Joint Beamforming for Intelligent Reflecting Surface Aided Wireless Communication Using Statistical CSI

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Abstract: A joint beamforming algorithm is proposed for intelligent reflecting surface (IRS) aided wireless multiple-input multiple-output (MIMO) communication using statistical channel state information (CSI). The beamforming is done by alternatively optimizing the IRS reflecting coefficients and the covariance matrix of the transmit symbol vector, such that the ergodic rate of the system is maximized. The algorithm utilizes only the second order momentum of the random channel matrices and does assume any specific channel distribution, leading to a general framework for ergodic rate evaluation. A practical channel correlation model is configured to validate the performance gain. It is found that the rate can be enlarged by the joint optimization algorithm, however, the gain over that of randomly deployed reflecting coefficients depends highly on the relative correlation distance of the IRS elements and the spatial position of the IRS. In particular, the results suggest that IRS should be placed in the vicinity of either the transmitter or the receiver. Placing IRS far away from those positions is non-beneficial.
Keywords: MIMO; beamforming; statistical CSI; intelligent reflecting surface (IRS); ergodic rate

I. INTRODUCTION

One of the main research goals of wireless communication in the physical layer is to boost the capacity with cost-efficient strategies. Conventional ways to scale up the capacity include utilizing additional channel resources and employing advanced signal processing methods. The former includes millimeter wave communication, Terahertz communication, and optical wireless communication. Multiple input multiple output (MIMO) and massive MIMO can also be classified into this category as they exploit spatial resource. The latter includes any capacity-approaching signal processing methods, such as advanced channel encoding and decoding, non-orthogonal multiple access (NOMA), turbo receiver, etc. In either case, the channel itself is only adapted by the transceiver, without any active optimization, since the transceiver of the communication system is incapable of actively controlling the propagation channel.

In recent years, with the development of artificial electromagnetic materials, controlling the communication environment through digital, programmable and reconfigurable methods becomes a reality [1-4]. Among them, intelligent reflecting surface (IRS), also known as reconfigurable intelligent surface (RIS), large intelligent surface/antenna (LISA), has drawn much attention in the past two years [5,6]. IRS consists of many tiny reflecting elements which have such property that the reflection behavior of each element can be actively and

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This paper studied a joint beamforming algorithm for IRS aided wireless MIMO communication based only on statistical CSI.

independently controlled. The reflection behavior refers to the reflecting coefficient here, which is a complex number whose norm is no larger than 1 due to the passive property. Utilizing this physical phenomenon, by carefully tuning the coefficients, IRS can be integrated into wireless communication systems to enhance various transmission performance metrics, such as capacity [7], wireless security [8], and energy efficiency [9]. IRS is also used in many wireless communication scenarios including MIMO [10], NOMA [11], and multicarrier modulation [12]. All those techniques lead to the so called IRS aided wireless communication. Indeed, as beamforming is one of the key issues in IRS, it can be foreseen that IRS will also find its role in related areas such as wireless information and power transfer [15] as well as unmanned aerial vehicle (UAV) based wireless communications [14].

In previous works, the performance was optimized mainly based on instantaneous channel state information (CSI). However, a main obstacle for IRS aided wireless communication is the difficulty of acquiring the accurate instantaneous CSI, especially the ones related to the IRS [15]. The reason is that IRS is a passive device when used in the reflecting mode. It cannot receive nor sample the incident signals, which is quite different from conventional active antenna array. For example, even in a single input single output system (MIMO configuration will only further complicate the situation), if there are N IRS elements, we need to estimate $2N$ IRS associated CSI plus one direct channel, all through a single antenna at either the transmitter or the receiver. This may require transmitting $(2N+1)$ pilot symbols with distinct associated IRS states, i.e., a snapshot of the N reflection coefficients, for each pilot symbol to avoid possible under determination in channel estimation. The overhead of signaling exchange is rather large. What is even worse is that the transition frequency for different states of IRS is actually not very fast nowadays, in the order of a few megahertz [16,17]. This hardware imperfection leads to discontinuity in the pilot transmission stage and may force the estimation time to be longer than the channel coherence time. While some works focused on fancy schemes of obtaining instantaneous CSI [18-21], it is more desirable to study how to exploit statistical CSI, which is a much stable quantity that changes much slower over time. The resultant system would have sufficient time to obtain and update the channel statistics. The overhead of signaling exchange and computation burden can be reduced, as the state of IRS needs not to be changed frequently. Therefore, configuring IRS coefficients in a long time scale exploiting statistical CSI is reasonable in practice.

As a new research direction, there were only limited works that touched this topic. The main difficulty compared with the schemes working on instantaneous CSI is how to properly capture the channel statistics in the interested performance metric and problem formulation. Specifically, [22] studied how to exploit statistical CSI in IRS aided wireless multiple input single output (MISO) communication. However, the work was based on Rician fading channel model with uniform linear array (ULA) assumption for both the base station and the IRS, which is not a general configuration especially for the IRS. In addition, the result cannot be readily used in MIMO configuration since the covariance matrix optimization is actually not done there. [23] proposed a two-timescale beamforming method where the passive IRS beamforming was done based on statistical CSI while the active beamforming of the transmit antennas was done based on instantaneous CSI. Here, as most existing literature adopted, the term "passive beamforming" refers to the setting of the IRS reflection coefficients while the term "active beamforming" refers to the setting of covariance matrix of the transmit symbol vector across the transmit antennas. While this approach can be a good candidate solution in practical deployment, it still depends on a specific fading model, i.e., the Rician fading. The independent and identically distributed (i.i.d.) Gaussian setup of the non-line-of-sight part of the channel matrix was a precondition, and also a key to the simplification procedure during the derivation of the final form of the optimization problem formulation. Moreover, the optimal IRS beamforming essentially does not match the beamforming of the transmit antennas since the latter changes much faster with time. Thus, the potential gain of exploiting only statistical CSI in MIMO communication has not been fully unveiled.

Motivated by the above issues, in this paper, we study a joint beamforming algorithm for IRS aided wireless MIMO communication using statistical CSI for both active and passive beamforming, with the goal of exposing the potential gain in ergodic rate by utilizing IRS and exploiting statistical CSI. The beamforming is done by alternatively optimizing the IRS reflecting coefficients and the covariance matrix of the transmit symbol vector under a total power constraint, such that the ergodic rate of the system is maximized. The contribution of this paper can be summarized as follows: (1) Different from previous works, the proposed scheme captures and utilizes only the second order momentum of the channel statistics and does not depend on any specific fading model nor instantaneous CSI. Therefore, it can be regarded as a general framework of IRS configuration based on statistical CSI. (2) Another contribution of this work is to provide a practical simulation environment that captures both the large-scale fading and the correlation effect between the IRS elements. It is found that both channel correlation and the position of IRS have great impacts on the ergodic rate.

The remaining of this paper is organized as follows. Section II provides the system model and problem formulation. Section III gives detailed optimization algorithm. Section IV provides simulation setup and results. Section V concludes the paper.

Notation: C denotes complex field. $(\cdot)^T$,$(\cdot)^*$ and $(\cdot)^H$ denote the transpose, complex conjugate and Hermitian transpose, respectively. $tr(\cdot)$ and $\det(\cdot)$ denote the trace and determinant of a matrix. $E\{\cdot\}$ denotes expectation with respect to random variables. $\otimes$ denotes Kronecker product. $vec(\cdot)$ denotes column-wise vectorization of a matrix.

II. System Model and Problem Formulation

Figure 1 shows the system model for IRS aided wireless MIMO communication system. It consists of a transmitter (TX) with M_T antennas, a receiver (RX) with M_R antennas, and an IRS module with N reflecting elements. The reflecting elements are controlled by the transmitter through an IRS controller. The received signal $\boldsymbol{y} \in \mathbb{C}^{M_R \times 1}$ is expressed as

$$\boldsymbol{y} = \left(\boldsymbol{H}_d + \boldsymbol{H}_2 \boldsymbol{\Theta} \boldsymbol{H}_1\right)\boldsymbol{x} + \boldsymbol{z}, \quad (1)$$

where $\boldsymbol{H}_d \in \mathbb{C}^{M_R \times M_T}$, $\boldsymbol{H}_1 \in \mathbb{C}^{N \times M_T}$, and $\boldsymbol{H}_2 \in \mathbb{C}^{M_R \times N}$ denote the three channel matrices, i.e., direct TX-RX channel, TX-IRS channel, and IRS-RX channel, respectively. $\boldsymbol{\Theta} \in \mathbb{C}^{N \times N}$ is a diagonal matrix whose entries on the main diagonal are given by $\boldsymbol{v} = [v_0, v_1, ..., v_{N\text{-}1}]^T$ with $|v_n| = 1$, $n = 0,1,...,N\text{-}1$. Here we only consider adjusting the phases of the reflecting coefficients and the amplitudes of the reflecting coefficients are set as 1. $\boldsymbol{x} \in \mathbb{C}^{M_T \times 1}$ is the transmitted symbol vector with zero mean and covariance matrix $\boldsymbol{C}_x = E\{\boldsymbol{x}\boldsymbol{x}^H\}$. The total power of $\boldsymbol{x}$ is given by $P_x = tr\left(\boldsymbol{C}_x\right)$. $\boldsymbol{z} \in \mathbb{C}^{M_R \times 1}$ is the noise vector whose elements are i.i.d. circularly symmetric complex Gaussian (CSCG) random variables with zero mean and variance σ_n^2.

In this paper, we assume that the instantaneous values of $\boldsymbol{H}_d$, $\boldsymbol{H}_1$, and $\boldsymbol{H}_2$ are unavailable, however, the statistical CSI is known,

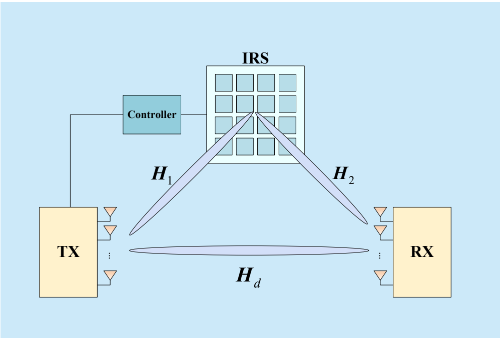

Fig. 1. *System model of IRS aided wireless MIMO communication.*

which is defined by (:= denotes definition)

$$\begin{cases} E\left\{\boldsymbol{h}_d\boldsymbol{h}_d^H\right\} = \boldsymbol{\Sigma}_d, & \boldsymbol{h}_d := vec\left(\boldsymbol{H}_d\right), \\ E\left\{\boldsymbol{h}_1\boldsymbol{h}_1^H\right\} = \boldsymbol{\Sigma}_1, & \boldsymbol{h}_1 := vec\left(\boldsymbol{H}_1\right), \\ E\left\{\boldsymbol{h}_2\boldsymbol{h}_2^H\right\} = \boldsymbol{\Sigma}_2, & \boldsymbol{h}_2 := vec\left(\boldsymbol{H}_2\right), \end{cases} \tag{2}$$

In addition, we assume $\boldsymbol{H}_d$, $\boldsymbol{H}_1$, and $\boldsymbol{H}_2$ are zero mean and mutually independent with each other. The ergodic rate (with unit bits/s/Hz) is given by

$$R_0 = E\left\{\log_2 \det\left(\boldsymbol{I} + \frac{1}{\sigma_n^2}\boldsymbol{H}\boldsymbol{C}_x\boldsymbol{H}^H\right)\right\}, \tag{3}$$

where $\boldsymbol{I}$ is an identity matrix with suitable size,$\boldsymbol{H} = \boldsymbol{H}_d + \boldsymbol{H}_2\boldsymbol{\Theta}\boldsymbol{H}_1$, and the expectation is taken over all random channel matrices. The joint beamforming problem is to find an optimal set of $\boldsymbol{C}_x$ and $\boldsymbol{v}$ simultaneously such that R_0 is maximized. It should be noted that this work only employs up to second order momentum of the statistical CSI and does not depend on the specific channel distributions, which can be regarded as a general framework.

III. JONIT BEAMFORMING

3.1 Overview of the algorithm

This section proposes a joint beamforming algorithm to maximize the ergodic rate given by (3). However, maximizing (3) directly is difficult. The reason is that it involves the expectation of the logarithm of the determinant of the effective channel matrix $\boldsymbol{H}$, which is a function of the optimization variable $\boldsymbol{v}$ and the random channels $\boldsymbol{H}_d$, $\boldsymbol{H}_1$, and $\boldsymbol{H}_2$ whose distributions are assumed to be unknown in this paper. Therefore, it may be impossible to find the expectation explicitly. In fact, even the specific distributions are given, after taken the expectation, the resulting rate will be quite cumbersome and do not admit analytical derivation of the optimal $\boldsymbol{v}$ and $\boldsymbol{C}_x$. Those make it difficult to handle (3) in its original form. Thus we resort to maximize its upper bound, which is a common approach [22,23] and the result is given by the following formula according to the property of determinant and Jensen's inequality:

$$R = \log_2 \det\left(\boldsymbol{I} + \frac{1}{\sigma_n^2}\boldsymbol{C}_x E\left\{\boldsymbol{H}^H\boldsymbol{H}\right\}\right). \tag{4}$$

In (4), the expectation $E\{\boldsymbol{H}^H\boldsymbol{H}\}$ depends only on the statistical CSI and is an unknown function of $\boldsymbol{v}$. In Section 3.2, we will find out this function of $\boldsymbol{v}$.

Then, the joint beamforming algorithm will optimize $\boldsymbol{C}_x$ and $\boldsymbol{v}$ in an alternating manner, i.e., it first optimizes $\boldsymbol{v}$ for a given and optimized $\boldsymbol{C}_x$ and then optimizes $\boldsymbol{C}_x$ for a given and optimized $\boldsymbol{v}$, and repeats the above procedure for sufficient number of iterations. We refer to the aforementioned iterations as outer iterations. At the beginning of the algorithm, $\boldsymbol{C}_x$ is initialized by an identity matrix with constraint $tr\left(\boldsymbol{C}_x\right) = P_x$. The details of the two suboptimization problems are given in the following subsections.

3.2 Optimizing $\boldsymbol{v}$ given $\boldsymbol{C}_x$

Here, we optimize $\boldsymbol{v}$ given that $\boldsymbol{C}_x$ is optimized and fixed. To proceed, we explicitly find $E\{\boldsymbol{H}^H\boldsymbol{H}\}$ as

$$\begin{aligned} &E\{\boldsymbol{H}^H\boldsymbol{H}\} = E\{\boldsymbol{H}_d^H\boldsymbol{H}_d + \boldsymbol{H}_d^H\boldsymbol{H}_2\boldsymbol{\Theta}\boldsymbol{H}_1 \\ &+ \boldsymbol{H}_1^H\boldsymbol{\Theta}^H\boldsymbol{H}_2^H\boldsymbol{H}_d + \boldsymbol{H}_1^H\boldsymbol{\Theta}^H\boldsymbol{H}_2^H\boldsymbol{H}_2\boldsymbol{\Theta}\boldsymbol{H}_1\}, \end{aligned} \tag{5}$$

where $E\{\boldsymbol{H}_d^H\boldsymbol{H}_2\boldsymbol{\Theta}\boldsymbol{H}_1\}$ and $E\{\boldsymbol{H}_1^H\boldsymbol{\Theta}^H\boldsymbol{H}_2^H\boldsymbol{H}_d\}$ are zeros due to the zero mean and mutual dependency of the channel matrices. Remaining terms are given by

$$E\left\{\boldsymbol{H}_d^H\boldsymbol{H}_d\right\} := \boldsymbol{A}, \tag{6}$$

where

$$\begin{aligned} \boldsymbol{A}\left[m,n\right] &= E\left\{\sum_{l=0}^{M_R-1}\boldsymbol{H}_d^*\left[l,m\right]\boldsymbol{H}_d\left[l,n\right]\right\} \\ &= \sum_{l=0}^{M_R-1}E\left\{\boldsymbol{H}_d^*\left[l,m\right]\boldsymbol{H}_d\left[l,n\right]\right\} \\ &= \sum_{l=0}^{M_R-1}E\left\{\boldsymbol{h}_d\left[l+M_Rn\right]\boldsymbol{h}_d^*\left[l+M_Rm\right]\right\} \\ &= \sum_{l=0}^{M_R-1}\boldsymbol{\Sigma}_d\left[l+M_Rn, l+M_Rm\right], \end{aligned} \tag{7}$$

and

$$E\left\{\boldsymbol{H}_1^H\boldsymbol{\Theta}^H\boldsymbol{H}_2^H\boldsymbol{H}_2\boldsymbol{\Theta}\boldsymbol{H}_1\right\} := \boldsymbol{B}, \tag{8}$$

where the entries of $\boldsymbol{B}$ is given by (9) at the top of the next page and

$$\begin{aligned} &\boldsymbol{G}_{m,n}\left[l,p\right] := \boldsymbol{\Sigma}_1\left[p+Nn, l+Nm\right] \\ &\cdot\sum_{k=0}^{M_R-1}\boldsymbol{\Sigma}_2\left[k+M_Rl, k+M_Rp\right]. \end{aligned} \tag{10}$$

$$
\begin{aligned}
\boldsymbol{B}[m,n] &= E\left\{\sum_{l=0}^{N-1}\sum_{k=0}^{M_R-1}\sum_{p=0}^{N-1}\boldsymbol{H}_1^*[l,m]v_l^*\boldsymbol{H}_2^*[k,l]\boldsymbol{H}_2[k,p]v_p\boldsymbol{H}_1[p,n]\right\} \\
&= \sum_{l=0}^{N-1}\sum_{k=0}^{M_R-1}\sum_{p=0}^{N-1}v_l^*v_pE\left\{\boldsymbol{H}_1[p,n]\boldsymbol{H}_1^*[l,m]\right\}E\left\{\boldsymbol{H}_2^*[k,l]\boldsymbol{H}_2[k,p]\right\} \\
&= \sum_{l=0}^{N-1}\sum_{k=0}^{M_R-1}\sum_{p=0}^{N-1}v_l^*v_pE\left\{\boldsymbol{h}_1[p+Nn]\boldsymbol{h}_1^*[l+Nm]\right\}E\left\{\boldsymbol{h}_2^*[k+M_Rl]\boldsymbol{h}_2[k+M_Rp]\right\} \qquad (9) \\
&= \sum_{l=0}^{N-1}\sum_{p=0}^{N-1}v_l^*v_p\boldsymbol{\Sigma}_1[p+Nn,l+Nm]\sum_{k=0}^{M_R-1}\boldsymbol{\Sigma}_2[k+M_Rl,k+M_Rp] \\
&= \sum_{l=0}^{N-1}\sum_{p=0}^{N-1}v_l^*\boldsymbol{G}_{m,n}[l,p]v_p = \boldsymbol{v}^H\boldsymbol{G}_{m,n}\boldsymbol{v}
\end{aligned}
$$

Thus

$$\boldsymbol{B} = \left(\boldsymbol{I}_{M_T}\otimes\boldsymbol{v}\right)^H\boldsymbol{G}\left(\boldsymbol{I}_{M_T}\otimes\boldsymbol{v}\right), \qquad (11)$$

$$\boldsymbol{G} = \begin{bmatrix} \boldsymbol{G}_{0,0} & \cdots & \boldsymbol{G}_{0,\boldsymbol{M_T}-1} \\ \vdots & \ddots & \vdots \\ \boldsymbol{G}_{\boldsymbol{M_T}-1,0} & \cdots & \boldsymbol{G}_{\boldsymbol{M_T}-1,\boldsymbol{M_T}-1} \end{bmatrix}. \qquad (12)$$

Therefore, the rate transforms to

$$R = \log_2\det\left(\boldsymbol{I}+\frac{\boldsymbol{C}_x}{\sigma_n^2}\left[\boldsymbol{A}+\left(\boldsymbol{I}_{M_T}\otimes\boldsymbol{v}\right)^H\boldsymbol{G}\left(\boldsymbol{I}_{M_T}\otimes\boldsymbol{v}\right)\right]\right). \qquad (13)$$

To find the optimal $\boldsymbol{v}$, we utilize a sequential optimization method by treating the entries of $\boldsymbol{v}$ in a sequential manner. At the beginning, $\boldsymbol{v}$ is set randomly. Then for each n, v_n is optimized by maximizing R while treating all other v_m, $m \neq n$, as known and fixed quantities. When all v_n, $n = 0,1,...,N$-1, have been optimized, an inner iteration has been done. Several inner iterations can be performed to make the rate convergent.

The complexity of the IRS passive beamforming algorithm is analyzed using order notation here. The main complexity burden is in the calculation of the determinant of the matrix in (13) which is in the order of $O(M_T^3)$ per calculation. Adding the number of IRS elements N and the total number of iterations T (the multiplication of the number of inner iterations and the number of outer iterations), the total complexity is in the order of $O(TNM_T^3)$, which grows linearly with N.

3.3 Optimizing C_x given v

When $\boldsymbol{v}$ is given and fixed, the rate is given by

$$R = \log_2\det\left(\boldsymbol{I}+\frac{\boldsymbol{C}_x}{\sigma_n^2}\left(\boldsymbol{A}+\boldsymbol{B}\right)\right). \qquad (14)$$

The problem is to find optimal $\boldsymbol{C}_x$ subject to $\boldsymbol{C}_x$=$\boldsymbol{C}_x^H$ and $tr\left(\boldsymbol{C}_x\right) = P_x$. This problem has been well studied in MIMO communication and the optimal solution is given by the water-filling method [24]. The details are omitted here. When $\mathbf{C}_x$ is found, an outer iteration is done. Several outer iterations can be involved to make the rate convergent.

IV. SIMULATIONS

This section presents numerical results of the proposed joint beamforming algorithm and exposes the roles of some key parameters on the achievable ergodic rate.

4.1 Simulation setup

The number of transmit and receive antennas are set as $M_T = 4$ and $M_R = 4$, respectively. The TX, IRS, and RX are placed at a two-dimensional plane. The coordinates (with unit of meter) of the TX, IRS, and RX are (0, 0), (d_x, d_y), (D,0), respectively. The distance between the transmitter and receiver is D=150 m. The number of reflecting elements of IRS is set as $N = 16$.

For the distance-dependent path loss of all channels, we adopt the commonly used model β=$\beta_0 d^{-\alpha}$, where β_0 is the path loss at the reference distance of 1 m and α is the path loss exponent [25]. α represents how fast the power decayed with distance which depends on the communication environment. In this paper, we assume the direct path between the transmitter and the receiver is blocked such that the channel is subject to shadowing effect. Then, IRS is deployed to compensate for the shadowing effect. Thus it is assumed that there exists direct path between the transmitter and IRS, which is also the case for the IRS-RX channel. Therefore, we set α_d=4 for the direct TX-RX channel and set α_1=α_2=2.5 for the IRS related channels. The factor β_0 represents several other factors including the effective aperture of the received antenna, which is determined by the gain and radiation patterns, as well as the spatial geometry, of both the transmit and receive antennas of a specific link. Since IRS reflecting elements are different from conventional antennas, at the reference distance, they may perceive different β_0. Here, we set $\beta_{0,d}$ = – 20 dB for the direct TX-RX channel and $\beta_{0,1}$=$\beta_{0,2}$ = – 25 dB for the IRS related channels, respectively.

For the small-scale fading, the direct TX-RX channel is assumed to be i.i.d. flat fading with unit power, which means $\boldsymbol{\Sigma}_d = \beta_{0,d} D^{-\alpha_d} \boldsymbol{I}_{M_T M_R}$. Note that no specific distribution is assumed here. For the IRS related channels, we consider two scenarios here. In the first scenario, the elements of the IRS is arranged regularly as a compact square, which to our knowledge is the case in all existing works. In such a case, the correlations between the IRS elements cannot be omitted. In this paper we use a simple model to capture the correlations between elements, which is detailed as follows.

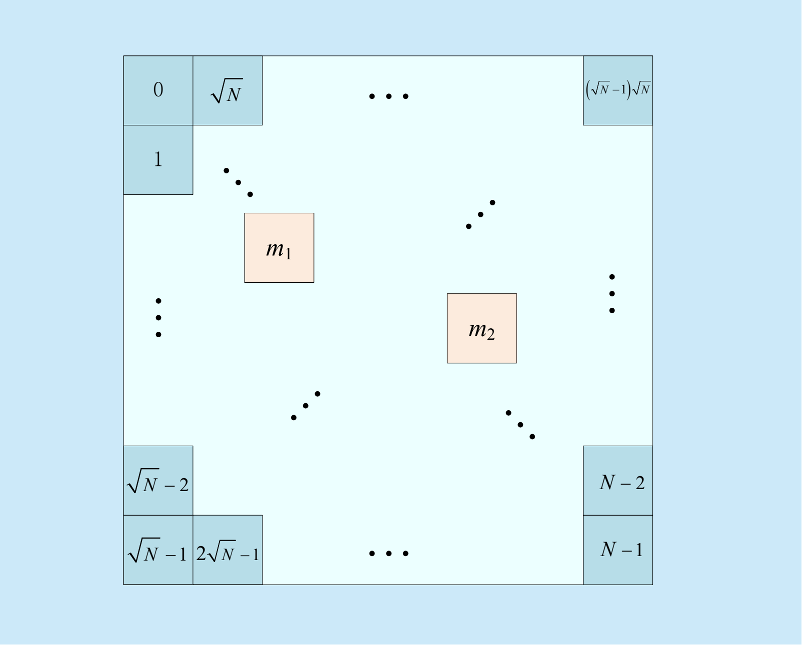

Fig. 2. *Regular arrangement of the IRS elements.*

As illustrated by Figure 2, we arrange the elements of IRS in a regular manner and assign an index for each element sequentially. For element m, it occupies the $r(m) := \left(m - \left\lfloor m/\sqrt{N} \right\rfloor \sqrt{N}\right)$-th row and $c(m) := \left\lfloor m/\sqrt{N} \right\rfloor$-th column in the square, respectively, where $\lfloor \cdot \rfloor$ denotes rounding toward negative infinity. For any two IRS elements numbered as m_1 and m_2, the correlation of the two subchannels, namely, the subchannel between the m_1-th element and an antenna (either at the transmitter side or at the receiver side) with index n, and the subchannel between the m_2-th element and the same antenna, is largely determined by the relative distance of the two elements:

$$\rho_{(m_1;n),(m_2;n)} = \exp\left(-\frac{d^2(m_1, m_2)}{\sigma_d^2}\right), \tag{13}$$

where

$$d(m_1, m_2) = \sqrt{\left[r(m_1) - r(m_2)\right]^2 + \left[c(m_1) - c(m_2)\right]^2}, \tag{14}$$

is the relative distance of the two IRS elements and σ_d represents the relative correlation distance [26]. In this paper, we assume that there is no antenna correlation neither at the transmitter nor at the receiver, i.e., $\rho_{(m_1;n_1),(m_2;n_2)} = 0$ for any m_1, m_2, n_1, and n_2, as long as $n_1 \neq n_2$.

For the second scenario, we envision such a configuration that the IRS is composed of many reflecting elements, typically not the same size or shape, in a distributed manner rather than a regular one, which may be realized in the future when the surfaces of surrounding objects are made of meta-materials. In this scenario, the correlation between different subchannels associated with different IRS elements completely diminishes, i.e., $\rho_{(m_1;n_1),(m_2;n_2)} = 0$ for any m_1, m_2, n_1, and n_2, as long as $m_1 \neq m_2$, or $n_1 \neq n_2$. This scenario can be viewed as the extreme case of the first scenario when the relative correlation distance σ_d approaches to a very small value.

In any of the above two scenarios, combined with the large-scale fading model, the IRS related channel correlation matrices are given by $\boldsymbol{\Sigma}_i = \beta_{0,i} d_i^{-\alpha_i} \bar{\boldsymbol{\Sigma}}_i$, i=1,2, where $d_1(d_2)$ is the distance between the IRS and the TX (RX), and the entries of $\bar{\boldsymbol{\Sigma}}_i$ are obtained using the correlation model in (13) with maximum value of 1, minimum value of 0, and minimum non-zero value of $\rho_{(0;n),(N-1;n)}$.

Besides our proposed scheme (denoted as "proposed" in the legend), other three schemes are also compared in the simulations as benchmarks. The first scheme is the conventional MIMO without IRS (denoted as "w/o IRS" in the legend), where only active beamforming based on statistical CSI is considered. The second scheme is MIMO with IRS (denoted as "random" in the legend), however, the reflecting coefficients of the IRS are randomly chosen and only the active beamforming is optimized based on statistical CSI. The third scheme is the one proposed in [22] (denoted as "existing" in the legend), for which the IRS coefficients were derived under the assumption that the active beamforming was done based on instantaneous CSI. To make a fair comparison within the same scenario, here we first derive the IRS coefficients using the algorithm proposed in [22], then, fixing those optimized IRS coefficients, we derive the optimal transmit covariance matrix that maximizes the ergodic rate using the proposed algorithm.

4.2 Simulation results

Two categories of simulation figures are provided here.

First of all, the ergodic rate of different schemes with respect to the signal-to-noise ratio (SNR) is provided, where SNR is defined as $\gamma = P_x/\sigma_n^2$. Figs. 3 and 4 show the rate performance with different relative correlation distance σ_d (where σ_d=0 represents the second scenario in which there is no channel correlation between different IRS elements) for different IRS positions (d_x, d_y). 4 outer iterations and 3 inner iterations are involved in those figures. Several facts can be observed from Figs.

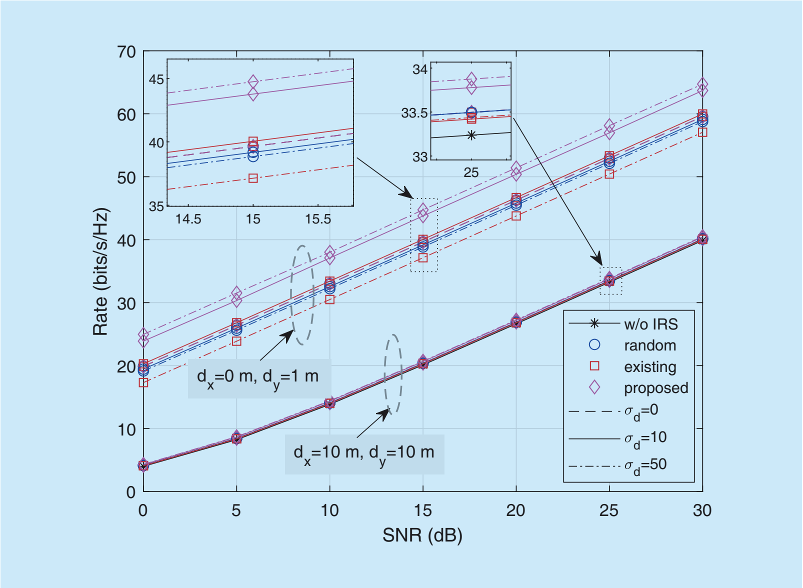

Fig. 3. *Rate performance of different schemes with IRS placed at coordinates (0,1) and (10,10).*

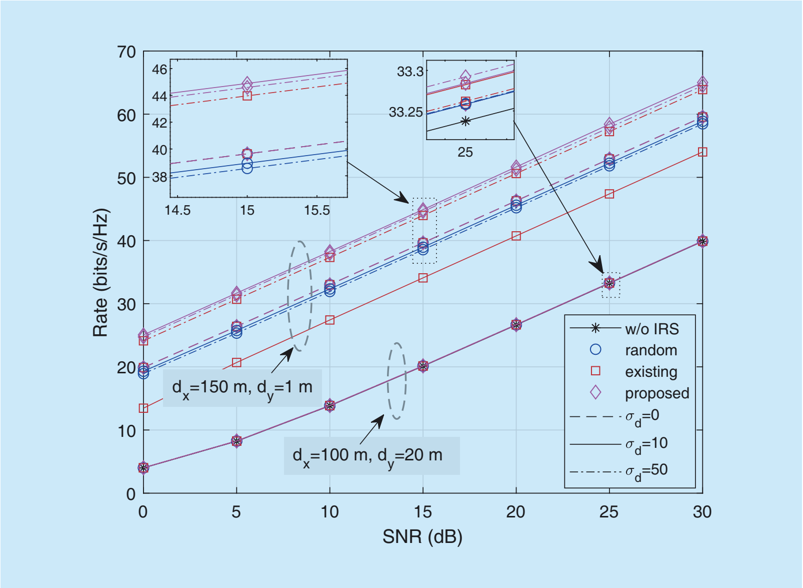

Fig. 4. *Rate performance of different schemes with IRS placed at coordinates (100,20) and (150,1).*

3 and 4.

Firstly, deployment of IRS is always beneficial. However, it should be noted that the rate of the conventional MIMO without IRS is evaluated here (and to our knowledge most existing literature) by ignoring possible reflected energy by the object at the IRS position, which means the rate can be only viewed as a lower bound. Accurate evaluation requires concise modeling of the reflection behavior, which may involve filed test that is beyond the scope of this paper. Nonetheless, the conventional MIMO rate can still be adopted as a useful benchmark.

Secondly, for IRS aided system, utilizing optimized reflection coefficients achieves improved rate performance compared with that by randomly configured reflection coefficients. However, the gain depends highly on two factors, i.e., the relative correlation distance and the position of IRS. In general, a larger relative correlation distance results in larger rate, for instance, the gain increases from close to 0 bits/s/Hz to 4.6 bits/s/Hz by increasing σ_d from 0 to 10 when IRS is placed at position of (0,1) at γ=15 dB. Further increasing σ_d to

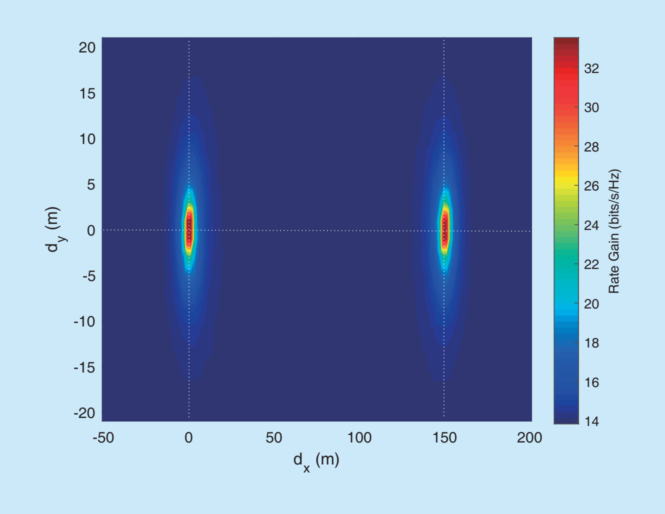

Fig. 5. *Rate performance of the proposed algorithm with different IRS positions.*

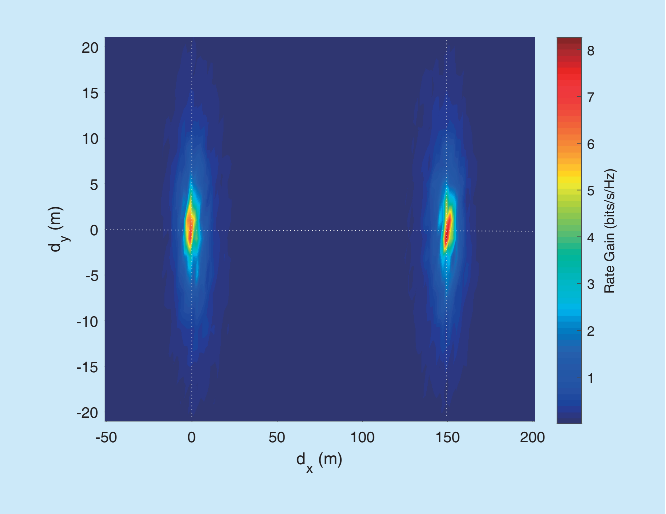

Fig. 6. *Rate gain of the proposed algorithm for IRS aided MIMO system over conventional MIMO without IRS.*

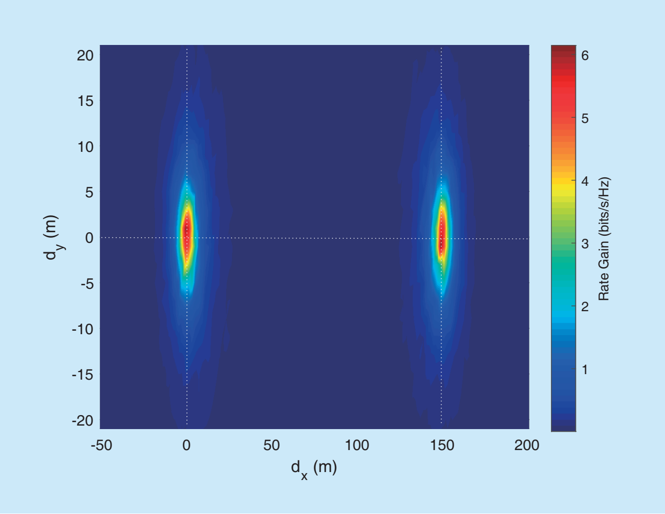

Fig. 7. *Rate gain of the proposed algorithm over randomly configured reflection coefficients with different IRS positions.*

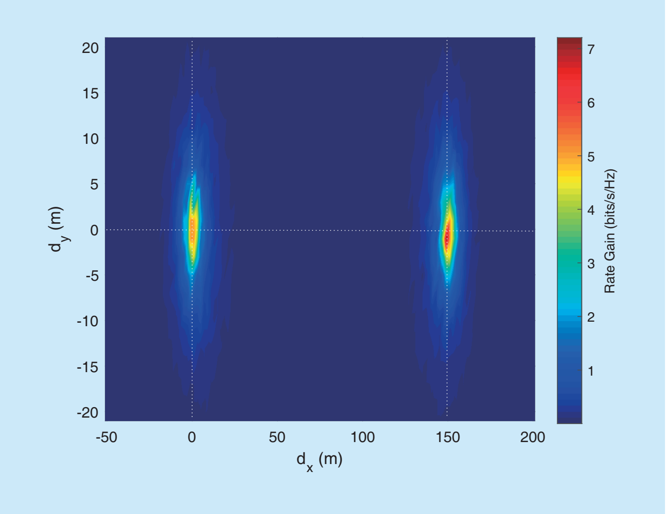

Fig. 8. *Rate gain of the proposed algorithm over existing algorithm with different IRS positions.*

50 brings only incremental gain, suggesting a saturation effect of the relative correlation distance. On the other hand, the rate gain diminishes when IRS moves to position of (10,10), which means the geographical position of the IRS may have even much greater impact on the ergodic rate performance as compared with the relative correlation distance.

Thirdly, the proposed algorithm also outperforms existing scheme in all configurations. Although the IRS coefficients in existing scheme is derived using statistical CSI, it has a precondition that the transmit covariance matrix is obtained based on instantaneous CSI. Therefore, the IRS coefficients derived in existing scheme is not optimal in the sense of maximizing the ergodic rate in this paper. In fact, it can be observed that the performance of the existing scheme varies very much, from close to the proposed algorithm, to even worse than the scheme with random coefficients.

Then, we investigate the impact of geographical position of the IRS on the ergodic rate in a more comprehensive manner. We set γ=10 dB and σ_d=50 here and vary the coordinates of the IRS in a wide range. The granularity is set as 2 meters and kept away from the TX and RX to avoid potential model mismatch induced by near field electromagnetic effect. Figure 5 shows the proposed rate performance at different IRS positions. Figure 6 shows the rate gain over that of conventional MIMO without IRS. Figure 7 shows the rate gain over that of randomly configured reflection coefficients. Figure 8 shows the rate gain over that of existing scheme. All of the simulation results strongly suggest that the position of the IRS has great impact on the rate performance. In general, the rate and the rate gain are pronounced only when the IRS is placed at the vicinity of either the transmitter or the receiver. Placing IRS far away from those areas does not achieve any performance gain. The intuition behind this phenomenon can be explained as follows. When IRS is placed far away from the transmitter or the receiver, the reflected signal travels a much longer path and is attenuated severely at the receiver side, which brings almost no gain. Only when the IRS is placed near the transmitter or the receiver, the reflected signal has sufficient large power at the receiver side and its contribution becomes pronounced.

V. Conclusion

This paper studied a joint beamforming algorithm for IRS aided wireless MIMO communication based only on statistical CSI. The beamforming are done by alternatively optimizing the reflection coefficients and the transmit covariance matrix. Only up to second order momentum of the channel statistics are employed and the algorithm does not rely on any specific channel fading model, which can be viewed as a general framework. By setting up a practical simulation environment, it is found that the ergodic rate is closely related to both the relative correlation distance and the IRS position. In particular, it is found that optimizing the reflection coefficients is beneficial in increasing the rate only when the IRS is placed in the vicinity of either the transmitter or the receiver. Otherwise, IRS is not beneficial as compared to the conventional MIMO system.

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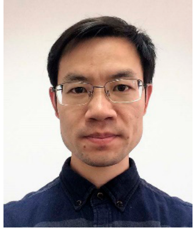

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