Cross-Entropy Optimization Oriented Antenna Selection for Clustering Management in Multiuser MIMO Networks

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Abstract. In this paper, antenna selection (AS) is considered for clustering management (CM) to improve the spectrum efficiency of asymmetric interference networks. Through the proposed CM scheme, the whole network can be divided into several clusters, which will lead to a relative redundance of antenna resource for each interference alignment (IA) pair in the IA cluster. Therefore, the AS technique is adopted to improve the performance through selecting the optimal antenna combination for IA pairs. Considering the high computational complexity of the exhaustive search (ES) AS method, the cross-entropy optimization (CEO) algorithm is used to perform the IA technique, which can achieve relatively high performance with low computational complexity. From the simulation results, we can find that the proposed AS method in clustering management can further enhance the performance of the IA-based network.

Keywords: Antenna selection · Cross-entropy optimization
Clustering management · Interference alignment

1 Introduction

As a novel interference management method, interference alignment (IA) has been proposed by Jafar in 2008 [1,2]. For the IA technique, the interference from different transmitters is constrained into a low dimensional vector-space at each receiver, and then the desired signal can be retrieved according to the remaining interference-free vector space. Recently, there is a great increase of research interest in IA, and it has been applied to all kinds of multiuser networks [3–7].

In most of existing IA-based researches, the network topology is assumed to be symmetric, which is difficult to be satisfied in practical wireless networks. Therefore, the asymmetric model of interference network is introduced into IA research recently [8–10]. In [9], authors expanded the idea of clustered IA proposed in [8] into the IA network. According to the distance information between

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pairs, the proposed topology management scheme in [9] can divide the whole network into one IA subnetwork and several spatial multiplexing (SM) subnetworks to improve the performance in the low and moderate signal-to-noise ratio (SNR) range. In [10], the resource management of [9] was further researched.

After performing topology management in the asymmetric interference network, antenna resource will be relatively redundant in the IA subnetwork [9]. Hence, the antenna selection (AS) technique can be applied in the IA subnetwork to select the optimal antenna combination to further improve the performance under the IA feasibility condition, which is a kind of methods based on opportunistic communications [11]. As known, the AS technique can provide selection gain and improve received SNR with simple and cheap hardware architecture, which has been successfully applied in several multi-input and multi-output (MIMO) systems [12–15]. In [12], Sanayei *et al.* presented an overview of the application of antenna selection in MIMO systems. Through two types of antenna selection, i.e., transmit and receive antenna selection, the received SNR and system capacity can be effectively improved. In [13], the AS technique was introduced into IA-based wireless networks. The performance of interference wireless networks was evaluated under several antenna selection criteria. Three suboptimal selection algorithms were proposed to achieve an acceptable performance with low computational complexity. In [14], Li *et al.* investigated the antenna selection problem in the IA-based cognitive radio network. The proposed antenna selection IA algorithm based on discrete stochastic optimization can achieve high performance with low computational complexity. In [15], the antenna switching based on reconfigurable antennas was utilized for IA networks.

Although the optimal antenna combination can be easily selected through the ES-based AS method, the high computational complexity makes it unpractical. Therefore, the cross-entropy optimization (CEO) method [16], which is an increasingly popular method to solving difficult combinatorial optimization problems, has been adopted to optimize the AS problem in MIMO systems [17,18]. In [17], a novel receive AS algorithm based on cross-entropy optimization was proposed to improve the capacity of MIMO systems over spatially correlated channel. Simulation results show that the proposed algorithm can achieve the optimal or near-optimal capacity with low computational complexity. In [18], Ali *et al.* introduced the CEO method into the IA-based network based on maximizing the minimum signal-to-interference plus noise ratio (SINR) metric. The proposed algorithm can effectively improve the bit-error-rate (BER) of the system.

In the paper, the CEO method is used to perform the AS technique to further improve the spectrum efficiency for the clustering management (CM) scheme of multiuser interference network. The rest of the paper is organized as follows. In Sect. 2, clustering management scheme is presented. Then, the cross-entropy optimization method in the CM scheme is introduced in Sect. 3. Section 4 discusses the simulation result. In Sect. 5, we conclude this paper.

2 Clustering Management Scheme

In this section, we consider the asymmetric interference network with K users as shown in Fig. 1, where $M^{[k]}$ and $N^{[k]}$ antennas are equipped at the k-th transmitter and its corresponding receiver, respectively. The received signal at the k-th Rx can be denoted as

$$\mathbf{y}^{[k]} = \sqrt{\rho^{[kk]}}\mathbf{U}^{[k]\dagger}\mathbf{H}^{[kk]}\mathbf{V}^{[k]}\mathbf{x}^{[k]} + \sum_{j=1,j\neq k}^{K} \sqrt{\rho^{[kj]}}\mathbf{U}^{[k]\dagger}\mathbf{H}^{[kj]}\mathbf{V}^{j}\mathbf{x}^{[j]} + \mathbf{U}^{[k]\dagger}\mathbf{z}^{[k]}. \quad (1)$$

where $\mathbf{H}^{[kj]} \in \mathbb{C}^{N^{[k]}\times M^{[j]}}$ is the small-scale fading gain matrix from the j-th Tx to the k-th Rx, whose entity is i.i.d. with the complex Gaussian distribution $\mathcal{CN}(0,1)$. The matrix $\mathbf{V}^{[j]} \in \mathbb{C}^{M^{j}\times d^{[j]}}$ is the precoding matrix of the k-th Tx, and the matrix $\mathbf{U}^{[k]} \in \mathbb{C}^{N^{k}\times d^{[k]}}$ is the decoding matrix of the k-th Tx. The transmitted signal $\mathbf{x}^{[k]}$ from the k-th Tx to k-th Rx satisfies a equal power constraint P_t, i.e., $\mathbf{E}\left[\left|\left|\mathbf{x}^{[k]}\right|\right|^2\right] = P_t^{[k]} = P_t$. $\mathbf{z}^{[k]} \in \mathbb{C}^{N^{k}\times 1}$ denotes the additive Gaussian noise with distribution $\mathcal{CN}(0, \sigma\mathbf{I}_{N^k})$. The lager-scale fading gain from the j-th Tx to the k-th Rx $\rho^{[kj]}$ can be given as

$$\rho^{[ji]} = \left(r^{[kj]}\right)^{-\alpha}. \quad (2)$$

where $r^{[kj]}$ expresses the distance between the j-th Tx and the k-th Rx, and α is the path-loss exponent, which is determined by different wireless environment.

In a feasible IA-based network satisfying the condition, i.e., $M + N = d(K+1)$, after performing the proposed CM scheme in [9], the whole network will be divided into several cluster as shown in Fig. 1, including one IA cluster and several SM clusters. Those pairs close to each other jointly comprise one IA cluster (the set $\mathcal{A}$), where the strong inner-interference among IA pairs is eliminated through linear IA and the weak inter-cluster interference is treated as noise. On the other hand, those pair far away others will act as some SM clusters independently (belonging to the set $\mathcal{S}$), in which the SM scheme is adopted and the weak inter-subnetwork interference is also treated as noise.

For the convenience of analysis, we assume that each pair has the same antenna configuration, i.e., $M^{[k]} = M, N^{[k]} = N, \forall k \in \{1, 2, \ldots, K\}$. Besides, the number of the transmitted data stream of each IA pair is set to $d^{[k]} = d, k \in \mathcal{A}$, and the number of the transmitted data stream of each SM pair is set to $d^{[k]} = \hat{d}, k \in \mathcal{S}$.

3 Cross-Entropy Optimization Method

In this section, we will first present the AS problem in the CM scheme. Then, antenna selection based on cross entropy optimization method will be presented to improve the performance.

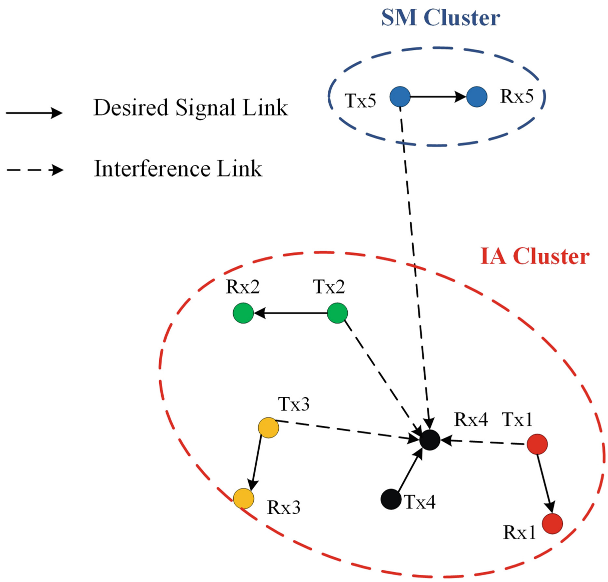

Fig. 1. A K-pair asymmetric IA-based interference network using clustering management scheme.

3.1 Antenna Selection in Cluster Management Scheme

After performing the CM scheme in the network, the number of IA pairs K_{IA} in the IA cluster will be generally smaller than K, i.e., $K_{\mathrm{IA}} < K$. Hence, antenna resource in the IA cluster will be relatively abundant, which can be utilized to perform the AS technique. In this paper, the AS technique is just performed at the Rx side of each IA pair to reduce the CSI feedback overhead.

Taking the network with the configuration $(M, N, K, d) = (3, 3, 5, 1)$ as an example to analyze the implementation of the AS technique in the IA cluster. Assuming that there exist one IA cluster and one SM cluster after performing the TM scheme. The number of the optional antenna combinations for the k-th pair is summarized in Table 1. There will be $z = (3+1)^4 = 256$ optional antenna combinations in the IA cluster, and the set of all the optional combinations is denoted as $\mathbf{\Phi} = \{\Omega_1, \Omega_2, \ldots, \Omega_z\}$.

Table 1. Number of optional antenna combinations for the j-th IA Pair

Configuration	Number of antenna combinations
$M_{\mathrm{IA}}^{[j]} = 3, N_{\mathrm{IA}}^{[j]} = 2, d = 1$	3
$M_{\mathrm{IA}}^{[j]} = 3, N_{\mathrm{IA}}^{[j]} = 3, d = 1$	1

We can select the optimal antenna combinations from the set $\mathbf{\Phi}$ to improve the spectrum efficiency of the IA cluster, and the problem can be expressed as

$$\Omega^* = \arg\max_{\Omega \in \mathbf{\Phi}} \left\{ \sum_{k=1}^{K} R_{\mathrm{IA}}^{[k]}(\Omega) \right\}. \tag{3}$$

The combinatorial optimization problem (3) can be easily solved through the ES-based AS method. However, when the size of the set $\mathbf{\Phi}$ is large, the computational complexity will become extremely high. To overcome the shortcoming, the cross entropy optimization method is applied to implement the AS technique, which can achieve the optimal or near-optimal performance with low computational complexity.

3.2 Cross-Entropy Optimization Method

The main idea of CEO for antenna selection is to iteratively update the probability vector $\mathbf{p}$, which can be defined as

$$\mathbf{p} = \left\{ p^{(1,1)}, \ldots, p^{(1,M)}, \ldots, p^{(k,j)}, \ldots, p^{(K,1)}, \ldots, p^{(K,M)} \right\}. \tag{4}$$

where $p^{(k,j)}$ represents the probability of the j-th antenna of the k-th Rx to be selected. To effectively update the probability vector $\mathbf{p}$, there are two iterative phrases which should be carefully designed as follows.

1. The random mechanism to generate a sample of random data. In this paper, Bernoulli probability mass functions $f\left(\Omega_q; \mathbf{p}\right)$ is used to generate Q samples

$$f(\Omega_q; \mathbf{p}) = \prod_{k=1}^{K} \prod_{i=1}^{M} \left[p^{(k,i)} \right]^{\Omega_q^{(k,i)}}, q = 1, \ldots, Q. \tag{5}$$

2. The way to update the parameters of the random mechanism. The probability vector $\mathbf{p}$ is updated according to the following equation

$$\mathbf{p}^{iter} = \frac{\sum_{q=1}^{Q} I_{\left\{S(\Omega_q^{iter}) >= \gamma^{iter}\right\}} \Omega_q^{iter}}{\sum_{q=1}^{Q} I_{\left\{S(\Omega_q^{iter}) >= \gamma^{iter}\right\}}}. \tag{6}$$

where $I_{\{x\}}$ is an indicator function. When the condition x is satisfied, $I_{\{x\}} = 1$, $I_{\{x\}} = 0$, otherwise. Ω_q^{iter} is the selected antenna vector for sample q at the $iter$-th iteration. $S\left(\Omega_q^{iter}\right)$ represents the minimum stream SINR of sample q at the $iter$-th iteration. $\gamma^{iter} = S^{(\lceil (1-\eta)Q \rceil)}$ is the $(1-\eta)$-th quantile in the sequence $S^{(1)} >= S^{(2)} >= \cdots >= S^{(Q)}$, $\lceil \cdot \rceil$ is the ceiling operation, and $\eta \in (0, 1)$. To smooth out the values of $\mathbf{p}$ and prevent some component $p^{(k,j)}$ of $\mathbf{p}$ from being zero or one in first few iteration, the smooth parameter $\lambda \in (0.7, 1]$ is introduced as follows

$$\mathbf{p}^{iter} = \lambda \mathbf{p}^{iter} + (1 - \lambda)\mathbf{p}^{iter-1}. \tag{7}$$

Hence, the implementation of the AS technique based on the CEO algorithm in the TM scheme can be summarized as follows

Algorithm 1. Antenna selection based on the CEO algorithm

Determine the set of the optional antenna combinations $\mathbf{\Phi}$ according to the feasibility conditions of IA in the IA subnetwork, i.e., the number of the selected antenna N_{IA} at the Rx side of each IA pair.
Set $iter = 0$ and initialize the probability vector $\mathbf{p}^0 = \frac{N_{\mathrm{IA}}}{N}\mathbf{1}$.
repeat
    Generate Q samples according to the random mechanism Bernoulli probability mass function (5).
    For each sample, calculate the precoding and decoding matrices based on the MinIL algorithm, and the minimum stream SINR.
    Sort the minimum SINRs in descending order.
    Update the probability vector $\mathbf{p}^{iter}$ by (4), and smoothen it by (7).
    $iter = iter + 1$.
until The stopping criterion is satisfied.

4 Simulation Results

In this section, the asymmetric interference network with the configuration $(M, N, K, d) = (3, 3, 5, 1)$ is considered. Assuming that the path-loss exponent α is set to 3. All the pairs are randomly and uniformly scattered in a $1\,\mathrm{km} \times 1\,\mathrm{km}$ square area, and the distance between the transmitter and its corresponding receiver is set to $100\,\mathrm{m}$.

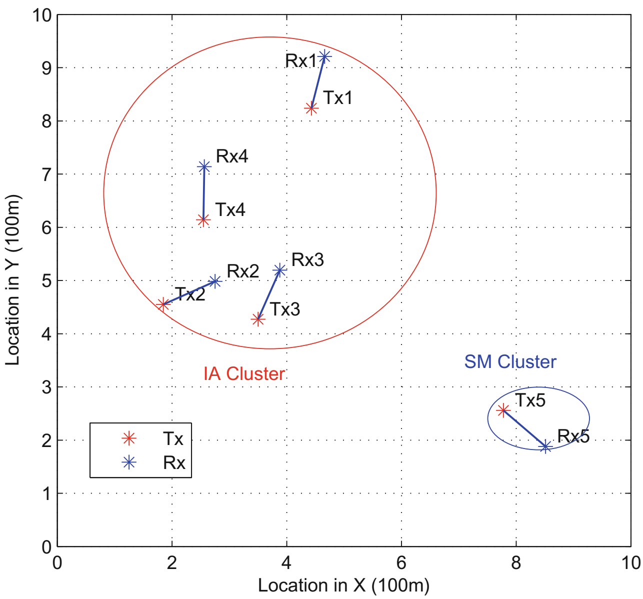

Fig. 2. The network topology after performing the clustering management scheme when the transmitted SNR is 12 dB.

A network shown in Fig. 2 is taken as an example to analyze the performance of the CEO-based AS method in the clustering management scheme. After performing the clustering management scheme in the network when the transmitted SNR is 12 dB, the whole network is divided into one IA cluster and one SM cluster. From the figure, we can observe that the four pairs, i.e., the 1-st, 2-nd, 3-rd and 4-th pair, jointly comprise the IA cluster, and the 5-th pair acts as the SM cluster independently.

According to the result of clustering, the spectrum efficiency of different schemes under various transmit SNRs is compared in Fig. 3. From the simulation results, we can find that the CEO-based AS method can effectively improve the performance of the IA cluster compared to the original clustering management scheme. However, compared to the ES-based AS method, there exist a little performance gap. Considering the high computational complexity of the ES-based AS method, the CEO-based AS method can achieve a balance between the spectrum efficiency and the computational complexity.

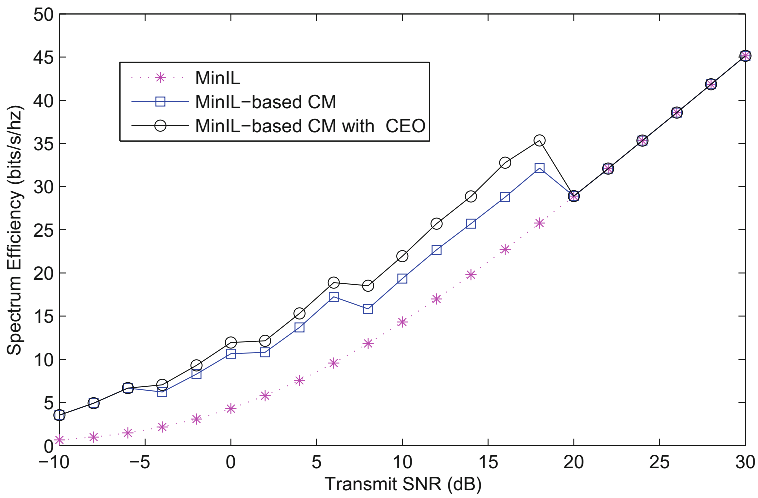

Fig. 3. The spectrum efficiency versus the transmit SNR under different schemes.

5 Conclusions

In this paper, the implementation of antenna selection in the clustering management scheme was analyzed. The redundant antenna resource was used to perform the AS technique. However, the ES-based AS method was unfriendly for performing in practical wireless networks due to the high computational complexity. The another effective combinatorial optimization method, i.e., cross-entropy optimization (CEO) algorithm, was selected as the substituted method. Finally, the simulation results were presented to show the effectiveness of the proposed CEO-based AS method in the clustering management scheme.

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