Sum-rate Maximization for Intelligent Reflecting Surface Based Terahertz Communication Systems

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***Abstract*—Terahertz (THz) communication system is envisioned as a promising alternative to support ultra-high speed data transmission for future indoor application scenarios. Due to the existence of the potential obstacles, the line-of-sight communication links for indoor THz communication are not reliable. In this paper, we thus investigate the utilization of intelligent reflecting surface (IRS) to enhance the reflecting transmission of the THz communication system. Specifically, an IRS consists of a large number of reflecting elements, and the phase-shift of each reflecting element is adjustable. Based on the principle of IRS, the propagation direction of THz signals can be changed via adjusting all the phase-shifts of IRS, and then we are able to improve the sum-rate performance by selecting the optimal values of the phase-shifts. Accordingly, we first propose a local search (LS) method, which can greatly decease the complexity compared with the traditional exhaustive search method. However, the LS method suffers a certain performance loss. To this end, we then propose a cross-entropy (CE) method that is feasible to promote the sum-rate compared with the LS method. Numerical results verify the above conclusions, and also show the merit of the IRS-enhanced THz communication system.**

***Index Terms*—Terahertz (THz), intelligent reflecting surface (IRS), sum-rate, local search (LS), cross-entropy (CE).**

I. Introduction

Terahertz (THz) communication is considered as a promising wireless technique for ultra-high data-rate transmission which enables various innovational applications [1]. Due to the frequency band ranging from 0.1 to 10 THz, THz communication suffers severe propagation attenuation and water-molecular absorption, which extremely influence transmission environment and propagation distance [2]. Therefore, most of THz communication systems are applied for indoor short-distance appliction scenarios, such as shopping malls, subway stations, home and so on. However, the indoor layout is usually complex and always destroys the line-of-sight communication links by physical obstacles between transmitters and receivers. In addition, THz wave has a worse ability of diffraction and penetration compared with microwaves and millimeter waves (mmWave). Thus, THz communication depends on the reflection transmission more [3]. Since traditional common reflecting surfaces (e.g., concrete walls) are uncontrolled, and lead to a high reflecting loss, intelligent reflecting surface (IRS) emerged in recent years to improve the reflection performance.

An IRS is a physical meta-surface consisting of a large number of small-unit reflectors. In general, the IRS is equipped with a simple low-cost sensor, and is controlled by a central processor [4]. Each element of the IRS is able to reflect incident electromagnetic waves independently with an adjustable phase-shift. For practical implementation, we consider discrete phase-shifts in this paper. With smartly adjust the phase-shift of all the elements for adaptive dynamic wireless channels, the IRS is able to achieve beamforming to support the communication and suppress the interference among multi-users [5], [6]. In addition, compared with traditional amplify-and-forward (AF) relays, the IRS is a power-save solution as it only reflects incident signals without any transmitter modulations. Previous works about the IRS are studied in [7]–[9]. In [7], an IRS with infinite-level phase-shifts serves for a single user, and the IRS enables a lower transmission power compared with the scenario without IRS. A multi-user communication case is studied in [8], and it is shown that the IRS with discrete phase-shifts can improve the sum-rate performance. A same conclusion is verified in [9] with a practical experimental test. However, all these works do not consider the peculiarities of the THz communication based on IRS while the two techniques rely on each other and help each other forward. Besides, although the research in [9] considers the IRS with finite phase-shifts, and selects the optimal phase-shift for each element by an exhaustive search method, the number of reflecting elements is usually large and will lead to a high computational complexity.

In this paper, as it has been verified that the massive antenna-array and IRS technique can be leveraged in the THz communication systme [10], [11], we use the traditional Saleh-Valenzuela channel model [12] to capture the characteristics of the THz indoor channel. Meanwhile, a hybrid precoding structure, which involves digital and analog precoding, is employed to support the THz communication for promising implementation [13]–[15]. Remarkably, the purpose of this paper is to maximize the sum-rate performance of the IRS-aided THz communication system by selecting the optimal phase-shift for each reflecting element. To achieve it, we firstly propose a local search method (LS), which can greatly decrease the complexity compared with the exhaustive search method. However, the LS method endures obvious performance loss. To improve the performance, we then propose a cross-entropy (CE) method for fast phase search. Simulation results verify that the proposed IRS-aided THz communication system can achieve a better sum-rate performance compared with the conventional system without IRS, and the CE-based method performs much better than the LS method in terms of the sum-rate performance.

Notations: x, $\mathbf{x}$, and $\mathbf{X}$ denote scalar, vector, and matrix, respectively; $(\cdot)^H$, $(\cdot)^+$, $\|\cdot\|_F$, and $|\cdot|$ denote conjugate transpose, pseudo-inversion operation, Frobenius norm of matrix, and absolute operator, respectively.

II. System Model

As shown in Fig. 1, we consider an IRS-aided multi-input multi-output (MIMO) wireless system, where a base station (BS) with N_t antennas simultaneously serves to K single-antenna users, via an IRS which consists of N reflecting elements. Due to the severe propagation loss in the THz communication, we only consider a single reflection signal by the IRS and ignore other signals reflected by the IRS more than one time. And we assume only one data stream needs to be transmitted for each user. Therefore, the $K \times 1$ received signal vector $\mathbf{y}$ for all K users can be expressed as

$$\mathbf{y} = \frac{1}{N}\mathbf{H}_{\mathrm{r}}\boldsymbol{\Theta}\mathbf{H}_{\mathrm{t}}\mathbf{F}_{RF}\mathbf{F}_{BB}\mathbf{s} + \mathbf{n}, \tag{1}$$

where $\mathbf{H}_{\mathrm{r}} = [\mathbf{h}_{\mathrm{r},1}, \mathbf{h}_{\mathrm{r},2}, \cdots, \mathbf{h}_{\mathrm{r},K}]^H$ of size $K \times N$ is the receiving channel matrix with $\mathbf{h}_{\mathrm{r},k} \in C^{N\times 1}$ denoting the channel vector between the IRS and user k; $\boldsymbol{\Theta} = \mathrm{diag}\left[e^{j\theta_1}, e^{j\theta_2}, \cdots, e^{j\theta_N}\right] \in C^{N\times N}$ is the phase-shift matrix of the IRS, where $\theta_n \in [0, 2\pi]$ represents the phase-shift for the nth reflecting element. For practical implementations, we consider θ_n as a discrete value and belongs to the set of $\mathcal{F} = \left\{0, \Delta\theta, \cdots, \Delta\theta\left(2^b - 1\right)\right\}$ where $\Delta\theta = 2\pi/2^b$ and b is the bit-quantization number. In addition, $\mathbf{H}_{\mathrm{t}} = [\mathbf{h}_{\mathrm{t},1}, \mathbf{h}_{\mathrm{t},2}, \cdots, \mathbf{h}_{\mathrm{t},N}]^H$ of size $N \times N_t$ is the transmitting channel matrix with $\mathbf{h}_{\mathrm{t},n} \in C^{N_t\times 1}$ expressing the channel vector between the BS and the reflecting element n; $\mathbf{F}_{RF} \in C^{N_t\times N_{RF}}$ and $\mathbf{F}_{BB} \in C^{N_{RF}\times K}$ are the analog precoder and digital precoder respectively, which satisfy the transmit power constraint as $\|\mathbf{F}_{RF}\mathbf{F}_{BB}\|_F^2 = \rho$, where ρ is the total transmit power. Finally, the transmission signal vector $\mathbf{s} \in C^{K\times 1}$ satisfies $\mathrm{E}\left[\mathbf{s}\mathbf{s}^H\right] = \mathbf{I}_K$; and the additive white Gaussian noise (AWGN) vector $\mathbf{n} \in C^{K\times 1}$ is zero mean and variance δ^2, where δ^2 is the noise power.

For the channel vector $\mathbf{h}_{\mathrm{t},n}$, motivated by [16], we use the traditional Saleh-Valenzuela model to capture the characteristics of the THz indoor channel, where only a few propagation paths are effective and massive antennas are need for combating the transmission loss and molecular absorption. Therefore, $\mathbf{h}_{\mathrm{t},n}$ can be written as

$$\mathbf{h}_{\mathrm{t},n} = \sqrt{\frac{N_t}{L_n}}\sum_{l=1}^{L_n}\alpha_n^{(l)}\mathbf{a}\left(N_t, \varphi^{(l)}\right), \tag{2}$$

where L_n is the number of paths from the BS to the nth reflecting element; $\varphi^{(l)} \in [0, 2\pi]$ is the angle of departure (AoD) in the horizontal azimuth domain for the path l; $\mathbf{a}\left(N_t, \varphi^{(l)}\right) \in C^{N_t\times 1}$ is the array steering vector of an uniform linear array (ULA), which can be written as $\mathbf{a}\left(N_t, \varphi^{(l)}\right) = \frac{1}{\sqrt{N_t}}\left[e^{j2\pi m(d_a/\lambda)\sin\left(\varphi^{(l)}\right)}\right]^T, m = 1, 2, \cdots, N_t,$ where d_a is the antenna space and λ is the signal wavelength. Finally, $\alpha_n^{(l)}$ is the complex gain of the lth path.

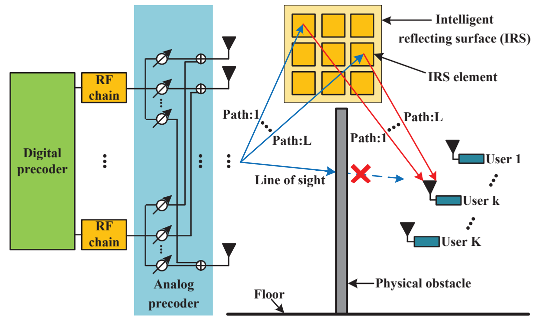

Fig. 1. An IRS-aided beamforming system.

Additionally, we assume the space between adjacent reflecting elements, d_r, is much larger than λ so that the channels among different reflecting elements are independent. Also, we assume the distance between the BS and the reflecting element is much larger than d_r so that only one beam pattern from the BS can serve the whole elements and each $\mathbf{h}_{\mathrm{t},n}$ can be composed of a same $\mathbf{a}\left(N_t, \varphi^{(l)}\right)$. Besides, each entry of $\mathbf{h}_{\mathrm{r},k}$ is modeled as a complex Gaussian distribution since there are no antenna arrays equipped at the user side.

III. IRS-Aided Beamforming Schemes

In this section, we first formulate a sum-rate maximization problem for the IRS-aided THz beamforming system. In order to find the maximal sum-rate, we temporarily couple the analog and digital precoder as a single matrix, and propose the LS and CE-based algorithm to select the optimal phase-shift for each reflecting element. Finally, decomposing the coupled matrix, we are able to get the practical analog and digital precoder at the same time.

A. Problem Formulation

Based on the system model, this paper aims to optimize the reflecting phase-shift matrix $\boldsymbol{\Theta}$, transmission analog precoder $\mathbf{F}_{RF}$, and digital precoder $\mathbf{F}_{BB}$ for the system sum-rate maximization. The achievable sum-rate R for all K users can be written as

$$R = \sum_{k=1}^{K}\log_2\left(1 + \gamma_k\right), \tag{3}$$

where γ_k is the signal-to-interference-plus-noise ratio (SINR) of the kth user and can be presented by

$$\gamma_k = \frac{\left|\mathbf{h}_{\mathrm{r},k}^H\boldsymbol{\Theta}\mathbf{H}_{\mathrm{t}}\mathbf{F}_{RF}\mathbf{f}_k^{BB}\right|^2}{\sum\limits_{i=1,i\neq k}^{K}\left|\mathbf{h}_{\mathrm{r},i}^H\boldsymbol{\Theta}\mathbf{H}_{\mathrm{t}}\mathbf{f}_i^{BB}\right|^2 + \sigma^2}, \tag{4}$$

where $\mathbf{f}_k^{BB}$ is the kth column of $\mathbf{F}_{BB}$. Then, the sum-rate maximization problem can be formulated as

$$\begin{aligned} \left(\boldsymbol{\Theta}^{\mathrm{opt}}, \mathbf{F}_{RF}^{\mathrm{opt}}, \mathbf{F}_{BB}^{\mathrm{opt}}\right) = \arg\max R, \\ \text{s.t.} \quad \theta_n \in \mathcal{F}, \forall n = 1, \cdots, N, \\ \mathbf{F}_{RF} \in \mathcal{F}_{RF}, \\ \|\mathbf{F}_{RF}\mathbf{F}_{BB}\|_F^2 = \rho, \end{aligned} \tag{5}$$

where $\mathcal{F}_{RF}$ is the set of feasible analog precoders with constant-magnitude entries and $\mathcal{F}$ is the set of possible phase-shift for each reflecting element.

B. Problem Approximation

In this subsection, we seek to design hybrid precoders $(\mathbf{F}_{RF}, \mathbf{F}_{BB})$ and the phase-shift matrix $\boldsymbol{\Theta}$ to maximize the sum-rate R in (3). However, directly maximizing (3) requires a joint optimization over three variables $(\mathbf{F}_{RF}, \mathbf{F}_{BB}, \boldsymbol{\Theta})$, which is intractable with the non-convex constraints on $\mathbf{F}_{RF}$ and $\boldsymbol{\Theta}$ in (5). To simplify the beamforming design, we temporarily couple $\mathbf{F}_{RF}$ and $\mathbf{F}_{BB}$ as a single matrix-variable $\mathbf{w}$, while the problem (5) is more solvable with only two variables $(\mathbf{w}, \boldsymbol{\Theta})$. And (5) can be rewritten as

$$\begin{aligned} \left(\boldsymbol{\Theta}^{\mathrm{opt}}, \mathbf{w}^{\mathrm{opt}}\right) = \arg\max R, \\ \text{s.t.} \quad \theta_n \in \mathcal{F}, \forall n = 1, \cdots, N, \\ \|\mathbf{w}\|_F^2 = \rho, \end{aligned} \tag{6}$$

where $\mathbf{w} \in C^{N_t \times K}$ is the hybrid precoder as $\mathbf{w} = \mathbf{F}_{RF}\mathbf{F}_{BB}$. Then, the achievable sum-rate R in (3) can be approximated as

$$R = \sum_{k=1}^{K} \log_2 \left(1 + \frac{\left|\mathbf{h}_{\mathrm{r},k}^H \boldsymbol{\Theta} \mathbf{H}_{\mathrm{t}} \mathbf{w}_k\right|^2}{\sum\limits_{i=1, i\neq k}^{K} \left|\mathbf{h}_{\mathrm{r},i}^H \boldsymbol{\Theta} \mathbf{H}_{\mathrm{t}} \mathbf{w}_i\right|^2 + \sigma^2} \right), \tag{7}$$

where $\mathbf{w}_k \in C^{N_t \times 1}$ is the kth vector of $\mathbf{w}$.

C. Exhaustive and Local Search Solution

To further analyze the problem in (6), we note that the number of possible $\boldsymbol{\Theta}$ is finite since θ_n belongs to the discrete phase set $\mathcal{F} = \left\{0, \frac{2\pi}{2^b}, \cdots, \frac{2\pi}{2^b}\left(2^b - 1\right)\right\}$. Therefore, (6) is feasible to be solved with an exhaustive search method [9]. In this method, we can first successively select one phase value for each θ_n from $\mathcal{F}$, and finally construct the candidate $\boldsymbol{\Theta}$. With a given $\boldsymbol{\Theta}$, the optimal $\mathbf{w}$ is able to be computed with an effective channel matrix $\mathbf{H}_{\mathrm{r}}\boldsymbol{\Theta}\mathbf{H}_{\mathrm{t}}$. And we can compare all the sum-rate R calculated by different $\boldsymbol{\Theta}$ and correlative $\mathbf{w}$. After the comparison operation, the maximal R, optimal $\boldsymbol{\Theta}$ and $\mathbf{w}$ can be got at the same time. Finally, decomposing $\mathbf{w}$, we are feasible to get the optimal $\mathbf{F}_{RF}$ and $\mathbf{F}_{BB}$ [13]. However, the exhaustive search method is not feasible for our system because of a non-negligible complexity. Since the IRS system requires to search N^{2^b} possible $\boldsymbol{\Theta}$ (e.g., $N = 9$, $b = 6$, $9^{2^6} \approx 1.179 \times 10^{61}$), which is an enormous value increased exponentially with the growth of b. To decrease the complexity, we propose a local search (LS) method.

The detailed step of the LS solution is illustrated in Algorithm 1. In step 1, we first initialize the phase-shift set $\mathcal{F}$ based on the bit-quantization number b. Then, in the ith iteration process, we fix the phase-shift of reflecting element $i+1$ to N, which are randomly generated from $\mathcal{F}$, and then select the optimal phase-shift for reflecting element i according to (7). Noting here that, in step 7, $\mathbf{w}^{ii}$ can be computed with the zero-forcing method as $\mathbf{w}^{ii} = \left(\mathbf{H}_{\mathrm{eq}}^{ii}\right)^{+}$, where $\mathbf{H}_{\mathrm{eq}}^{ii} = \mathbf{H}_{\mathrm{r}}\boldsymbol{\Theta}^{ii}\mathbf{H}_{\mathrm{t}}$. Continuing the iteration procedure, we can successively find the optimal phase-shift for all the reflecting elements from 1 to N. The LS method is feasible to decrease the complexity compared with the exhaustive search method. For example, when $N = 9$ and $b = 6$, the total number of search times is $9 \times 2^6 = 576$, which is much smaller than 1.179×10^{61}.

Algorithm 1 Local Search Algorithm

Input: channel matrix $\mathbf{H}_{\mathrm{t}}$ and $\mathbf{H}_{\mathrm{r}}$, bit-quantization number b

1: Initialize $\mathcal{F} = \left\{0, \frac{2\pi}{2^b}, \cdots, \frac{2\pi}{2^b}\left(2^b - 1\right)\right\}$
2: **for** $i = 1 : N$ **do**
3: Randomly generate $\theta_{i+1}, \theta_{i+2}, \cdots, \theta_N$ from $\mathcal{F}$
4: **for** $ii = 1 : 2^b$ **do**
5: $\theta_i = \mathcal{F}(ii)$
6: Construct $\boldsymbol{\Theta}^{ii}$ as $\boldsymbol{\Theta}^{ii} = \mathrm{diag}\left(e^{j\theta_1}, e^{j\theta_2}, \cdots, e^{j\theta_N}\right)$
7: Compute $\mathbf{w}^{ii}$ based on the effective channel $\mathbf{H}_{\mathrm{eq}}^{ii}$
8: Calculate the sum-rate R^{ii} (7)
9: **end for**
10: Select the maximal sum-rate $R^{\max}$ from all R^{ii}
11: Set $\theta_i = \mathcal{F}(\max)$
12: **end for**
13: Decomposing $\mathbf{w}$ into $\mathbf{F}_{RF}^{\mathrm{opt}}$ and $\mathbf{F}_{BB}^{\mathrm{opt}}$ [13]

Output: $R^{\max}$, $\mathbf{F}_{RF}^{\mathrm{opt}}$, $\mathbf{F}_{BB}^{\mathrm{opt}}$, $\boldsymbol{\Theta}^{\mathrm{opt}}$

Algorithm 2 CE-based Algorithm

Input: channel matrix $\mathbf{H}_{\mathrm{t}}$ and $\mathbf{H}_{\mathrm{r}}$, bit-quantization number b, number of candidates S, number of optimal samples S_{elite}, number of iterations I

1: Initialize $\mathcal{F} = \left\{0, \frac{2\pi}{2^b}, \cdots, \frac{2\pi}{2^b}\left(2^b - 1\right)\right\}$, $\mathbf{p}^{(0)} = \frac{1}{2^b} \times \mathbf{1}_{2^b \times N}$
2: **for** $i = 1 : N$ **do**
3: Randomly generate S candidates $\{\boldsymbol{\Theta}^s\}_{s=1}^S$ based on $\Xi(\boldsymbol{\Theta}; \mathbf{p}^{(i)})$
4: Compute $\{\mathbf{w}^s\}_{s=1}^S$ based on the effective channel $\mathbf{H}_{\mathrm{eq}}^s = \mathbf{H}_{\mathrm{r}}\boldsymbol{\Theta}^s\mathbf{H}_{\mathrm{t}}$
5: Calculate the sum-rate $\{R(\boldsymbol{\Theta}^s)\}_{s=1}^S$ (7)
6: Sort $\{R(\boldsymbol{\Theta}^s)\}_{s=1}^S$ in a descend order as $R\left(\boldsymbol{\Theta}^{(1)}\right) \geq R\left(\boldsymbol{\Theta}^{(2)}\right) \geq \cdots \geq R\left(\boldsymbol{\Theta}^{(S)}\right)$
7: Select S_{elite} optimal samples $\boldsymbol{\Theta}^{(1)}, \boldsymbol{\Theta}^{(2)}, \cdots, \boldsymbol{\Theta}^{(S_{\mathrm{elite}})}$
8: Update $\mathbf{p}^{(i+1)}$ based on $\{\boldsymbol{\Theta}^s\}_{s=1}^{S_{\mathrm{elite}}}$
9: **end for**
10: Decomposing $\mathbf{w}$ into $\mathbf{F}_{RF}^{\mathrm{opt}}$ and $\mathbf{F}_{BB}^{\mathrm{opt}}$ [13]

Output: $R^{\max}$, $\mathbf{F}_{RF}^{\mathrm{opt}}$, $\mathbf{F}_{BB}^{\mathrm{opt}}$, $\boldsymbol{\Theta}^{\mathrm{opt}}$

D. CE-based Solution

Although the LS method is able to decrease the complexity, it will lead to some performance loss compared to the exhaustive method. And the loss gap will expand with the increasing

N and b. Therefore, we propose a cross-entropy (CE) method, which is feasible to improve the sum-rate performance with a low complexity.

The CE algorithm was developed in Rubinstein (1999) to solve both discrete multi-extremal and continuous combinatorial optimization problems [17]. As (6) is a two-variable combination optimization problem, the CE method is able to solve it with an iterative stochastic procedure. In each iteration process, the CE method first generates S random data samples (e.g., possible reflecting phase-shift $\mathbf{\Theta}$ in our problem) based on an original probability distribution. Next, it can calculate the objective value (e.g., the sum-rate performance in this paper) of each sample, and choose S_{elite} ($S_{\text{elite}} < S$) optimal samples according to their objective values. Then, based on the S_{elite} samples, the probability distribution can be updated [18], and a better sample is able to be produced in the next iteration with the new probability. Repeating the above procedure, it is feasible to find the best sample in the end.

The detailed step of the CE-based search solution is illustrated in Algorithm 2. At the beginning, we formulate $\mathbf{\Theta}$ as $\mathbf{\Theta} = \text{diag}[e^{j\theta_1}, e^{j\theta_2}, \cdots, e^{j\theta_N}]$, and set the corresponding probability matrix as $\mathbf{p} = [\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_N] \in C^{2^b \times N}$ where $\mathbf{p}_n = \left[p_{n,1}, p_{n,2}, \cdots, p_{n,2^b}\right]^T$ of size $2^b \times 1$ is the probability parameter for θ_n, and each entry $p_{n,i}$ satisfies the probability constraint $0 \le p_{n,i} \le 1$ and $\sum\limits_{i=1}^{2^b} p_{n,i} = 1$. Then, in step 1, we initialize $\mathbf{p}^{(0)} = \frac{1}{2^b} \times \mathbf{1}_{2^b \times N}$ ($\mathbf{1}$ is the all-one matrix) since we assume that θ_n belongs to $\mathcal{F} = \left\{0, \frac{2\pi}{2^b}, \cdots, \frac{2\pi}{2^b}\left(2^b - 1\right)\right\}$ with an equal probability before the first iteration procedure. And then, in the ith iteration, we randomly generate S candidate $\{\mathbf{\Theta}^s\}_{s=1}^{S}$ according to the probability distribution function $\Xi(\mathbf{\Theta}; \mathbf{p}^{(i)})$, which can be expressed as

$$\Xi\left(\mathbf{\Theta}; \mathbf{p}^{(i)}\right) = \prod_{n=1}^{N} \left(\left(\prod_{l=1}^{2^b-1} \left(p_{n,l}^{(i)}\right)^{\Gamma(\theta_n, \mathcal{F}(l))} \right) \times \left(1 - \prod_{l=1}^{2^b-1} \left(p_{n,l}^{(i)}\right)^{\Gamma(\theta_n, \mathcal{F}(l))} \right) \right), \tag{8}$$

where $\mathcal{F}(l)$ is the lth entry of $\mathcal{F}$, and $\Gamma(\theta_n, \mathcal{F}(l))$ is a judge function which can be written as

$$\Gamma(\theta_n, \mathcal{F}(l)) = \begin{cases} 1, & \theta_n = \mathcal{F}(l) \\ 0, & \theta_n \neq \mathcal{F}(l) \end{cases}. \tag{9}$$

Next, in step 4, we compute the corresponding $\{\mathbf{w}^s\}_{s=1}^{S}$ based on the effective channel $\mathbf{H}_{\text{eq}}^s = \mathbf{H}_{\text{r}}\mathbf{\Theta}\mathbf{H}_{\text{t}}$ for $1 \le s \le S$, where $\mathbf{w}^s = \left(\mathbf{H}_{\text{eq}}^s\right)^+$. Then in step 5, we are able to calculate the achievable sum-rate $\{R(\mathbf{\Theta}^s)\}_{s=1}^{S}$ in (7) with the obtained $\mathbf{\Theta}^s$ and $\mathbf{w}^s$. After that, in step 6, we sort $\{R(\mathbf{\Theta}^s)\}_{s=1}^{S}$ in a descend order. And in step 7, we select the first S_{elite} samples from the order, and consider them as optimal samples. According to the S_{elite} samples, in step 8, the probability for the next iteration $\mathbf{p}^{(i+1)}$ can be updated, which can be formulated as [18]

$$\mathbf{p}^{(i+1)} = \arg\max_{\mathbf{p}^{(i)}} \frac{1}{S} \sum_{s=1}^{S_{\text{elite}}} \ln \Xi\left(\mathbf{\Theta}^s; \mathbf{p}^{(i)}\right). \tag{10}$$

Such the above process will be continued until i reaches to the iteration threshold I. After that, the optimal $\mathbf{\Theta}$ is able to be output as $\mathbf{\Theta}^{\text{opt}} = \mathbf{\Theta}^{(1)}$.

IV. Numerical Results

In this section, numerical results are presented to compare the IRS-aided beamforming system with the system without IRS in terms of the sum-rate performance, and also to compare the proposed CE-based method to the proposed LS method in the IRS-aided system according to the sum-rate performance. As the THz channel is sparse, we assume that the total number of effective rays for each reflecting element is $L_n = 3$, and the complex gain is $\alpha_n^{(l)} \sim \mathcal{CN}(0, 1)$. Besides, we assume the signal wavelength is $\lambda = \frac{3\times10^8}{220\times10^9} = 1.36\text{mm}$, $d_a = \lambda/2$, $\varphi^{(l)}$ follows the uniform distribution $\mathcal{U}(0, 2\pi)$, and the number of users is $K = 4$. In addition, we assume that perfect channel state information is available for the IRS. And we generate the transmission channel according to (2). Finally, we define the signal-to-noise ratio as $\text{SNR} = \frac{\rho}{\sigma^2}$, and average all the results over 5000 random channel realizations.

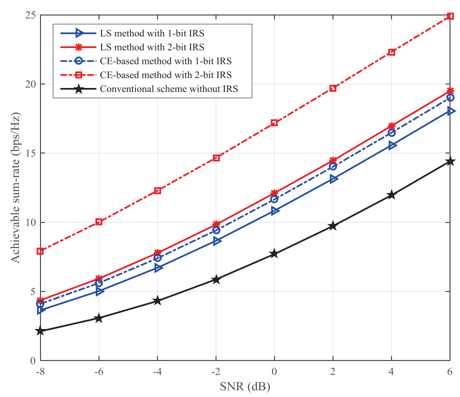

Fig. 2. Sum-rate comparison with $N_t = 16$, $N = 64$, $K = 4$.

Fig. 2 shows the sum-rate performance comparison in a THz massive MIMO system with $N_t = 16$, $N = 64$, $K = 4$. In Fig. 2, we set $S = 200$, $S_{\text{elite}} = 40$, $I = 15$ for the proposed CE-based method in Algorithm 2. For comparison, in the system without IRS, we assume that each diagonal entry of $\mathbf{\Theta}$ follows a complex Gaussian distribution, which means the magnitude and phase-shift of the incidental signal are randomly changed. As shown in Fig. 2, it is obvious that the system with IRS achieves a better sum-rate than the system without IRS. In addition, for the system with IRS, the sum-rate of the proposed CE-based method is better than that of the proposed LS method. Furthermore, when the bit-quantization number b grows, this advantage is becoming more and more obvious. Specifically, the performance gap between the CE-based and LS method is about 1 bps/Hz when $b = 1$ bit, while this gap is more than 5 bps/Hz when $b = 2$ bit. The reason is that the LS method is pretty dependent on original values. If the original value is close to the optimal result, the LS method will have a good ability to converge to the optimal value. If not, the performance of the LS method will not be good, such as that in this paper since we randomly set the original value. In contrast, the CE-based method is a probabilistic iterative algorithm which does not rely on the original value and can converge to the optimal result.

Fig. 3 plots the sum-rate performance achieved in the system with $\mathrm{SNR} = 6$ dB, $N = 64$, $K = 4$. In Fig. 3, the sum-rate performance of both the system with IRS and the system without IRS are improved with the increasing number of transmission antennas. This is because the gain of the transmission antennas is grew with increasing N_t. Furthermore, it is easy to see the sum-rate of the system without IRS is more and more close to the line of the system with IRS when N_t increases.

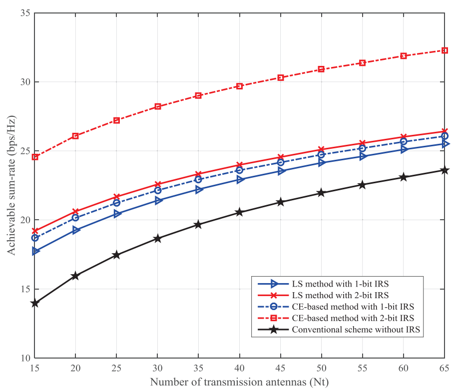

Fig. 3. Sum-rate comparison with $\mathrm{SNR} = 6$ dB, $N = 64$, $K = 4$.

Fig. 4 depicts the comparison of the sum-rate performance achieved in the system with $\mathrm{SNR} = 6$ dB, $N_t = 16$, $K = 4$. As shown in Fig. 4, the sum-rate of the system with IRS is increased with the growing number of IRS elements, while the sum-rate of the system without IRS is unchanged when N increases. But, it is worth note that the number of IRS elements can not be infinite since the narrow beam in THz communications can only cover a certain number of reflecting elements. Therefore, analyzing the practical number of coverable IRS elements is our future work.

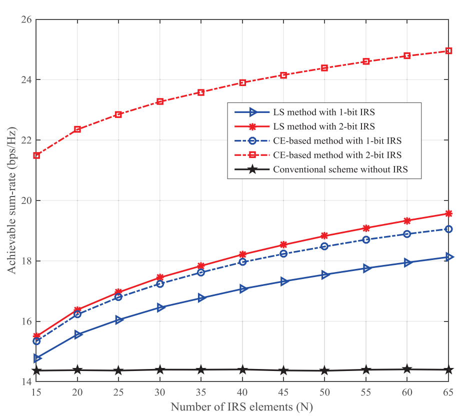

Fig. 4. Sum-rate comparison with $\mathrm{SNR} = 6$ dB, $N_t = 16$, $K = 4$.

V. Conclusions

In this paper, we investigate a new approach to enhance the performance of the THz reflecting communication by employing the IRS with discrete phase-shifts. Specifically, the THz system with IRS can greatly improve the sum-rate performance compared with the system without IRS. And this advantage can be more and more obvious when the bit-quantization value or the number of reflecting elements increases. Ultimately, we believe that the THz system with IRS will play an important role in future indoor wireless communication systems.

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