Sum-Rate Maximization Schemes for K-User MISO Interference Channels With a Cognitive Relay

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***Abstract*—In this paper, we consider K-user multiple-input single-output interference channels with a cognitive relay. Assuming that data of all transmitters and channel state information are known at the cognitive relay, we design a linear precoder for the cognitive relay with the aim of maximizing the sum-rate without changing the transmitter operations at all transmitters. We first define the receiver set as a set which contains a part of the receivers, and then introduce a performance metric called "partial signal-to-interference-plus-noise ratio" (PSINR) based on the receiver set. Then, we can obtain a precoder at the cognitive relay by solving the PSINR maximization problem. The optimal receiver set which yields the maximum sum-rate can be identified by checking all possible receiver sets. Since this exhaustive search has prohibitive complexity, we develop a low complexity set search method by utilizing the properties of the optimal receiver set. Combining the PSINR maximization problem and the low complexity search method, we finally propose a precoder design scheme for the sum-rate maximization. Numerical simulation results confirm that the proposed scheme shows performance close to the projected gradient method with much reduced complexity.**

***Index Terms*—MIMO systems, cognitive relay, interference channels with a cognitive relay.**

I. Introduction

ONE of key challenges in future wireless communication systems lies in satisfying the explosively increasing demand for higher throughput. A data throughput improvement utilizing additional frequency bands is not desirable due to the bandwidth limitation of current wireless systems. To address this problem, cognitive networks have recently garnered a lot of interests [2], [3]. The cognitive network is defined as the network where some nodes sense the surrounding radio environment and obtain information such as channel state information (CSI) and exploit this acquired knowledge to enhance the system performance [4].

The interference channel with a cognitive relay (IFC-CR) [5] where the cognitive relay intervenes in classical interference channels (IFC) [6]–[8] to aid transmitters is one example of cognitive networks. In the IFC-CR, the term "cognitive" is named to indicate that the relay node knows the messages of the transmitters as in [9]–[12], whereas the same term has been often used for spectrum sharing in the cognitive radio [13]–[15]. The acquisition of the messages of the transmitters can be done via a back-haul link, and then the cognitive relay sends the transmitters' messages to the receivers.

Since the IFC-CR model generalizes important network models such as IFC, broadcast channels and relay channels, there have been extensive studies on the IFC-CR in the area of information theory. The authors in [5] first investigated the IFC-CR model and introduced an achievable rate region for the Gaussian IFC-CR using dirty paper coding (DPC). An improved achievable rate region in the Gaussian IFC-CR was found in [9] by the aid of Han-Kobayashi coding and the DPC. In [10], based on Gel'fand-Pinsker coding, an inner bound that includes the results in [5] and [9] was provided. Also, a general inner bound which contains the inner bounds of the IFC-CR in [5], [9], [10] were examined in [11], and the bound was shown to be optimal for a very strong interference regime. Recently, an approximated capacity region for the symmetric Gaussian IFC-CR was characterized except for some regimes in [12]. In addition, the degree of freedom (DOF) was studied in [16] for K-user IFC-CR with interference neutralization and asymptotic interference alignment.

Along with the information theoretic importance of the IFC-CR model, the IFC-CR also has practical motivations. Over the decades, service operators have deployed small cells such as picocell and femtocell to offload drastically increased traffic [17], [18]. However, inter-cell interference and inter-tier interference become critical due to the homogeneity of networks and dense cell deployment. For this interference limited environment, the cognitive relay can be one of effective techniques. For instance, a remote radio head or an idle eNodeB can play a role of the cognitive relay to improve system performance and this flexibility enables a service provider to easily set up the cognitive relay in existing interference networks.

The techniques in [5], [9]–[12] resort to non-linear methods, and thus they may not be suitable for practical systems due to high complexity. For this reason, linear methods have been generally adopted to practical systems which allow low complexity implementation [19]–[21]. A simple linear precoding

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which cancels interference at receivers was provided in [22] for multiple-input multiple-output (MIMO) IFC-CR. However, the method in [22] is not always available, since a cognitive relay may not be able to nullify interference due to power constraint. The authors in [23] modified interference by selectively rejecting or rotating the interference by means of a precoder at the cognitive relay to improve the symbol error rate. The works in [22] and [23] are applicable only to the two user IFC-CR case.

In this paper, we investigate linear precoder designs at the cognitive relay for K-user multiple-input single-output (MISO) IFC-CR for sum-rate maximization. All transmitters in K-user IFC-CR are assumed to provide their data and local CSI to the cognitive relay through a back-haul link, and we do not consider cooperative transmission among transmitters since it naturally invokes some drawbacks. First of all, the CSI sharing and the beamforming vector distribution required for the cooperative transmission incur additional back-haul latency. Moreover, the increased amount of the data traffic at the back-haul link can be a bottleneck for limited-capacity back-haul systems. In addition, the cooperation among transmitters imposes higher computational complexity, and thus this can be a heavy burden for practical systems. Therefore, we design a precoder only for the cognitive relay, while the transmission operations at transmitters remain the same. Our main contributions are summarized as follows:

- *Introduction of "partial signal-to-interference-plus-noise ratio" (PSINR)*

Since the sum-rate maximization problem is non-convex, it is not feasible to compute a precoder directly from the sum-rate function. Instead, defining a receiver set as a subset of receiver nodes in the network, we introduce a performance metric PSINR which is defined as the ratio of sum signal power to sum interference plus noise power in a given receiver set. Then, the precoder at the cognitive relay can be obtained by maximizing the PSINR metric.

- *Derivation of the optimal solution for the PSINR maximization problem*

We first derive an optimal analytic solution for the PSINR maximization problem when a receiver set contains of only one receiver. Next, for a general case, we reformulate the PSINR maximization problem into a quadratically constrained quadratic program (QCQP), and then we relax this QCQP as a semidefinite program (SDP) by semidefinite relaxation (SDR). We show that these problem reformulation and relaxation does not cause any loss of equivalence. Therefore, we can compute the optimal solution for the original problem by solving the relaxed SDP which can be efficiently solved by numerical methods.

- *Development of a receiver set determination algorithm*

In order to find the optimal receiver set which yields the maximum sum-rate, it is necessary to solve the PSINR maximization problems for all possible receiver sets. To reduce the number of candidates, we present a low complexity receiver set search method by exploiting the properties of the optimal receiver set chosen from exhaustive search. Finally, we propose a sum-rate maximization technique by combining a solution for the PSINR maximization problem and the proposed low complexity receiver set search method. From simulation results, we confirm that the proposed scheme efficiently improves the sum-rate and exhibits performance close to the projected gradient method with much reduced complexity.

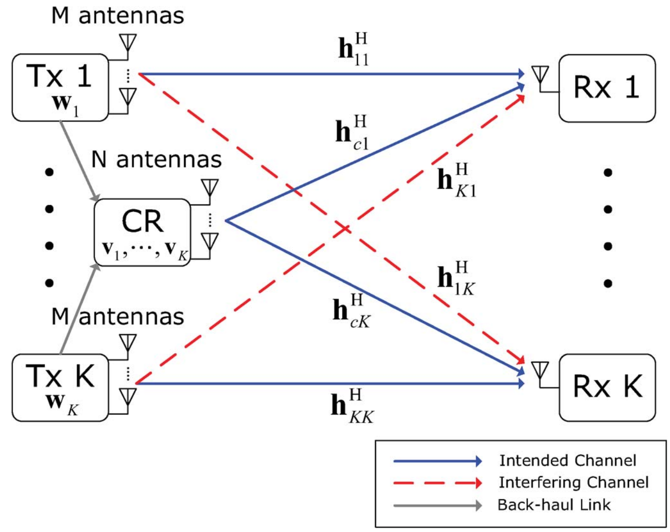

Fig. 1. System model of the K-user MISO interference channel with a cognitive relay.

Throughout this paper, the boldface capital letters represent matrices and the boldface small letters denote column vectors. In addition, $\mathbf{a}^{\mathrm{T}}$, $\mathbf{a}^{\mathrm{H}}$, and $\mathbf{a}^*$ stand for transpose, conjugate transpose and conjugate of a vector $\mathbf{a}$, respectively. We designate $|a|$, $\angle a$, and $\Re\{a\}$ as the magnitude, the phase and the real part of a complex scalar value a, respectively. The expectation operation is given as $\mathbb{E}[\cdot]$, and $\mathbf{I}_N$ and $\mathbf{0}_{M\times N}$ denote an $N \times N$ identity matrix and an $M \times N$ zero matrix, respectively.

II. System Model and Problem Formulation

Fig. 1 depicts the K-user MISO IFC-CR where each transmitter communicates with its corresponding receiver in the same band and the cognitive relay transmits the precoded signal to all receivers for improving the network performance. Here, transmitter i $(i = 1, \cdots, K)$ equipped with M antennas supports receiver i with a single antenna, and the cognitive relay with N antennas serves all receivers.

Let us denote x_i $(i = 1, \cdots, K)$ as the transmitted signal from transmitter i to receiver i with $\mathbb{E}[|x_i|^2] = 1$ and $\mathbb{E}[x_i^* x_j] = 0$ for $\forall j \neq i$ and $\mathbf{w}_i \in \mathbb{C}^M$ as the beamforming vector of transmitter i with $\|\mathbf{w}_i\|^2 = P_i$. We define the precoded signal vector $\mathbf{x}_c$ at the cognitive relay as $\mathbf{x}_c = \sum_{i=1}^{K} \mathbf{v}_i x_i$ where $\mathbf{v}_i \in \mathbb{C}^N$ is the beamforming vector at the cognitive relay for receiver i. Then, the received signal at receiver i is given by

$$\begin{aligned} y_i &= \sum_{j=1}^{K} \mathbf{h}_{ji}^{\mathrm{H}} \mathbf{w}_j x_j + \mathbf{h}_{ci}^{\mathrm{H}} \mathbf{x}_c + n_i \\ &= \left(\mathbf{h}_{ii}^{\mathrm{H}} \mathbf{w}_i + \mathbf{h}_{ci}^{\mathrm{H}} \mathbf{v}_i\right) x_i + \sum_{j=1, j\neq i}^{K} \left(\mathbf{h}_{ji}^{\mathrm{H}} \mathbf{w}_j + \mathbf{h}_{ci}^{\mathrm{H}} \mathbf{v}_j\right) x_j + n_i, \quad (1) \end{aligned}$$

where $\mathbf{h}_{ji}^{\mathrm{H}}$ and $\mathbf{h}_{ci}^{\mathrm{H}}$ indicate the flat fading channel coefficient from transmitter j to receiver i and from the cognitive relay to receiver i, respectively, and n_i represents the complex Gaussian noise with zero mean and unit variance at receiver i.

When each receiver treats interference as noise,[1] the signal-to-interference-plus-noise ratio (SINR) at receiver i becomes

$$\gamma_i = \frac{\left|\mathbf{h}_{ii}^{\mathrm{H}}\mathbf{w}_i + \mathbf{h}_{ci}^{\mathrm{H}}\mathbf{v}_i\right|^2}{\sum_{j=1,j\neq i}^{K}\left|\mathbf{h}_{ji}^{\mathrm{H}}\mathbf{w}_j + \mathbf{h}_{ci}^{\mathrm{H}}\mathbf{v}_j\right|^2 + 1}. \tag{2}$$

Then, the sum-rate maximization problem can be formulated as

$$\begin{aligned} \max_{\{\mathbf{v}_i\}} \quad & R_\Sigma \\ \text{subject to} \quad & \sum_{i=1}^{K}\|\mathbf{v}_i\|^2 \leq P_c, \end{aligned} \tag{3}$$

where R_Σ is defined as $R_\Sigma \triangleq \sum_{i=1}^{K}\log(1+\gamma_i)$ and P_c stands for the maximum transmit power at the cognitive relay. It is important to note that the beamforming vector at transmitter $\{\mathbf{w}_i\}$ is not the optimization variable since we control only the cognitive relay and the operations at transmitters remain unaffected. Due to the interference term, problem (3) is non-convex, and thus it is difficult to solve analytically. To tackle this problem, in what follows, we present a performance metric from which we can establish a lower bound of the sum-rate, and then provide a sum-rate maximization scheme based on the performance metric.

III. Partial SINR Maximization

In this section, we introduce a performance metric and investigate the optimization of the metric. For IFC, the authors in [24] introduced the metric "total SINR" as the ratio of the sum signal power to the sum interference plus noise power across the network, which is represented as

$$\Gamma_{\text{total}} = \frac{\sum_{i=1}^{K} S_i}{\sum_{i=1}^{K} I_i + K}, \tag{4}$$

where the intended signal power S_i and the interference power I_i at receiver i are given by

$$S_i = \left|\mathbf{h}_{ii}^{\mathrm{H}}\mathbf{w}_i + \mathbf{h}_{ci}^{\mathrm{H}}\mathbf{v}_i\right|^2,\ I_i = \sum_{j=1,j\neq i}^{K}\left|\mathbf{h}_{ji}^{\mathrm{H}}\mathbf{w}_j + \mathbf{h}_{ci}^{\mathrm{H}}\mathbf{v}_j\right|^2,$$

respectively. Also, a relation between the total SINR and the sum-rate is provided in [24] as

$$R_\Sigma \geq \log\left(1 + \sum_{i=1}^{K}\gamma_i\right) \geq \log\left(1+\Gamma_{\text{total}}\right). \tag{5}$$

[1] We consider single user detection since joint detection is much more complex than single user detection and receivers need more information such as modulations of transmitters.

One can notice that $\log(1+\Gamma_{\text{total}})$ is not particularly a tight lower bound for R_Σ. In this paper, we establish a tighter lower bound for the sum-rate by introducing a receiver set Ω which indicates a non-empty set consisting of partial receivers. Then, for a given receiver set Ω, we define the "partial SINR" (PSINR) as

$$\Gamma(\Omega) = \frac{\sum_{i\in\Omega} S_i}{\sum_{i\in\Omega} I_i + |\Omega|}, \tag{6}$$

where $|\Omega|$ is the cardinality of the set Ω. Note that the PSINR metric generalizes and extends the total SINR approach in [24] since $\Gamma(U)$ represents Γ_{total} where U represents the universal set. The following lemma states that the PSINR can be a tighter bound for the sum-rate than the total SINR.

Lemma 1: There always exists a receiver set Ω such that $\Gamma(\Omega) \geq \Gamma(U)$, and thus $\log(1+\Gamma(\Omega))$ becomes a tighter bound of R_Σ than $\log(1+\Gamma(U))$.

Proof: See Appendix A. □

From the result in Lemma 1, we can establish a tighter lower bound of the sum-rate by employing $\Gamma(\Omega)$ instead of Γ_{total} in (5). The sum-rate R_Σ yields the optimal performance, while this expression does not allow tractable analysis. In contrast, the total SINR Γ_{total} is very simple but lacks in performance. We emphasize that the PSINR metric bridges the gap between these two metrics by judiciously determining the receiver set Ω. Adopting $\Gamma(\Omega)$ as a performance metric parameterized by Ω, we have the PSINR maximization problem as

$$\begin{aligned} \max_{\{\mathbf{v}_i\}} \quad & \frac{\sum_{i\in\Omega}\left|\mathbf{h}_{ii}^{\mathrm{H}}\mathbf{w}_i + \mathbf{h}_{ci}^{\mathrm{H}}\mathbf{v}_i\right|^2}{\sum_{i\in\Omega}\sum_{j=1,j\neq i}^{K}\left|\mathbf{h}_{ji}^{\mathrm{H}}\mathbf{w}_j + \mathbf{h}_{ci}^{\mathrm{H}}\mathbf{v}_j\right|^2 + |\Omega|} \\ \text{subject to} \quad & \sum_{i=1}^{K}\|\mathbf{v}_i\|^2 \leq P_c. \end{aligned} \tag{7}$$

It is important to note that problem (7) does not mean that the cognitive relay supports only the receivers in Ω. The operational meaning is that the precoder at the cognitive relay is optimized by focusing on the receivers in Ω. As seen in (7), $\mathbf{v}_j$ for $j \in \Omega^c$ is determined to minimize I_i for $i \in \Omega$ regardless of S_j, and thus a solution of problem (7) makes the receivers only in Ω have high SINR. While the precoder for the IFC with the total SINR metric can easily be computed using generalized eigendecomposition in [24], problem (7) is still hard to solve since the beamforming vectors are coupled with each other. To overcome this difficulty, we first present the analytic optimal solution for the special case of $|\Omega| = 1$, and then investigate the optimal solution for the general case where there is no restriction on $|\Omega|$.

A. Special Case of $|\Omega| = 1$

In this subsection, we provide the analytic optimal solution for problem (7) when $|\Omega| = 1$. In this case, $\Gamma(\Omega)$ means the actual SINR of the only one receiver, and we can identify an analytic solution which will be utilized in algorithms in

Section IV. Without loss of generality, we suppose $\Omega = \{1\}$. Then, we have the SINR maximization problem as

$$\begin{aligned} \max_{\{\mathbf{v}_i\}} \quad & \frac{\left|\mathbf{h}_{11}^{\mathrm{H}}\mathbf{w}_1 + \mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_1\right|^2}{\sum_{j=2}^{K}\left|\mathbf{h}_{j1}^{\mathrm{H}}\mathbf{w}_j + \mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_j\right|^2 + 1} \\ \text{subject to} \quad & \sum_{i=1}^{K}\|\mathbf{v}_i\|^2 \le P_c. \end{aligned} \tag{8}$$

Let $\{\mathbf{v}_{i,\mathrm{opt}}\}$ be the optimal solution for problem (8). Then, the following lemma describes the beamforming direction and the consumed power of the cognitive relay for the optimal solution of problem (8).

Lemma 2: $\{\mathbf{v}_{i,\mathrm{opt}}\}$ should be aligned to $\mathbf{h}_{c1}$. Also, the cognitive relay must utilize full power to maximize the objective function in problem (8).

Proof: See Appendix B. □

By utilizing the result in Lemma 2, we can establish an ensuing theorem, which allows us to compute the analytic optimal solution for problem (8).

Theorem 1: The optimal beamforming vector $\{\mathbf{v}_{i,\mathrm{opt}}\}$ at the cognitive relay is given by

$$\mathbf{v}_{i,\mathrm{opt}} = v_{i,\mathrm{opt}}\frac{\mathbf{h}_{c1}}{\|\mathbf{h}_{c1}\|^2}. \tag{9}$$

where $\{v_{i,\mathrm{opt}}\}$ is the analytic optimal solution for the following equivalent problem.

$$\begin{aligned} \max_{\{v_i\}} \quad & \frac{|h_{11} + v_1|^2}{\sum_{j=2}^{K}|h_{j1} + v_j|^2 + 1} \\ \text{subject to} \quad & \sum_{i=1}^{K}|v_i|^2 = \tilde{P}_c. \end{aligned} \tag{10}$$

Here, we have $h_{j1} = \mathbf{h}_{j1}^{\mathrm{H}}\mathbf{w}_j$ for $j = 1, \cdots, K$ and $\tilde{P}_c = \|\mathbf{h}_{c1}\|^2 P_c$.

Proof: See Appendix C. □

Note that $\mathbf{v}_{i,\mathrm{opt}}$ is determined by $v_{i,\mathrm{opt}}$, which is the inner product between $\mathbf{h}_{c1}$ and $\mathbf{v}_{i,\mathrm{opt}}$. Hence, solving problem (8) is equivalent to adjusting inner products to maximize the SINR. A solution for $\Omega = \{m\}$ with $m \ne 1$ can be computed in a similar way.

B. General Case

An extension of the result in the previous subsection to the general case of $|\Omega| \ne 1$ is non-trivial. To this end, we provide an optimal solution for the general case by reformulating the PSINR maximization problem (7) in this subsection. Let us denote $\mathbf{v}$ and $\mathbf{w}$ as $\mathbf{v} = \left[\mathbf{v}_1^{\mathrm{T}} \ \cdots \ \mathbf{v}_K^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^{NK}$ and $\mathbf{w} = \left[\mathbf{w}_1^{\mathrm{T}} \ \cdots \ \mathbf{w}_K^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{C}^{MK}$, respectively. Also, we define $\mathbf{L}_{\mathbf{v},i}$ and $\mathbf{L}_{\mathbf{w},i}$ as

$$\begin{aligned} \mathbf{L}_{\mathbf{v},i} &= \left[\mathbf{0}_{N\times(i-1)N} \ \mathbf{I}_N \ \mathbf{0}_{N\times(K-i)N}\right] \\ \mathbf{L}_{\mathbf{w},i} &= \left[\mathbf{0}_{M\times(i-1)M} \ \mathbf{I}_M \ \mathbf{0}_{M\times(K-i)M}\right]. \end{aligned}$$

Then, from the relation of $\mathbf{v}_i = \mathbf{L}_{\mathbf{v},i}\mathbf{v}$ and $\mathbf{w}_i = \mathbf{L}_{\mathbf{w},i}\mathbf{w}$, problem (7) can be rewritten as

$$\begin{aligned} \max_{\mathbf{v}} \quad & \frac{\mathbf{v}^{\mathrm{H}}\mathbf{A}\mathbf{v} + 2\Re\{\mathbf{w}^{\mathrm{H}}\mathbf{B}\mathbf{v}\} + \mathbf{w}^{\mathrm{H}}\mathbf{C}\mathbf{w}}{\mathbf{v}^{\mathrm{H}}\mathbf{D}\mathbf{v} + 2\Re\{\mathbf{w}^{\mathrm{H}}\mathbf{E}\mathbf{v}\} + \mathbf{w}^{\mathrm{H}}\mathbf{F}\mathbf{w}} \\ \text{subject to} \quad & \|\mathbf{v}\|^2 \le P_c, \end{aligned} \tag{11}$$

where

$$\begin{aligned} \mathbf{A} &= \sum_{i\in\Omega}\mathbf{L}_{\mathbf{v},i}^{\mathrm{H}}\mathbf{h}_{ci}\mathbf{h}_{ci}^{\mathrm{H}}\mathbf{L}_{\mathbf{v},i}, \\ \mathbf{B} &= \sum_{i\in\Omega}\mathbf{L}_{\mathbf{w},i}^{\mathrm{H}}\mathbf{h}_{ii}\mathbf{h}_{ci}^{\mathrm{H}}\mathbf{L}_{\mathbf{v},i}, \\ \mathbf{C} &= \sum_{i\in\Omega}\mathbf{L}_{\mathbf{w},i}^{\mathrm{H}}\mathbf{h}_{ii}\mathbf{h}_{ii}^{\mathrm{H}}\mathbf{L}_{\mathbf{w},i}, \\ \mathbf{D} &= \sum_{i\in\Omega}\sum_{j=1,j\ne i}^{K}\mathbf{L}_{\mathbf{v},j}^{\mathrm{H}}\mathbf{h}_{ci}\mathbf{h}_{ci}^{\mathrm{H}}\mathbf{L}_{\mathbf{v},j}, \\ \mathbf{E} &= \sum_{i\in\Omega}\sum_{j=1,j\ne i}^{K}\mathbf{L}_{\mathbf{w},j}^{\mathrm{H}}\mathbf{h}_{ji}\mathbf{h}_{ci}^{\mathrm{H}}\mathbf{L}_{\mathbf{v},j}, \\ \mathbf{F} &= \sum_{i\in\Omega}\sum_{j=1,j\ne i}^{K}\mathbf{L}_{\mathbf{w},j}^{\mathrm{H}}\mathbf{h}_{ji}\mathbf{h}_{ji}^{\mathrm{H}}\mathbf{L}_{\mathbf{w},j} + \frac{|\Omega|}{\sum_{i=1}^{K}P_i}\mathbf{I}_{MK}. \end{aligned}$$

To get rid of the denominator in the objective function in (11), we introduce a complex auxiliary variable t and substitute $\tilde{\mathbf{v}} = t\mathbf{v}$. Then, after letting $\hat{\mathbf{v}} = \left[\tilde{\mathbf{v}}^{\mathrm{T}} \ t\right]^{\mathrm{T}} \in \mathbb{C}^{NK+1}$ and some manipulations, the maximization problem (11) can be reformulated as the following equivalent homogeneous QCQP problem

$$\begin{aligned} \max_{\hat{\mathbf{v}}} \quad & \hat{\mathbf{v}}^{\mathrm{H}}\mathbf{G}_0\hat{\mathbf{v}} \\ \text{subject to} \quad & \hat{\mathbf{v}}^{\mathrm{H}}\mathbf{G}_1\hat{\mathbf{v}} \le 1 \\ & \hat{\mathbf{v}}^{\mathrm{H}}\mathbf{G}_2\hat{\mathbf{v}} \le 0, \end{aligned} \tag{12}$$

where $\mathbf{G}_0$, $\mathbf{G}_1$, and $\mathbf{G}_2$ are expressed by

$$\begin{aligned} \mathbf{G}_0 &= \begin{bmatrix} \mathbf{A} & \mathbf{B}^{\mathrm{H}}\mathbf{w} \\ \mathbf{w}^{\mathrm{H}}\mathbf{B} & \mathbf{w}^{\mathrm{H}}\mathbf{C}\mathbf{w} \end{bmatrix}, \\ \mathbf{G}_1 &= \begin{bmatrix} \mathbf{D} & \mathbf{E}^{\mathrm{H}}\mathbf{w} \\ \mathbf{w}^{\mathrm{H}}\mathbf{E} & \mathbf{w}^{\mathrm{H}}\mathbf{F}\mathbf{w} \end{bmatrix}, \\ \mathbf{G}_2 &= \begin{bmatrix} \mathbf{I}_{NK} & \mathbf{0}_{NK\times 1} \\ \mathbf{0}_{1\times NK} & -P_c \end{bmatrix}. \end{aligned}$$

The detailed proof for equivalence between (11) and (12) is presented in Appendix D.

To make the problem more tractable, we relax problem (12) by using SDR technique which introduces $\mathbf{V} = \hat{\mathbf{v}}\hat{\mathbf{v}}^{\mathrm{H}}$ and eliminates the rank one condition for the solution. Then, the relaxed problem for problem (12) is given by

$$\begin{aligned} \max_{\mathbf{V}} \quad & \mathrm{Tr}(\mathbf{G}_0\mathbf{V}) \\ \text{subject to} \quad & \mathrm{Tr}(\mathbf{G}_1\mathbf{V}) \le 1 \\ & \mathrm{Tr}(\mathbf{G}_2\mathbf{V}) \le 0 \\ & \mathbf{V} \succeq \mathbf{0}, \end{aligned} \tag{13}$$

where $\mathbf{V} \succeq \mathbf{0}$ indicates that $\mathbf{V}$ is a positive semidefinite matrix.

In general, SDR does not yield an exact solution to its original QCQP, since the SDR cannot guarantee a rank-one solution. It was shown in [25] that for complex valued homogeneous QCQP with m constraints, the optimal solution for SDR has rank of less than $\sqrt{m}$. Fortunately, as there are only two conditions in problem (12), problem (13) must have a rank-one optimal solution. Therefore, we can confirm that the relaxation on the rank-one condition does not incur any loss of optimality.

The optimal solution for problem (13) can be efficiently obtained by interior-point methods based algorithms. For example, let $\mathbf{v}_{\text{opt}}$, $\hat{\mathbf{v}}_{\text{opt}}$ and $\mathbf{V}_{\text{opt}}$ be the optimal solutions obtained for problems (11), (12), and (13), respectively. Once $\mathbf{V}_{\text{opt}}$ is computed, $\hat{\mathbf{v}}_{\text{opt}}$ can be determined from the unique nonzero eigenvalue and the corresponding eigenvector of $\mathbf{V}_{\text{opt}}$. Then, we can calculate $\mathbf{v}_{\text{opt}}$ from $\hat{\mathbf{v}}_{\text{opt}}$ by dividing the first NK elements of $\hat{\mathbf{v}}_{\text{opt}}$ by the last element of $\hat{\mathbf{v}}_{\text{opt}}$. So far, we have derived a solution for maximization of PSINR when a receiver set Ω is given. Next, we will provide a method to efficiently determine the receiver set.

IV. Determination of a Receiver Set

In the previous section, we have identified the precoder at the cognitive relay by addressing the PSINR maximization problem. We have $2^K - 1$ precoder candidates for all possible receiver sets, and thus we need to select the optimal receiver set Ω_{opt} which yields the maximum sum-rate. Ω_{opt} can be computed by applying exhaustive search to determine the one which generates the best sum-rate among all possible receiver sets. However, the required number of SDPs for the exhaustive search is $2^K - K - 1$, which becomes prohibitively complex with large K. To reduce the complexity burden in calculating Ω_{opt}, we propose a greedy search method and a low complexity search method with a negligible performance loss compared to the exhaustive search method.

First, we present the greedy search for receiver set determination. The greedy search determines a new candidate set among all possible sets which exclude one element from the current candidate set in terms of the sum-rate. The search procedure is terminated when the sum-rate does not increase any more. The greedy search is summarized in **Algorithm 1**. Here, $\Omega^{(n)}$ and $R_\Sigma(\Omega)$ denote the candidate set at step n and the sum-rate of the PSINR maximization problem with Ω, respectively. Also, $\Xi(\Omega)$ is defined as the set of all possible sets obtained by discarding one element from Ω, i.e., $\Xi(\{1, 2, 3\}) = \{\{1, 2\}, \{1, 3\}, \{2, 3\}\}$. For the greedy search method, the worst case number of SDPs equals $\frac{1}{2}K^2 + \frac{1}{2}K - 2$. As each SDP can be solved in polynomial time and the greedy search method has polynomial search complexity, the greedy search method has polynomial complexity.

Algorithm 1 Greedy search method

Initialize $n \leftarrow 1$ and $\Omega^{(n)} \leftarrow U$
Repeat
  Set $\Omega^{(n+1)} \leftarrow \arg \max_{\Omega \in \Xi(\Omega^{(n)})} R_\Sigma(\Omega)$
  Set $n \leftarrow n + 1$
Until $R_\Sigma(\Omega^{(n)}) \le R_\Sigma(\Omega^{(n-1)})$ **or** $|\Omega^{(n)}| = 1$

Next, we introduce a low complexity search method which further reduces the search complexity. From numerical simulations, we observe that in most cases, Ω_{opt} contains the receiver which yields the largest SINR among all singleton sets.[2] Also, the larger the SINR for a singleton set, the higher the chance of being included in Ω_{opt}. Based on these observations, we describe a simple method as follows: We first determine a receiver index sequence by sorting SINR for all singleton sets in descending order using solution (9). Then, we construct two sets from the first two elements of the receiver index sequence, and choose the best one as a new candidate set. This procedure is repeated until the sum-rate decreases. Since the number of SDPs is always two at each step, the worst case number of SDPs reduces to $2K - 3$.

Algorithm 2 Proposed low complexity search method

Calculate $\gamma(i)\ \forall i$ using (9) and obtain $\{i_1, \cdots, i_K\}$
Initialize $n \leftarrow 1$, $\Omega^{(n)} \leftarrow \{i_1\}$, and $\Psi \leftarrow (i_2, \cdots, i_K)$
Repeat
  Set $\Omega_1 \leftarrow \Omega^{(n)} \cup \{\psi_1\}$ and $\Omega_2 \leftarrow \Omega^{(n)} \cup \{\psi_2\}$
  Calculate $j = \arg \max_{i=1,2} R_\Sigma(\Omega_i)$
  Set $\Omega^{(n+1)} \leftarrow \Omega_j$ and $\Psi \leftarrow \Psi \setminus \psi_j$
  Set $n \leftarrow n + 1$
Until $R_\Sigma(\Omega^{(n)}) \le R_\Sigma(\Omega^{(n-1)})$ **or** $\Omega^{(n)} = U$

The proposed low complexity search method is summarized in **Algorithm 2**. Here, i_k represents the receiver index which corresponds to the k-th largest SINR in $\{\gamma(1), \cdots, \gamma(K)\}$ where $\gamma(i)$ stands for the SINR of the receiver i using solution (9) for $\Omega = \{i\}$. Ψ and ψ_j indicate a receiver index sequence and the j-th element of Ψ, respectively. Also, $\Psi \setminus \psi_j$ is defined as a sequence where ψ_j is excluded from Ψ. For notational conveniences, when the length of Ψ is 1, we consider ψ_2 as a null element, and thus $\{\psi_2\} = \emptyset$ and $\Psi \setminus \psi_2 = \Psi$. As will be shown in the simulation results, the developed search method shows performance very close to the exhaustive search method with much reduced complexity.

V. Implementation Issues

For practical implementation of the cognitive relay, we should consider the overhead due to data exchange among nodes and computational complexity. Although we assume that all transmitters forward their local CSI to the cognitive relay, it is sufficient to send the scalar effective CSI $\{\mathbf{h}_{ij}^{\text{H}}\mathbf{w}_i\}$ only, since the beamforming vectors at transmitters are fixed. Therefore, each transmitter can send $K + 1$ complex numbers which includes the data symbol to the cognitive relay, and thus the total number of data to exchange is $K^2 + K$.

Once the data exchange procedure is terminated, the cognitive relay computes its precoder using the algorithms in the previous section. As an alternative method on the sum-rate maximization, the precoder can be computed by a projected

[2] Singleton set, also known as unit set, means a set having exactly one element.

TABLE I
COMPUTATIONAL COMPLEXITY COMPARISON

PG	$\mathcal{O}\left(n_{\text{init}}\,(M+N)\,K^4\frac{1}{\sqrt{\epsilon}}\right)$
PSINR-E	$\mathcal{O}\left(N^{3.5}K^{3.5}2^K\log\frac{1}{\epsilon}\right)$
PSINR-G	$\mathcal{O}\left(N^{3.5}K^{5.5}\log\frac{1}{\epsilon}\right)$
Proposed	$\mathcal{O}\left(N^{3.5}K^{4.5}\log\frac{1}{\epsilon}\right)$

gradient (PG) method which finds a stationary point in the feasible set based on the gradient information. However, the convergence to the global optimum is out of reach due to non-convexity of the original sum-rate expression. In order to improve the performance of the PG method, several initial points should be employed. We consider the PG method as an upper bound for linear precoders. We examine the computational complexity among the following schemes with the cognitive relay.

- Projected gradient: The best local optimal solution is computed using a PG method with multiple initial points. The step size is determined by Armijo rule with parameters in [26].
- PSINR with the universal set (PSINR-U): A solution for the PSINR maximization problem in the Section III-B is obtained with $\Omega = U$.
- PSINR with the singleton sets (PSINR-S): A solution which chooses the best one among solutions for the PSINR maximization problems with the all possible singleton sets.
- PSINR with greedy search (PSINR-G): **Algorithm 1** is evaluated.
- PSINR with exhaustive search (PSINR-E): A solution of the PSINR maximization with Ω_{opt} is found by the exhaustive search.

The computational complexity comparison is summarized in Table I where n_{init} and ϵ are the number of initial points and the solution accuracy, respectively. The PG method seems to be less affected by M, N, and K compared to the other schemes as the exponent of the PG method is smaller than the others. However, the PG method requires multiple initial points due to non-convexity of problem (3) and exhibits quite poor convergence behavior. While the PSINR based schemes have the convergence rate of $\mathcal{O}(\log 1/\epsilon)$ [27], the convergence rate of the PG method with backtracking line search for non-convex problems is $\mathcal{O}(1/\sqrt{\epsilon})$ [28], and thus much more iterations are necessary for the PG method compared to the other schemes even for low solution accuracy. Moreover, the PG method can be very slow due to the poor scaling property of gradient based algorithms, and this undesired phenomenon occurs in the high signal-to-noise ratio (SNR) scenario.

VI. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed scheme and identify the effectiveness of the PSINR metric. Throughout this section, we assume that all transmitters and the cognitive relay have the same power as P, i.e., $P_i = P, \forall i$ and $P_c = P$. Then, the definition of SNR is given as P. Additionally, all channels are independently generated as complex Gaussian vectors with zero mean and identity covariance matrix, i.e., $E[\mathbf{h}_{ii}\mathbf{h}_{ii}^{\mathrm{H}}] = \mathbf{I}_M, \forall i$, $E[\mathbf{h}_{ij}\mathbf{h}_{ij}^{\mathrm{H}}] = \mathbf{I}_M, \forall i \neq j$ and $E[\mathbf{h}_{ci}\mathbf{h}_{ci}^{\mathrm{H}}] = \mathbf{I}_N$, $\forall i$, and the beamforming vectors at transmitters are set to the maximal ratio transmission (MRT) vectors, i.e., $\mathbf{w}_i = \sqrt{P_i}\frac{\mathbf{h}_{ii}}{\|\mathbf{h}_{ii}\|}, \forall i$, since transmitters are unaware of interferences at receivers. We use the CVX tool to solve the SDP in the PSINR maximization problem for $|\Omega| \neq 1$ [29].

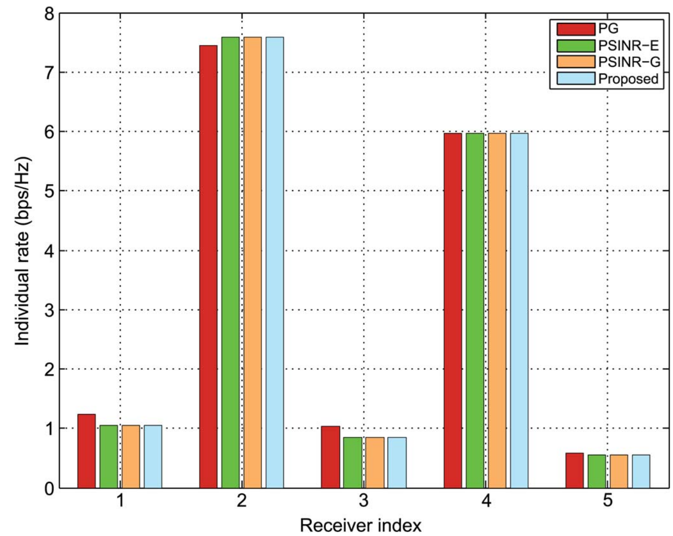

Fig. 2. Individual rates when $(M, N, K) = (5, 5, 5)$ and SNR = 15 dB.

First, we confirm the effectiveness of the PSINR metric and the algorithms in Section IV. Individual rates with $(M, N, K) = (5, 5, 5)$ and SNR = 15 dB for a given channel realization are illustrated in Fig. 2. For this channel realization, the optimal receiver set from PSINR-E is $\Omega_{\text{opt}} = \{2, 4\}$. The proposed scheme and PSINR-G successfully produce the optimal receiver set as well. Interestingly, the individual rates for the PG method are very similar to the PSINR based schemes. This implies that we can achieve the performance close to the PG method as long as the receiver set Ω is properly chosen.

Next, we compare the average sum-rate of the proposed scheme with reference schemes. Along with reference schemes in Section V, we additionally consider three simple schemes for reference, i.e., minimizing interference (MI), time division multiple access (TDMA) and MRT. The MI scheme minimizes the sum of interference at the receivers by solving a simple convex QCQP using a bi-section method. For the TDMA scheme, transmitters send the signal in orthogonal time slots with round-robin scheduling and the cognitive relay assists only one transmitter corresponding to each time slot. Also the MRT scheme aligns the precoder at the cognitive relay to its channel, i.e., $\mathbf{v}_i = \sqrt{P_c}\frac{\mathbf{h}_{ci}}{\|\mathbf{h}_{ci}\|}, \forall i$.

Figs. 3 and 4 illustrate the average sum-rate for various schemes with $(M, N, K) = (3, 3, 3)$ and $(5, 5, 5)$, respectively. First, it can be seen that PSINR-E shows at most a 5% loss compared to the PG method. Also, both PSINR-G and the proposed scheme exhibit the performance very close to that of PSINR-E with reduced complexity. Also comparing PSINR-S and PSINR-U with the proposed scheme, we can check that

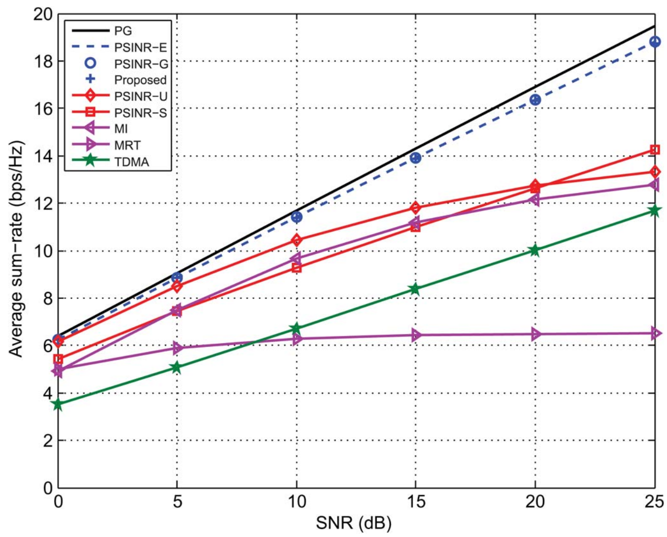

Fig. 3. Average sum-rate performance when $(M, N, K) = (3, 3, 3)$.

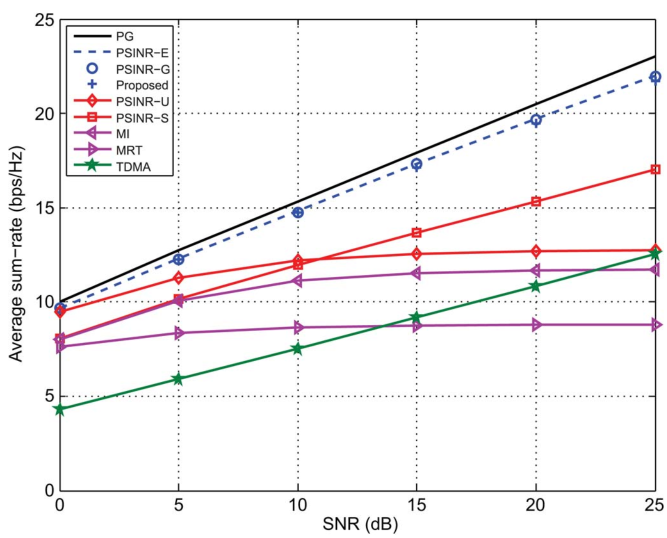

Fig. 4. Average sum-rate performance when $(M, N, K) = (5, 5, 5)$.

optimizing Ω is critical in maximizing the performance. The performance of PSINR-U is shown to be better than PSINR-S at the low SNR region. However, a cross-over point occurs over the moderate SNR region. For PSINR-U, the cognitive relay designs the precoder considering the SINRs of all transmitters, and thus this invokes substantial interference which incurs performance degradations. Therefore, at the high SNR region, PSINR-S outperforms PSINR-U. Also, comparing Figs. 3 and 4, we can see that the cross-over point exists at lower SNR as K grows, since a larger K causes more interference. The performance of MI shows trend similar to PSINR-U, but there is a performance gap between both scheme. Also, TDMA shows the same slope as PSINR-S and a performance gap between TDMA and PSINR-S exists since the PSINR-S supports more transmitters, and this performance gap gets lager as K increases. The performance of MI, MRT and PSINR-U are saturated at the high SNR region due to the interference limited environment.

Fig. 5 shows the average sum-rate performance with the different number of antennas and transmitters. Comparing

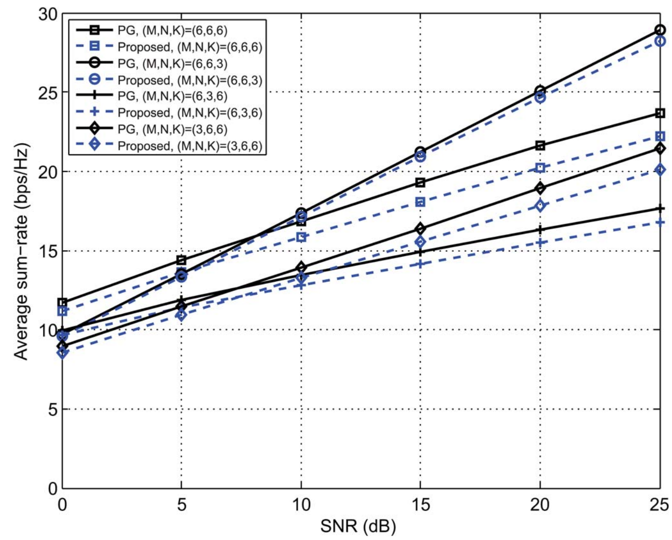

Fig. 5. Average sum-rate performance for various system configurations.

$(M, N, K) = (6, 6, 6)$ and $(6, 6, 3)$, we can see that the slope of the latter is higher than that of the former since a larger K invokes more interference. Also, a performance loss of the proposed scheme over the PG method slightly increases as K gets large since the set search size increases in terms of K and the proposed scheme may fail to find Ω_{opt}. Also, it is observed that the performance of $(M, N, K) = (3, 6, 6)$ and $(6, 3, 6)$ is inferior to that of $(M, N, K) = (6, 6, 6)$. Particularly, the case of $(M, N, K) = (6, 3, 6)$ has the lowest slope among all configurations. This implies that the number of antennas at the cognitive relay should be equal to or larger than that of receivers.

Finally, we investigate the impact of the strength of interfering channels and the cognitive relay channel on the performance. To take into account the intensity of channels, we generate interference channels and channels from the cognitive relay with $E[\mathbf{h}_{ij}\mathbf{h}_{ij}^{\mathrm{H}}] = \alpha \mathbf{I}_M, \forall i \neq j$ and $E[\mathbf{h}_{ci}\mathbf{h}_{ci}^{\mathrm{H}}] = \beta \mathbf{I}_N, \forall i$ where the strength of channels is adjusted by two parameters α and β. For instance, the receivers experience stronger interferences as α increases, and a large β strengthen the signal from the cognitive relay. Fig. 6 represents the average sum-rate with respect to α when $\beta = 1$, $(M, N, K) = (5, 5, 5)$ and $\text{SNR} = 15$ dB. In this plot, we can observe that performance of all schemes except TDMA get worse as α increases since a larger α incurs more interference. Also, the cross-over point of PSINR-U and PSINR-S occurs when α is about 0.8. PSINR-U performs better than PSINR-S with small α, which implies that the cognitive relay concentrates on more receivers when the interfering channel is weaker. On the other hand, PSINR-S not only outperforms PSINR-U but also approaches the proposed scheme as α increases. In addition, the performance gap between the proposed scheme and the PG method is negligible, and the proposed scheme shows large gains over other schemes at small α.

Fig. 7 exhibits the average sum-rate with respect to β when $\alpha = 1$, $(M, N, K) = (5, 5, 5)$ and $\text{SNR} = 15$ dB. In Fig. 7, it is remarkable that a performance gain of the proposed scheme over PSINR-S and PSINR-U greatly increases with respect to β. In practice, a cognitive relay is often located closer to a

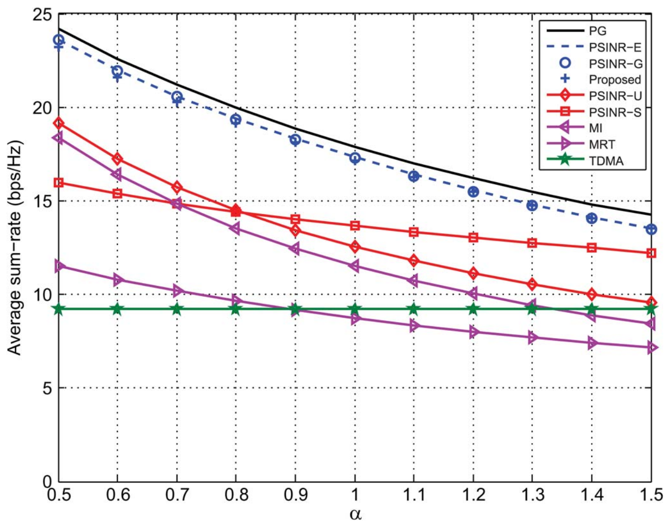

Fig. 6. Average sum-rate in terms of α when $\beta = 1$, $(M, N, K) = (5, 5, 5)$ and SNR = 15 dB.

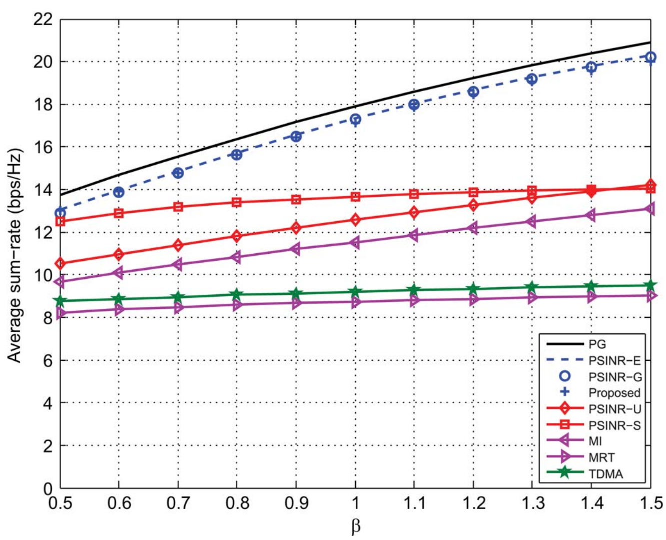

Fig. 7. Average sum-rate in terms of β when $\alpha = 1$, $(M, N, K) = (5, 5, 5)$ and SNR = 15 dB.

receiver compared to other transmitters, and thus the gain of the proposed scheme will be more pronounced in such a scenario. Furthermore, we can see that the cognitive relay can manage greater interference as β increases from the observation that the slope of the PSINR-U curve is higher than that of PSINR-S. Lastly, TDMA shows very poor performance for large β, which explains that the orthogonal transmission is not a good strategy when the channels from the cognitive relay are strong.

VII. Conclusion

In this paper, we have investigated linear precoders at the cognitive relay which maximize the sum-rate performance in K-user MISO IFC-CR. First, we have introduced a performance metric called PSINR. Also, we have presented the optimal solution for the PSINR maximization problem. Next, we have studied receiver set search methods and developed a low complexity set search scheme. Combining a solution for the PSINR maximization problem and the low complexity set search method, we have proposed a sum-rate maximization scheme. In numerical results, we have confirmed that our proposed scheme efficiently maximizes the sum-rate and shows a negligible performance loss compared to the PG method with much reduced complexity.

Appendix A
Proof for Lemma 1

Let Ω^c be the complement set of Ω. Then, $\Gamma(\Omega) - \Gamma(U)$ becomes

$$\begin{aligned}
&\Gamma(\Omega) - \Gamma(U)\\
&= \frac{\Sigma_{i\in\Omega} S_i \left(\Sigma_{i=1}^{K} I_i + K\right) - \Sigma_{i=1}^{K} S_i \left(\Sigma_{i\in\Omega} I_i + |\Omega|\right)}{\left(\Sigma_{i\in\Omega} I_i + |\Omega|\right)\left(\Sigma_{i=1}^{K} I_i + K\right)}\\
&= \frac{\Sigma_{i\in\Omega} S_i \left(\Sigma_{i\in\Omega^c} I_i + |\Omega^c|\right) - \Sigma_{i\in\Omega^c} S_i \left(\Sigma_{i\in\Omega} I_i + |\Omega|\right)}{\left(\Sigma_{i\in\Omega} I_i + |\Omega|\right)\left(\Sigma_{i=1}^{K} I_i + K\right)} \quad (14)
\end{aligned}$$

where the last equality comes from $K = |U| = |\Omega| + |\Omega^c|$.

The condition $\Gamma(\Omega) - \Gamma(U) \geq 0$ occurs when the numerator of (14) is non-negative. Therefore, $\Gamma(\Omega) \geq \Gamma(U)$ is satisfied as long as

$$\frac{\sum_{i\in\Omega} S_i}{\sum_{i\in\Omega} I_i + |\Omega|} \geq \frac{\sum_{i\in\Omega^c} S_i}{\sum_{i\in\Omega^c} I_i + |\Omega^c|}. \quad (15)$$

Since the inequality (15) implies $\Gamma(\Omega) \geq \Gamma(\Omega^c)$, we see that $\Gamma(\Omega) - \Gamma(U) \geq 0$ is equivalent to $\Gamma(\Omega) \geq \Gamma(\Omega^c)$. As it is possible to find Ω such that $\Gamma(\Omega) \geq \Gamma(\Omega^c)$ by simply interchanging Ω with Ω^c when $\Gamma(\Omega) \leq \Gamma(\Omega^c)$, Ω which fulfills $\Gamma(\Omega) \geq \Gamma(U)$ always exists.

Then, one can easily check that $\log(1 + \Gamma(\Omega))$ is also a lower bound of R_Σ as

$$\begin{aligned}
R_\Sigma &= \sum_{i\in\Omega} \log\left(1+\gamma_i\right) + \sum_{i\in\Omega^c} \log\left(1+\gamma_i\right)\\
&\geq \sum_{i\in\Omega} \log\left(1+\frac{S_i}{\sum_{i\in\Omega} I_i + |\Omega|}\right) + \sum_{i\in\Omega^c} \log\left(1+\frac{S_i}{\sum_{i\in\Omega^c} I_i + |\Omega^c|}\right)\\
&\geq \log\left(1+\Gamma(\Omega)\right) + \log\left(1+\Gamma(\Omega^c)\right)\\
&\geq \log\left(1+\Gamma(\Omega)\right). \quad (16)
\end{aligned}$$

We can now conclude that $\log(1+\Gamma(\Omega))$ becomes a tighter lower bound of the sum-rate than $\log(1 + \Gamma(U))$ with the relation $\Gamma(\Omega) \geq \Gamma(U)$.

Appendix B
Proof for Lemma 2

The Lagrangian function for (8) is given by

$$\mathcal{L}\left(\{\mathbf{v}_i\}, \lambda\right) = \frac{\left|\mathbf{h}_{11}^{\mathrm{H}}\mathbf{w}_1 + \mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_1\right|^2}{\sum_{j=2}^{K}\left|\mathbf{h}_{j1}^{\mathrm{H}}\mathbf{w}_j + \mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_j\right|^2 + 1} - \lambda\left(\sum_{i=1}^{K}\|\mathbf{v}_i\|^2 - P_c\right), \quad (17)$$

where λ is the Lagrange multiplier. Taking a derivative of (17) with respect to $\mathbf{v}_i$, it follows:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{v}_i} = \begin{cases} \dfrac{(\mathbf{h}_{11}^{\mathrm{H}}\mathbf{w}_1+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_1)^*\mathbf{h}_{c1}^{\mathrm{H}}}{\sum_{j=2}^{K}\left|\mathbf{h}_{j1}^{\mathrm{H}}\mathbf{w}_j+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_j\right|^2+1} - \lambda\mathbf{v}_1^{\mathrm{H}}, & \text{for } i=1 \\ -\dfrac{|\mathbf{h}_{11}^{\mathrm{H}}\mathbf{w}_1+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_1|^2(\mathbf{h}_{i1}^{\mathrm{H}}\mathbf{w}_i+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_i)^*\mathbf{h}_{c1}^{\mathrm{H}}}{\left(\sum_{j=2}^{K}\left|\mathbf{h}_{j1}^{\mathrm{H}}\mathbf{w}_j+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_j\right|^2+1\right)^2} - \lambda\mathbf{v}_i^{\mathrm{H}}, & \text{otherwise.} \end{cases} \tag{18}$$

When $\lambda = 0$ in (18), the stationary condition becomes $\gamma_1 = 0$ since $\mathbf{h}_{11}^{\mathrm{H}}\mathbf{w}_1 + \mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_1$ should be zero. Therefore, λ must be positive, which leads to $\sum_{i=1}^{K}\|\mathbf{v}_{i,\mathrm{opt}}\|^2 = P_c$ due to the complementary slackness condition. With a nonzero λ, the stationary condition becomes

$$\mathbf{v}_i = \begin{cases} \dfrac{(\mathbf{h}_{11}^{\mathrm{H}}\mathbf{w}_1+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_1)}{\lambda\left(\sum_{j=2}^{K}\left|\mathbf{h}_{j1}^{\mathrm{H}}\mathbf{w}_j+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_j\right|^2+1\right)}\mathbf{h}_{c1}, & \text{for } i=1 \\ -\dfrac{|\mathbf{h}_{11}^{\mathrm{H}}\mathbf{w}_1+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_1|^2(\mathbf{h}_{i1}^{\mathrm{H}}\mathbf{w}_i+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_i)}{\lambda\left(\sum_{j=2}^{K}\left|\mathbf{h}_{j1}^{\mathrm{H}}\mathbf{w}_j+\mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_j\right|^2+1\right)^2}\mathbf{h}_{c1}, & \text{otherwise.} \end{cases} \tag{19}$$

Thus, it is clear that the optimal beamforming vectors should be aligned to $\mathbf{h}_{c1}$.

Appendix C
Proof for Theorem 1

Since the optimal beamforming vectors at the cognitive relay should be aligned to $\mathbf{h}_{c1}$ from Lemma 2, the beamforming vector $\{\mathbf{v}_i\}$ can be expressed as

$$\mathbf{v}_i = v_i \frac{\mathbf{h}_{c1}}{\|\mathbf{h}_{c1}\|^2}, \tag{20}$$

where v_i is the inner product between $\mathbf{h}_{c1}$ and $\mathbf{v}_i$ as $v_i = \mathbf{h}_{c1}^{\mathrm{H}}\mathbf{v}_i$. By changing the inequality in problem (8) to the equality in accordance with Lemma 2 and plugging (20) into problem (8), the equivalent problem (10) is obtained.

Now, we derive the analytic optimal solution for the equivalent problem (10) from the Karush-Khun-Tucker (KKT) condition. The Lagrange function for problem (10) is given by

$$\mathcal{L}(\{v_i\}, \mu) = \frac{|h_{11}+v_1|^2}{\sum_{j=2}^{K}|h_{j1}+v_j|^2+1} + \mu\left(\sum_{i=1}^{K}|v_i|^2 - \tilde{P}_c\right), \tag{21}$$

where μ is a Lagrange multiplier. By taking the derivative of $\mathcal{L}$ with respect to v_2 and considering the stationary condition,[3] it follows:

$$\mathcal{L}_d(v_2) \triangleq \frac{\partial \mathcal{L}}{\partial v_2} = -\frac{|h_{11}+v_1|^2(h_{21}+v_2)^*}{\left(\sum_{j=2}^{K}|h_{j1}+v_j|^2+1\right)^2} + \mu v_2^* = 0. \tag{22}$$

[3]Although we differentiate $\mathcal{L}$ with respect v_2 for simplicity, the optimal solution does not change as long as $\mathcal{L}$ is differentiated with respect to v_m for $m \neq 1$.

After solving $v_n^*\mathcal{L}_d(v_2) = v_2^*\mathcal{L}_d(v_n)$ for $n \neq 1$ and 2, we obtain

$$v_n = \frac{h_{n1}}{h_{21}} v_2. \tag{23}$$

By plugging (23) into problem (10), we have

$$\begin{aligned} \max_{v_1, v_2} \quad & \frac{|h_{11}+v_1|^2}{\zeta|h_{21}+v_2|^2+1} \\ \text{subject to} \quad & |v_1|^2 + \zeta|v_2|^2 = \tilde{P}_c, \end{aligned} \tag{24}$$

where $\zeta \triangleq \sum_{j=2}^{K}|h_{j1}|^2/|h_{21}|^2$.

Since the objective function is maximized when $\angle v_1 = \angle h_{11}$ and $\angle v_2 = \pi + \angle h_{21}$, problem (24) is reduced to

$$\begin{aligned} \max_{x_1 \geq 0, x_2 \geq 0} \quad & \frac{(|h_{11}|+x_1)^2}{\zeta\,(|h_{21}|-x_2)^2+1} \\ \text{subject to} \quad & x_1^2 + \zeta x_2^2 = \tilde{P}_c, \end{aligned} \tag{25}$$

where $x_1 = |v_1|$ and $x_2 = |v_2|$, respectively.

Then, the Lagrangian function for (25) is written by

$$\begin{aligned} &\mathcal{J}(x_1, x_2, \lambda_1, \lambda_2, \nu) \qquad (26) \\ &= \frac{(|h_{11}|+x_1)^2}{\zeta\,(|h_{21}|-x_2)^2+1} + \lambda_1 x_1 + \lambda_2 x_2 + \nu\left(x_1^2 + \zeta x_2^2 - \tilde{P}_c\right), \end{aligned}$$

where λ_1, λ_2, and ν are Lagrange multipliers. The stationary conditions are expressed as

$$\begin{aligned} &\mathcal{J}_d(x_1) \triangleq \frac{\partial \mathcal{J}}{\partial x_1} = \frac{2\,(|h_{11}|+x_1)}{\zeta\,(|h_{21}|-x_2)^2+1} + \lambda_1 + 2\nu x_1 = 0 \\ &\mathcal{J}_d(x_2) \qquad (27) \\ &\triangleq \frac{\partial \mathcal{J}}{\partial x_2} = \frac{2\zeta\,(|h_{11}|+x_1)^2\,(|h_{21}|-x_2)}{\left(\zeta\,(|h_{21}|-x_2)^2+1\right)^2} + \lambda_2 + 2\nu\zeta x_2 = 0. \end{aligned}$$

If $x_1 = 0$ or $x_2 = 0$, then the stationary condition leads to negative λ_1 or λ_2, which violates the dual feasibility conditions $\lambda_1 \geq 0$ and $\lambda_2 \geq 0$. Thus, the Lagrange multipliers λ_1 and λ_2 must be zero to satisfy the complementary slackness condition. Solving $\zeta x_2 \mathcal{J}_d(x_1) = x_1 \mathcal{J}_d(x_2)$ yields

$$\left(\zeta\,(|h_{21}|-x_2)^2+1\right)x_2 = (|h_{11}|+x_1)\,(|h_{21}|-x_2)\,x_1. \tag{28}$$

Substituting $x_1^2 = \tilde{P}_c - \zeta x_2^2$ to (28), it follows:

$$\begin{aligned} &|h_{11}|\,(|h_{21}|-x_2)\,x_1 \\ &= -|h_{21}|\zeta x_2^2 + \left(\tilde{P}_c + \zeta|h_{21}|^2+1\right)x_2 - |h_{21}|\tilde{P}_c. \end{aligned} \tag{29}$$

Then, squaring both sides of (29) and plugging $x_1^2 = \tilde{P}_c - \zeta x_2^2$ again, we arrive at the following quartic equation as

$$c_4 x_2^4 + c_3 x_2^3 + c_2 x_2^2 + c_1 x_2 + c_0 = 0, \tag{30}$$

where

$$c_4 = \zeta \left(\zeta |h_{21}|^2 + |h_{11}|^2\right),$$
$$c_3 = -2\zeta |h_{21}| \left(|h_{11}|^2 + \tilde{P}_c + \zeta |h_{21}|^2 + 1\right),$$
$$c_2 = 2\zeta \tilde{P}_c |h_{21}|^2 + \left(\tilde{P}_c + \zeta |h_{21}|^2 + 1\right)^2 + |h_{11}|^2 \left(\zeta |h_{21}|^2 - \tilde{P}_c\right),$$
$$c_1 = 2\tilde{P}_c |h_{21}| \left(|h_{11}|^2 - \tilde{P}_c - \zeta |h_{21}|^2 - 1\right),$$
$$c_0 = \tilde{P}_c |h_{21}|^2 \left(\tilde{P}_c - |h_{11}|^2\right),$$

Denoting $x_{2,\mathrm{opt}}$ as the optimal solution for problem (25), $x_{2,\mathrm{opt}}$ can be chosen as one of positive roots of (30) which maximizes the objective function in (25) with $x_{1,\mathrm{opt}} = \sqrt{\tilde{P}_c - \zeta x_{2,\mathrm{opt}}^2}$. Finally, for given $x_{1,\mathrm{opt}}$ and $x_{2,\mathrm{opt}}$ the optimal solution for problem (10) is computed by

$$v_{i,\mathrm{opt}} = \begin{cases} x_{1,\mathrm{opt}} \frac{h_{11}}{|h_{11}|}, & \text{for } i = 1 \\ -x_{2,\mathrm{opt}} \frac{h_{i1}}{|h_{21}|}, & \text{otherwise} \end{cases} \tag{31}$$

where $v_{i,\mathrm{opt}}$ for $i = 3, \cdots, K$ is obtained by using relation (23).

Appendix D
Proof for the Equivalence Between (11) and (12)

By introducing a complex auxiliary variable t and substituting $\tilde{\mathbf{v}} = t\mathbf{v} \in \mathbb{C}^{NK}$ into (11), problem (11) can be rewritten as

$$\begin{aligned} \max_{\tilde{\mathbf{v}},t} \quad & f_1(\tilde{\mathbf{v}}, t) \\ \text{subject to} \quad & \|\tilde{\mathbf{v}}\|^2 \le |t|^2 P_c, \end{aligned} \tag{32}$$

where

$$f_1(\tilde{\mathbf{v}}, t) \triangleq \frac{\tilde{\mathbf{v}}^{\mathrm{H}}\mathbf{A}\tilde{\mathbf{v}} + 2\Re\{t^* \mathbf{w}^{\mathrm{H}}\mathbf{B}\tilde{\mathbf{v}}\} + |t|^2 \mathbf{w}^{\mathrm{H}}\mathbf{C}\mathbf{w}}{\tilde{\mathbf{v}}^{\mathrm{H}}\mathbf{D}\tilde{\mathbf{v}} + 2\Re\{t^* \mathbf{w}^{\mathrm{H}}\mathbf{E}\tilde{\mathbf{v}}\} + |t|^2 \mathbf{w}^{\mathrm{H}}\mathbf{F}\mathbf{w}}.$$

Now, consider the following maximization problem:

$$\begin{aligned} \max_{\tilde{\mathbf{v}},t} \quad & f_2(\tilde{\mathbf{v}}, t) \\ \text{subject to} \quad & \|\tilde{\mathbf{v}}\|^2 \le |t|^2 P_c \\ & g(\tilde{\mathbf{v}}, t) \le 1, \end{aligned} \tag{33}$$

where

$$f_2(\tilde{\mathbf{v}}, t) \triangleq \tilde{\mathbf{v}}^{\mathrm{H}}\mathbf{A}\tilde{\mathbf{v}} + 2\Re\{t^* \mathbf{w}^{\mathrm{H}}\mathbf{B}\tilde{\mathbf{v}}\} + |t|^2 \mathbf{w}^{\mathrm{H}}\mathbf{C}\mathbf{w},$$
$$g(\tilde{\mathbf{v}}, t) \triangleq \tilde{\mathbf{v}}^{\mathrm{H}}\mathbf{D}\tilde{\mathbf{v}} + 2\Re\{t^* \mathbf{w}^{\mathrm{H}}\mathbf{E}\tilde{\mathbf{v}}\} + |t|^2 \mathbf{w}^{\mathrm{H}}\mathbf{F}\mathbf{w}.$$

Note that the objective function in problem (32) $f_1(\tilde{\mathbf{v}}, t)$ is identical to $f_2(\tilde{\mathbf{v}}, t)/g(\tilde{\mathbf{v}}, t)$.

Let $\mathcal{S}_1$ and $\mathcal{S}_2$ be the feasible set of problems (32) and (33), respectively. Denoting $\tilde{\mathbf{v}}_{1,\mathrm{opt}}$ and $t_{1,\mathrm{opt}}$ as the optimal solutions for problem (32), it can be easily checked that $(\tilde{\mathbf{v}}_2, t_2)$ belongs to $\mathcal{S}_2$ where

$$\tilde{\mathbf{v}}_2 = \frac{\tilde{\mathbf{v}}_{1,\mathrm{opt}}}{\sqrt{g(\tilde{\mathbf{v}}_{1,\mathrm{opt}}, t_{1,\mathrm{opt}})}}, \; t_2 = \frac{t_{1,\mathrm{opt}}}{\sqrt{g(\tilde{\mathbf{v}}_{1,\mathrm{opt}}, t_{1,\mathrm{opt}})}}. \tag{34}$$

Then, we have

$$\begin{aligned} \max_{(\tilde{\mathbf{v}},t)\in\mathcal{S}_1} f_1(\tilde{\mathbf{v}}, t) &= f_1(\tilde{\mathbf{v}}_{1,\mathrm{opt}}, t_{1,\mathrm{opt}}) \\ &= f_2(\tilde{\mathbf{v}}_2, t_2) \\ &\le \max_{(\tilde{\mathbf{v}},t)\in\mathcal{S}_2} f_2(\tilde{\mathbf{v}}, t). \end{aligned} \tag{35}$$

Similarly, defining $\tilde{\mathbf{v}}_{2,\mathrm{opt}}$ and $t_{2,\mathrm{opt}}$ as the optimal solutions for problem (33), we obtain

$$\begin{aligned} \max_{(\tilde{\mathbf{v}},t)\in\mathcal{S}_2} f_2(\tilde{\mathbf{v}}, t) &= f_2(\tilde{\mathbf{v}}_{2,\mathrm{opt}}, t_{2,\mathrm{opt}}) \\ &\overset{(a)}{\le} f_1(\tilde{\mathbf{v}}_{2,\mathrm{opt}}, t_{2,\mathrm{opt}}) \\ &\overset{(b)}{\le} \max_{(\tilde{\mathbf{v}},t)\in\mathcal{S}_1} f_1(\tilde{\mathbf{v}}, t), \end{aligned} \tag{36}$$

where the inequality (a) follows from the inequality constraint of problem (33) and the inequality (b) holds since $(\tilde{\mathbf{v}}_{2,\mathrm{opt}}, t_{2,\mathrm{opt}})$ also belongs to $\mathcal{S}_1$. As a result, we can check that the optimal values of both problems (32) and (33) are identical since the inequalities (35) and (36) hold simultaneously, and thus we can see that $(\tilde{\mathbf{v}}_2, t_2)$ is the optimal solution for (33), which reveals the equivalance between problems (32) and (33). Furthermore, problem (33) can be easily recast as the homogeneous QCQP (12) by letting $\hat{\mathbf{v}} = \left[\tilde{\mathbf{v}}^{\mathrm{T}} \; t\right]^{\mathrm{T}}$. This concludes the proof.

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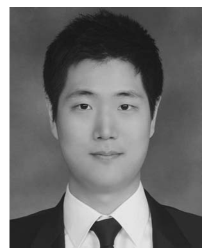

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