Transceiver Designs to Improve Spectrum Utilization in MIMO Interference Channels

Le Ty Khanh, Ha Hoang Kha, and Nguyen Minh Hoang

Abstract—This paper is concerned with a multiple-input multiple-output (MIMO) multi-user wireless networks in which multiple secondary users (SUs) can share the same radio spectrum with a single primary user (PU). The design problems of the transceivers in such MIMO interference channels are to find the precoding matrices at the transmitters and the receiving matrices at the receivers to minimize the mean square error (MSE) or to maximize the sum-rate of the SUs while guaranteeing the interference power at the PU receiver below an acceptable threshold. In this paper, we consider to design the transceivers using the interference alignment techniques. The objective is to align the interference at the SUs and maintain an acceptable leakage interference level from the SUs into the signal subspace of the PU receiver. Due to the nonlinearity and nonconvexity of the underlying problems, we develop an alternating algorithm which efficiently solves a convex optimization in each iteration. The numerical results are provided to validate the performance of our algorithm.

Index Terms—Transceiver design, MIMO interference channel, interference alignment, convex optimization.

1. Introduction

With the explosive growth in wireless applications in recent years, the radio spectrum scarcity has emerged as a major concern in the next generation of wireless communications. The transmission strategies where multiple users cooperate to share the same frequency at the same time are of great interest. Cognitive radio (CR) has been a promising technique to make an efficient exploitation of the limited radio spectrum [1], [2]. Such typical interference channels are cognitive radio wireless networks. Cognitive radio strategies are typically categorized as interweave, and overlay, underlay. In interweave schemes the SUs detect and exploit the spectral holes used by PUs. In overlay systems the SUs overhear and enhance the transmissions of the PUs while achieving some additional bandwidth for their own communication. Finally, in underlay cognitive radio strategies, the SUs are permitted to access the licensed spectrums without spectrum sensing provided that the interference powers at the PUs are kept below an acceptable level [1], [2]. The focus of this paper is on the underlay cognitive radio networks in which multiple SUs share the same spectrum with a single PU. In order to exploit additional spatial dimensions for interference management, multiple antenna techniques can be used. Particularly, we consider the wireless cognitive radio networks which consist of the K multiple-input multiple-output (MIMO) SU pairs and a single MIMO PU pair. Each SU transmitter delivers its signals to the intended user while causing interference to other PU and SU receivers. Such wireless networks are also known as MIMO interference channel models [3]. The research of interest is how to mitigate the multiuser interference between the SUs and the interference at the PU.

The joint transceiver design in MIMO interference channels is challenging since the underlying optimization problem is nonconvex in multiple matrix variables [4]. The performance metrics which are widely used in the design of MIMO cognitive radio networks are the sum rate, sum of mean square error (MSE), and signal to interference plus noise ratio (SINR) [5], [6]. In general, finding the optimal transceivers based on the above-mentioned metrics is challenging since the resultant optimization problems are non-convex. An alternative approach to deal with interference is interference alignment techniques which have been recently introduced in [7], [8]. The key idea of interference alignment (IA) is to divide the received signal space into interference and desired signal subspaces. The design problem is to seek the precoding matrices at the transmitters and receiving matrices (or receive subspace) at the receivers such that all interfering signals are aligned into the interference subspace of the lowest dimension and the desired signal is placed in the other subspace. IA techniques have been extensively studied for MIMO interference channels see, for example [8]–[10], and references therein. Most previous works with IA schemes focus on non-cognitive radio networks [8]–[10]. Since interference alignment efficiently handles interference, it has been recently extended from non-cognitive MIMO wireless networks to cognitive MIMO ones [11]–[13].

In this paper, we consider the optimal design of SU
transceivers in the MIMO cognitive radio wireless networks in which multiple secondary links coexist concurrently with a primary link. The design problem of interest is to seek the transmit and receive strategies of SUs such that the total degree of freedom at the SU links is optimized while the interference from the SUs to PU is avoided. That is, the interfering signals at each SU receivers are aligned into the interference subspace while the interfering signals from the SUs to PU do not lie in the desired direction of primary link communication. This is different from [12] where the transmitted power and precoding vectors are designed by adopting the sum-rate metric. By exploiting the subspace distance [14], we formulate the transmission strategies as an optimization problem in which the objective is to minimize the total interference outside the interference subspace subject to the constraint of total interference into the desired signal subspace at the PU. Note that the total interference from the SUs to the PU is of practical concern. Thus, in this paper, the total interference constraint at the PU is imposed instead of the separate constraints on interference caused by each SU as in [11], [13]. Since the relevant optimization problems are jointly nonconvex in the variable matrices, we use an alternating optimization to find the solution. More specifically, we alternatively iterate to find the optimal precoding matrices for fixed receiving matrices and vice versa. At each iteration, by introducing the new variables, we recast the optimization problem into convex one and thus its optimal solution can be efficiently found. Since the objective value is improved over iteration, the convergence of the iterative algorithm is guaranteed. The numerical results in terms of the total sum rate, outage probability at the SUs, and the sum rate of the PU are provided to validate the effectiveness of the proposed method. Unlike most previous methods [11]–[13] which evaluate the system performance for the Rayleigh channels, we investigate the sum-rate performance of the system for the more general MIMO Rician channels.

The remainder of the paper is organized as follows. Section 2 introduces the MIMO cognitive radio models and signal processing at the transmitters and receivers. In Section 3, we present the alternating optimization method to find the optimal transceivers. The numerical results are provided in Section 4. Finally, Section 4 presents concluding remarks.

Notation: Lower-case and upper case bold letters represent vectors and matrices respectively. (.)\(^T\) and (.)\(^H\) denote transpose and conjugate transpose operations. The \(i\)-th column of matrix \(X\) is denoted by \(X(:,i)\). \(I\) and \(0\) are identity and zero matrices with the appropriate dimensions. \(\text{trace}(.)\), \(\text{rank}(.)\) and \(\mathbb{E}(.)\) indicate the trace, rank and expectation operators, respectively. \(|x|_2\) denotes the Euclidean norm while and \(|X|_F\) presents the Frobenius norm. \(x \sim \mathcal{CN}(\bar{x}, \mathbf{R}_x)\) means \(x\) is a vector of Gaussian random variables with means \(\bar{x}\) and covariance \(\mathbf{R}_x\).

2. System Model

Consider the underlay MIMO CR networks as shown in Fig. 1 in which \(K + 1\) user-pairs simultaneously transmit in the same frequency. Without loss of generality, we assume that users \(k \in K = \{1,..., K\}\) are the secondary users while user \(K + 1\) is the PU. The \(k\)-th transmitter and receiver are equipped with \(N_{tk}\) and \(N_{tk}\) antennas, respectively. Transmitter \(k\) sends

\[ x_k = [x_{k,1}, x_{k,2}, \ldots, x_{k,dk}]^T \in \mathbb{C}^{d_k \times 1} \]

receiver \(k\), where \(d_k \leq \min\{N_{tk}, N_{tk}\}\) is the number of the data streams of user \(k\). Assume that the transmitted symbols \(x_k\) are independent and satisfy \(\mathbb{E}[x_kx_k^H] = I_{d_k}\). The data symbols are linearly processed by the precoding matrices \(F_k \in \mathbb{C}^{N_{tk} \times d_k}\) which yields

\[ s_k = F_kx_k. \]

The average transmitted power at transmitter \(k\) is computed by

\[ P_k = \mathbb{E}[||s_k||^2] = \text{trace}(F_k \mathbf{F}_k^H). \]

The channel is assumed to be a block-fading which remains unchanged for a frame duration and vary independently for every frame [15]. The channel entries are independent and identical distributed (i.i.d.) complex Gaussian variables and their magnitudes follow Rician distribution. An \(N_{rk} \times N_{tk}\) channel matrix is given by

\[ H_{k,\ell} = \sqrt{\frac{\kappa_{k,\ell}}{1 + \kappa_{k,\ell}}} H_{los}^{k,\ell} + \sqrt{\frac{1}{1 + \kappa_{k,\ell}}} H_{nlos}^{k,\ell} \]

where \(H_{los}^{k,\ell} \in \mathbb{C}^{N_{rk} \times N_{tk}}\) is the specular component of the channels and given by

\[ H_{los}^{k,\ell} = a_k(\theta_T)^H a_k(\theta_R) \]

Here \(a_k(\theta_T)\) and \(a_k(\theta_R)\) are the array response vectors for uniform linear array antennas, which are defined by [16]

\[ a_k(\theta_T) = [1, e^{j2\pi \delta_k \cos(\theta_T)}, \ldots, e^{j2\pi \delta_k (N_{tk} - 1) \cos(\theta_T)}] \]

\[ a_k(\theta_R) = [1, e^{j2\pi \delta_k \cos(\theta_R)}, \ldots, e^{j2\pi \delta_k (N_{tk} - 1) \cos(\theta_R)}] \]

where \(\delta_k\) is antenna spacings in wavelengths and \(\theta_T\) and \(\theta_R\) are the angles of the departure and arrival. \(H_{nlos}^{k,\ell}\) is the scatter component and has the Rayleigh distribution, i.e., \(H_{nlos}^{k,\ell}(i,j) \sim \mathcal{CN}(0,1), \kappa_{k,\ell}\) is the Rician \(\kappa\)-factor defined as the power ratio of the specular to the random components.

Assume that the PU transmitter is far away from the CR receivers such that the interference from the PU transmitter to CR receivers is negligible and considered as noise. This assumption is commonly made in the CR wireless networks [6], [13]. The received signal at the
where $y_k \in \mathbb{C}^{N_r \times 1}$ with $k \in K$ is the received signal vector at the $k$th SU receiver. $n_k \in \mathbb{C}^{N_r \times 1}$ is an additive noise vector which is assumed the zero-mean complex Gaussian distribution with $n_k ~ \mathcal{CN}(0, \sigma_n^2 I_{N_r})$ and independent of the transmitted symbols $s_k$ and channels $H_{k,\ell}$. The received signal $y_k$ is linearly processed by the matrix $W_k$ to suppress interference and to recover the $d_k$ desired data streams. The resulting signal then is given by

$$r_k = W_k^H y_k = W_k^H H_{k,k} F_k x_k + \sum_{\ell=1, \ell \neq k}^{K} W_k^H H_{k,\ell} F_k x_k + W_k^H n_k \quad \text{for } k \in K.$$ 

Similarly, the received signal at the PU receiver is

$$y_{K+1} = H_{K+1,k}^k s_k + \sum_{\ell=1}^{K} H_{K+1,\ell}^k s_\ell + n_{K+1},$$

which is processed by the receiving matrix $W_{K+1}$ and is expressed as

$$r_{K+1} = W_{K+1}^H y_{K+1} = W_{K+1}^H H_{K+1,k} F_k x_k + \sum_{\ell=1}^{K} W_{K+1}^H H_{K+1,\ell} F_k x_\ell + W_{K+1}^H n_{K+1}.$$ 

As the interference cancellation is not performed at the receivers, the interference is treated as noise and the total sum rate of CR links is defined as [17]

$$R_{\text{sum}} = \sum_{k=1}^{K} \log_2 |I_{N_r,k} + H_{k,k} F_k F_k^H H_{k,k} R_k^{-1}|$$

where

$$R_k = \sigma^2_k I_{N_r,k} + \sum_{\ell=1, \ell \neq k}^{K} H_{k,\ell} F_\ell F_\ell^H H_{k,\ell}$$

is the covariance matrix of interference and noise. Since the sum rate (9) is a highly nonlinear and nonconvex in the design matrix variables, it is intractable for finding the optimal solutions [6]. Recently, the total degrees of freedom (DoF) is defined as

$$\text{DoF} = \lim_{\text{SNR} \to \infty} \frac{R_{\text{sum}}(\text{SNR})}{\log_2(\text{SNR})},$$

which is an alternative measure for the sum capacity of networks at high SNR. The DoF can be interpreted as the number of interference free signal dimensions [18]. The technique to obtain the DoF is interference alignment which was introduced in [7], [19]. The key idea of IA is to jointly optimize the precoding and receiving matrices such that all the interference signals at each receiver fall into a lowest dimension of subspace while the desired signals can be recovered without inter-user interference. The interference alignment conditions in [8] can be extended for cognitive radio wireless networks as follows.

$$W_{K+1}^H H_{K+1,k} F_k = 0 \quad \text{for } k \in K.$$ (11a)

$$W_{K+1}^H H_{k,\ell} F_\ell = 0 \quad \text{for } k, \ell \in K, k \neq \ell.$$ (11b)

$$\text{rank}(W_{k}^H H_{k,k} F_k) = d_k \quad \text{for } k \in K.$$ (11c)

Condition (11a) guarantees that no interference from the SU transmitters is present in the desired signal subspace at the PU receiver. Constraint (11b) ensures that no interference from the unintended SUs is spilled into the output of each SU receiver while constraint (11c) guarantees the dimension $d_k$ of the desired signal subspace.

The interference power from SU transmitter $k$ to the PU receiver is given by

$$I_k(F_k) = \text{trace}(W_{K+1}^H H_{K+1,k} F_k F_k^H H_{K,k}^k W_{K+1}).$$ (12)

The total interference from SUs spilled into the desired signal subspace of the PU receiver is

$$I = \sum_{k=1}^{K} I_k(F_k).$$ (13)

The paper aims at seeking the transmission strategies of the secondary links such that all interfering signals are aligned into a subspace at each SU receiver while the interference at PU is kept below an acceptable threshold. The detailed approach will be presented in the next section.

### 3. Transmission strategies with interference alignment

This section will present the transmission strategies of the transceiver such that the SU links can achieve the given DoF while the interference at the PU link is guaranteed below an acceptable tolerance. We assume that the global channel state information is available at each user.

#### 3.1. Transmission of the primary link

First, we study the transmission strategy of the primary link. It is commonly true that the primary user is not aware of the presence of the cognitive transmitters and, therefore, the primary link can apply the eigen-mode transmission. The singular value decomposition (SVD) of matrix $H_{K+1,K+1}$ in Eq. (7) is given by

$$H_{K+1,K+1} = U_{K+1} \Sigma_{K+1} V_{K+1}^H$$

where $U_{K+1} \in \mathbb{C}^{N_r(K+1) \times N_r(K+1)}$ and $V_{K+1} \in \mathbb{C}^{N_t(K+1) \times N_t(K+1)}$ are orthogonal column matrices and $\Sigma_{K+1} \in \mathbb{R}^{N_r(K+1) \times N_t(K+1)}$ is rectangular diagonal matrix. Therefore, the receiver matrix at the PU receiver is chosen by

$$W_{K+1} = \psi_{\text{max}}^{d_{K+1}} [H_{K+1,K+1}]$$

where $\psi_{\text{max}}^{d_{K+1}} [H_{K+1,K+1}]$ denotes the $d_{K+1}$ vectors of $U_{K+1}$ corresponding to the $d_{K+1}$ largest singular values. That is, the PU uses $d_{K+1}$ eigen modes for its transmission and, thus, the SU transmitters can align their signals into the free eigen modes of the PU channel.

#### 3.2. Transmission of the secondary links

Each SU transmits $d_k$ data streams which are interference-free from the other unintended users. Therefore, the dimension of the desired signal subspace should be $d_k$ and all interference should be confined into
the other subspace of \( N_{rk} - d_k \) dimensions. Define \( \mathbf{U}_k \in \mathbb{C}^{N_{rk} \times N_{rk} - d_k} \) is an orthonormal basis of the received interference subspace \( \mathbf{U}_k \) at SU receiver \( k \). The key idea of interference alignment is to seek the receive subspace and precoding matrices such that all interference components fall into the interference subspace. To measure the alignment of interfering signals into a subspace, we adopt the distance metric between the

\[
\mathcal{J}(\mathbf{A}, \mathbf{U}) = \| \mathbf{A} - \mathbf{U} \mathbf{A}^H \mathbf{U} \|_F.
\]

where \( \mathbf{U} \) is an orthonormal basis of \( \mathcal{U} \). As a result, the total distances of the interfering signals to interference subspaces are

\[
\mathcal{J}(\{ \mathbf{F}_k, \mathbf{U}_k \}_{k=1}^K) = \sum_{k=1}^K \sum_{\ell=1, \ell \neq k}^K \| \mathbf{H}_{k,\ell} \mathbf{F}_\ell - \mathbf{U}_k \mathbf{U}_k^H \mathbf{H}_{k,\ell} \mathbf{F}_\ell \|_F^2.
\]

The problem of interest is mathematically posed as

\[
\begin{align*}
\min_{\{ \mathbf{F}_k, \mathbf{U}_k \}_{k=1}^K} & \quad \mathcal{J}(\{ \mathbf{F}_k, \mathbf{U}_k \}_{k=1}^K) \\
\text{s.t.} & \quad \mathbf{F}_k^H \mathbf{F}_k = \frac{P_{\max,k}}{d_k} \mathbf{I} \quad \forall k \in \mathcal{K} \\
& \quad \mathbf{U}_k^H \mathbf{U}_k = \mathbf{I} \quad \forall k \in \mathcal{K} \\
& \quad \sum_{k=1}^K \mathcal{I}_k \leq I_{th}. 
\end{align*}
\]

The objective function is to confine all interference at each SU \( k \) into a subspace \( \mathcal{U}_k \). Constraints (18b) and (18c) guarantee the orthogonality of the precoding and receive matrices while constraint (18d) ensures the total interference leakage into the signal subspace of the PU below the acceptable threshold \( I_{th} \). Note that the orthogonality property of precoding matrices is desired for practical implementation with limited feedback [20].

Since the design matrix variables are coupled in the optimization (18), it is challenging to jointly find the optimal solutions. Nevertheless, the optimization problem (18) is amenable to an alternating optimization approach. For a fixed set of the interference subspace \( \mathcal{U}_k \), the precoding matrix design is expressed as

\[
\begin{align*}
\min_{\{ \mathbf{F}_k \}_{k=1}^K} & \quad \sum_{k=1}^K \sum_{\ell=1, \ell \neq k}^K \| \mathbf{H}_{k,\ell} \mathbf{F}_\ell - \mathbf{U}_k \mathbf{H}_{k,\ell} \mathbf{F}_\ell \|_F^2 \\
\text{s.t.} & \quad \mathbf{F}_k^H \mathbf{F}_k = \frac{P_{\max,k}}{d_k} \mathbf{I} \quad \forall k \in \mathcal{K} \\
& \quad \sum_{k=1}^K \mathcal{I}_k \leq I_{th}. 
\end{align*}
\]

By defining \( \mathbf{Q}_k = \mathbf{F}_k \mathbf{F}_k^H \in \mathbb{C}^{N_T \times N_r} \), the optimization problem (19) can be rewritten as

\[
\begin{align*}
\min_{\{ \mathbf{Q}_k \}_{k=1}^K} & \quad \sum_{k=1}^K \sum_{\ell=1, \ell \neq k}^K \text{trace}(\mathbf{H}_{k,\ell}^H (\mathbf{I}_{N_{rk}} - \mathbf{U}_k \mathbf{U}_k^H) \mathbf{H}_{k,\ell} \mathbf{Q}_\ell) \\
\text{s.t.} & \quad \text{trace}(\mathbf{Q}_k) = P_{\max,k} \forall k \in \mathcal{K} \\
& \quad \sum_{k=1}^K \text{trace}(\mathbf{H}_{K+1,k}^H \mathbf{W}_{K+1} \mathbf{H}_{K+1,k} \mathbf{Q}_k) \leq I_{th}
\end{align*}
\]

It is obvious that problem (20) is a semi-definite programming and, therefore, it can be efficiently solved by interior point methods [21]. To recover the precoding matrix solution, we use the singular value decomposition \( \mathbf{Q}_k = \mathbf{F}_k \Sigma_k \mathbf{F}_k^H \), and obtain the precoding matrix by

\[
\mathbf{F}_K = [\mathbf{F}_k(1), \mathbf{F}_k(2), ..., \mathbf{F}_k(:, d_k)] \text{diag}(\sigma_1^2, \sigma_2^2, ..., \sigma_{d_k}^2)
\]

where \( \sigma_i \) is the \( i \)th largest eigenvalue of matrix \( \mathbf{Q}_k \) and \( \mathbf{F}_k(:, i) \) is its corresponding eigenvector.

Plugging in the optimal precoding matrices in the cost function, finding the optimal interference subspaces can be presented as

\[
\begin{align*}
\min_{\{ \mathbf{U}_k \}_{k=1}^K} & \quad \sum_{k=1}^K \sum_{\ell=1, \ell \neq k}^K \text{trace}(\mathbf{F}_k^H \mathbf{H}_{k,\ell}^H (\mathbf{I}_{N_{rk}} - \mathbf{U}_k \mathbf{U}_k^H) \mathbf{H}_{k,\ell} \mathbf{F}_\ell) \\
\text{s.t.} & \quad \mathbf{U}_k^H \mathbf{U}_k = \mathbf{I} \quad \forall k \in \mathcal{K}
\end{align*}
\]

which is equivalently to

\[
\begin{align*}
\max_{\mathbf{U}_k} & \quad \text{trace} \left( \mathbf{U}_k^H \left( \sum_{\ell=1, \ell \neq k}^K \mathbf{F}_\ell^H \mathbf{H}_{k,\ell}^H \mathbf{H}_{k,\ell} \mathbf{F}_\ell \right) \mathbf{U}_k \right) \\
\text{s.t.} & \quad \mathbf{U}_k^H \mathbf{U}_k = \mathbf{I}.
\end{align*}
\]

The solution to the optimization problem can be found by [8], [14]

\[
\mathbf{U}_k = \psi_{N_{rk} - d_k}(\sum_{\ell=1, \ell \neq k}^K \mathbf{F}_\ell^H \mathbf{H}_{k,\ell}^H \mathbf{H}_{k,\ell} \mathbf{F}_\ell).
\]

The alternating optimization is presented in Algorithm 1 as follows.

**Algorithm 1**

**Initialization:** Choose arbitrarily \( \mathbf{U}_{k=1}^K \), \( \forall k \in \mathcal{K} \). repeat

- Obtain the precoding matrices by solving (20).
- Obtain the interference subspace by Eq.(24).

until Convergence or maximum iteration reached.

The above-mentioned alternating optimization algorithm fixes \( \{ \mathbf{U}_k \} \) to find \( \{ \mathbf{F}_k \} \) and, then, finds \( \{ \mathbf{U}_k \} \) for fixed \( \{ \mathbf{F}_k \} \). The globally optimal solution in each iteration is obtained since problem (20) is convex and (24) is the global solution of (23). It immediately implies that

\[
\mathcal{J}(\{ \mathbf{F}_k(n) , \mathbf{U}_k(n) \}_{k=1}^K) \geq \mathcal{J}(\{ \mathbf{F}_k(n+1) , \mathbf{U}_k(n+1) \}_{k=1}^K) \geq \mathcal{J}(\{ \mathbf{F}_k(0) , \mathbf{U}_k(0) \}_{k=1}^K),
\]

where \( n \) is the iteration index. As a result, the objective function \( \mathcal{J}(\{ \mathbf{F}_k , \mathbf{U}_k \}_{k=1}^K) \) monotonically reduces over iterations. In addition, the objective is lower bounded by zero. Thus, Algorithm 1 is guaranteed to converge to at least local optimum. In terms of computational complexity, it should be noted that the convex optimization problem (20) can be efficiently solved with polynomial time-complexity while the computational complexity to find the optimal interference subspaces (24) is that of eigenvector computation. For the sake of simplicity, we define \( n = \max \{ N_{rk}, N_{rk} \} \). The computational complexity to solve (20) is \( O(KN^3) \) [22]. Calculating the interference subspaces from (24) which includes the matrix multiplication and singular value decomposi-
tion (SVD) operations has the complexity of \(O(K^2N^3)\). Thus, the major computational complexity of Algorithm 1 is about \(O(K^2N^3 + K N^{3.5})\) for each iteration.

4. Numerical Results
In this section, the performance of the proposed approach is numerically evaluated via Monte-Carlo simulations. All the simulation results are obtained by averaging over 200 channel realizations. The iteration algorithm is terminated when the objective value is less than \(10^{-9}\) or the number of iteration is reached to 200 iterations.

This example investigates the performance of the multi-user MIMO interference for the cognitive wireless networks while the performance of non-cognitive networks is provided as a benchmark for comparison. All users are equipped with the same number of antennas, \(N_{rk} = N_{rk} = 6\), and each user transmit \(d_k = 2\) data streams. Without loss of generality, noise variances are normalized \(\sigma_k^2 = \sigma^2 = 1\), the maximum transmitted power at all transmitter is identical, i.e., \(P_{\text{max}, k} = P_{\text{max}, r}\) and the signal to noise ratio defined as \(SNR = P_{\text{max}}/\sigma^2\). In the simulations, the SNR is set \(SNR = \{0, 5, 10, 15, 20, 25, 30, 35, 40\} \text{ dB}\).

Two scenarios are considered: no PU and 3 SUs, and 1 PU and 3 SUs. The Rayleigh channels (\(\kappa_{k, k} = \kappa = 0\)) and Rician channels with \(\kappa_{k, k} = \kappa = 10\) are simulated. Fig. 2 illustrates the average sum rate versus SNR. It is apparent that the average sum rate is reduced when there is the presence of the PU since the SU transmission is constrained by the interference level allowable at the PU. In other words, the SUs trade off their sum rate to keep the acceptable interference level to the PU. However, at the high SNR regime where the IA is optimal, the performance gap between the cognitive and noncognitive scenarios is negligible. In addition, it can be seen from Fig. 2 that the Rician channels offers the total achievable sum rate lower than the Rayleigh channels. This is attributed to the fact that the strong correlation of the specular components in Rician channel models reduces the dimension of signal subspaces.

Fig. 3 presents the outage probability of the cognitive radio networks with 1 PU and 3 SUs for Rayleigh channels. As expected as the sum rate is better as the SNR increases. In addition, we investigate the sum rate performance of the PU in the cases with and without SUs. The data rate of the PU is shown in Fig. 4. It is clear from Fig. 4 the PU suffers the negligible sum rate degradation when there is the presence of 3 SUs. The reason is that the signals of the SUs are aligned into the unused eigen-modes of the PU.

5. Concluding Remarks
The paper has presented the optimal strategies for efficient spectrum exploitation in underlay MIMO cognitive radio networks. The PU exploits the eigen mode transmission while the SUs are coordinated to align all interferences into the interference subspaces at each SU receiver and simultaneously guaranteed the acceptable interference at the PU. The alternating optimization approach has been adopted to find the SU strategies. The numerical results have indicated that the IA techniques can apply into the cognitive radio wireless networks to align interference into unused eigen modes of the PU link. It can been seen that the sum rate of PU is not significant degradation if the the received signal subspaces at PU is known at the SUs.

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References
Fig. 4. Average rate versus SNR for the PU with 3 SUs and without SU.

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