A Novel Interference Alignment Scheme Based on Sequential Antenna Switching in Wireless Networks

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Abstract—Interference alignment (IA) is a promising technique that can effectively eliminate the interference in wireless networks. However, in traditional IA schemes, the signal to interference plus noise ratio (SINR) may significantly degrade, and the quality of service (QoS) may be unacceptable. In this paper, a novel IA scheme based on antenna switching (AS-IA) is proposed to improve the SINR of the received signal while guaranteeing the QoS in IA wireless networks. In the proposed scheme, some of the antennas are replaced by reconfigurable ones that can switch among preset modes, and the best channel coefficients are selected. Furthermore, to reduce the computational complexity, a sequential antenna switching IA (SAS-IA) scheme is proposed with only one antenna switching in each time slot, and the communication proceeds during the process of searching for the optimal solution. To further improve the performance of the SAS-IA scheme under imperfect channel state information (CSI), a filtering SAS-IA scheme is proposed through averaging the estimated CSI during the iterations of the distributed IA algorithm. Simulation results are presented to show the effectiveness and efficiency of the proposed schemes in improving the QoS of IA wireless networks.

Index Terms—Interference alignment, antenna switching, reconfigurable antenna, computational complexity, channel state information.

I. INTRODUCTION

INTERFERENCE alignment (IA) is an emerging technique of signal constructing where the interference casts overlapping shadows at the unintended receivers, while the desired signals can still be distinguished at the intended receivers free of interference [2], [3]. In the IA schemes, precoding matrices should be suitably selected to constrain all the interferences into one half of the signal space at each receiver and leave the other half without interference for the desired signal. Then the expected signal can be obtained by using properly generated interference suppression matrices [4]. Degrees of freedom (DoFs) and sum rate of K-user interference networks through IA are studied in [2], and distributed IA algorithms are proposed in [5] that utilize the reciprocity of wireless networks. To mitigate the influence of the delayed channel state information (CSI), an IA scheme based on channel prediction is proposed using linear predictors [6]. Since the channel state information at the transmitters (CSIT) is usually difficult to obtain, blind IA algorithms are designed based on reconfigurable antennas in [7]. In [8], relay-aided IA schemes for K-user X channel are proposed without any knowledge of CSIT. Due to the promising performance of IA, it has been successfully applied to cognitive radio, femtocell wireless networks, and multi-cell OFDMA networks [9], [10], [11], [12], [13].

Although IA schemes can eliminate interference in the wireless networks effectively, the signal to interference plus noise ratio (SINR) may decrease dramatically when the desired signal and the interferences are aligned in similar directions. Accordingly, the bit error rate (BER) will be larger under these channel coefficients, and the quality of service (QoS) can become unacceptable [4], [1]. Thus, this problem should be carefully considered and solved to make IA algorithms suitable for practical networks. Unfortunately, most previous works focus on sum rate as the performance measure of IA algorithms [2], [13], [14]. Consequently, only a few research works have concentrated on the SINR, BER or outage probability, which directly measure the performance of IA wireless networks [11], [15], [16]. In [11], the minimum received SINR is leveraged to measure the QoS requirements of macrocell users in femtocell networks. BER and outage probability of the IA scheme are analyzed in [15], [16], respectively. In addition, traditional IA schemes usually seek perfect solutions to eliminate the interference completely. However, when the interference is completely eliminated, the received SINR in IA may not be maximal. In [5], a max-SINR IA algorithm is proposed to obtain the maximal SINR of the received signal, and thus can optimize the QoS of the wireless networks. However, when SINR becomes larger, the advantage of the max-SINR IA algorithm tends to be lost. An improved blind IA algorithm is proposed in [17] that can increase the SINR of the desired signal by changing power allocation in transmitted streams. However, this scheme may only be used for blind IA scenarios [7].

Against this background, a novel IA scheme is proposed

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in this paper that incorporates recent advances in antenna switching techniques using reconfigurable antennas [18], [19], [7] to improve the performance of IA networks. Compared to traditional smart antennas, in which the antenna elements themselves do not possess any intelligence, reconfigurable antennas introduce an additional degree of freedom by treating the antenna array configuration and its radiation/polarization properties as an additional component in the joint optimization of the adaptive system parameters. Thus they can be leveraged to improve the performance of IA. The motivations behind this work are as follows.

- Antenna selection is usually utilized in multiple-input multiple-output (MIMO) to improve the QoS [20], [21], [22], [23]. However, additional antennas should be equipped at the transceivers, leading to high complexity and large size. To reduce the complexity and size of an antenna selection MIMO system, antenna switching based on reconfigurable antennas can be used. A reconfigurable antenna can have several preset modes with different channel coefficients, and antenna switching can be performed to switch among these modes using microelectromechanical switches (MEMSs) [18].

- Antenna switching is usually done in a selfish manner, in which each receiver chooses the mode that enables the greatest signal strength for itself [24], [22], [23]. On the other hand, IA usually operates in an unselfish manner, in which all the users seek the best precoding and interference suppression matrices to achieve the optimal sum rate of the whole system. If we combine antenna switching with IA, better performance can be achieved.

The main contributions of this work are summarized as follows.

- The SINR (and consequently BER) QoS performance in IA wireless networks is analyzed theoretically, and different factors that can affect the performance are discussed.
- A novel IA scheme based on antenna switching (AS-IA) is proposed through using reconfigurable antennas to improve the QoS of IA wireless networks.
- To reduce the computational complexity and CSI-feedback overhead, a sequential antenna switching IA (SAS-IA) scheme is proposed with guaranteed QoS performance.
- The performance of the conventional IA, AS-IA, and SAS-IA schemes is analyzed to show the better performance of the AS-IA and SAS-IA schemes.
- The computational complexity and CSI overhead of the AS-IA and SAS-IA schemes are compared to show the advantages of the SAS-IA scheme.
- A filtering SAS-IA (FSAS-IA) scheme is proposed to improve the performance of the SAS-IA scheme under imperfect CSI.

The rest of the paper is organized as follows. In Section II, we present the system model. Different factors that affect the SINR in IA networks are analyzed in Section III. In Section IV, AS-IA scheme is proposed, and three objective functions are presented. In Section V, the SAS-IA scheme is presented to reduce the computational complexity of the AS-IA scheme.

The performance of the SAS-IA, AS-IA, and IA schemes is analyzed and proven in Section VI. In Section VII, simulation results are given and discussed. Finally, we conclude this study in Section VIII.

Notation: $\mathbf{I}_d$ represents the $d \times d$ identity matrix. $\mathbf{A}^{\mathrm{T}}$, $\mathbf{A}^{\mathrm{H}}$ and $\mathbf{A}_{*d}$ are the transpose, conjugate transpose and dth column of matrix $\mathbf{A}$, respectively. $\|\mathbf{a}\|$ and $(\mathbf{a})_d$ are the norm and dth element of the vector $\mathbf{a}$, respectively. $|a|$ is the absolute value of a. $\mathbf{a} \cdot \mathbf{b} = \mathbf{a}^{\mathrm{T}}\overline{\mathbf{b}}$ is the dot product of the vectors $\mathbf{a}$ and $\mathbf{b}$, where $\overline{\mathbf{b}}$ is the conjugation of $\mathbf{b}$.

II. SYSTEM DESCRIPTION

Consider a K-user MIMO interference channel, and the kth transmitter and receiver are equipped with $M^{[k]}$ and $N^{[k]}$ antennas, respectively. The received signal at the kth receiver can be represented as

$$\mathbf{Y}^{[k]}(n) = \sum_{l=1}^{K} \mathbf{H}^{[kl]}(n)\mathbf{X}^{[l]}(n) + \mathbf{Z}^{[k]}(n), \ \forall k \in \{1, 2, ..., K\}, \quad (1)$$

where, at the discrete-time instant n, $\mathbf{Y}^{[k]}(n)$ and $\mathbf{Z}^{[k]}(n)$ are the $N^{[k]} \times 1$ received signal vector and additive white Gaussian noise (AWGN) vector at the kth receiver, respectively. $\mathbf{X}^{[l]}(n)$ is the $M^{[l]} \times 1$ signal vector transmitted by the lth transmitter, and $\mathbf{H}^{[kl]}(n)$ is the $N^{[k]} \times M^{[l]}$ matrix of channel coefficients between the lth transmitter and the kth receiver.

When IA is performed through using matrices $\mathbf{V}^{[k]}(n)$ at the kth transmitter and $\mathbf{U}^{[k]}(n)$ at the kth receiver at the time instant n, $k \in \{1, 2, ..., K\}$, the DoFs achieved by the kth user is $d^{[k]}$. The received signal at the kth receiver can be denoted as

$$\mathbf{y}^{[k]}(n) = \mathbf{U}^{[k]}(n)^{\mathrm{H}}\mathbf{H}^{[kk]}(n)\mathbf{V}^{[k]}(n)\mathbf{x}^{[k]}(n)$$
$$+ \sum_{l=1,l\neq k}^{K} \mathbf{U}^{[k]}(n)^{\mathrm{H}}\mathbf{H}^{[kl]}(n)\mathbf{V}^{[l]}(n)\mathbf{x}^{[l]}(n) + \mathbf{N}^{[k]}(n), \quad (2)$$

where $\mathbf{V}^{[k]}(n)$ and $\mathbf{U}^{[k]}(n)$ are $M^{[k]} \times d^{[k]}$ precoding matrix and $N^{[k]} \times d^{[k]}$ interference suppression matrix of the kth user, respectively. $\mathbf{x}^{[k]}(n)$ is the transmitted signal vector of $d^{[k]}$ DoFs at the kth transmitter. $\mathbf{N}^{[k]}(n)$ is a $d^{[k]} \times 1$ AWGN vector corresponding to each DoF at the kth receiver, with zero mean and each element's variance equal to σ^2.

The interferences in IA can be efficiently eliminated only when the following conditions are satisfied

$$\mathbf{U}^{[k]}(n)^{\mathrm{H}}\mathbf{H}^{[kj]}(n)\mathbf{V}^{[j]}(n) = 0, \ \forall j \neq k, \quad (3)$$

$$\mathrm{rank}\left(\mathbf{U}^{[k]}(n)^{\mathrm{H}}\mathbf{H}^{[kk]}(n)\mathbf{V}^{[k]}(n)\right) = d^{[k]} > 0. \quad (4)$$

Thus (2) can be rewritten as

$$\mathbf{y}^{[k]}(n) = \mathbf{U}^{[k]}(n)^{\mathrm{H}}\mathbf{H}^{[kk]}(n)\mathbf{V}^{[k]}(n)\mathbf{x}^{[k]}(n) + \mathbf{N}^{[k]}(n), \quad (5)$$

because the interferences are assumed to be completely eliminated as in (3).

When each transmitting and receiving node has M antennas, the capacity of the whole MIMO interference network achieved by IA can be denoted as [5]

$$C_{\sum}(\mathrm{SNR}) = \frac{KM}{2}\log(\mathrm{SNR}) + o(\log(\mathrm{SNR})), \quad (6)$$
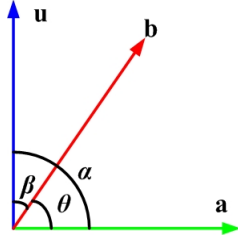
Fig. 1.   Illustration of the angles between the vectors $\mathbf{a}$, $\mathbf{b}$ and $\mathbf{u}$.

so that the capacity per user is $\frac{M}{2}\log(\text{SNR}) + o(\log(\text{SNR}))$. Here signal-to-noise ratio (SNR) is defined as the transmit power of each transmitter when the local noise power at each receiver is normalized to unity. The $o(\log(\text{SNR}))$ term can be negligible compared with $\log(\text{SNR})$ when SNR is high.

III. ANALYSIS OF SINR PERFORMANCE IN IA WIRELESS NETWORKS

Although IA can eliminate the interference in wireless networks completely through the precoding matrix and the interference suppression matrix constrained by (3) and (4), the SINR may degrade dramatically when the desired signal and the interferences are aligned in the similar directions. We present Theorem 1 to show this when DoFs of each user are 1, and the conclusion with larger DoFs can be similarly obtained. The time instant n is henceforth suppressed to avoid cumbersome notation.

Theorem 1: The received SINR after IA depends on the vector length of desired signal at the receiver when DoFs of each user are 1, and the maximal SINR achieved depends on angle θ between the directions of the desired signal and interference. In a special case when 2 antennas are equipped at each receiver, the received SINR depends exactly on the vector length of desired signal and angle θ.

Proof: In the typical K-user IA model [2], M and N antennas are equipped at each transmitter and receiver, respectively, and consider the case with DoFs $d^{[k]} = 1$. $\forall k \in \{1, 2, ..., K\}$, at receiver k, the interferences $\mathbf{H}^{[kj]}\mathbf{v}^{[j]}x^{[j]}$, $j = 1, 2, ..., K, j \neq k$, are aligned in the same direction different from the direction of the desired signal $\mathbf{H}^{[kk]}\mathbf{v}^{[k]}x^{[k]}$. Thus we can assume that

$$\mathbf{H}^{[kj]}\mathbf{v}^{[j]} = g_j^{[k]} \left[a_1^{[k]}, a_2^{[k]}, ..., a_N^{[k]} \right]^{\mathrm{T}} = g_j^{[k]}\mathbf{a}^{[k]},$$
$$j = 1, 2, ..., K, \ j \neq k, \ \left\| \mathbf{a}^{[k]} \right\| = 1. \quad (7)$$

$$\mathbf{H}^{[kk]}\mathbf{v}^{[k]} = c_k \left[b_1^{[k]}, b_2^{[k]}, ..., b_N^{[k]} \right]^{\mathrm{T}} = c_k\mathbf{b}^{[k]}, \ \left\| \mathbf{b}^{[k]} \right\| = 1. \quad (8)$$

To eliminate the interferences at receiver k, the interference suppression vector $\mathbf{u}^{[k]}$ is applied as

$$\mathbf{u}^{[k]} = \left[u_1^{[k]}, u_2^{[k]}, ..., u_N^{[k]} \right]^{\mathrm{T}}, \ \left\| \mathbf{u}^{[k]} \right\| = 1. \quad (9)$$

Assume that the angle between the vectors $\mathbf{u}^{[k]}$ and $\mathbf{a}^{[k]}$ is α, the angle between the vectors $\mathbf{u}^{[k]}$ and $\mathbf{b}^{[k]}$ is β, and the angle between the vectors $\mathbf{b}^{[k]}$ and $\mathbf{a}^{[k]}$ is θ, as shown in Fig. 1.

From (3), we can know that the interferences at receiver k can be eliminated completely by the interference suppression vector, and we can obtain that

$$\mathbf{u}^{[k]} \cdot g_j^{[k]}\mathbf{a}^{[k]} = g_j^{[k]}\mathbf{u}^{[k]} \cdot \mathbf{a}^{[k]} = 0. \quad (10)$$

From the equation, we can know that the vectors $\mathbf{u}^{[k]}$ and $\mathbf{a}^{[k]}$ are orthogonal, and the angle between them, α, is equal to $\pi/2$.

Therefore, the magnitude of the received signal at receiver k can be calculated through $\mathbf{u}^{[k]}$ as

$$
\begin{aligned}
\left| y^{[k]} \right| &= \left| \mathbf{u}^{[k]\mathrm{H}}\mathbf{H}^{[kk]}\mathbf{v}^{[k]}x^{[k]} \right| \\
&= \left| \mathbf{u}^{[k]} \cdot c_k\mathbf{b}^{[k]}x^{[k]} \right| \\
&= \left| c_k\mathbf{u}^{[k]} \cdot \mathbf{b}^{[k]}x^{[k]} \right| \\
&= \left| c_k \cos\beta \| \mathbf{u}^{[k]} \| \| \mathbf{b}^{[k]} \| x^{[k]} \right| \\
&= \left| c_k \cos\beta x^{[k]} \right|, \quad (11)
\end{aligned}
$$

where $|c_k|$ is the length of the vector containing the desired signal of user k.

With the power of $x^{[k]}$, $k = 1, 2, ..., K$, normalized to unity, the power of the received signal $y^{[k]}$ at receiver k after IA can be calculated as

$$P^{[k]} = \left| y^{[k]} \right|^2 = c_k^2 \cos^2\beta. \quad (12)$$

From the analysis in Fig. 2, we can obtain that

$$0 = c_k^2 \cos^2(\pi/2) \leq P^{[k]} \leq c_k^2 \cos^2(\pi/2 - \theta) = c_k^2 \sin^2\theta. \quad (13)$$

When vector $\mathbf{u}^{[k]}$ is orthogonal to the plane constructed by the vectors $\mathbf{a}^{[k]}$ and $\mathbf{b}^{[k]}$, $P^{[k]} = 0$; when vector $\mathbf{u}^{[k]}$ is lying in the same plane as the vectors $\mathbf{a}^{[k]}$ and $\mathbf{b}^{[k]}$, $P^{[k]} = c_k^2 \sin^2\theta$. Thus we can conclude that the maximum value of the received power of user k that can be achieved after IA, $P_{\max}^{[k]}$, is equal to $c_k^2 \sin^2\theta$.

Although the power of the received signal after IA may decrease, the power of the noise at the receivers will be unchanged. The SINR of the received signal at receiver k can be described as

$$\text{SINR}^{[k]} = \frac{P^{[k]}}{\left| \mathbf{u}^{[k]\mathrm{H}} \sum_{j=1, j \neq k}^{K} \mathbf{H}^{[kj]}\mathbf{v}^{[j]} \right|^2 + \sigma^2\mathbf{u}^{[k]\mathrm{H}}\mathbf{u}^{[k]}}. \quad (14)$$

Assume the interferences are almost zero after IA scheme and $\mathbf{u}^{[k]}$ is normalized to unity , thus we have

$$0 \leq \text{SINR}^{[k]} \approx \frac{P^{[k]}}{\sigma^2} \leq \frac{c_k^2 \sin^2\theta}{\sigma^2}. \quad (15)$$

We can see from (15) that the maximum value of the SINR of the received signal can be achieved at receiver k after IA, $\text{SINR}_{\max}^{[k]}$, is equal to $c_k^2 \sin^2\theta/\sigma^2$. The conclusion thus can be obtained that the SINR of the received signal after IA depends on the vector length containing the desired signal on the antennas at the receiver, and the maximum value of the SINR that can be achieved depends on angle θ between the vectors $\mathbf{b}$ and $\mathbf{a}$.

In a special case, $N = 2$ antennas are equipped at each receiver. The vectors $\mathbf{u}^{[k]}$, $\mathbf{a}^{[k]}$ and $\mathbf{b}^{[k]}$ are all two dimensional

vectors, and they are definitely lying in the same plane. Thu the SINR of the received signal at receiver k can be expresse as

$$\text{SINR}^{[k]} \approx \frac{c_k^2 \sin^2 \theta}{\sigma^2}. \tag{16}$$

Therefore, the SINR of the received signal after IA schem when $N = 2$ antennas are equipped at each receiver i depending on the acute angle θ and the vector length $\mathbf{H}^{[kk]}\mathbf{v}^{[k]}$ When θ and the length of vector $\mathbf{H}^{[kk]}\mathbf{v}^{[k]}$ become large higher SINR can be achieved.

Particularly, when $\theta = \pi/2$, the SINR of the received signa is maximal, and the QoS is relatively high. When $\theta = 0$ the SINR of the received signal is zero, and the QoS of th communication system cannot be guaranteed. ∎

When the DoFs of each user are larger than 1, the SINR of each DoF (data stream) of a user depends on the length of the vector containing the signal of desired DoF on the antennas at the receiver, and the acute angle between the directions of the signal of desired DoF and the corresponding interference suppression vector for the DoF. The proof of the above conclusion with larger DoFs can be easily extended from Theorem 1, and it will not be included here for the conciseness of the paper.

From the analysis above, it can be seen that the SINR of the received signal in IA schemes is sometimes extremely low, the BER is high, the QoS is poor, and thus the communication may even be terminated. Hence, we should improve the SINR of the IA scheme to enhance its adaptability when it is applied to practical wireless systems.

IV. IA SCHEME BASED ON ANTENNA SWITCHING

Although IA can eliminate the interferences in wireless networks completely in theory, from Theorem 1 we can see that the SINR of the desired signal could decrease significantly after IA, and the QoS cannot be guaranteed. In this section, a novel IA scheme based on antenna switching is proposed to improve the performance of IA wireless networks.

A. Reconfigurable Antennas

Antenna selection can be applied to improve the QoS of MIMO systems, however, its complexity is high and its size is large. To reduce the complexity and size of an antenna selection MIMO system, antenna switching based on reconfigurable antenna can be leveraged. Several preset modes can be operated on one reconfigurable antenna, and the channel coefficients are different when working in these modes. Thus, the optimal channel coefficients can be selected through antenna switching, and it can be applied to IA to improve its performance.

In this section, we propose a novel IA scheme based on antenna switching. For simplicity of implementation, we consider only two preset modes on each reconfigurable antenna, and some of the antennas at each receiver are replaced by reconfigurable antennas [19], [18]. An example of 3-user IA network with 1 DoF of each user based on antenna switching is shown in Fig. 2, and one reconfigurable antenna is equipped at each receiver.
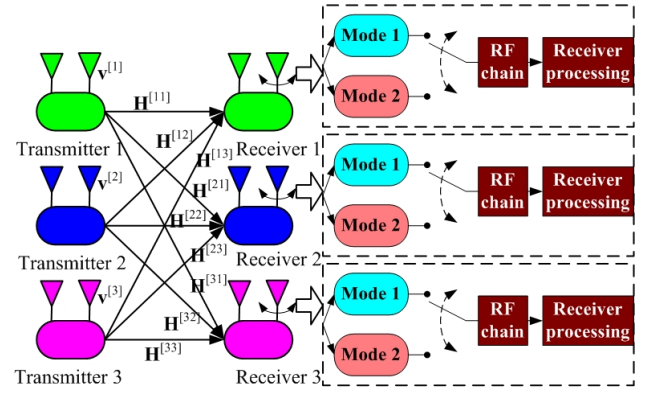

Fig. 2. An example of interference alignment system on a 3-user MIMO interference channel based on antenna switching through reconfigurable antenna. The conceptual depiction of the reconfigurable antenna is also presented.

The reconfigurable antenna in Fig. 2 can switch between these two preset modes, and the channel coefficients between all the antennas at the transmitters and this reconfigurable antenna change values accordingly. Thus the combination of the channel coefficients in the network with the optimal performance can be selected, and all the reconfigurable antennas switch modes according to this combination.

B. Objective Functions

Based on the reconfigurable antennas equipped at the receivers, antenna switching can be performed according to some objective functions to improve the performance of wireless IA networks. In this subsection, several objective functions are proposed and discussed.

Suppose there are K receivers in the IA wireless networks with N antennas at each receiver, Rn of which are reconfigurable antennas. Thus there are $D = (2^{Rn})^K$ available solutions, because each reconfigurable antenna has two preset modes. Assume $S = \{A_1, A_2, ..., A_D\}$ is the set that consists all the combinations of the available selected modes on the reconfigurable antennas, and in the AS-IA scheme, we should switch the reconfigurable antennas to the modes according to the optimal mode combination A_{opt}, through which the best performance can be achieved.

In the existing research works, the performance of IA schemes is mostly measured by the sum rate of the network [2], [5], [13], [14]. Thus, we present the first objective function for the AS-IA scheme based on the maximal sum rate achieved, which can be described as

$$A_{\text{opt}-\text{Rate}} = \arg\max_{A_p} \left\{ \sum_{k=1}^{K} R^{[k]}, p = 1, ..., \left(2^{Rn}\right)^K \right\}, \tag{17}$$

where $R^{[k]}$ is the rate achieved by the kth user, which can be defined as [5]

$$R^{[k]} = \log \left| \mathbf{I}_{d^{[k]}} + \frac{P^{[k]}}{d^{[k]}} \overline{\mathbf{H}}^{[kk]} \overline{\mathbf{H}}^{[kk]\text{H}} \right|, \tag{18}$$

where $\overline{\mathbf{H}}^{[kk]} = \mathbf{U}^{[k]\text{H}} \mathbf{H}^{[kk]} \mathbf{V}^{[k]}$.

Although the antenna switching based on the objective function described in (17) can maximize the sum rate of the network, QoS is not optimal with the maximal sum rate. Usually, QoS is measured by SINR of the received signal, and thus the SINR should be used to improve the QoS of IA schemes.

We propose the objective function of the AS-IA scheme based on SINR for the optimal solution as (19) (on the next page).

In (19), $\text{SINR}_i^{[k]}$ is the received SINR of the ith data stream (DoF) at receiver k, and can be calculated as

$$\text{SINR}_i^{[k]} = \frac{\left| \mathbf{U}_{*i}^{[k]\text{H}} \mathbf{H}^{[kk]} \mathbf{V}_{*i}^{[k]} \left(\mathbf{x}^{[k]} \right)_i \right|^2}{\left| \sum_{j=1,j\neq k}^{K} \sum_{d=1}^{d^{[j]}} \mathbf{U}_{*i}^{[k]\text{H}} \mathbf{H}^{[kj]} \mathbf{V}_{*d}^{[j]} \left(\mathbf{x}^{[j]} \right)_d \right|^2 + \sigma^2}. \quad (20)$$

Based on (19), the minimal received SINR of all the streams of the users is calculated in each solution, and the solution with the maximal value among the minimal SINRs is selected as the optimal solution. In other words, the worst case of all the streams is optimized to improve the average SINR performance of the networks. The computational complexity of (19) is $O\left(\left(2^{Rn} \right)^K \right)$. When K and Rn are relatively small, brute-force search can be utilized to enumerate all the possible candidates for the solution. When K and Rn become larger, it is an NP-hard problem [25], and advanced search algorithms, such as ant colony optimization and discrete stochastic optimization, can be applied to obtain the optimal solution with lower computational complexity [26], [27], [28].

In Section III, we can find that the received power of the desired signal after processed by the interference suppression vector can be calculated using angle β and the length of the vector of the desired signal from (12). Thus, we propose the objective function of the AS-IA scheme based on the signal power for the optimal solution as (21) (on the next page).

In (21), $P_i^{[k]}$ is the received power of the ith data stream at the kth receiver, and it can be represented as

$$P_i^{[k]} = \left| \mathbf{U}_{*i}^{[k]\text{H}} \mathbf{H}^{[kk]} \mathbf{V}_{*i}^{[k]} \left(\mathbf{x}^{[k]} \right)_i \right|^2. \quad (22)$$

The problem in (21) is also a max-min problem. From (3) we can see that the interferences are assumed to be completely eliminated using IA in the theoretical analysis. However the closed form expressions for the transmit precoding matrices are usually difficult to obtain [5]. Thus in the practical networks, easy-implemented algorithms should be selected, and the interferences cannot be eliminated ideally. Although the remaining part of the interference is trivial, it will still affect the SINR of the desired signal, especially when SNR is relatively high. Therefore, the performance of the AS-IA scheme based on (19) is better than that based on (21), while the computational complexity of (21) is less than that of (19), as it does not need to estimate the power of the background noise to calculate the SINR.

C. The Proposed IA Scheme Based on Antenna Switching

The timing of one frame transmission in the proposed AS-IA scheme is illustrated in Fig. 3, and the proposed scheme
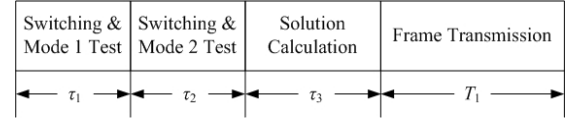

Fig. 3. The timing structure of one frame transmission in the AS-IA scheme.

in the transmission of one frame can be represented by the following steps:

1) All the reconfigurable antennas are switched to Mode 1 in duration τ_1. The channel coefficients corresponding to Mode 1 of the reconfigurable antennas are estimated and available for IA.
2) All the reconfigurable antennas are switched to Mode 2 in duration τ_2. The channel coefficients corresponding to Mode 2 of the reconfigurable antennas are estimated and available for IA.
3) The objective functions defined in (17), (19) or (21) are calculated in duration τ_3, and the solution with the optimal performance is applied to IA.
4) The frame of information is transmitted in duration T_1 using IA scheme with the optimal channel coefficients obtained in Step 3).
5) The transmission of one frame is finished, and another frame will be started.

Assume that the duration of one frame is T, and it can be denoted as

$$T = \tau_1 + \tau_2 + \tau_3 + T_1, \quad (23)$$

where $\tau_1 \approx \tau_2$. Block fading channel model is used in this paper. The channel remains constant over N consecutive symbol periods [29]. The length of T_1 is dependent on the coherence time of the channel. When K and Rn are relatively small, $\tau_1, \tau_2, \tau_3 \ll T_1$. Thus τ_1, τ_2 and τ_3 can be ignored compared to T_1. However, when K and Rn become larger, it is an NP-hard problem, and all the $\left(2^{Rn} \right)^K$ possible solutions should be calculated to find the optimal solution in the duration of τ_3. Thus τ_3 can no longer be ignored compared to T_1 with larger K and Rn when brute-force search is used, and it becomes unpractical. To reduce the duration of τ_3, advanced search algorithms can be applied to search for the optimal solution with lower computational complexity.

Remark 1: It is improper to apply the distributed IA [5] to the AS-IA scheme, and the closed form solutions of IA [2] should be exploited, which will lead to considerable amount of CSI feedback.

All the transceivers in the IA network should have the accurate CSI knowledge of the whole network, and it is difficult to achieve this in practical networks. When the closed form solutions of IA are applied to the K-user AS-IA scheme with M antennas at each transmitter and N antennas (Rn are reconfigurable antennas) at each receiver, K^2 CSI matrices with $(N + Rn) \times M$ dimension should be shared among all the nodes. Thus it is unpractical when the CSI feedback is applied.

The distributed IA algorithm can avoid large amount CSI feedback through using the reciprocity of the wireless networks. However, it is difficult to be leveraged in the AS-

$$A_{\text{opt}-\text{SINR}} = \arg \max_{A_p} \left\{ \min_{\{k,i\}} \left\{ \text{SINR}_i^{[k]}, k = 1, ..., K, i = 1, ..., d^{[k]} \right\}, p = 1, ..., \left(2^{Rn}\right)^K \right\}. \tag{19}$$

$$A_{\text{opt}-\text{POWER}} = \arg \max_{A_p} \left\{ \min_{\{k,i\}} \left\{ P_i^{[k]}, k = 1, ..., K, i = 1, ..., d^{[k]} \right\}, p = 1, ..., \left(2^{Rn}\right)^K \right\}. \tag{21}$$
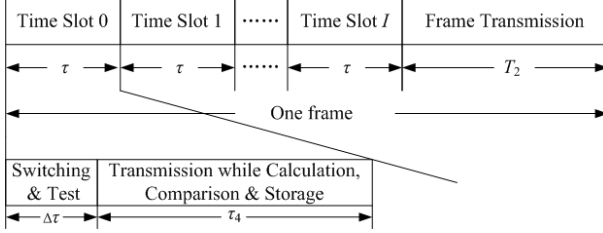
Fig. 4. One frame transmission in the proposed SAS-IA scheme, $I \le I_{th}$.

TABLE I
SWITCHING ORDER IN THE 3-USER SAS-IA SCHEME WITH 8 AVAILABLE SOLUTIONS ACCORDING TO GRAY CODE

Switching Order	0	1	2	3
Antenna Status	000	001	011	010
Switching Order	4	5	6	7
Antenna Status	110	111	101	100

IA scheme, because the communication is performed in the forward and inverse directions alternately in the iterations, and only one solution of the AS-IA scheme can be used in the iterative duration. Thus the proposed AS-IA scheme should be revised to reduce the overhead of the CSI feedback.

V. SEQUENTIAL ANTENNA SWITCHING IA SCHEME

The performance of IA wireless networks can be improved by the AS-IA scheme significantly, however its computational complexity and CSI-feedback overhead are high, which hinders the applications of AS-IA to practical systems. In this section, the SAS-IA scheme is proposed to reduce the complexity and CSI overhead of the AS-IA scheme, and both perfect CSI and imperfect CSI are considered.

A. Sequential Antenna Switching IA Scheme with Perfect CSI

The proposed IA scheme based on antenna switching in Section IV can improve the performance of IA wireless networks effectively, however, it is an NP-hard problem with its computational complexity equal to $\left(2^{Rn}\right)^K$. Besides, the overhead of the CSI feedback in the AS-IA scheme is considerable. Thus it may not be suitable for practical networks. In this section, a sequential antenna switching IA scheme is proposed, and perfect CSI is considered first. One frame transmission in the proposed SAS-IA scheme is depicted in Fig. 4.

In the SAS-IA scheme described in Fig. 4, only one antenna switches in a time slot, and the value of the objective function F is calculated and compared with the preset threshold λ. If $F > \lambda$, the sequential antenna switching stops and frame transmission continues with the optimal modes of the reconfigurable antennas; if $F \le \lambda$, the next antenna switching performs according to the order defined by Gray code as in Table I. During each time slot, the distributed IA algorithm is performed, and the communication between users still performs.

In Table I, the 3-bit Gray Code "xxx" defines the operating modes of the reconfigurable antennas for the 3-user interference network with 1 DoF each user. For the K-user interference network with Rn reconfigurable antennas at each receiver, $(K \cdot Rn)$-bit Gray Code can be applied. For example, "010" means that the reconfigurable antenna at receiver 1 operates in Mode 1, the reconfigurable antenna at receiver 2 operates in Mode 2, and the reconfigurable antenna at receiver 3 operates in Mode 1. The switching order is according to the Gray Code for the reason that only one reconfigurable antenna should perform switching in each time slot. If the value of F is larger than λ or the antenna switching has already performed I_{th} times, the antenna switching stops and the frame transmission continues according to the optimal modes achieved.

We should also consider the computational complexity and the duration of antenna switching in the algorithm. When $K \cdot Rn$ is relatively small, the preset largest antenna switching times I_{th} in Fig. 4 of the SAS-IA scheme can be set as $I_{th} = \left(2^{Rn}\right)^K$. However, when $K \cdot Rn$ becomes larger, it becomes an NP-hard problem if all the available solutions is calculated in $\left(2^{Rn}\right)^K$ time slots, and thus we should set $I_{th} < \left(2^{Rn}\right)^K$. The antenna switching times I in each frame transmission should abide by $I \le I_{th}$.

Although the performance is not optimal in the early switching, the communication in the IA network still performs. In Fig. 4, the duration of one frame in the SAS-IA scheme can be denoted as

$$T = I \times \tau + T_2 = I \times (\Delta\tau + \tau_4) + T_2. \tag{24}$$

In each time slot of antenna switching of Fig. 4, antenna switching and mode test are performed in the duration of $\Delta\tau$, and the communication still performs in the duration of τ_4 while the calculation, comparison, and storage are carried on at the same time. Assume that the duration of one frame in the AS-IA and SAS-IA schemes is the same, and from (23) and (24) we can obtain that

$$\tau_1 + \tau_2 + \tau_3 + T_1 = I \times (\Delta\tau + \tau_4) + T_2, \tag{25}$$

where $\Delta\tau < \tau_1 \approx \tau_2$, because only one antenna should be switched and only one antenna's CSI should be tested in the duration $\Delta\tau$ of the SAS-IA scheme.

Thus when I is relatively small, $I \times \Delta\tau < \tau_1 + \tau_2 + \tau_3$, and the transmission time in one frame of the SAS-IA scheme is longer than that of the AS-IA scheme. When I is relatively

large, $I \times \Delta\tau > \tau_1 + \tau_2 + \tau_3$, and the transmission time in one frame of the SAS-IA scheme is shorter than that of the AS-IA scheme.

Because the solution obtained in the SAS-IA scheme is sub-optimal, the transmission rate is decreased compared to that of the AS-IA scheme. Due to the communication in the duration τ_4 of each time slot of antenna switching in the SAS-IA scheme, the throughput loss compared to the AS-IA scheme can be somewhat filled up. Besides, as the switching times for the SAS-IA scheme are not larger than $\left(2^{Rn}\right)^K$, the computational complexity of the SAS-IA scheme is also lower than that of the AS-IA scheme. We will have more comparisons in Section VII.

In the SAS-IA scheme, the value F of the objective function should be compared with the threshold λ. The objective function (19) based on the SINR of received signal has the optimal performance, and SINR is usually exploited to measure the quality of the communication. Thus the SINR objective function is adopted in the SAS-IA scheme, and the value of F can be defined as

$$F = \min_{\{k,i\}} \left\{ \text{SINR}_i^{[k]}, k = 1, ..., K, i = 1, ..., d^{[k]} \right\}. \quad (26)$$

The proposed SAS-IA scheme based on the received SINR can be represented by the following steps:

1) When one frame starts, j is set to 1.
2) If $j = 1$, the value F_j is calculated according to (26) with the optimal antenna status in the last frame; else, antenna switching performs according to the Gray code order, and the value F_j is calculated using (26) with the new antenna status.
3) Compare the value F_j with the preset threshold λ. If F_j is larger than λ, go to Step 5), and thus $I = j$; else go to Step 4).
4) $j = j + 1$. If $j \leq I_{th}$, go to Step 2); else go to Step 5), and thus $I = I_{th}$. In the Steps 2) to 4), the transmission of the frame still performs based on the current antenna status.
5) Antenna switching stops, and frame transmission continues through the modes of the reconfigurable antennas defined by F_j. After the transmission for the duration T_1, one frame ends, and go to Step 1). The length of T_1 is dependent on the coherence time of the channel.

In the above described SAS-IA scheme, if antenna switching is performed $\left(2^{Rn}\right)^K$ times in one frame transmission, the optimal solutions can be expressed as in (19). When antenna switching is performed $I < \left(2^{Rn}\right)^K$ times in a certain frame, the optimal solutions can be denoted as (27) (on the next page).

In (27), $\{B_p : p = 1, 2, ..., I\}$ are the solutions calculated in the above SAS-IA scheme in one frame. From the above analysis, we can also know that $I \leq I_{th} \leq \left(2^{Rn}\right)^K$.

Remark 2: In the SAS-IA scheme, due to the utilization of the distributed IA algorithm, the overhead of the CSI feedback and computational complexity are significantly reduced, and the communication still performs during antenna switching. Thus it is more suitable to be applied to practical systems than the AS-IA scheme.

In [5], the convergence proof of the distributed IA algorithm is presented, and it is pointed out that the convergence to global minimum is not guaranteed due to the nonconvex nature of the interference optimization problem. On the other hand, the simulation results in [5] show that the performance of the distributed IA algorithm and centralized IA (closed-form IA) algorithm is very close, and exploiting distributed IA will not reduce the performance of the SAS-IA scheme obviously.

B. Sequential Antenna Switching IA Scheme with Imperfect CSI

In practical wireless communication networks, there exist errors in CSI estimation. Thus the CSI used in the SAS-IA scheme is usually imperfect, which will affect its performance inevitably. In this subsection, a filtering SAS-IA (FSAS-IA) scheme is proposed to improve the performance of the SAS-IA scheme under imperfect CSI.

In the proposed SAS-IA scheme, the distributed IA algorithm is applied to obtain the solutions of IA. If imperfect CSI is utilized in the distributed IA, the solutions will not fit for the accurate CSI exactly, which will degrade the performance of the SAS-IA scheme. Define N_I as the number of iterations in the distributed IA algorithm of the SAS-IA scheme, and the estimated imperfect CSI at time instant n of the distributed IA can be defined as

$$\widehat{\mathbf{H}}^{[kj]}(n) = \mathbf{H}^{[kj]}(n) + a\mathbf{G}(n), k = 1, 2, ..., K,$$
$$j = 1, 2, ..., K, n = 1, 2, ..., N_I, \quad (28)$$

where $\mathbf{G}(n)$ is the matrix whose elements are complex normal random variables with zero mean, and their variances are the same as those of the elements in $\mathbf{H}^{[kj]}(n)$. a is a positive parameter that reflects the accuracy of the estimated CSI. The estimated CSI is more accurate with smaller a.

In the proposed FSAS-IA scheme, the estimated CSI is filtered through averaging during the iterations, and applied to the distributed IA in each iteration. The filtered CSI in the nth iteration of distributed IA can be expressed as

$$\widetilde{\mathbf{H}}^{[kj]}(n) = \frac{1}{n} \sum_{m=1}^{n} \widehat{\mathbf{H}}^{[kj]}(m), n = 1, 2, ..., N_I. \quad (29)$$

Through the filtering in (29), the CSI becomes accurate as iterations carried on, and the estimation error decreases. By exploiting the filtered CSI $\widetilde{\mathbf{H}}^{[kj]}$, the performance of the SAS-IA scheme is significantly improved by the FSAS-IA scheme, which will be shown in Section VII.

VI. PERFORMANCE ANALYSIS

In this section, the performance of the conventional IA, AS-IA, and SAS-IA schemes is analyzed.

Theorem 2: The performance of the SAS-IA scheme is better than that of the IA scheme, and worse than that of the AS-IA scheme.

Proof: In the proof, only the SINR performance is considered, and the throughput performance can be similarly proven.

For a certain frame, define the sets consisting all the available solutions of the AS-IA scheme as

$$S_{\text{AS-IA}} = \{A_1, A_2, ..., A_D\}, \quad (30)$$

$$B_{\text{opt}-\text{SINR}} = \arg\max_{B_p} \left\{ \min_{\{k,i\}} \left\{ \text{SINR}_i^{[k]}, k = 1, ..., K, i = 1, ..., d^{[k]} \right\}, p = 1, ..., I \right\}. \tag{27}$$

where $D = \left(2^{Rn}\right)^K$. Assume that the channel coefficients are i.i.d., and thus A_d is also i.i.d., $d = 1, 2, ..., D$. Thus without loss of generality, we can define the sets consisting all the available solutions of the SAS-IA scheme as

$$S_{\text{SAS}-\text{IA}} = \{A_1, A_2, ..., A_I\}, \tag{31}$$

where $I \leq I_{th} \leq D = \left(2^{Rn}\right)^K$. We can also define the solution of the IA scheme as $S_{\text{IA}} = \{A_1\}$, due to the i.i.d. characteristic of A_d.

To simplify the expression, we define $\gamma_i^{[k]}(A_j)$ as the received SINR of the ith DoF of user k according to the solution of A_j. From the SINR expression in (20), we can easily know that $\gamma_i^{[k]}(A_j)$ is i.i.d..

In the AS-IA, SAS-IA and IA schemes, we can define

$$LS(A_j) = \min_{\{k,i\}} \left\{ \gamma_i^{[k]}(A_j), k = 1, ..., K, i = 1, ..., d^{[k]} \right\}, \tag{32}$$

which is the lowest SINR of the data streams of all the users based on the solution A_j. The AS-IA and SAS-IA schemes aim at maximizing $LS(A_j)$ for $j = 1, 2, ..., D$ and $j = 1, 2, ..., I$, respectively.

In the AS-IA scheme, its optimal solution can be defined as

$$A_{\text{opt}-\text{AS}-\text{IA}} = \arg\max_{A_j} \{LS(A_j), j=1, 2, ..., D\} = A_{\text{opt}1}. \tag{33}$$

In the SAS-IA scheme, its optimal solution can be defined as

$$A_{\text{opt}-\text{SAS}-\text{IA}} = \arg\max_{A_j} \{LS(A_j), j=1, 2, ..., I\} = A_{\text{opt}2}. \tag{34}$$

In the IA scheme, its solution is defined as

$$A_{\text{IA}} = A_1 = A_{\text{opt}3}. \tag{35}$$

Due to $1 \leq I \leq D$, it can be obtained that

$$LS(A_{\text{opt}1}) = \min_{\{k,i\}} \left\{ \gamma_i^{[k]}(A_{\text{opt}1}) \right\}$$
$$\geq LS(A_{\text{opt}2}) = \min_{\{k,i\}} \left\{ \gamma_i^{[k]}(A_{\text{opt}2}) \right\}$$
$$\geq LS(A_{\text{opt}3}) = \min_{\{k,i\}} \left\{ \gamma_i^{[k]}(A_{\text{opt}3}) \right\}. \tag{36}$$

From (36) we can observe that the lowest SINR of all the data streams in the AS-IA scheme is larger than or equal to that of the SAS-IA scheme, and the lowest SINR of all the data streams in the SAS-IA scheme is larger than or equal to that of the IA scheme. Thus we can conclude that the performance of the SAS-IA scheme is better than that of the IA scheme, and worse than that of the AS-IA scheme. ∎

From Theorem 2, we can see that, although the performance of the AS-IA scheme is better than that of the SAS-IA scheme, the CSI feedback overhead and the computational complexity of the AS-IA scheme can be reduced significantly by the SAS-IA scheme, and it will be further demonstrated through simulation in Section VII.
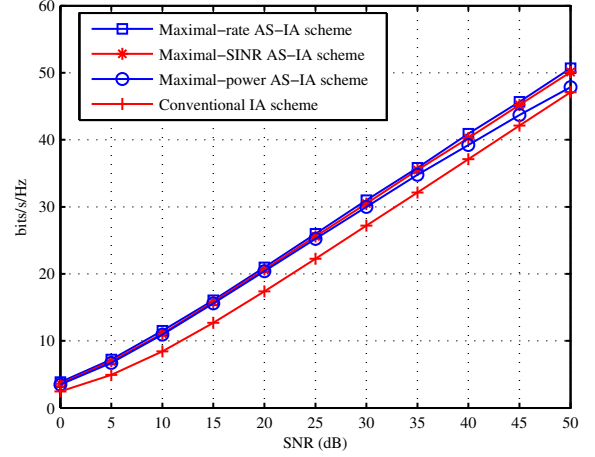

Fig. 5. Sum rate comparison of the AS-IA schemes based on three different objective functions as well as the sum rate of the conventional IA scheme. There are 3 users and 1 DoF of each user.

VII. SIMULATION RESULTS AND DISCUSSIONS

In the first two subsections, we consider a MIMO interference network consisting of $K = 3$ users, as shown in Fig. 2, and DoFs of each user is set to 1. $M = 2$ antennas are equipped at each transmitter, and one ordinary antenna and one reconfigurable antenna ($Rn = 1$) are equipped at each receiver. In the third and fourth subsection, more DoFs and more users are considered, respectively. All the channels are under Rayleigh fading. We assume that the CSI obtained at both receivers and transmitters are perfect in these four subsections. In the fifth subsection, the performance of the SAS-IA scheme with imperfect CSI is discussed.

In the simulation of the AS-IA scheme, the closed form solutions of IA is applied, while in the simulation of the SAS-IA scheme, the distributed IA algorithm based on the reciprocity of wireless networks is adopted to calculate the precoding and interference suppression matrices.

A. Performance of the Antenna Switching IA Scheme

We first study the performance of the AS-IA scheme proposed in Section IV. Fig. 5 shows the average sum rate of the AS-IA network based on the objective functions defined in (17), (19) and (21), as well as the average sum rate of the conventional IA network. From the results, we can observe that the sum rate of the IA network is increased through antenna switching, and the sum rate of the maximal-rate AS-IA scheme is the largest among these schemes, as it aims at improving the sum rate directly.

Sum rate is not the only performance measure we should consider, since larger sum rate does not necessarily mean better communication performance. Thus, the BER achieved by these schemes is compared in Fig. 6. For all the users, binary phase shift keying (BPSK) modulation and coherent detection is adopted for easier analysis, and the proposed
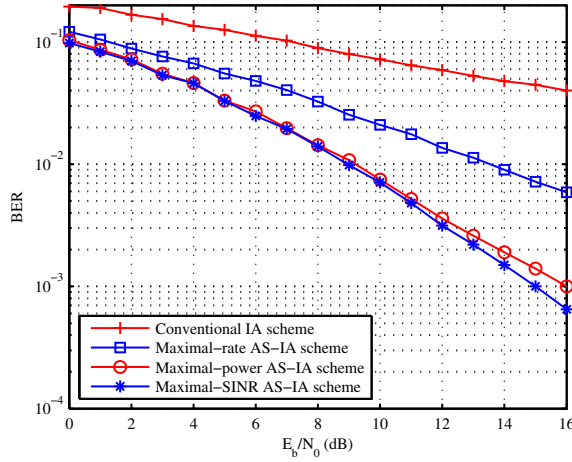
Fig. 6.   BER comparison of the AS-IA schemes based on three different objective functions as well as the BER of the conventional IA scheme. There are 3 users and 1 DoF of each user.

Fig. 7.   Outage probability comparison of the SAS-IA schemes with different values of threshold λ, the AS-IA scheme, and the conventional IA scheme. There are 3 users and 1 DoF of each user. The target rate for each user is set to 5 bits/s/Hz.

scheme can be extended to other more complex modulations easily. The baseband symbol rate is 2Mbps.

From the results in Fig. 6, we can see that the BER performance of the three AS-IA schemes is much better than that of the conventional IA scheme. Although the sum rate is the largest when the maximal-rate solution of the AS-IA scheme is applied, its BER is still much higher than that based on the maximal-SINR solution. The BER of the maximal-SINR AS-IA scheme is the lowest among these schemes, and the BER performance of the AS-IA scheme based on the maximal-power solution is close to that of the AS-IA scheme based on the maximal-SINR solution with lower computational complexity.

B. Performance of the Sequential Antenna Switching IA Scheme

From the simulation results in Fig. 5 and Fig. 6, we can see that the proposed AS-IA scheme can improve the QoS of IA wireless networks effectively. However, the computational complexity of the AS-IA scheme is high and becomes unacceptable for wireless networks with larger K and Rn, because its computational complexity is $O\left(\left(2^{Rn}\right)^{K}\right)$. The SAS-IA scheme proposed in Section V can reduce the computational complexity without obvious decrease of its QoS. In this subsection, the performance of the SAS-IA scheme is studied, and the maximal-SINR objective function defined in (19) is applied.

One important drawback of IA is that the SINR may decrease dramatically when the desired signal and the interferences are aligned in the similar directions, and the power of the received signal may even become zero under some channel coefficients. The QoS of the IA networks cannot be satisfied in these situations, and the communication may even be terminated especially in the voice communication systems. Outage probability can reflect the variability of the quality of the received signal, and it is suitable for analyzing the QoS of IA algorithms. Thus the outage probability of the proposed SAS-IA scheme is considered [30]. If the transmitter encodes
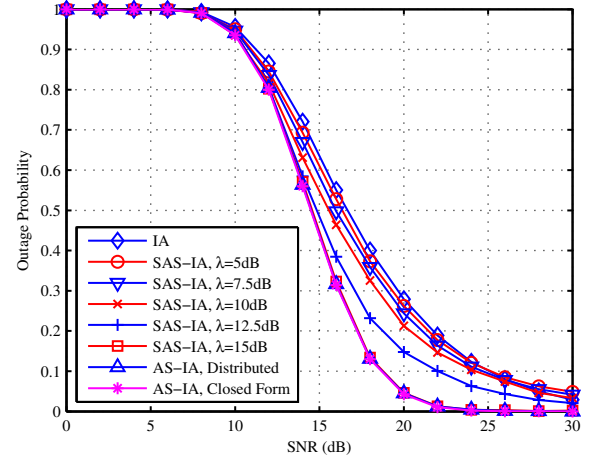
data at rate R (bits/s/Hz), the outage probability is a certain probability that the decoding error probability cannot be made arbitrarily small. The outage probability in the IA scheme can be defined as [16]

$$\Pr\{\text{outage}\} = \Pr\left\{\log_2\left(1 + \text{SINR}_i^{[k]}\right) \leq R_{th,i}^{[k]}\right\}, \quad (37)$$

where $\text{SINR}_i^{[k]}$ is the SINR of the ith data stream of the desired signal at receiver k, $R_{th,i}^{[k]}$ is the target rate set for the ith data stream of the kth user. The outage probability of the SAS-IA scheme with different values of threshold λ of 5dB, 7.5dB, 10dB, 12.5dB and 15dB, the AS-IA scheme with maximal-SINR objective function, and the conventional IA scheme is compared in Fig. 7, and the target rate for each user is 5 bits/s/Hz.

From the results in Fig. 7, we can observe that the outage probability of the SAS-IA scheme is much lower than that of the conventional IA scheme with all the threshold values utilized, and it is lower with larger λ. When λ is larger than 15dB, the outage probability is close to that of the AS-IA scheme based on the maximal-SINR solution.

The convergence of the distributed IA algorithm is proven in [5], however the convergence to global minimum is not guaranteed due to the nonconvex nature of the interference optimization problem. To study the usability of the distributed IA algorithm, the outage probability of the AS-IA scheme using distributed IA algorithm is shown in Fig. 7. From the results, we can see that the outage probability of the AS-IA scheme using distributed IA algorithm is very close to that of the AS-IA scheme with the closed form solutions of IA, which is also reflected in [5]. Thus, the distributed IA algorithm can be leveraged in the SAS-IA schemes, and will not cause obvious degradation of its performance.

Compared to the AS-IA scheme, the key advantage of the SAS-IA scheme is its low computational complexity. Thus, we will focus on its computational complexity, and the average switching times are studied with different values of threshold λ in Fig. 8. In the simulation, $K = 3$, $Rn = 1$, and we set $I_{th} = \left(2^{Rn}\right)^{K} = 8$.
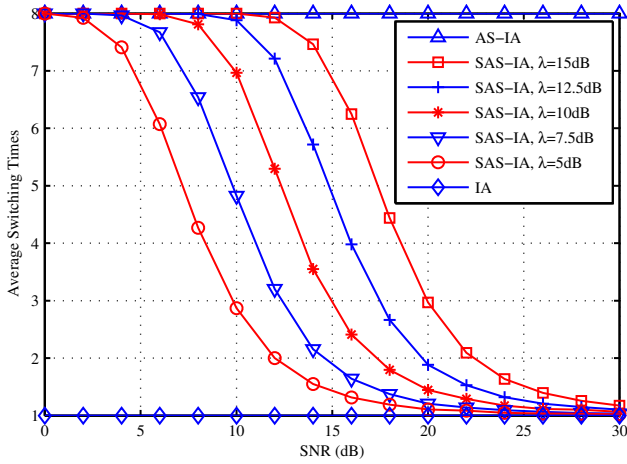
Fig. 8. Average switching times in the SAS-IA scheme with different values of threshold λ in the MIMO interference network with 3 users and 1 DoF of each user.
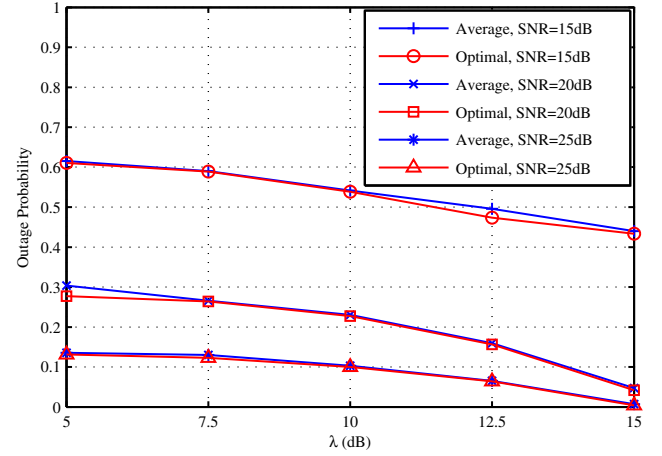

Fig. 9. Average and optimal outage performance comparison of the SAS-IA schemes. There are 3 users and 1 DoF of each user. The target rate for each user is set to 5 bits/s/Hz.

The average switching times determine the computational complexity of the SAS-IA scheme directly. In Fig. 8, it is shown that, with the increase of threshold λ, the switching times become larger accordingly with better outage probability performance. On the other hand, for a given λ, the switching times decrease quickly and converge at 1 when the SNR becomes larger.

In Fig. 7, we only show the performance of the SAS-IA scheme when the threshold λ is met. However, the communication still performs in τ_4 of each time slot of the antenna switching, and the performance in the early switching should also be considered. Thus in Fig. 9, we show the average performance of the SAS-IA scheme (including early switching) compared with the optimal performance when λ is met. In the simulation, we assume that 10-bit data are transmitted in each time slot of switching, and 1000-bit data are transmitted in the frame transmission period T_2 in each frame.

From the results in Fig. 9, we can see that the average outage performance is a little bit worse than that of the optimal outage performance, due to the sub-optimal configuration in the early switching. However, the performance loss is not very significant. In addition, we can observe that the performance of the SAS-IA scheme becomes better with larger λ. However, larger λ may cause longer time to find the optimal solution. Thus, there is a tradeoff between the computational complexity and performance. In practical systems, λ should be set according to the requirements of the communication systems, e.g., different types of service.

C. SAS-IA Scheme with More DoFs

In the above simulations, only the IA network with 3 users and 1 DoF of each user is considered. In this subsection, we will study a more complicated case of the SAS-IA scheme with more DoFs.

Consider a MIMO interference network consisting of $K = 3$ users, and the DoFs of each user are set to 2. $M = 4$ antennas are equipped at each transmitter. $N = 4$ antennas are equipped at each receiver, two of which are reconfigurable

antennas, that is $Rn = 2$. The feasibility of IA is investigated in [31], and it can be referred to determine the number of the antennas equipped at each transmitter and receiver according to the number of users and DoFs. Thus the number of all the available solutions is $\left(2^{Rn}\right)^K = 64$. To reduce the computational complexity of the SAS-IA scheme, we set $I_{th} = 16 < \left(2^{Rn}\right)^K = 64$.

The outage probability achieved by the SAS-IA scheme with different values of threshold λ of 7.5dB, 10dB, 12.5dB, 15dB and 17.5dB is compared in Fig. 10 with 2 DoFs of each user. In the figure, the performance of the AS-IA scheme with maximal-SINR objective function and the conventional IA scheme is also compared, and the target rate for each data stream of the users is 5 bits/s/Hz. From the simulation results, we can see that the outage probability of the SAS-IA scheme is much lower than that of the conventional IA scheme, and it becomes lower when the threshold λ is larger. The outage probability of the SAS-IA scheme cannot converge to that of the AS-IA scheme with larger λ, because I_{th} is set much smaller than $\left(2^{Rn}\right)^K$, and the computational complexity can be reduced dramatically.

The computational complexity is also analyzed, and the average switching times with different values of threshold λ are shown in Fig. 11. From the results, it is shown that when the threshold λ becomes larger, the switching times become larger accordingly with better outage probability performance. On the other hand, for a given λ the switching times decrease quickly and converge at 1 when the SNR becomes larger. Besides, the computational complexity of the SAS-IA scheme is much lower than that of the AS-IA scheme.

In Fig. 10 and Fig. 11, I_{th} is set to 16, and we should also study the performance of the SAS-IA scheme with different values of I_{th}. The outage probability of the SAS-IA scheme with 3 users and 2 DoFs each with varying I_{th} is compared in Fig. 12. λ is set to 15dB, and the target rate for each user is 5 bits/s/Hz. From the results we can observe that the outage performance becomes better when I_{th} is larger, however, the computational complexity is also increased. Thus a tradeoff should be made between the performance and complexity
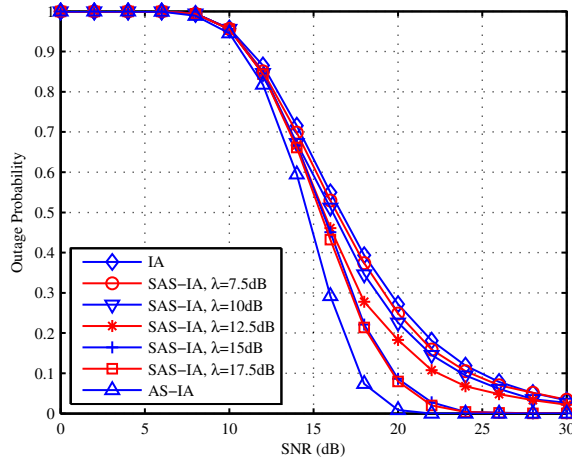
Fig. 10. Outage probability comparison of the SAS-IA scheme based on maximal-SINR objective function with different values of threshold λ in the 3-user MIMO interference network with 2 DoFs of each user.
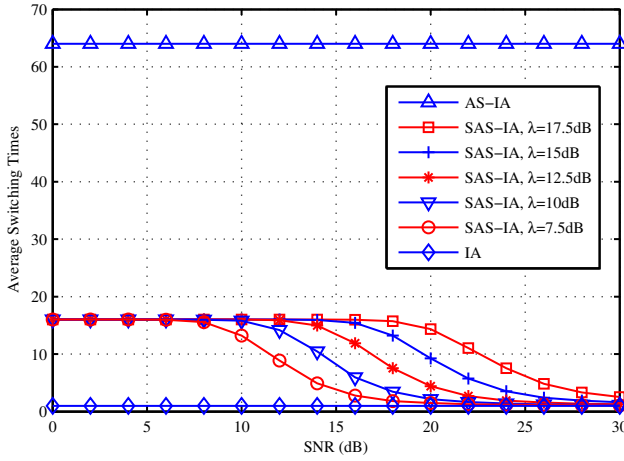

Fig. 12. Outage probability comparison of the SAS-IA scheme with different values of I_{th} in the 3-user MIMO interference network with 2 DoFs of each user. λ is set to 15dB.

Fig. 11. Average switching times comparison in the SAS-IA scheme with different values of threshold λ in the 3-user MIMO interference network with 2 DoFs of each user.

Fig. 13. Outage probability comparison of the SAS-IA schemes with different values of threshold λ, the AS-IA scheme, and the conventional IA scheme. There are 5 users and 1 DoF of each user. The target rate for each user is set to 5 bits/s/Hz.

when setting I_{th}.

Moreover, we have also obtained the average switching times in the SAS-IA scheme when $I_{th}=64$. The average switching times are 64, 61.6550, 40.5175, and 14.1620 when the SNRs are 12.5dB, 15dB, 17.5dB, and 20dB, respectively. From the above analysis and the results in Fig. 12, we can see that, when SNR is extremely low for a certain λ, I_{th} should not be set to a large value, because the performance can be hardly improved even when $I_{th} = \left(2^{Rn}\right)^{K}$. I_{th} can be set larger with higher SNR for a certain λ, because the actual switching time I is usually much smaller than I_{th} when SNR is high enough.

D. SAS-IA Scheme with More Users

In this subsection, the performance of the SAS-IA scheme with more users is considered. Fig. 13 shows the outage probability achieved by the SAS-IA scheme with different values of threshold λ, 10dB, 12.5dB, and 15dB. In the figure, the performance of the AS-IA scheme with maximal-SINR objective function and conventional IA scheme is also
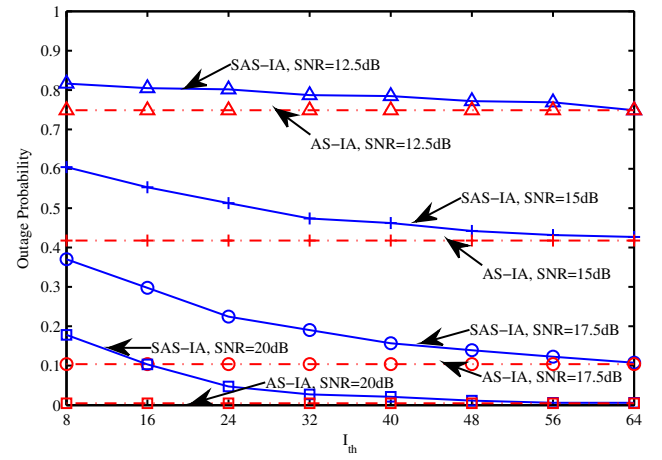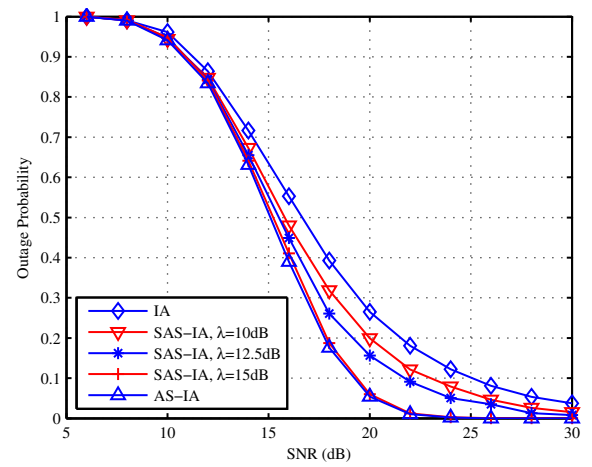
compared. There are 5 users and 1 DoF of each user. The target rate for each user is set to 5 bits/s/Hz. $M = 3$ antennas are equipped at each transmitter. $N = 3$ antennas are equipped at each receiver, one of which is reconfigurable antenna, that is, $Rn = 1$. Thus the number of all the available solutions is $\left(2^{Rn}\right)^{K} = 32$. I_{th} is set to 32. From the simulation results, we can see that the outage probability of the SAS-IA scheme is much lower than that of the conventional IA scheme, and it becomes lower when the threshold is larger. When λ is larger than 15dB, the outage probability is close to that of the AS-IA scheme based on the maximal-SINR solution.

The average switching times are studied with different values of threshold λ in Fig. 14. It is shown that, with the increase of threshold λ, the switching times become larger accordingly with better outage probability performance. On the other hand, for a given λ, the switching times decrease quickly and converge at 1 when the SNR becomes larger.

From these two figures, we can see that the performance of the SAS-IA scheme with more users is very similar to that of
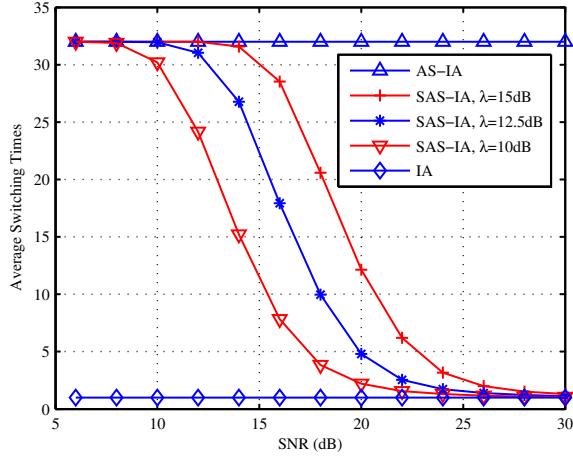
Fig. 14. Average switching times in the SAS-IA scheme with different values of threshold in the MIMO interference network with 5 users and 1 DoF of each user.
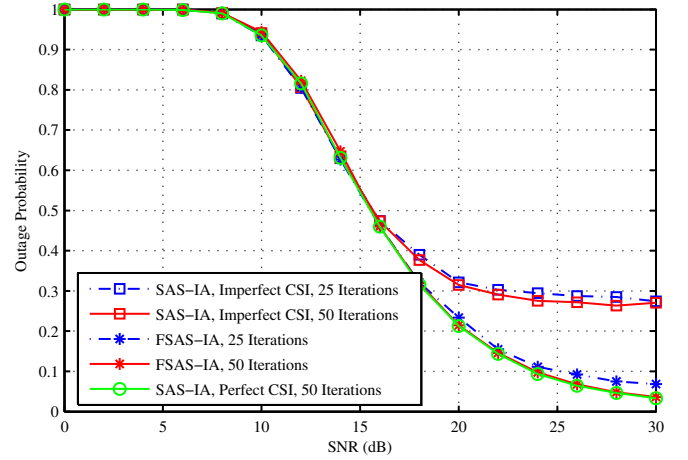

Fig. 15. Outage probability comparison of the SAS-IA scheme under perfect CSI, the SAS-IA scheme under imperfect CSI, and the FSAS-IA scheme under imperfect CSI. There are 3 users and 1 DoF of each user. The threshold $\lambda = 10$dB.

the SAS-IA scheme with more DoFs, which is presented in Subsection VII-C.

E. SAS-IA Scheme under Imperfect CSI

In practical wireless networks, the CSI used in the SAS-IA scheme is imperfect, and it will affect the communication performance inevitably. The FSAS-IA scheme is proposed to improve the performance of the SAS-IA scheme in Subsection V-B. The outage probability of the SAS-IA scheme under perfect CSI, the SAS-IA scheme under imperfect CSI, and the FSAS-IA scheme under imperfect CSI is compared in Fig. 15. In the network, $K = 3$, $M = N = 2$, and 1 DoF of each user. The threshold λ in the SAS-IA and FSAS-IA schemes is 10dB, the parameter a in (28) is set to 0.1.

From the results, we can see that the performance of the SAS-IA scheme degrades seriously under imperfect CSI when SNR is high, and the FSAS-IA scheme can reduce the influence caused by the imperfect CSI significantly.

F. Further Discussions

The AS-IA scheme proposed in Section IV can achieve better performance, while the SAS-IA scheme proposed in Section V operates with lower computational complexity and CSI-feedback overhead. Therefore, these two antenna switching IA schemes should be properly selected according to different requirements in practical networks. When the number of users in a MIMO interference network becomes larger, the computational complexity of the AS-IA scheme and SAS-IA scheme increases significantly. To reduce the computational complexity, we can equip reconfigurable antennas at only some immobile receivers with high computation capability and large size, and the performance of users in the network will all be improved. The number of the reconfigurable antennas equipped should be balanced between the computational complexity and the required performance of the system.

VIII. CONCLUSIONS AND FUTURE WORK

In this paper, we have analyzed the problem of SINR degradation in conventional IA schemes, which makes them

difficult to use in practical wireless networks. A novel IA scheme based on antenna switching through reconfigurable antenna has been proposed to improve the QoS of IA wireless networks, and three objective functions for antenna switching have been presented. Moreover, to reduce the computational complexity and CSI-feedback overhead, we have presented a sequential antenna switching interference alignment scheme. To further improve the performance of the SAS-IA scheme under imperfect CSI, FSAS-IA scheme has been proposed through averaging the estimated CSI. Simulation results have showed that the proposed antenna switching IA schemes can improve the QoS in IA wireless networks significantly.

Block fading channel model is used in this paper, in which the channel remains constant in each frame. However, the channel might vary in each frame. Thus, in our future work, we will do further research on the antenna switching IA schemes under more realistic time-varying channels.

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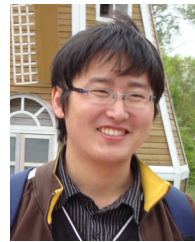
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