Transceiver Optimization for the Multi-Antenna Downlink in MIMO Cognitive System

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Abstract

Transceiver optimization in multiple input multiple output (MIMO) cognitive systems is studied in this paper. The joint transceiver beamformer design is introduced to minimize the transmit power at secondary base station (SBS) while simultaneously controlling the interference to primary users (PUs) and satisfying the secondary users (SUs) signal-to-interference-plus-noise ratio (SINR) based on the convex optimization method. Due to the limited cooperation between SBS and PUs, the channel state information (CSI) usually cannot be obtained perfectly at the SBS in cognitive system. In this study, both perfect and imperfect CSI scenarios are considered in the beamformer design, and the proposed method is robust to CSI error. Numerical results validate the effectiveness of the proposed algorithm.

Keywords: cognitive radio, multiple input multiple output, transceiver beamforming, convex optimization, robust

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1. Introduction

With the rapid development of the wireless mobile communication technology, the scarcity of the radio spectrum becomes an urgently called-for problem. In order to alleviate this problem and improve the bandwidth efficiency, Dr. J. Mitola proposed the concept of cognitive radio (CR) in 1999[1]. In a cognitive radio system, secondary systems can work in the spectrum of primary systems with spectrum sensing while ensuring that the interference to primary systems is below an acceptable level. Because of the coexistence of different systems, the interference suppression is an important issue in cognitive system. Multiple input multiple output (MIMO) has been exploited in cognitive systems, and has emerged as an efficient and promising approach to suppress the interference and improve the spectrum efficiency.

In cognitive MIMO systems, the SBS utilizes multiple antennas to form a directional beam which steers energy with beam patterns towards the receiver within a certain area to suppress the interference and improve the system performance [2-8]. A novel statistically robust cognitive radio beamformer was proposed in [3], where the total SBS transmit power is minimized subject to the outage probability constraints of PUs and SUs. Dana [4] proposed an iterative transmit beamforming and power allocation technique for interference limited cognitive networks. Ref. [5] proposed a robust cognitive beamformer to maximize the minimum of the received signal-to-interference-plus-noise ratio of the SUs, while [6] designed a new beamformer to maximize the service probability of the SUs. An optimal relay selection and beamforming scheme is studied in [7], where the capacity of the secondary user is maximized by selecting the best cognitive MIMO relay. The performance of the cognitive radio system can also be enhanced by designing the optimal received beamformer. Huiqin Du [8] designed a joint transceiver beamformer to improve the performance of MIMO cognitive radio networks by using the second-order cone programming method. In a cognitive radio system, the existence of the primary system may also cause interference to the secondary system and cannot be neglected in some practical scenarios. However, this kind of interference is usually not considered in traditional beamforming methods, resulting in the performance loss at SUs.

In this paper, the transceiver optimization scheme is studied and a joint transmit and receive beamformer is designed to minimize the transmit power of SBS subject to both quality-of-service (QoS) constraints of SUs and interference limits of PUs. In the practical cognitive radio scenarios, CSI sometimes cannot be perfectly obtained at SBS [8-10]. Therefore, both perfect and imperfect CSI conditions are considered in the algorithm design. The interference from PBS to SUs is also taken into account to design the optimal transceiver beamformer. Since the original transceiver optimization problem is NP-hard, we propose an iterative algorithm by applying variable separation method based on the convex optimization theory. Simulation results show that the proposed algorithm can improve the performance of secondary system in both perfect and imperfect CSI scenarios and has a fast convergence speed.

The remainder of this paper is organized as follows. In section 2, the system model is introduced. The transceiver optimization problem is formulated in Section 3. To solve this problem, a novel transceiver beamforming algorithm is introduced in section 4. In section 5, simulation results are given and finally, conclusions are drawn in section 6.

2. System Model

The scenario of cognitive radio system is shown in **Fig. 1**. The multiple SU links consisting of one SBS and K SUs coexist with the multiple PU links consisting of one primary base station (PBS) and L PUs. The number of antennas equipped at SBS and SUs are N_t and N_r, respectively. The rest of nodes in the system are configured with single antenna.

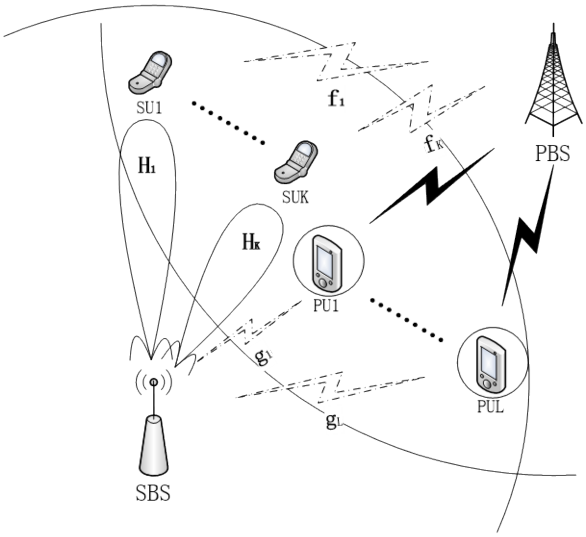

Fig. 1. CR-MIMO System Model

The downlink channels from the SBS to the i th SU and the j th PU are represented by $\mathbf{H}_i \in \mathbb{C}^{N_r \times N_t}$ and $\mathbf{g}_j \in \mathbb{C}^{N_t}$, $i = 1,2...K$, $j = 1,2...L$, respectively. The channel from the PBS to the i th SU is denoted as $\mathbf{f}_i \in \mathbb{C}^{N_r}$. All of above channel coefficients are assumed to be independent circularly symmetric complex Gaussian random variables with zero mean and unit variance. The received signal at the k th SU is given by

$$y_k^s = \mathbf{r}_k^H (\mathbf{H}_k \mathbf{t}_k s_k + \sum_{\substack{i=1 \\ i \neq k}}^{K} \mathbf{H}_k \mathbf{t}_i s_i + \sum_{l=1}^{L} \sqrt{\frac{P_p}{L}} \mathbf{f}_k u_l + \mathbf{n}_k^s) \tag{1}$$

where $\mathbf{t}_k \in \mathbb{C}^{N_t}$ and $\mathbf{r}_k \in \mathbb{C}^{N_r}$ are the transmit and receive cognitive beamformers for the k th SU, and $\|\mathbf{r}_k\|^2 = 1$. The total transmit power of the SBS is $\sum_{k=1}^{K} \mathbf{t}_k^H \mathbf{t}_k$. $\mathbf{n}_k^s$ is the white Gaussian noise at the k th SU, whose entries are complex additive Gaussian distributed, i.e., $\mathbf{n}_k^s \sim CN(0, \sigma_k^{s2}\mathbf{I})$, $k = 1...K$. s_k and u_l donate the message-bearing symbols transmitted to the k th SU and the l th PU with the power constraints $E\left[\|s_k\|^2\right] = 1$, $E\left[\|u_l\|^2\right] = 1$, respectively. P_p denotes the transmit power of PBS and the power allocated to each PUs is P_p/L. Then the downlink receiving SINR of the k th SU can be written as

$$SINR_{SU_k} = \frac{\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_k\right\|^2}{\sum_{i=1,i\neq k}^{K}\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_i\right\|^2 + \sum_{l=1}^{L}\left\|\sqrt{\frac{P_p}{L}}\mathbf{r}_k^H \mathbf{f}_k\right\|^2 + \sigma_k^{s2}}, k = 1...K \tag{2}$$

where the numerator is the desired signal power and the denominator is the interference plus noise power. The received interference signal at the l th PU can be expressed as

$$y_l^p = \sum_{i=1}^{K} \mathbf{g}_l^H \mathbf{t}_i s_i, l = 1...L \tag{3}$$

and the interference power at the l th PU can be written as

$$I_{PU_l} = \sum_{i=1}^{K}\left\|\mathbf{g}_l^H \mathbf{t}_i\right\|^2, l = 1...L \tag{4}$$

3. Transceiver Optimization with Perfect CSI

In this section, we formulate the transceiver optimization problem with perfect CSI at the transmitter. Given the SINR boundary of SUs and acceptable interference level of PUs, the transceiver optimization problem to minimize the transmit power of SBS can be formulated as

$$\min_{\{\mathbf{t}_k, \mathbf{r}_k\}_{k=1}^{K}} \quad \sum_{k=1}^{K} \mathbf{t}_k^H \mathbf{t}_k \tag{5a}$$

$$s.t. \frac{\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_k\right\|^2}{\sum_{i=1,i\neq k}^{K}\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_i\right\|^2 + \sum_{l=1}^{L}\left\|\sqrt{\frac{P_p}{L}}\mathbf{r}_k^H \mathbf{f}_k\right\|^2 + \sigma_k^{s2}} \geq \gamma_k \quad k = 1,2...K \tag{5b}$$

$$\sum_{i=1}^{K}\left\|\mathbf{g}_l^H \mathbf{t}_i\right\|^2 \leq \xi_l, l = 1,2...L \tag{5c}$$

$$\left\|\mathbf{r}_k\right\|^2 = 1 \quad , k = 1,2...K \tag{5d}$$

where γ_k denotes the received SINR requirement of the k th SU, and ξ_l is the acceptable interference threshold of the l th PU. $\mathbf{t}_k, \mathbf{r}_k, k = 1,...,K$ are the transmit and receive beamforming vectors of the k th SU. The problem (5) is a non-convex quadratically constrained quadratic programming (QCQP) problem which is difficult to be solved by traditional methods [3][11]. Instead of solving the problem (5) directly, we introduce a two-step strategy to solve this problem. Firstly, transform the optimization problem (5), which includes two kinds of variables $\mathbf{t}_k, \mathbf{r}_k, k = 1,...,K$, into two problems with single kind of variable. Then solve these two problems separately. Accordingly, we first reformulate the problem (5) by fixing $\mathbf{r}_k$. The following optimization problem is obtained.

$$\min_{\{\mathbf{t}_k\}_{k=1}^{K}} \quad \sum_{k=1}^{K} \mathbf{t}_k^H \mathbf{t}_k \tag{6a}$$

$$s.t. \frac{\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_k\right\|^2}{\sum_{i=1,i\neq k}^{K} \left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_i\right\|^2 + \sum_{l=1}^{L} \left\|\sqrt{\frac{P_p}{L}} \mathbf{r}_k^H \mathbf{f}_k\right\|^2 + \sigma_k^{s2}} \geq \gamma_k \quad k=1,2...K \tag{6b}$$

$$\sum_{i=1}^{K} \left\|\mathbf{g}_l^H \mathbf{t}_i\right\|^2 \leq \xi_l, l=1,2...L \tag{6c}$$

According to [12], the problem (6) can be efficiently solved and the optimal transmit beamforming vector $\mathbf{t}_k$ can be obtained. Then we formulated the other one by fixing the remaining variable $\mathbf{t}_k$ as follows.

$$\min_{\{\mathbf{r}_k\}_{k=1}^{K}} \; -\sum_{k=1}^{K} \frac{\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_k\right\|^2}{\sum_{i=1,i\neq k}^{K} \left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_i\right\|^2 + P_p \left\|\mathbf{r}_k^H \mathbf{f}_k\right\|^2 + \sigma_k^{s2}} \tag{7a}$$

$$s.t. \qquad \mathbf{r}_k^H \mathbf{r}_k = 1, \qquad k = 1...K \tag{7b}$$

The problem (7) can be viewed as a receiving beamformer problem that maximizes the total SINR of SUs. The optimal receive beamforming vector $\mathbf{r}_k$ can be obtained from problem (7) by fixing the transmit beamformer $\mathbf{t}_k$. The specific steps of algorithm will be given in the next section.

4. Robust Transceiver Optimization with Imperfect CSI

In section III, we formulate the transceiver optimization problem in the perfect CSI condition and introduce a two-step beamforming strategy. In the practical cognitive radio scenarios, the CSI between SBS and PU and between PBS and SU cannot be obtained perfectly at SBS and PBS. In this section, we consider a more practical scenario that the downlink channels, from SBS to PUs and from PBS to SUs, are imperfect due to the inaccurate channel estimation, outdated CSI, etc. Assume that the estimations of channels from the SBS to the l th PU and from the PBS to the k th SUs, denoted as $\mathbf{g}_l$ 、 $\mathbf{f}_k$, are obtained with errors at SBS. $\boldsymbol{\alpha}_l$ 、 $\boldsymbol{\beta}_k$ are donated as estimation errors between the estimated CSI and the true one. Assume that channel estimation errors are all bounded. That is, $\left\|\boldsymbol{\alpha}_l\right\| \leq \delta$ and $\left\|\boldsymbol{\beta}_k\right\| \leq \varepsilon$, where δ and ε are assumed to be known at the SBS. Then we can reformulate the problem (6) as:

$$\min_{\{\mathbf{t}_k\}_{k=1}^{K}} \quad \sum_{k=1}^{K} \mathbf{t}_k^H \mathbf{t}_k \tag{8a}$$

$$s.t.\frac{\left\|\mathbf{r}_k^H\mathbf{H}_k\mathbf{t}_k\right\|^2}{\sum_{i=1,i\neq k}^{K}\left\|\mathbf{r}_k^H\mathbf{H}_k\mathbf{t}_i\right\|^2+\max_{\|\boldsymbol{\beta}_k\|\le\varepsilon}\sum_{l=1}^{L}\left\|\sqrt{\frac{P_p}{L}}\mathbf{r}_k^H\left(\mathbf{f}_k+\boldsymbol{\beta}_k\right)\right\|^2+\sigma_k^{s2}}\ge\gamma_k \quad k=1,2...K \tag{8b}$$

$$\max_{\|\boldsymbol{\alpha}_l\|\le\delta}\sum_{i=1}^{K}\left\|\left(\mathbf{g}_l^H+\boldsymbol{\alpha}_l\right)\mathbf{t}_i\right\|^2\le\xi_l, l=1,2...L \tag{8c}$$

Note that both the SINR boundary and the interference threshold constraints should be satisfied in the worst CSI condition. Using the triangle inequality and Cauchy-Schwarz inequality, we have

$$\begin{aligned}
&\max_{\|\boldsymbol{\beta}_k\|\le\varepsilon}\left\|\mathbf{r}_k^H\left(\mathbf{f}_k+\boldsymbol{\beta}_k\right)\right\|^2\le\left(\left|\mathbf{r}_k^H\mathbf{f}_k\right|+\left|\mathbf{r}_k^H\boldsymbol{\beta}_k\right|\right)^2\\
&\le\left(\left|\mathbf{r}_k^H\mathbf{f}_k\right|+\varepsilon\left\|\mathbf{r}_k\right\|\right)^2\le\left|\mathbf{r}_k^H\mathbf{f}_k\right|^2+\varepsilon\left\|\mathbf{r}_k\right\|^2(\varepsilon+2\left\|\mathbf{f}_k\right\|)\\
&\max_{\|\boldsymbol{\alpha}_l\|\le\delta}\left\|\left(\mathbf{g}_l^H+\boldsymbol{\alpha}_l\right)\mathbf{t}_i\right\|^2\le\left(\left|\mathbf{g}_l^H\mathbf{t}_i\right|+\left|\boldsymbol{\alpha}_l\mathbf{t}_i\right|\right)^2\\
&\le\left(\left|\mathbf{g}_l^H\mathbf{t}_i\right|+\delta\left\|\mathbf{t}_i\right\|\right)^2\le\left|\mathbf{g}_l^H\mathbf{t}_i\right|^2+\delta\left\|\mathbf{t}_i\right\|^2(\delta+2\left\|\mathbf{g}_l^H\right\|)
\end{aligned}$$

Then substitute the above formulas into the problem (8), the problem (9) is obtained.

$$\min_{\{\mathbf{t}_k\}_{k=1}^K,\,p} \quad p \tag{9a}$$

$$s.t.\frac{\left\|\mathbf{r}_k^H\mathbf{H}_k\mathbf{t}_k\right\|^2}{\sum_{i=1,i\neq k}^{K}\left\|\mathbf{r}_k^H\mathbf{H}_k\mathbf{t}_i\right\|^2+P_p\left(\left|\mathbf{r}_k^H\mathbf{f}_k\right|^2+\varepsilon\left\|\mathbf{r}_k\right\|^2\left(\varepsilon+2\left\|\mathbf{f}_k\right\|\right)\right)+\sigma_k^{s2}}\ge\gamma_k \quad k=1,2...K \tag{9b}$$

$$\sum_{i=1}^{K}\left(\left|\mathbf{g}_l^H\mathbf{t}_i\right|^2+\delta\left\|\mathbf{t}_i\right\|^2\left(\delta+2\left\|\mathbf{g}_l^H\right\|\right)\right)\le\xi_l \quad l=1,2...L \tag{9c}$$

$$\sum_{k=1}^{K}\left\|\mathbf{t}_k\right\|^2\le p \tag{9d}$$

Following [12], the problem (9) can be formulated as a SOCP problem as follows.

$$\min_{\{\mathbf{t}_k\}_{k=1}^K,\,p} \quad p \tag{10a}$$

$$s.t.\begin{bmatrix}\sqrt{1+\frac{1}{\gamma_k}}\mathbf{r}_k^H\mathbf{H}_k\mathbf{t}_k\\ \mathbf{r}_k^H\mathbf{H}_k\mathbf{T}\\ \sqrt{P_p\left(\left|\mathbf{r}_k^H\mathbf{f}_k\right|^2+\varepsilon\left\|\mathbf{r}_k\right\|^2\left(\varepsilon+2\left\|\mathbf{f}_k\right\|\right)\right)+\sigma_k^{s2}}\end{bmatrix}\succeq 0 \quad k=1...K \tag{10b}$$

$$\begin{bmatrix} \sqrt{\xi_l} \\ \mathbf{T}^H \sqrt{\left\|\mathbf{g}_l^H\right\|^2 + \delta\left(\delta + 2\left\|\mathbf{g}_l^H\right\|\right)\mathbf{I}} \end{bmatrix} \succeq 0 \qquad l = 1 \ldots L \tag{10c}$$

$$\begin{bmatrix} \sqrt{p} \\ \mathbf{T} \end{bmatrix} \succeq 0 \tag{10d}$$

where $\mathbf{T} = \left[\mathbf{t}_1\ \mathbf{t}_2\ \mathbf{t}_3\ \ldots\ \mathbf{t}_K\right]$. In the problem (10), the transformation $\begin{bmatrix} t \\ \mathbf{T} \end{bmatrix} \succeq 0 \Leftrightarrow \left\|\mathbf{T}\right\| \le t$ is used to simplify the problem (9), which is defined in [14]. The problem (10) is a convex problem and can be solved effectively by interior point methods. Similarly, reformulate the problem (7) in imperfect CSI condition as follows.

$$\min_{\{\mathbf{r}_k\}_{k=1}^K} -\sum_{k=1}^K \frac{\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_k\right\|^2}{\sum_{i=1, i\ne k}^K \left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_i\right\|^2 + \max_{\|\boldsymbol{\beta}_k\|\le\varepsilon} P_p \left\|\mathbf{r}_k^H (\mathbf{f}_k + \boldsymbol{\beta}_k)\right\|^2 + \sigma_k^{s2}} \tag{11a}$$

$$s.t.\quad \mathbf{r}_k^H \mathbf{r}_k = 1, \qquad k = 1 \ldots K \tag{11b}$$

By using the triangle inequality and Cauchy-Schwarz inequality, we have

$$\begin{aligned} &\max_{\|\boldsymbol{\beta}_k\|\le\varepsilon} \left\|\mathbf{r}_k^H (\mathbf{f}_k + \boldsymbol{\beta}_k)\right\|^2 \ge \left(\left|\mathbf{r}_k^H \mathbf{f}_k\right| - \left|\mathbf{r}_k^H \boldsymbol{\beta}_k\right|\right)^2 \\ &\ge \left(\left|\mathbf{r}_k^H \mathbf{f}_k\right| - \varepsilon\left\|\mathbf{r}_k\right\|\right)^2 \ge \left|\mathbf{r}_k^H \mathbf{f}_k\right|^2 + \varepsilon\left\|\mathbf{r}_k\right\|^2 (\varepsilon - 2\left\|\mathbf{f}_k\right\|) \end{aligned}$$

Then the problem (11) can be expressed as

$$\min_{\{\mathbf{r}_k\}_{k=1}^K} -\sum_{k=1}^K \frac{\left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_k\right\|^2}{\sum_{i=1, i\ne k}^K \left\|\mathbf{r}_k^H \mathbf{H}_k \mathbf{t}_i\right\|^2 + P_p \left(\left|\mathbf{r}_k^H \mathbf{f}_k\right|^2 + \varepsilon\left\|\mathbf{r}_k\right\|^2 \left(\varepsilon - 2\left\|\mathbf{f}_k\right\|\right)\right) + \sigma_k^{s2}} \tag{12a}$$

$$s.t.\quad \mathbf{r}_k^H \mathbf{r}_k = 1, \qquad k = 1 \ldots K \tag{12b}$$

Note that the problem (12) can be split into K independent problems. Transform the k th problem into fractional semi-definite programming (SDP) form.

$$\max_{\mathbf{R}_k} \quad \frac{\mathrm{tr}\left(\mathbf{A}_k \mathbf{R}_k\right)}{\mathrm{tr}\left(\mathbf{B}_k \mathbf{R}_k\right) + \sigma_k^{s2}} \tag{13a}$$

$$s.t.\quad \mathrm{tr}\left(\mathbf{R}_k\right) = 1 \tag{13b}$$

$$rank\left(\mathbf{R}_k\right) = 1 \tag{13c}$$

where $\mathbf{A}_k = \mathbf{H}_k \mathbf{t}_k \mathbf{t}_k^H \mathbf{H}_k^H$, $\mathbf{R}_k = \mathbf{r}_k \mathbf{r}_k^H$ $\mathbf{B}_k = \sum_{i=1, i \neq k}^{K} \mathbf{H}_k \mathbf{t}_i \mathbf{t}_i^H \mathbf{H}_k^H + P_p \left(\mathbf{f}_k \mathbf{f}_k^H + \varepsilon \left(\varepsilon - 2 \left\| \mathbf{f}_k \right\| \right) \right)$. According to [15], the rank-one constraint (13c) can be relaxed as follows.

$$\max_{\mathbf{R}_k} \quad \frac{\operatorname{tr}\left(\mathbf{A}_k \mathbf{R}_k\right)}{\operatorname{tr}\left(\mathbf{B}_k \mathbf{R}_k\right) + \sigma_k^{s2}} \tag{14a}$$

$$s.t. \quad \operatorname{tr}\left(\mathbf{R}_k\right) = 1 \tag{14b}$$

By using the Charnes-Cooper transformation [13], the problem (14) can be formulated as a convex SDP problem [7]. Let $\operatorname{tr}\left(\mathbf{B}_k \mathbf{R}_k\right) + \sigma_k^{s2} = 1/n_k$ and $\mathbf{M}_k = n_k \mathbf{R}_k$. The problem (14) can be written as

$$\max_{\mathbf{M}_k, n_k} \quad \operatorname{tr}\left(\mathbf{A}_k \mathbf{M}_k\right) \tag{15a}$$

$$s.t. \quad \operatorname{tr}\left(\mathbf{B}_k \mathbf{M}_k\right) + n_k \sigma_k^{s2} = 1 \tag{15b}$$

$$\operatorname{tr}\left(\mathbf{M}_k / n_k \right) = 1 \tag{15c}$$

$$\mathbf{M}_k \succeq 0, n_k \geq 0 \tag{15d}$$

The problem (15) is a convex optimization problem which can be solved by using the interior point method. Then the optimal received beamformer can be obtained from $\mathbf{M}_k$ by using randomization technique.

Accordingly, the original optimization problem can be solved by using the problem (10) and the problem (15) iteratively. The specific iterative algorithm can be described as follows. At the mth iteration, a new $\mathbf{t}_k^{(m+1)}$ can be obtained from the problem (10) with the fixed $\mathbf{r}_k^{(m)}$. Then fix $\mathbf{t}_k^{(m+1)}$ and update $\mathbf{r}_k^{(m+1)}$ from the problem (15). Continue this alternating optimization procedure until convergence. Define η as the stopping criterion of iterations which is represented by the difference between the optimal transmit powers obtained in the mth and the (m+1)th iterations. The proposed algorithm is summarized in **Table 1**.

Table 1. Iterative algorithm

1: initialization m = 0, $\mathbf{r}_k^{(0)} = [1, 0, 0, ..., 0]^T$ and $\eta > 0$
2: **repeat**
3: Fixing $\mathbf{r}_k^{(m)}$, solve $\mathbf{t}_k^{(m+1)}$ from the problem (10);
4: if $m > 0$ and $\left| \sum_{k=1}^{K} \left\| \mathbf{t}_k^{(m+1)} \right\|^2 - \sum_{k=1}^{K} \left\| \mathbf{t}_k^{(m)} \right\|^2 \right| < \eta$, the iterative algorithm converge to a certain point and the transceiver beamformer is obtained; Otherwise, turn to step 5.
5: Fixing $\mathbf{t}_k^{(m+1)}$, solve $\mathbf{r}_k^{(m+1)}$ from the problem (15);
6: m = m+1;
7: **until** the iterative algorithm converges.

Since the proposed algorithm is an iterative method, the total computational complexity of this method depends on the arithmetic complexity in one iteration and the number of iterations.

In the proposed method, a SOCP problem and a SDP problem are involved in each iteration. According to [15], the arithmetic complexity of the SOCP problem (10) is $o((KN_t+1)^{3.5})$ and the arithmetic complexity of the SDP relaxation problem (15), which has been be broken into K independent problems, can be reduced to $o(KN_r{}^{3.5})$. The number of iterations is usually difficult to determine exactly. However, the convergence performance evaluation is given in the simulation part. The simulation results show that the proposed algorithm can usually converge to a fixed point in less than 10 times.

5. Simulation Results

In this section, we present the simulation results to evaluate the performance of the proposed method. Since the performance trends will not be affected as the number of SUs and PUs increased, the case of $K=2$ SUs and $L=1$ PU is considered for simplicity in the simulation. The SBS is equipped with 8 transmit antennas and each of SUs has two receive antennas. Assume that the total transmit power of the PBS is 1W and the noise variance $\sigma_k^{s2}=1$. The interference threshold of the PU is 2W. The stopping criterion η during iterations is 10^{-6}.

Fig. 2 depicts the transmit power of the SBS versus the SINR boundary of the SUs with different CSI-error boundaries. It indicates that the total transmit power increases when the SINR boundary increases. It is also shown that in the perfect CSI conditions (denoted as the blue line with square in the condition of $\varepsilon=0,\delta=0$), the SBS need minimum transmit power to fulfill the QoS of SUs. If CSI is imperfect at SBS, higher transmit power of SBS is needed for the downlink transmission, which implies that the channel estimation error, either from SBS to PUs or from PBS to SUs, may cause performance loss.

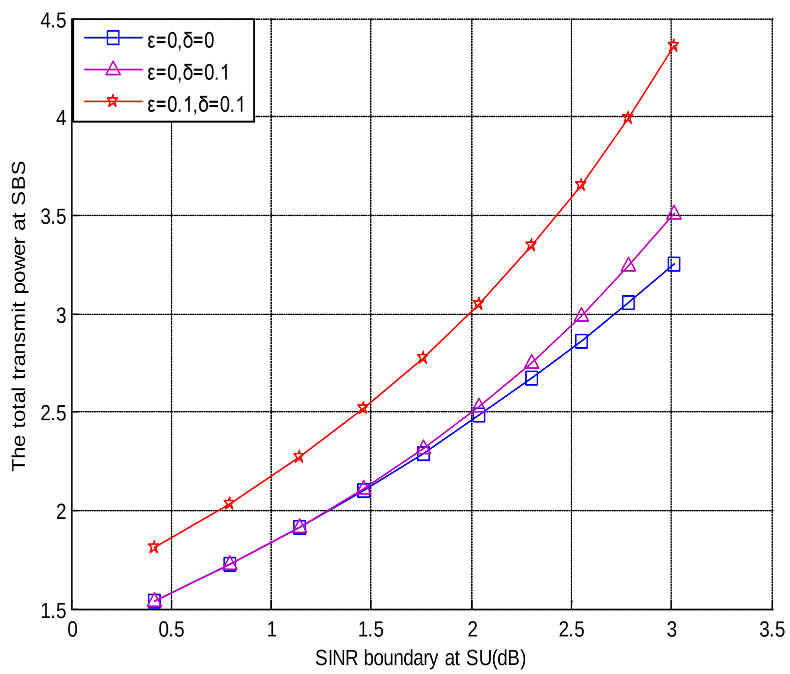

Fig. 2. transmit power of SBS versus SINR boundary of SU

The interference suppression performance of the proposed algorithm is evaluated in this simulation. **Fig. 3** shows the total interference from SBS to PUs versus the SINR boundary of SUs with different CSI-error boundaries. It depicts that the interference increases when the SINR boundary increases, but it will not exceed the interference threshold of PU (2W), which indicates that the proposed cognitive transceiver design can efficiently control the interference to PU in both perfect and imperfect CSI conditions. It is not surprising that the interference is more serious in the imperfect CSI condition than that in the perfect CSI condition.

Fig. 4 depicts the capacity performance of the proposed algorithm. Note that the proposed algorithm considers the interference from primary system to secondary system in the beamformer design, while conventional methods usually do not. However, the interference from primary system is always suffered from the secondary system and sometimes cannot be neglected in the practical scenarios. In order to show the effectiveness of this consideration, the traditional algorithm which ignores this interference is also simulated just for comparison. **Fig. 4** shows that the proposed algorithm outperforms the one which ignore the interference.

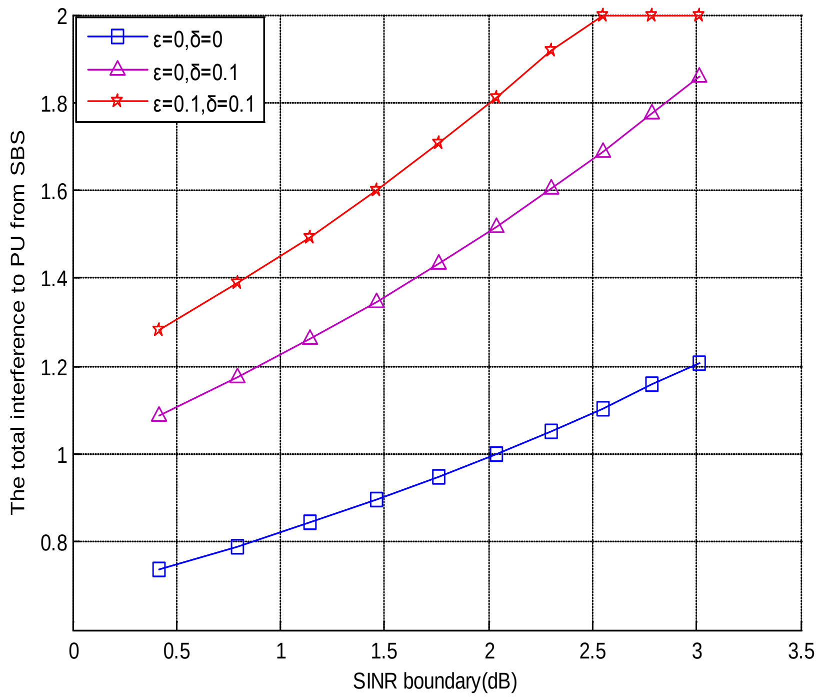

Fig. 3. interference at the PUs versus SINR boundary of SUs

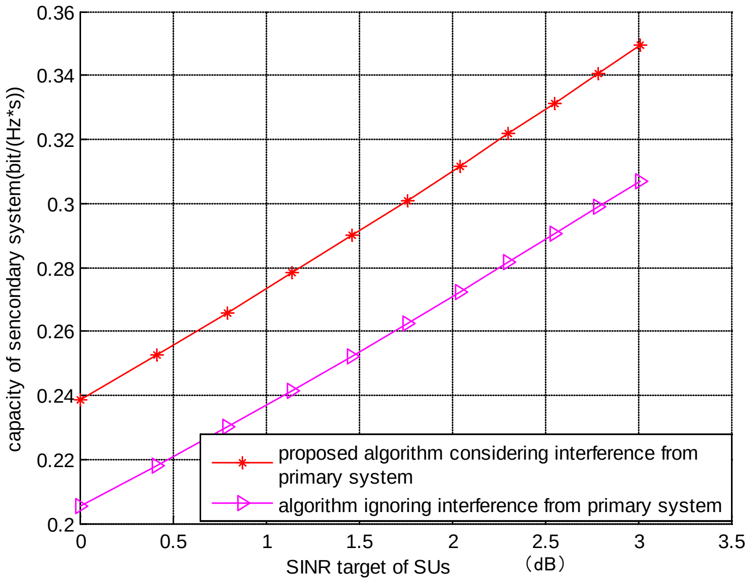

Fig. 4. The capacity performance versus SINR boundary of SUs

Fig. 5 illustrates the convergence performance of the proposed iterative algorithm. The distributed algorithm proposed in [8] is also simulated just for comparison. The SINR boundary for SUs is equal to 1. From Fig. 5, it can be concluded that the proposed algorithm has better convergence speed, which implies that the proposed one has lower computational complexity. Also, we find that the two algorithms converge to the same optimal solution.

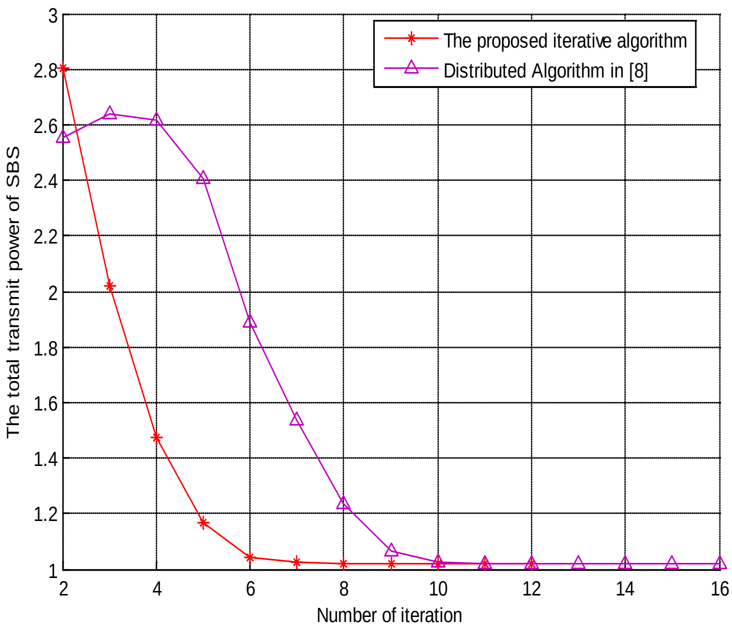

Fig. 5. The convergence performance

6. Conclusion

In this paper, the transceiver optimization problem is studied in the CR MIMO system. A novel joint transmit and receive beamformer is designed to minimize the transmit power of SBS while satisfying the SINR requirements of SUs and the interference threshold of PUs. Both the perfect and imperfect CSI conditions have been considered in this study and the proposed method is robust to some CSI errors. Simulation results show that the proposed algorithm can enhance the performance of the secondary system while controlling the interference to the PUs.

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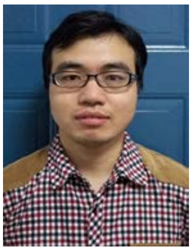

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