One-Bit Symbol-Level Precoding for MU-MISO Downlink with Intelligent Reflecting Surface

Silei Wang, Qiang Li and Mingjie Shao

Abstract

Intelligent reflecting surface (IRS) has recently drawn great attention due to its potential in boosting system spectral efficiency by using large number of low-cost passive reflecting elements. By smartly adjusting the reflecting phase shifts of the elements, IRS is able to on-demand enhance the desired signal’s power or suppress interference. In this paper, we consider IRS-aided symbol-level precoding (SLP) for multiuser multi-input single-output (MISO) downlink transmission. Specifically, by assuming one-bit transmit signals at the base station (BS), which arises from the use of low-resolution DACs in the regime of massive transmit antennas, a joint design of one-bit SLP at the BS and the phase shifts at the IRS is proposed with a goal of minimizing the worst-case symbol error probability (SEP) of the users under the PSK modulation. This joint design problem is essentially a mixed integer nonlinear program (MINLP). To tackle it, we employ the SEP upper bound approximation and the alternating optimization to obtain a tractable solution. The key to our approach is of the recently developed gradient extrapolated majorization-minimization (GEMM) algorithm and the accelerated projected gradient (APG) method. Numerical results demonstrate that the proposed joint design can attain better SEP performance than the conventional linear precoding with naive one-bit quantization.

Index Terms

Intelligent reflecting surface, passive beamforming, accelerated projected gradient, symbol-error probability

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I. INTRODUCTION

The network capacity proliferation and ubiquitous wireless connectivity in the forthcoming wireless network pose great challenges to the existing wireless transmission technology. Seeking for new techniques with low cost, high spectral and energy efficiency is crucial for 6G networks [1]. To this end, intelligent reflecting surface (IRS) has recently been brought forward as a promising cost-and-energy efficient solution. IRS is a software-controlled metasurface (a planar array) composed of numerous low-cost passive elements, each of which is embedded several electronic devices, such as positive-intrinsic-negative (PIN) diodes, field-effect transistors (FETs). Triggered by a smart controller integrated in the IRS, each element is able to independently reflect the incident electromagnetic wave with preprogrammed phase shifts and/or reflecting amplitudes such that the reflected signal can be beneficially (resp. destructively) aligned at the intended (resp. non-intended) receiver, which is referred to as software-controlled smart radio environments [2], [3].

There have been a flow of works on IRS-aided wireless communications. Specifically, joint transmit beamforming at the base station (BS) and phase shifts at the IRS design problems were considered in [4] and [5], where the former aimed to minimize the total transmit power at the BS, and the latter considered maximizing the sum-rate of all users. Moreover, IRSs have also been utilized to enhance physical layer security [6], [7], to improve throughput in non-orthogonal multiple access (NOMA) systems [8] and to enhance the wireless power transfer in simultaneous wireless information and power transfer (SWIPT) systems [9].

It is worthwhile to mention that most of the existing works on IRS-assisted wireless communications are built upon linear precoding schemes. However, conventional linear precoder is based on fully-digital signal processing with high-resolution digital-to-analog converters (DACs), which could induce prohibitive hardware cost and power consumption in the case of large-scale antenna arrays, e.g., massive multiple-input multiple-output (MIMO). As such, using low-resolution DACs, especially one-bit DACs, in massive MIMO is seen as a promising way to circumvent this problem. Under the one-bit signaling, the design of the transmit signal is performed in a per-symbol time manner by utilizing both the symbol information and channel state information (CSI) to directly synthesize the desired symbols at the receivers. Symbol error probability (SEP) and mean squared error (MSE) are usually adopted as the design metrics for one-bit symbol-level precoding (SLP). Interested readers are referred to [10], [11] for more details.

One-bit SLP for massive MIMO uplink/downlink has been widely studied and proved to achieve prominent performance [12]–[14]. However, in the context of the IRS-aided communications, we are not aware of any work concerning the one-bit SLP with IRS. The most relevant works are those in [15],
where SLP with IRS is studied without considering the one-bit constraint. In light of this, this paper considers an IRS-assisted multiuser multiple-input single-output (MISO) downlink communications, where one-bit DACs are deployed at the BS. We jointly design the one-bit transmit signals at the BS and the phase shifts at the IRS, so that the worst-case SEP of all the users is minimized under the PSK modulation. The resulting problem is non-convex and intractable. To tackle this min-max SEP problem, we first transform the SEP function into a more tractable form via upper bound approximation [14]. Then, we alternately optimize the one-bit signals and the phase shifts. Specifically, for the one-bit signals design, it is reformulated as a continuous optimization problem by using the exact penalty method, and then a gradient extrapolated majorization-minimization (GEMM) algorithm [10] is employed to find an approximate solution. For the phase shifts design, an accelerated projected gradient (APG) method is applied. Since both GEMM and APG are first-order methods with closed-form updates, the alternating optimization can be performed very efficiently. Simulation results demonstrate the effectiveness of our proposed joint design and show superior SEP performance than conventional linear precoding with naive one-bit quantization.

II. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a downlink MISO wireless communication system, where an IRS with \( N \) reflecting elements is deployed to assist the communications from an \( M \)-antenna BS to \( K \) single-antenna users. The BS makes use of the symbol information and the CSI to perform one-bit precoding for \( K \) data streams, one for each user, simultaneously. Denote the baseband equivalent channels from BS to user \( k \), from BS to IRS, and from IRS to user \( k \) by \( h_{d,k} \in \mathbb{C}^{M \times 1} \), \( G \in \mathbb{C}^{N \times M} \), and \( h_{r,k} \in \mathbb{C}^{N \times 1} \), \( \forall k \in K \equiv \{1, \ldots, K\} \), respectively (resp.).

Let \( \theta = [\theta_1, \ldots, \theta_N]^T \), \( \theta_n \in \mathcal{F} \equiv \{ \theta \in \mathbb{C} | |\theta| = 1 \}, \forall n \). Define \( \Theta = \sqrt{a} \text{Diag}(\theta) \), where \( \text{Diag}(\theta) \) denotes a diagonal matrix with diagonal entries \( \theta \), as the phase shift matrix of IRS with \( \theta_n \) and \( a \in [0, 1] \) being the phase shift and reflecting amplitude of each reflecting element, resp. For simplicity, we consider constant reflecting amplitude \( a = 1 \) and focus on designing \( \theta \). Assuming frequency-flat fading channels, the received signal at user \( k \) at symbol time \( t \) is given by

\[
y_{k,t} = h_{d,k}^H x_t + h_{r,k}^H \Theta G x_t + n_{k,t} \\
= (h_{d,k}^H + \theta^T W_{r,k}^H G) x_t + n_{k,t},
\]

for \( k \in K \), \( t \in T \equiv \{1, \ldots, T\} \), where \( W_{r,k} = \text{Diag}(h_{r,k}) \) and \( x_t \) is the transmit signal at symbol time \( t \); \( n_{k,t} \sim \mathcal{CN}(0, \sigma^2) \) is the additive white Gaussian noise (AWGN); \( T \) is the length of the transmission
block. Under the one-bit signaling, the transmit signal $x_t$ takes the following form:

$$x_t \in \mathcal{X}^M, \quad \mathcal{X} \triangleq \left\{ \pm \sqrt{P/2M} \pm j \sqrt{P/2M} \right\},$$

for $t = 1, \ldots, T$, where $P$ is the total transmit power and $j$ denotes the imaginary unit.

The idea of one-bit SLP is to judiciously choose $\{x_t\}_{t=1}^T$ and $\theta$ so that user $k$’s received signal $\{y_{k,t}\}_{t=1}^T$ is close to the desired symbol $\{s_{k,t}\}_{t=1}^T$ during the whole transmission block. In this paper, we consider the $L$-ary PSK constellation, i.e., $s_{k,t} \in \mathcal{S} = \{ s = e^{j\ell(2\pi/L)}, \ell = 0, \ldots, L-1 \}$, where $L$ is the number of constellation points. At the receiver, each user detects their own symbol stream via

$$\hat{s}_{k,t} = \text{dec}(y_{k,t}),$$

where $\text{dec} : \mathbb{C} \rightarrow \mathcal{S}$ denotes the $L$-ary PSK decision function, i.e., if the phase angle of $y_{k,t} \in \left[ \frac{2\pi}{L} \ell - \frac{\pi}{L}, \frac{2\pi}{L} \ell + \frac{\pi}{L} \right]$, then $\hat{s}_{k,t} = e^{j2\pi\ell/L}$. Let

$$\text{SEP}_{k,t} = \Pr(\hat{s}_{k,t} \neq s_{k,t} | s_{k,t})$$

be the SEP of the symbol conditioned on $s_{k,t}$. The problem of one-bit SLP with IRS is formulated as

$$\min_{\theta, X} \max_{k \in K, t \in T} \text{SEP}_{k,t}$$

subject to

$$x_t \in \mathcal{X}^M, \quad t = 1, \ldots, T,$$

and

$$|\theta_n| = 1, \quad n = 1, \ldots, N,$$

where $X = [x_1, \ldots, x_T]$. Problem (2) aims to minimize the worst SEPs among all users during the whole transmission block, while satisfying the one-bit and phase-shift constraints.

One of the challenges of problem (2) is that the SEP does not admit a simple closed form. Instead of tackling problem (2) directly, we first convert $\text{SEP}_{k,t}$ into a more tractable form by applying the following upper bound approximation:

**Lemma 1** ([14, Corollary 1]) Let $y = z + v$ with $z \in \mathbb{C}$ and $v \sim \mathcal{CN}(0, \sigma^2)$. Let $s \in \mathcal{S}$, where $\mathcal{S}$ is the $L$-ary PSK constellation set, and let $\hat{s} = \text{dec}(y)$. It holds that

$$\Pr(\hat{s} \neq s | s) \leq 2Q\left( \frac{\alpha}{\sigma / \sqrt{2} \sin \frac{\pi}{L}} \right),$$

where $Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-z^2/2}dz$, and

$$\alpha = \Re \{ zs^* \} - |\Im \{ zs^* \}| \cot (\pi/L).$$

By invoking Lemma 1, we achieve an upper-bound approximation of $\text{SEP}_{k,t}$, i.e.,

$$\text{SEP}_{k,t} \leq 2Q\left( \frac{\alpha_{k,t}}{\sigma / \sqrt{2} \sin \frac{\pi}{L}} \right),$$

(3)
where
\[
\alpha_{k,t} = \Re \left\{ (h^H_{d,k} + \theta^T W^H_{r,k} G)x_t s^*_{k,t} \right\} - \left| \Im \left\{ (h^H_{d,k} + \theta^T W^H_{r,k} G)x_t s^*_{k,t} \right\} \right| \cot(\pi/L). 
\]

(4)

Since \( Q(\cdot) \) is monotonically decreasing, problem (2) can be approximated as
\[
\min_{\theta, X} \quad \max_{k \in K, t \in T} - \alpha_{k,t} \\
\text{s.t.} \quad \text{(2b) and (2c).} 
\]

(5a)

In the next section, we will focus on solving problem (5).

III. AN ALTERNATING OPTIMIZATION APPROACH TO PROBLEM (5)

Problem (5) is a mixed integer nonlinear program (MINLP), which is generally NP-hard. However, since the variables in the constraints of problem (5) are decoupled, we apply the alternating optimization (AO) method to tackle problem (5) by alternately optimizing \( X \) with fixed \( \theta \), and vice versa. The details of AO are given in the following two subsections.

A. Optimizing \( X \) with fixed \( \theta \)

For any given phase shifts \( \theta \), define \( h^H_k = h^H_{d,k} + \theta^T W^H_{r,k} G \) as the combined channel from BS to user \( k \). Then, \( \alpha_{k,t} \) in (4) can be expressed as the function of \( x_t \), given by
\[
\alpha_{k,t} = \Re \left\{ h^H_k x_t s^*_{k,t} \right\} - \left| \Im \left\{ h^H_k x_t s^*_{k,t} \right\} \right| \cot(\pi/L). 
\]

(6)

Let \( \bar{x}_t = [\Re(x_t)^T, \Im(x_t)^T]^T \) and through some efforts, the transmit signal design problem can be simplified as
\[
\min_{\bar{x}_t} \quad \max_{k=1,\ldots,2K} \quad c_k^T \bar{x}_t \\
\text{s.t.} \quad \bar{x}_t \in \mathcal{L}^{2M}, \quad \text{for } t = 1, \ldots, T, \quad \text{where}
\]
\[
\mathcal{L} \triangleq \left\{ +\sqrt{P/2M}, -\sqrt{P/2M} \right\}, \\
a_k = [\Re(s^*_{k,t} h^H_k), - \Im(s^*_{k,t} h^H_k)]^T, \quad \forall k \in K, \forall t \in T, \\
b_k = \cot(\pi/L) [\Im(s^*_{k,t} h^H_k), \Re(s^*_{k,t} h^H_k)]^T, \quad \forall k \in K, \forall t \in T, \\
c_k = \begin{cases} 
-\alpha_k + b_k, & k = 1, \ldots, K, \\
-\alpha_k - K - b_{k-1}, & k = K + 1, \ldots, 2K,
\end{cases}
\]
It is worth noting that problem (7) is decoupled across the time $t$. For notational brevity, we suppress the subscript \( t \) in the following derivation.

Our first challenge is the binary constraint in (7b). We leverage the following result to turn it into a continuous one.

**Lemma 2 (\cite{10, Theorem 1})** Consider the following two problems

\[
\min_{x \in \mathcal{L}} f(x) \quad (8)
\]

and

\[
\min_{x \in \tilde{\mathcal{L}}} f(x) - \eta \|x\|^2, \quad (9)
\]

where $\eta > 0$, $\tilde{\mathcal{L}} = \text{conv}(\mathcal{L})$ denotes the convex hull of $\mathcal{L}$ and $f : \mathbb{C}^M \rightarrow \mathbb{R}$ is Lipschitz continuous on $\tilde{\mathcal{L}}^M$. Then there exists a constant $\bar{\eta} > 0$ such that for any $\eta > \bar{\eta}$, any optimal solution to Problem (9) is also an optimal solution to Problem (8). The converse also holds. In particular, we have $\bar{\eta} = \sqrt{2} \mu$ for one-bit case, where $\mu$ denotes a Lipschitz constant of $f$ on $\tilde{\mathcal{L}}^M$.

By applying Lemma 2, problem (7) can be equivalently reformulated as

\[
\min_{\bar{x} \in \tilde{\mathcal{L}}^M} \left\{ \max_{k=1, \ldots, 2K} c_k^T \bar{x} \right\} - \eta \|\bar{x}\|^2, \quad (10)
\]

for some $\eta > 0$, where $\tilde{\mathcal{L}} = \text{conv}\mathcal{L} = \left[-\sqrt{\frac{P}{2M}}, \sqrt{\frac{P}{2M}}\right]$ is the convex hull of $\mathcal{L}$.

We handle problem (10) by the gradient extrapolated majorization minimization (GEMM) method \cite{10}, which combines the idea of majorization minimization (MM) and accelerated projected gradient (APG) method. First, we smoothly approximate (10) as

\[
\min_{\bar{x} \in \tilde{\mathcal{L}}^M} F_\eta(\bar{x}) \triangleq f(\bar{x}) - \eta \|\bar{x}\|^2, \quad (11)
\]

where $f(\bar{x}) \triangleq \delta \log \sum_{k=1}^{2K} \exp \left( \frac{c_k^T \bar{x}}{\delta} \right)$ is the smooth approximation of $\max_k c_k^H \bar{x}$ with $\delta > 0$ being the smoothing parameter. Note that the approximation becomes accurate as $\delta \rightarrow 0$.

Next, by using the first-order inequality for concave function $-\|\bar{x}\|^2$, $F_\eta(\bar{x})$ can be upper bounded as follows:

\[
F_\eta(\bar{x}) \leq f(\bar{x}) - 2\eta \langle \bar{y}, \bar{x} - \bar{y} \rangle - \eta \|\bar{y}\|^2 \triangleq G_\eta(\bar{x}|\bar{y}) \quad (12)
\]

for any $\bar{x}$ and $\bar{y}$, i.e., $G_\eta(\bar{x}|\bar{y})$ is a convex and smooth majorizer of $F_\eta(\bar{x})$. By replacing $F_\eta(\bar{x})$ with its majorizer, a solution of problem (11) can be obtained by repeatedly solving the following problems:

\[
\bar{x}^{r+1} = \arg \min_{\bar{x} \in \tilde{\mathcal{L}}^M} G_\eta(\bar{x}|\bar{x}^r), \quad r = 0, 1, 2 \ldots \quad (13)
\]
Notice that problem (13) is convex with simple structured constraints. The GEMM algorithm advocates to use (inexact) APG method to perform the update in (13), which gives

$$\bar{x}^{r+1} = \Pi_{\tilde{L}^{2M}}(z^r - \frac{1}{\rho^r} \nabla \bar{x} \mathcal{G}_\eta(z^r|\bar{x}^r)), \quad r = 0, 1, 2, \ldots$$

(14)

where $z^r$ is the extrapolated point

$$z^r = \bar{x}^r + \psi_r (\bar{x}^r - \bar{x}^{r-1})$$

with

$$\psi_r = \frac{\zeta_r - 1}{\zeta_r}, \quad \zeta_r = \frac{1 + \sqrt{1 + 4\zeta_{r-1}^2}}{2}, \quad \zeta_{-1} = 0.$$  

(15)

In (14), $1/\rho^r$ is the step size and can be obtained by backtracking line search [17]; $\nabla \bar{x} \mathcal{G}_\eta(z^r|\bar{x}^r)$ represents the gradient of $\mathcal{G}_\eta(\cdot|\bar{x}^r)$ at the point $z^r$; $\Pi_{\tilde{L}^{2M}}$ is elementwise projection operator on $\tilde{L}^{2M}$, which is given by

$$\Pi_{\tilde{L}}(x) = \min \{\sqrt{P/2M}, \max\{x, -\sqrt{P/2M}\}\}.$$  

Algorithm 1 summarizes the procedure of GEMM for problem (11). We should mention that it is preferable to start with a small penalty $\eta$ to avoid ill-conditioned problem, and the $\eta$ is gradually increased so that the equivalence in Lemma 2 is satisfied at the final stage of the iteration.

Algorithm 1. GEMM Method for Problem (11)

1: given a feasible point $\bar{x}^0 \in \tilde{L}^{2M}$, threshold $\epsilon$, integers $J \geq 1$, $\kappa > 1$, an initial penalty coefficient $\eta > 0$ and penalty upper bound $\eta_{up}$;
2: Set $\bar{x}^{-1} = \bar{x}^0$ and $r = 0$
3: repeat
4: $$z^r = \bar{x}^r + \psi_r (\bar{x}^r - \bar{x}^{r-1}).$$
5: $$\bar{x}^{r+1} = \Pi_{\tilde{L}^{2M}}(z^r - \frac{1}{\rho^r} \nabla \bar{x} \mathcal{G}_\eta(z^r|\bar{x}^r))$$
6: Update $\eta = \eta \kappa$ every $J$ iter. or $||\bar{x}^{r+1} - \bar{x}^r||^2 \leq \epsilon$.
7: $r = r + 1$.
8: until $\eta > \eta_{up}$.  

B. Optimizing $\theta$ with fixed $X$

In this subsection, we focus on optimizing the phase shifts $\theta$ for given transmit signal $X$. Define $u_{k,t} = W_r^H G x_t s_{k,t}^*$ and $v_{k,t} = h_{d,k}^H x_t s_{k,t}^*$; thus $\alpha_{k,t}$ in (4) can be rewritten as

$$\alpha_{k,t} = \Re\{\theta^T u_{k,t} + v_{k,t}\} - \Im\{\theta^T u_{k,t} + v_{k,t}\} \cot(\pi/L),$$

for all $k$ and $t$. Through complex-to-real transformation, the phase-shift design problem becomes

$$\min_{\tilde{\theta}} \max_{k=1,\ldots,2K, t=1,\ldots,T} \tilde{\theta}^T \lambda_{k,t} - \bar{v}_{k,t}$$

s.t. $\tilde{\theta} \in \Phi$,

where

$$\tilde{\theta} = [\Re\{\theta\}^T, \Im\{\theta\}^T]^T,$$

$$\Phi \triangleq \{ \theta \in \mathbb{R}^{2N} | \tilde{\theta}_n^2 + |\tilde{\theta}_{n+N}|^2 = 1, \ n = 1,\ldots, N \} ,$$

$$\lambda_{k,t} = \begin{cases} -q_{k,t} + p_{k,t}, & k = 1,\ldots, K, \\ -q_{k-K,t} - p_{k-K,t}, & k = K + 1,\ldots, 2K, \end{cases} \forall t,$$

$$q_{k,t} = [\Re\{u_{k,t}\}, -\Im\{u_{k,t}\}]^T, \ \forall k \in K, \forall t \in T,$$

$$p_{k,t} = \cot(\pi/L) [\Im\{u_{k,t}\}, \Re\{u_{k,t}\}]^T, \ \forall k \in K, \forall t \in T,$$

$$\bar{v}_{k,t} = \begin{cases} -\Re\{v_{k,t}\} + \Im\{v_{k,t}\} \cot(\pi/L), & k = 1,\ldots, K, \\ -\Re\{v_{k-K,t}\} - \Im\{v_{k-K,t}\} \cot(\pi/L), & k = K + 1,\ldots, 2K. \end{cases}$$

As before, we apply APG to handle problem (16). We replace (16a) with its smooth approximation

$$h(\tilde{\theta}) = \delta \log \left( \sum_{t=1}^T \sum_{k=1}^{2K} \exp \left( \frac{\tilde{\theta}^T \lambda_{k,t} - \bar{v}_{k,t}}{\delta} \right) \right),$$

and perform the APG update for $\tilde{\theta}$

$$\tilde{\theta}^{r+1} = \Pi_{\Phi} \left( z^r - \frac{1}{\tau^r} \nabla \tilde{h}(z^r) \right), \ r = 0, 1, 2, \ldots ,$$

until convergence, where $z^r$ is defined as

$$z^r = \tilde{\theta}^r + \psi_r(\tilde{\theta}^r - \tilde{\theta}^{r-1});$$

$\psi_r$ is given in (15); $1/\tau^r$ is the step size. The projection $\hat{\tilde{\theta}} \triangleq \Pi_{\Phi}(\tilde{\theta})$ for some $\tilde{\theta} \in \mathbb{R}^{2N}$ is given by

$$\hat{\tilde{\theta}}_n = \begin{cases} \tilde{\theta}_n / \left( |\tilde{\theta}_n|^2 + |\tilde{\theta}_{n+N}|^2 \right), & n = 1,\ldots, N, \\ \tilde{\theta}_n / \left( |\tilde{\theta}_{n-N}|^2 + |\tilde{\theta}_n|^2 \right), & n = N + 1,\ldots, 2N. \end{cases}$$
IV. Numerical Results

In this section, we evaluate the performance of our proposed algorithm by simulations. The simulation settings are as follows: the locations of the BS and the IRS are set to (0, 0) and (20, 10), resp. There are $K = 14$ users randomly distributed in a circle area centered at (30, 0) with radius 10m. We set $M = 128$, $T = 10$ and $P = 20$dB. The path loss with respect to the large-scale fading is modeled as $L(d) = C_0 \varrho d^{-\varsigma}$, where $C_0$ denotes the path loss at the reference distance 1 meter, $\varrho$ denotes the product of the source and the terminal gain, $d$ and $\varsigma$ represent the link distance and the path loss exponent, resp. In particular, concerning the direct link between the BS and $k$-th user, we set $C_0 \varrho_{B,k} = -15$dB and $\varsigma_{B,k} = 3.2$, $\forall k \in K$. As for the IRS-aided link, the total path loss can be written as $C_0^2 \varrho_{B,I,k}(d_{B,I})^{-\varsigma_{B,I}}(d_{I,k})^{-\varsigma_{I,k}}$ corresponding to the concatenating channel model, in which we set $C_0^2 \varrho_{B,I,k} = -20$dB and $\varsigma_{B,I} = \varsigma_{I,k} = 2$. To characterize small-scale fading, we assume Rayleigh fading model for all channels. The parameters of Algorithm 1 are chosen as $\delta = 0.01$, $\eta = 0.01$, $\eta_{up} = 100$, $\kappa = 5$, $J = 500$ and $\epsilon = 10^{-2}$.

We compare our proposed design with the following benchmark schemes: 1) One-bit precoding without IRS [14], named “one-bit, without IRS”; 2) Zero-forcing (ZF) followed by one-bit quantization with IRS, named “ZF-OB, with IRS”. The results of this scheme are obtained by running AO with Algorithm 1 replaced with the ZF precoder
\[ x_{t}^{ZF} = cH^H(HH^H)^{-1}s_t, \quad \forall t = 1, \cdots, T, \] (18)
where $c$ is determined such that $E[\|x_{t}^{ZF}\|^2] = P$ and $s_t = [s_{1,t}, \cdots, s_{K,t}]^T$. After convergence, we element-wise one-bit quantize $x_{t}^{ZF}$ and perform another phase-shift design based on the quantized transmit signals; 3) Directly one-bit quantizing the output of the ZF precoder (18) without IRS, named “ZF-OB, without IRS”; 4) ZF under infinite-resolution DACs with IRS, named “ZF with IRS”, which is similar to “ZF-OB, with IRS”, except that no one-bit quantization is performed after convergence of AO. Since “ZF with IRS” relaxes the one-bit constraints on $X$, it serves as the performance lower bound. All the results were obtained by averaging over 1,000 channel realizations.

Fig. 1(a) and Fig. 1(b) show the BER performance versus the reciprocal of the noise power $1/\sigma^2$ for QPSK and 8-ary PSK, resp., when fixing the number of IRS elements to $N = 32$. First, it can be observed that by introducing IRS, the proposed design outperforms the one-bit precoding without IRS and effectively eliminates the error floor effects. This demonstrates the constructive role of IRS in improving the symbol error performance under the one-bit constraints. Moreover, both the one-bit SLP designs with and without the IRS have better BER performance than their corresponding one-bit quantized ZF schemes. This is because the former explicitly takes the symbol information into account, while the latter does not during the precoder design.
V. CONCLUSIONS

This paper considered a joint one-bit symbol-level precoding and phase shifts design for the IRS-aided MU-MISO downlink communications. A minimum-SEP-based formulation is studied for PSK constellations. We develop an efficient approximate algorithm based on alternating optimization. Simulation results demonstrate the efficacy of incorporating IRS to improve the system BER performance. Moreover, by explicitly taking into account the symbol information, the proposed design attains superior performance as compared with conventional linear beamforming with naive one-bit quantization.

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