. The Lagrangian can be derived as follows,

$$L\left(\zeta_{m,u},\lambda\right)=\zeta_{m,u}-\lambda\left(\sum_{u=1}^{U}\alpha_{m,u}-P_m\right) . \tag{6}$$

To maximize the modified SLNR model in (6), we calculate the sub-gradient of (6) w.r.t. the power factor $\alpha_{m,u}$, and the maximum extreme point is achieved when the sub-gradient is zero. The sub-gradient is given in (7),

$$\frac{\partial L\left(\zeta_{m,u},\lambda\right)}{\partial\left(\alpha_{m,u}\right)}= \frac{\mathbf{V}_{m,u}^H\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}\mathbf{V}_{m,u}\mathbf{V}_{m,u}^H\left(UN_RN_0/P_m\right)\mathbf{I}_{N_T}\mathbf{V}_{m,u}}{\left(\mathbf{V}_{m,u}^H\left(\alpha_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+\left(UN_RN_0/P_m\right)\mathbf{I}_{N_T}\right)\mathbf{V}_{m,u}\right)^2}-\lambda=0 . \tag{7}$$

Since $\left(\mathbf{V}_{m,u}^H\left(\alpha_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+\left(UN_RN_0/P_m\right)\mathbf{I}_{N_T}\right)\mathbf{V}_{m,u}\right)^2$ is a positive scalar, (7) is simplified as,

$$\lambda\left(\alpha_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+N_RN_0\mathbf{I}_{N_T}\right)^2=\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}N_RN_0 . \tag{8}$$

The term $\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}$ in (8) is a semi-positive hermit matrix with dimension $N_T\times N_T$, and it can decomposed as,

$$\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}=\mathbf{U}_{m,u}\sqrt{\mathbf{\Lambda}_{m,u}}\mathbf{U}_{m,u}^H\mathbf{U}_{m,u}\sqrt{\mathbf{\Lambda}_{m,u}}\mathbf{U}_{m,u}^H , \tag{9}$$

where $\mathbf{U}_{m,u}$ denotes the orthogonal base vectors for the space spanned by $\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}$, the diagonal matrix can be obtained as $\mathbf{\Lambda}_{m,u}=\mathbf{U}_{m,u}^H\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}\mathbf{U}_{m,u}$, and the operation $\sqrt{\cdot}$ means the square-root element-wise (details given in Appendix A). Then, the power factor of the *u*-th user in the *m*-th cell ($\alpha_{m,u}$ in (8)) can be obtained as a function of the Lagrange λ. Substituting $\alpha_{m,u}$ in the power constraint $\sum_{u=1}^{U}\alpha_{m,u}=P_m$, we obtain the optimal power allocation factor $\tilde{\alpha}_{m,u}$,

$$\tilde{\alpha}_{m,u}= \left\|\frac{\mathbf{U}_{m,u}\sqrt{\mathbf{\Lambda}_{m,u}}\mathbf{U}_{m,u}^H\left(P_m\left(\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}\right)+UN_RN_0\mathbf{I}_{N_T}\right)}{\sum_{k=1}^{U}\mathbf{U}_{m,k}\sqrt{\mathbf{\Lambda}_{m,k}}\mathbf{U}_{m,k}^H-N_RN_0\mathbf{I}_{N_T}}\right\|\Big/\left\|\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}\right\| . \tag{10}$$

C. Precoder Design

After obtaining the optimal power factor $\tilde{\alpha}_{m,u}$, the precoder optimization problem in (5) can be formulated as,

$$\underset{\mathbf{q}_{m,u}}{\text{maxmize}}\ \zeta_{m,u}=\frac{\tilde{\alpha}_{m,u}\mathbf{V}_{m,u}^H\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}\mathbf{V}_{m,u}}{\mathbf{V}_{m,u}^H\left(\tilde{\alpha}_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+N_RN_0\mathbf{I}_{N_T}\right)\mathbf{V}_{m,u}} . \tag{11}$$

$$\text{s.t. } \left\|\mathbf{V}_{m,u}\right\|=1$$

Both $\mathbf{A}_{m,u}=\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}$ in the numerator and $\mathbf{B}_{m,u}=\tilde{\alpha}_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+N_RN_0\mathbf{I}_{N_T}$ in the denominator are semi-positive hermit matrices, and both matrices belong to $\mathbb{C}^{N_T\times N_T}$. It has been proved that for the matrix pencil $\left(\mathbf{A}_{m,u},\mathbf{B}_{m,u}\right)$ [15][18], there exists a series of eigenvalues $\left\{\lambda_{m,u}\right\}$ and corresponding eigenvectors $\left\{\mathbf{x}_{m,u}\right\}$ that makes $\mathbf{A}_{m,u}\mathbf{x}_{m,u}/\mathbf{B}_{m,u}\mathbf{x}_{m,u}=\lambda_{m,u}$. The same principle holds for (11), and the corresponding matrix pencil is,

$$\left(\tilde{\alpha}_{m,u}\mathbf{H}_{m,u}^H\mathbf{H}_{m,u},\ \tilde{\alpha}_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+N_RN_0\mathbf{I}_{N_T}\right). \tag{12}$$

When the precoder is the primary eigenvector of (12), the SLNR is maximized as the corresponding eigenvalue. To calculate the eigenvectors of (12), we adopt the generalized schur decomposition method [18] to derive the equivalent matrix of (12), and obtain the closed-form solution of the optimal precoder as follows:

$$\mathbf{V}_{m,u}^o=eig\left(\left(\tilde{\alpha}_{m,u}\bar{\mathbf{H}}_{m,u}^H\bar{\mathbf{H}}_{m,u}+N_RN_0\mathbf{I}_{N_T}\right)^{-1}\tilde{\alpha}_{m,u}\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}\right) \tag{13}$$

where operation $eig(\cdot)$ denotes the unit-norm primary eigenvector, and the SLNR for the u-th user in the *m*-th cell is maximized when $\zeta_{m,u}=\max\left(\lambda_{m,u}\left(\mathbf{A}_{m,u},\mathbf{B}_{m,u}\right)\right)$.

D. Algorithm Description

The proposed algorithm can be implemented in a distributed way for each cell. The closed-form solution of the 2-D optimization problem of precoder and transmitting power can be obtained without iterations. Take the *m*-th cell as an example, we present the pseudo-code of the algorithm in Table I:

TABLE I. ALGORITHM DESCRIPTION

for user u = 1 to U **do**
1. Calculate the optimal power factor $\tilde{\alpha}_{m,u}$ as in (10);
2. Formulate the equivalent matrix pencil as in(12);
3. Derive the precoder $\mathbf{V}_{m,u}^o$ as in (13);
end for
The *m*-th BS transmit signal $\mathbf{x}_m=\sum_{u=1}^{U}\mathbf{V}_{m,u}\sqrt{\tilde{\alpha}_{m,u}}s_{m,u}$.

IV. SIMULATION RESULTS

In this section, we describe our simulation and analyze the proposed algorithms. We consider a multi-cell MU-MIMO downlink wireless system of M cells, where each BS is equipped with N_T transmitting antennas and allocated in the center of each cell. U users with N_R receiving antennas are randomly distributed in each cell. For the *m*-th cell, the effective channel and the leakage channel are assumed of Rayleigh fading as $\mathbf{H}_m(i,j)\sim\mathcal{CN}(0,1)$ and $\bar{\mathbf{H}}_m(i,j)\sim\mathcal{CN}\left(0,\eta^2\right)$, respectively, where η is the interference factor. In order to carry out a comparative analysis, we consider five existing precoder design algorithms. The SLNR-based algorithm [12] designs precoder using the SLNR metric with equal transmitting power allocation, which can not properly adapt to varying channel conditions for different users, and the precoder obtained by the SLNR maximization problem is generally not optimal for the cell throughput maximization problem. The maximum ratio transmission (MRT) algorithm [5]-[8] can achieve the Nash equilibrium in the low SNR region. The MRT algorithm designs the precoder as $\mathbf{V}_m = \mathbf{H}_m^H / \left\| \mathbf{H}_m^H \right\|$ for the m-th cell. On the other hand, the zero-forcing (ZF) algorithm [5]-[8] designs the precoder as $\mathbf{V}_m = \boldsymbol{\Pi}_{\bar{\mathbf{H}}_m^H}^{\perp} \mathbf{H}_m^H / \left\| \boldsymbol{\Pi}_{\bar{\mathbf{H}}_m^H}^{\perp} \mathbf{H}_m^H \right\|$ to fully eliminate the noise and interference with the precoder, where $\boldsymbol{\Pi}_{\bar{\mathbf{H}}_m^H}^{\perp} = \mathbf{I} - \bar{\mathbf{H}}_m^H \left(\bar{\mathbf{H}}_m \bar{\mathbf{H}}_m^H \right)^{-1} \bar{\mathbf{H}}_m$ denotes the orthogonal null space of $\bar{\mathbf{H}}_m^H$. The ZF algorithm is optimal in the high SNR region but strict dimension constraint is required. The orthogonal transmission algorithm [5]-[8] allocates orthogonal precoders statically, which can not adapt to the time varying channels. The exhaustive search algorithm [21] tries to reach the pareto optimal boundary by searching in the corresponding codebook as $\mathbf{V}_m = \arg\max_{\left\|\mathbf{V}_m\right\|^2=1} P\left|\mathbf{H}_m \mathbf{V}_m\right|^2 / \left(N_0 N_R + P\left|\bar{\mathbf{H}}_m \mathbf{V}_m\right|^2 \right)$. However, it requires global CSI and has high computational complexity.

Different from the above algorithms, we propose a distributed algorithm with much better performance. The distributed algorithm for precoder design and power control can achieve the pareto optimum without iterations. The algorithm strengthens the effective signals while suppressing the interference leakage signals. The corresponding power allocation scheme adapts well to varying channel conditions for each user, and hence improves the system power efficiency. The proposed algorithm can significantly increase the average throughput while reducing the system overhead. We run Matlab simulations to evaluate the performance of our algorithm. Next, we present our simulation results.

Fig. 1 plots the average cell throughput for different transmitting SNRs. Fig. 1 shows that our proposed power-precoder optimal algorithm achieves higher throughput than other algorithms, especially when SNR increases. When equal transmitting power allocation is assumed, the existing SLNR-based algorithm appears to be a good compromise between the extreme ZF algorithm and MRT algorithm, which is shown to be a pareto-optimal model for maximizing the system throughput. Using an appropriate power allocation strategy, the average cell throughput achieved by our algorithm is 1.84~7.95 bps/Hz higher than the existing SLNR scheme, and the advantage is more obvious in the low SNR region. Our proposed power-precoder optimal algorithm jointly optimizes the distributed precoder and the power factors, which can get full use of power resource and thus improve the power efficiency. When the transmitting SNR is low, the power must be increased to ensure effective communications. This is an example that shows power allocation is necessary for performance improvement.

Fig. 2 plots the average cell throughput v.s. different number of transmitting antennas. For different space dimensions, our proposed power-precoder optimal algorithm achieves the highest system throughput, while the static orthogonal transmission mode performs the worst. The ZF algorithm is restricted to the dimension constraint, and it can be used only when the condition $N_T \geq U * N_R$ is satisfied. The MRT algorithm achieves higher system throughput when the number of transmitting antennas increases. However, the throughput increase of MRT is limited because the interference is not eliminated. Fig. 2 shows that the existing SLNR-based scheme has good performance. When the space dimension resource is abundant, optimization of power control becomes more important, and our proposed power-precoder optimal algorithm can definitely improve system throughput, as shown in Fig. 2.

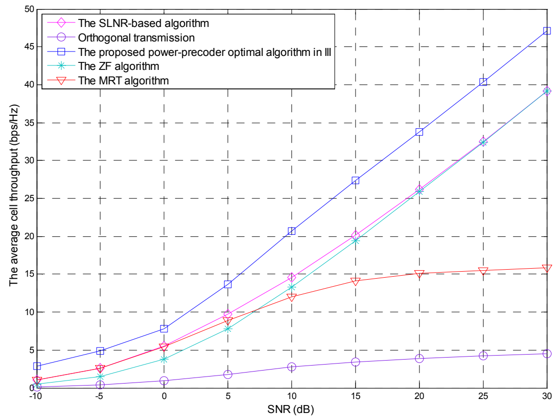

Figure 1. The average cell throughput for different transmitting SNR (M=2,NT=8,NR=1,U=4, η=0.5)

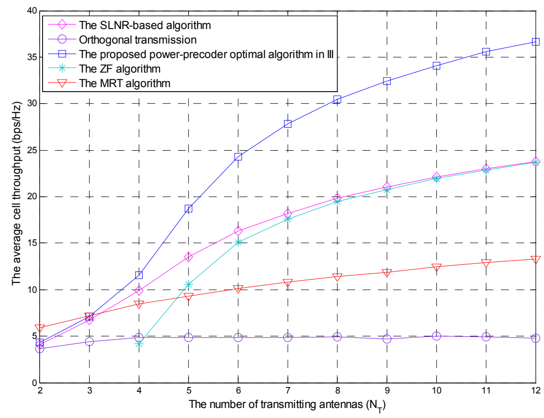

Figure 2. The effect of transmitting antennas on throughput (M=2, NR=1,U=4, SNR=15dB, η=0.5)

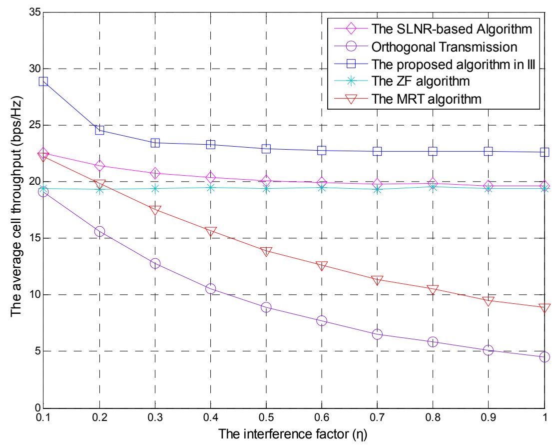

Figure 3. The effect of interference factors on throughput (M=2,NT=8,NR=1,U=3, SNR=15dB)

Fig. 3 plots the effect of interference factors on average cell throughputs. When the interference increases, for all the algorithms the system performance degrades in some extent. However, our proposed power-precoder optimal algorithm degrades gracefully. On the other hand, the throughput of the orthogonal transmission mode and the MRT algorithm drops rapidly because they do not use effective interference elimination techniques. Fig. 3 shows that the performance of the ZF algorithm is not affected by the interference factor because the ICI is fully cancelled. Different from the above algorithms, our proposed power-precoder optimal algorithm can gain higher system throughput because the SLNR model is pareto-optimal. Our power allocation scheme can handle strong interference and hence achieves the highest average cell throughput, so the proposed power-precoder algorithm can effectively eliminate the interference, and thus achieve a better system performance.

V. Conclusion

In this paper, we presented a distributed pareto-optimal precoder design algorithm for multi-cell MIMO systems. We formulated the distributed SLNR-based precoder design and power allocation as a two-dimension joint optimization problem, and we obtained a closed-form solution for pareto-optimal precoders and power factors. The proposed algorithm only uses local CSI and it can be implemented in each cell. This significantly reduces system overhead. Our simulation results confirmed that the proposed distributed algorithm can significantly increase the average cell throughput while reducing the overhead.

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References

[1] J. G. Andrews, W. Choi, and R. W. Heath, "Overcoming Interference in Spatial Multiplexing MIMO Cellular Networks," *IEEE Wireless Communications*, vol. 14, pp. 95–104, December 2007.

[2] H. Sung, S.-H. Park, K.-J. Lee, and I. Lee, "Linear Precoder Designs for *K*-user Interference Channels," *IEEE Transactions on Wireless Communications*, vol. 9, pp. 291–301, January 2010.

[3] R. H. Etkin, D. N. C. Tse, and H. Wang, "Gaussian Interference Channel Capacity to within One Bit," *IEEE Transactions on Information Theory*, vol. 54, pp. 5534–5562, December 2008.

[4] P. Viswan sath and D. N. C. Tse, "Sum capacity of the vector Gaussian broadcast channel and uplink-downlink duality," *IEEE Trans. Inf. Theory*, vol. 49, no. 8, pp. 1912-1921, Aug. 2003.

[5] G. Caire and S. Shamai (Shitz), "On the achievable throughput of a multiantenna Gaussian broadcast channel," *IEEE Trans. Inf. Theory*, vol. 49, no. 7, pp. 1691-1706, July 2003..

[6] J. G. Andrews, W. Choi, and R. W. Heath Jr., "Overcoming interference in spatial multiplexing MIMO cellular networks," *IEEE Wireless Commun. Mag.*, vol. 14, no. 6, pp. 95-104, Dec. 2007.

[7] G. Boudreau, J. Panicker, N. Guo, R. Chang, N. Wang, and S. Vrzic, "Interference coordination and cancellation for 4G networks," *IEEE Commun. Mag.*, vol. 47, no. 4, pp. 74-81, Apr. 2009.

[8] A. Tölli, H. Pennanen, and P. Komulainen, "SINR balancing with coordinated multi-cell transmission," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Apr. 2009, pp. 1-6.

[9] D. W. H. Cai, T. Q. S. Quek, and C. W. Tan, "Coordinated max-min SIR optimization in multicell downlink–duality and algorithm," in *Proc. IEEE Int. Conf. Commun.*, June 2011, pp. 1-6.

[10] M. Sadek, A. Tarighat, and A. H. Sayed, "A leakage-based precoding scheme for downlink multi-user MIMO channels," *IEEE Trans. WirelessCommun.*, vol. 6, no. 5, pp. 1711-1721, May 2007.

[11] H. Zhang, N. B. Mehta, A. F. Molisch, J. Zhang, and H. Dai, "Asynchronous interference mitigation in cooperative base station systems,"*IEEE Trans. Wireless Commun.*, vol. 7, no. 1, pp. 155-165, Jan. 2008.

[12] W.W.L. Ho, T.Q.S. Quek, S. Sun, R.W. Heath, "Decentralized Precoding for Multicell MIMO Downlink," in *IEEE Trans,Wireless Commun*, June 2011, pp. 798-1809.

[13] B. O. Lee, H. W. Je, I. Sohn, O.-S. Shin, and K. B. Lee, "Interferenceaware decentralized precoding for multicell MIMO TDD systems," in *Proc. IEEE Global Commun. Conf.*, Nov. 2008, pp. 1-5.

[14] R. A. Horn and C. R. Johnson, *Matrix Analysis*. Cambridge University Press, 1990.

[15] Stewart G W. On the sensitivity of the eigenvalue problem *Ax* = *λ Bx*. SIAM J Num Anal, 1972,9: 669~686.

[16] G H Golub, C F Van Loan, Matrix Computation. 2nd ed. Baltimore: The John Hopkins University Press, 1989.

[17] R A Horn, C R Johnson. Matrix Analysis. Cambridge: Cambridge University Press, 1985.

[18] C B Moler, G W Stewart. An algorithm for generalized matrix eigenvalue problem, SIAM J Num Anal, 1973, 10:241~256.

[19] A H Sayed, T. Kailath, A state-space approach to adaptive RLS filtering. IEEE Signal Processing Mag, 1994, 11:18~60.

[20] G H Golub, C F Van Loan, Matrix Computation. 2nd ed. Baltimore: The John Hopkins University Press, 1989.

[21] E.A. Jorswieck and E.G. Larsson. The MISO interference channel from a game-theoretic perspective: A combination of selfishness and altruism achieves Pareto optimality. In Proc. Int'l Conf. Acoustics, Speech and Sig. Proc. (ICASSP), Las Vegas, March 31 - April 4 2008.

Appendix A. Hermit Matrix Decomposition of Channel Matrix

Matrix analysis theory [14][15] has proved that, for a semi-positive hermit matrix $\mathbf{A} \in \mathbb{C}^{n\times n}$ with $rank(\mathbf{A}) = k$, it can be orthogonal decomposed as,

$$\mathbf{A} = \mathbf{v}_1\mathbf{v}_1^H + \mathbf{v}_2\mathbf{v}_2^H + \cdots + \mathbf{v}_k\mathbf{v}_k^H \quad , \tag{14}$$

where $\{\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_k\}$ is the base vectors for the space F^n. A unitary matrix $\mathbf{U} = (\mathbf{u}_1 \quad \mathbf{u}_2 \quad \cdots \quad \mathbf{u}_n)$ can be obtained from normalizing the base vectors. Let $\mathbf{\Lambda} = diag(\lambda_1, \cdots \lambda_k, 0, \cdots, 0)$, where $\mathbf{v}_i = \sqrt{\lambda_i}\mathbf{u}_i$, and λ_i is proved to be nonnegative since the matrix $\mathbf{A}$ is assumed to be semi-positive. Then, the matrix $\mathbf{A}$ can be decomposed as,

$$\mathbf{A} = \mathbf{U\Lambda U}^H = \mathbf{U}\sqrt{\mathbf{\Lambda}}\sqrt{\mathbf{\Lambda}}\mathbf{U}^H = \left(\mathbf{U}\sqrt{\mathbf{\Lambda}}\mathbf{U}^H\right)\left(\mathbf{U}\sqrt{\mathbf{\Lambda}}\mathbf{U}^H\right) \tag{15}$$

where the unitary matrix $\mathbf{U}=\left(\mathbf{u}_1 \quad \mathbf{u}_2 \quad \cdots \quad \mathbf{u}_n\right)$ is the orthogonal base vectors for space F^n, and diagonal matrix $\sqrt{\mathbf{\Lambda}}=diag\left(\sqrt{\lambda_1},\cdots\sqrt{\lambda_k},0,\cdots,0\right)$.

Based on the above analysis, the semi-positive hermit matrix $\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}$ in (8) can be decomposed as,

$$\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}=\mathbf{U}_{m,u}\sqrt{\mathbf{\Lambda}_{m,u}}\mathbf{U}_{m,u}^H\mathbf{U}_{m,u}\sqrt{\mathbf{\Lambda}_{m,u}}\mathbf{U}_{m,u}^H \tag{16}$$

where the unitary matrix $\mathbf{U}_{m,u}$ is the set of unit-norm orthogonal base vectors for space $\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}$, the diagonal matrix $\mathbf{\Lambda}_{m,u}=\mathbf{U}_{m,u}^H\mathbf{H}_{m,u}^H\mathbf{H}_{m,u}\mathbf{U}_{m,u}$ which is semi-positive, and the operation $\sqrt{\cdot}$ means the extraction of root element-wise.