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Adaptive Beamforming for Non-Line-of-Sight IRS-Assisted Communications without CSI

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***Abstract*—Channel acquisition is a major bottleneck in fully exploiting the potential of intelligent reflecting surfaces (IRSs) to improve the wireless environment. In order to bypass such difficulty, an alternative is to optimize IRS based on the received signal statistics rather than channel state information (CSI), namely blind beamforming. The two recent methods, RFocus and conditional sample mean (CSM), fall into this category, both of which have been shown highly effective in practice. Nevertheless, we find a subtle drawback with the existing blind beamforming methods that they may not work well for the non-line-of-sight (NLoS) case for two reasons. First, many more signal samples are needed when the direct propagation diminishes. Second, if the direct propagation is completely blocked then the existing blind beamforming methods cannot work whatsoever. To address this issue, we propose an adaptive strategy for blind beamforming, which guarantees an approximation ratio of the global optimum. Field tests and simulations show that the proposed blind beamforming method is much more suited for NLoS environment than the existing ones.**

I. Introduction

Intelligent reflecting surface (IRS), also known as reconfigurable intelligent surface (RIS), aims to improve the wireless environment by exploiting signal reflections. One of its typical applications is to induce cascaded reflected channels and thereby enable non-line-of-sight (NLoS) communications. The realization of this emerging technology entails coordinating phase shifts across many reflective elements (RE) efficiently. Differing from most existing methods that first estimate channels and then optimize phase shifts, this work proposes a blind approach to the IRS beamforming problem in the absence of channel state information (CSI).

The idea of "*blind beamforming*" without channel acquisition dates back to [1] in which the on-off status of each RE is decided based on the received signal statistics in lieu of CSI. The more recent work [2] develops the applications and theory of blind beamforming further, showing that the optimal signal-to-noise ratio (SNR) boost can be achieved within a constant fraction under certain conditions. The major motivation behind blind beamforming is that [1], [2] find it difficult to incorporate the additional channel estimation for IRS into their prototype IRS-assisted communication system because of the network protocol and the hardware issues.

Actually, this paper stems from a novel observation that the existing blind beamforming methods in [1], [2] cannot work well when the direct propagation from transmitter to receiver is extremely weak, for two main reasons. First, the random sample size required for computing the received signal statistics grows fast as the direct channel diminishes. Second, if the direct propagation is completely blocked, then the existing blind beamforming methods [1], [2] cannot work whatsoever. The main goal of this paper is to address the above issue by devising an adaptive strategy for blind beamforming with provable performance.

The IRS beamforming problem has been considered extensively in the literature assuming perfect CSI. If phase shifts can be chosen arbitrarily, i.e., the continuous beamforming, then clearly it is optimal to align all the reflected channels with the direct channel on the complex plane in order to maximize the overall channel superposition. The problem becomes much more difficult if phase shifts can only take on values in a discrete set as required by practical implementations. To cope with discrete beamforming, [3] proposes to round the continuous solution to the closest point in the discrete set, [4] suggests optimizing one phase shift at a time while holding the rest phase shifts fixed, and [5] proposes an approximation algorithm that is capable of reaching at least half of the global optimum. In order to solve the discrete IRS beamforming problem exactly, a line of studies [6], [7] employ the branch-and-bound algorithm, thus incurring an exponential time complexity. In contrast, a recent work [8] shows that the discrete IRS beamforming problem can be optimally solved in linear time for the single-IRS single-user scenario. Moreover, [9] considers applying the self-supervised learning technique to the discrete IRS beamforming problem with imperfect CSI, while [10] proposes optimizing phase shifts in the long run based on the statistical CSI.

There also has been a growing interest in optimizing phase shifts for IRS without any channel information. Aside from the aforementioned [1], [2] that build upon statistics, many other attempts are empirically based. For instance, [11] treats the blind beamforming problem as a particle swarm optimization and thus suggests using the evolutionary algorithm, [12], [13]

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consider directly mapping the received pilot signals to the phase shift decision by means of supervised learning, and [14] uses reinforcement learning to learn the optimal beam pattern based on the user location.

It turns out that whether the direct channel can be neglected is of crucial importance in many works about IRS. On the one hand, for the conventional approaches, ignoring the direct channel can simplify channel estimation [15], [16] and phase shift optimization [17], [18]. In particular, it would be far more challenging to coordinate multiple IRSs in the presence of the direct channel [8], [19]. But on the other hand, as pointed out in Section III-C, the performance of the existing blind beamforming approach [1], [2] cannot be guaranteed anymore if the direct channel is too weak. This work seeks an extension of blind beamforming with provable performance to the NLoS transmission case in which the direct propagation is feeble.

II. System Model

Consider wireless transmission with the aid of an IRS that comprises N REs. Each RE, indexed by $n = 1, \ldots, N$, induces a cascaded reflected channel $h_n \in \mathbb{C}$ from the transmitter to the receiver. In addition, denote by $h_0 \in \mathbb{C}$ the direct channel from the transmitter to the receiver. Throughout the paper, the channels are frequently written in an exponential form as

$$h_n = \beta_n e^{j\alpha_n},\ n = 0, 1, \ldots, N, \tag{1}$$

where $\beta_n \geq 0$ is the magnitude and $\alpha_n \in [0, 2\pi)$ is the phase. Let $\theta_n \in [0, 2\pi)$ be the phase shift decision for RE n. In practice, the choice of each θ_n is often restricted to a uniform discrete set

$$\Phi_K = \{0, \omega, \ldots, (K-1)\omega\}, \tag{2}$$

where

$$\omega = \frac{2\pi}{K} \tag{3}$$

for some given integer $K \geq 2$. The relationship between the transmit signal $X \in \mathbb{C}$ and the received signal $Y \in \mathbb{C}$ is

$$Y = \left(h_0 + \sum_{n=1}^{N} h_n e^{j\theta_n}\right) X + Z, \tag{4}$$

where $Z \sim \mathcal{CN}(0, \sigma^2)$ is the additive Gaussian noise with power σ^2. If the transmit power equals P so that $\mathbb{E}[|X|^2] = P$, then the received SNR can be computed as a function of the phase shift vector $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_n)$:

$$\mathrm{SNR}(\boldsymbol{\theta}) = \left|h_0 + \sum_{n=1}^{N} h_n e^{j\theta_n}\right|^2 \frac{P}{\sigma^2}. \tag{5}$$

We aim to maximize the SNR by optimizing $\boldsymbol{\theta}$, i.e.,

$$\underset{\boldsymbol{\theta}}{\text{maximize}} \quad \mathrm{SNR}(\boldsymbol{\theta}) \tag{6a}$$

$$\text{subject to} \quad \theta_n \in \Phi_K,\ \text{for } n = 1, \ldots, N. \tag{6b}$$

We wish to emphasize two assumptions made about the above problem: (i) the channel information $\{h_0, h_n\}$ is completely unknown; (ii) the direct propagation is NLoS so that $h_0 \to 0$.

III. Preliminary

A. CPP: A Near-Optimal Algorithm when CSI is Available

We start with a simplified version of problem (6) in which CSI is assumed to be already precisely known. The discrete constraint Φ_K is then deemed to be the main difficulty. Nevertheless, as $K \to \infty$, i.e., when each θ_n can be arbitrarily chosen from the interval $[0, 2\pi)$, the discrete problem reduces to the continuous, and consequently, it is optimal to align each reflected channel with the direct channel, i.e.,

$$\theta_n^{\infty} = \alpha_0 - \alpha_n \mod 2\pi,\ \text{for } n = 1, \ldots, N. \tag{7}$$

To tackle the finite-K case, a natural idea is to round the above continuous solution to the closest point in the discrete set Φ_K:

$$\theta_n^{\mathrm{CPP}} = \min_{\varphi \in \Phi_K} |\varphi - \theta_n^{\infty}|, \tag{8}$$

namely the *closest point projection (CPP)* method. Denoting the global optimum by $\mathrm{SNR}^{\star}$, it can be shown that [2], [3]

$$\cos^2(\frac{\pi}{K}) \cdot \mathrm{SNR}^{\star} \leq \mathrm{SNR}(\boldsymbol{\theta}^{\mathrm{CPP}}) \leq \mathrm{SNR}^{\star}. \tag{9}$$

Thus, $\mathrm{SNR}(\boldsymbol{\theta}^{\mathrm{CPP}}) \geq \frac{1}{2} \cdot \mathrm{SNR}^{\star}$ when $K \geq 4$. Furthermore, the recent work [8] shows a fairly surprising result that the global optimum of the finite-K problem can be reached in linear time when CSI is available. But CPP still enjoys two advantages in comparison. First, CPP is easier to implement than the optimal algorithm in [8]. Second, more importantly, CPP can be somehow performed implicitly in the absence of CSI, as discussed in the next subsection.

B. Blind Implementation of CPP without CSI

The *CSM* method in [2] is based on the following intuition. Suppose that we try out a total of T random samples of the solution space Φ_K^N, each written as $\boldsymbol{\theta}_t = (\theta_{1t}, \ldots, \theta_{Nt})$ for $t = 1, \ldots, T$. With respect to each sample t, we measure the corresponding received signal power

$$\rho_t = \left|\left(h_0 + \sum_{n=1}^{N} h_n e^{j\theta_{nt}}\right) X_t + Z_t\right|^2. \tag{10}$$

To evaluate how good a particular phase shift $\varphi \in \Phi_K$ is for RE n, a simple and natural idea is to fix $\theta_n = \varphi$ and compute the resulting conditional sample mean of received signal power when the rest phase shifts are all randomized:

$$\hat{\mathbb{E}}[\rho|\theta_n = \varphi] = \frac{1}{|\mathcal{Q}_{n\varphi}|} \sum_{t \in \mathcal{Q}_{n\varphi}} \rho_t, \tag{11}$$

where $\mathcal{Q}_{n\varphi} \subseteq \{1, \ldots, T\}$ refers to the set of all those random samples with $\theta_{nt} = \varphi$, and $|\mathcal{Q}_{n\varphi}|$ refers to the set cardinality. The CSM method decides each θ_n according to $\hat{\mathbb{E}}[\rho \,|\, \theta_n = \varphi]$, i.e.,

$$\theta_n^{\mathrm{CSM}} = \arg\max_{\varphi \in \Phi_K} \hat{\mathbb{E}}[\rho|\theta_n = \varphi]. \tag{12}$$

As a major result from [2], it turns out that the above heuristic approach is equivalent to CPP when T is sufficiently large. We remark that the RFocus method in [1] is based on a similar idea, but it aims to optimize the on-off status of each RE rather than phase shift. In the sequel, we will elaborate on this connection and also explain why CSM may not work well when the direct channel is weak.

C. Why RFocus [1] and CSM [2] Fail the NLoS Transmission

To see why CSM may fail in the NLoS channel case, we first need to understand how CSM is related to CPP. The computation in (11) can be further developed into

$$\hat{\mathbb{E}}[\rho|\theta_n=\varphi]=2P\beta_0\beta_n\cos(\varphi+\alpha_n-\alpha_0)+P\sum_{m=0}^{N}\beta_m^2 + C_1+C_2+C_3+C_4+C_5, \quad (13)$$

where

$$C_1=\frac{2P}{|\mathcal{Q}_{nk}|}\sum_{a=1}^{N}\sum_{b=1,b\neq a}^{N}\sum_{t\in\mathcal{Q}_{nk}}\mathfrak{Re}\{h_a\bar{h}_b e^{j(\theta_{at}-\theta_{bt})}\}, \quad (14)$$

$$C_2=\frac{2P}{|\mathcal{Q}_{nk}|}\sum_{a=1}^{N}\sum_{t\in\mathcal{Q}_{nk}}\mathfrak{Re}\{h_a\bar{h}_0 e^{j\theta_{at}}\}, \quad (15)$$

$$C_3=\frac{2\sqrt{P}}{|\mathcal{Q}_{nk}|}\sum_{t\in\mathcal{Q}_{nk}}\mathfrak{Re}\left\{h_0\bar{Z}_t\right\}, \quad (16)$$

$$C_4=\frac{2\sqrt{P}}{|\mathcal{Q}_{nk}|}\sum_{t\in\mathcal{Q}_{nk}}\mathfrak{Re}\left\{\sum_{n=1}^{N}h_n e^{j\theta_{nt}}\bar{Z}_t\right\}, \quad (17)$$

$$C_5=\frac{1}{|\mathcal{Q}_{nk}|}\sum_{t\in\mathcal{Q}_{nk}}|Z_t|^2, \quad (18)$$

where $\bar{(\cdot)}$ represents the conjugate of a complex number. By the law of large numbers, C_1 through C_4 all tend to zero while C_5 tends to σ^2 as $T\to\infty$, so $\hat{\mathbb{E}}[\rho|\theta_n=\varphi]$ tends to

$$\mathbb{E}[\rho|\theta_n=\varphi]=2P\beta_0\beta_n\cos(\varphi+\alpha_n-\alpha_0)+\mathrm{const}. \quad (19)$$

Thus, for T sufficiently large, the CSM method in (12) now boils down to maximizing the first term of $\mathbb{E}[\rho|\theta_n=\varphi]$, i.e., $2P\beta_0\beta_n\cos(\varphi+\alpha_n-\alpha_0)$. It is obvious that the optimal φ is the closest point in Φ_K to $\alpha_0-\alpha_n$, namely the CPP method. The equivalence between CSM and CPP is therefore established as $T\to\infty$.

From a practical standpoint, we are more interested in the behavior of CSM when T is finite. Our ultimate goal is to make $\boldsymbol{\theta}^{\text{CSM}}=\boldsymbol{\theta}^{\text{CPP}}$. Toward this end, we require the condition $\hat{\mathbb{E}}[\rho|\theta_n=\theta_n^{\text{CPP}}]>\hat{\mathbb{E}}[\rho|\theta_n=\varphi]$ to hold for any $\varphi\neq\theta_n^{\text{CPP}}$, for which a sufficient condition follows [2]:

$$\left|\hat{\mathbb{E}}[\rho|\theta_n=\varphi]-\mathbb{E}[\rho|\theta_n=\varphi]\right|<2\beta_0\beta_n\epsilon_n, \quad (20)$$

where $\epsilon_n>0$ is the difference between the highest value and the second highest value of $\cos(\varphi+\alpha_n-\alpha_0)$ across all possible $\varphi\in\Phi_K$. As $\beta_0\to 0$, the error probability can be bounded as

$$\begin{aligned}
&\Pr\left\{\boldsymbol{\theta}^{\text{CSM}}\neq\boldsymbol{\theta}^{\text{CPP}}\right\}\\
&\overset{(a)}{\leq}\sum_{n=1}^{N}\Pr\left\{\theta_n^{\text{CSM}}\neq\theta_n^{\text{CPP}}\right\}\\
&\overset{(b)}{\leq}\sum_{n=1}^{N}\Pr\left\{\left|\hat{\mathbb{E}}[\rho|\theta_n=\varphi]-\mathbb{E}[\rho|\theta_n=\varphi]\right|>2\beta_0\beta_n\epsilon_n\right\}\\
&\overset{(c)}{\leq}\sum_{n=1}^{N}\frac{\mathrm{Var}(C_1+C_2+C_3+C_4+C_5)}{4|\mathcal{Q}_{nk}|\beta_0^2\beta_n^2\epsilon_n^2}\\
&\overset{(d)}{\lesssim}\frac{K}{4T\beta_0^2}\sum_{n=1}^{N}\frac{\mathrm{Var}(C_1+C_4+C_5)}{\beta_n^2\epsilon_n^2},
\end{aligned} \quad (21)$$

where (a) follows by the union bound, (b) follows by the sufficient condition (20), (c) follows by Chebyshev's inequality, and (d) follows by the fact that $C_2,C_3\to 0$ as $\beta_0\to 0$ and also the fact that $|\mathcal{Q}_{nk}|\approx T/K$. Notice that neither the $\mathrm{Var}(C_1+C_4+C_5)$ nor ϵ_n^2 depends on β_0. As a result, given the target error probability, the above bound suggests that the sample size T grows quadratically if the direct propagation diminishes. We remark that the RFocus method in [1] has the above issue as well. Furthermore, the following example discusses the extreme case.

Example 1: If the direct propagation is completely blocked so that $h_0=0$, then the $\hat{\mathbb{E}}[\rho|\theta_n=\varphi]$ in (13) reduces to the same value $P\sum_{m=0}^{N}\beta_m^2+\sigma^2$ for any choice φ as $T\to\infty$, so CSM cannot decide θ_n in this setting.

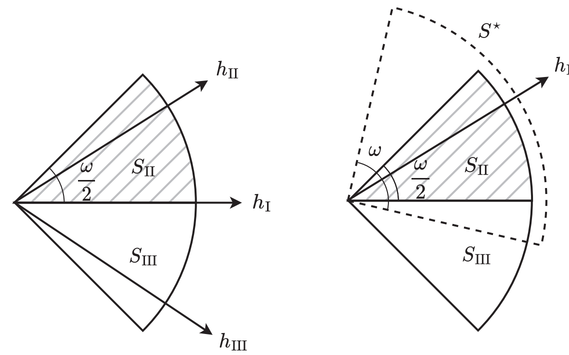


Fig. 1. Visualization of the procedure in Algorithm 1.

Algorithm 1 Adaptive Blind Beamforming Method

1: Divide reflected channels into two groups $\mathcal{S}_{\text{I}}$ and $\mathcal{S}_{\text{I}}^C$.
2: Take T_1 random samples of $\{\theta_n\}$ for those reflected channels $h_n\in\mathcal{S}_{\text{I}}^C$.
3: **1st-Time CSM:** Compute $\hat{\mathbb{E}}[\rho|\theta_n=\varphi]$ in (11) and decide θ_n for each $h_n\in\mathcal{S}_{\text{I}}^C$ according to (12).
4: Determine $\mathcal{S}_{\text{II}}$ and $\mathcal{S}_{\text{III}}$ according to (22).
5: Take T_2 random samples of $\{\theta_n\}$ for those reflected channels $h_n\in\mathcal{S}_{\text{I}}\cup\mathcal{S}_{\text{III}}$.
6: **2nd-Time CSM:** Compute $\hat{\mathbb{E}}[\rho|\theta_n=\varphi]$ in (11) and decide θ_n for each $h_n\in\mathcal{S}_{\text{I}}\cup\mathcal{S}_{\text{III}}$ according to (12).

IV. Proposed Adaptive CSM Method

Since h_0 being too weak is the cause of the above issue, a natural idea is to enhance the direct channel by adding some reflected channels to it. Specifically, one may divide the reflected channels into two groups, and then perform CSM for

Fig. 2. Field test with an IRS prototype that consists of 400 REs and provides 4 phase shift options $\{0, \pi/2, \pi, 3\pi/2\}$ on each RE.

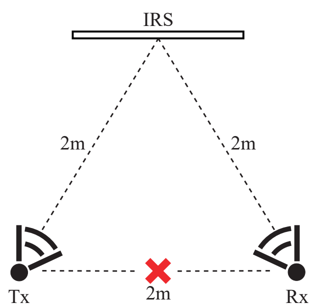


Fig. 3. Layout drawing of the testbed. The transmit and receive antennas are oriented such that the direct propagation is nullified.

one group at a time while treating the other group as a part of the "virtual direct channel" which is much stronger than h_0 alone. But this alternating method has two shortcomings. First, the iteration between the two groups can consume a large number of samples. Second, the iteration may not even converge.

We propose a more sophisticated way of creating the virtual direct channel. First, divide the reflected channels $\{h_1, \ldots, h_N\}$ into two groups $\mathcal{S}_{\text{I}}$ and $\mathcal{S}_{\text{I}}^C$. Fixing θ_n for $\mathcal{S}_{\text{I}}$, we optimize θ_n in $\mathcal{S}_{\text{I}}^C$ by CSM, i.e., the reflected channels in $\mathcal{S}_{\text{I}}^C$ are now treated as parts of the virtual direct channel denoted by h_{I}. With h_{I} being much stronger than h_0, CSM now works well. As a result, every $h_n \in \mathcal{S}_{\text{I}}^C$ would be rotated to the closest possible position to the virtual direct channel h_{I}. Notice that the optimized reflected channels must lie in the two sectors adjacent to h_{I}, both having an angle of $\omega/2$, as illustrated in Fig. 1(a).

We denote by $\mathcal{S}_{\text{II}} \subseteq \mathcal{S}_{\text{I}}^C$ the subset of optimized reflected channels lying in the upper sector (which is shaded in Fig. 1(a)), and $\mathcal{S}_{\text{III}} \subseteq \mathcal{S}_{\text{I}}^C$ the subset of optimized reflected channels lying in the lower sector. Moreover, we use h_{II} to denote the superposition of the channels in $\mathcal{S}_{\text{II}}$, and h_{III} the superposition of the channels in $\mathcal{S}_{\text{III}}$. The sequel shows that $\mathcal{S}_{\text{II}}$ and $\mathcal{S}_{\text{III}}$ can be determined by comparing $\hat{\mathbb{E}}[\rho|\theta_n = \varphi]$. Consider an optimized reflected channel $h_n e^{j\theta_n}$ that currently lies in $\mathcal{S}_{\text{II}}$. Notice that $h_n e^{j(\theta_n - \omega)}$ is closer to h_{I} than $h_n e^{j(\theta_n + \omega)}$ is, so $\hat{\mathbb{E}}[\rho|\theta_n = \varphi - \omega]$ must be larger than $\hat{\mathbb{E}}[\rho|\theta_n = \varphi + \omega]$. By symmetry, if $h_n e^{j\theta_n}$ currently lies in $\mathcal{S}_{\text{III}}$, we have $\hat{\mathbb{E}}[\rho|\theta_n = \varphi + \omega]$ be larger than $\hat{\mathbb{E}}[\rho|\theta_n = \varphi - \omega]$. In summary, we can tell which sector each $h_n e^{j\theta_n}$ belongs to by comparing its associated conditional sample means, i.e.,

$$\hat{\mathbb{E}}[\rho|\theta_n = \varphi + \omega] \underset{\mathcal{S}_{\text{III}}}{\overset{\mathcal{S}_{\text{II}}}{\lessgtr}} \hat{\mathbb{E}}[\rho|\theta_n = \varphi - \omega]. \tag{22}$$

The first stage of the proposed method is now completed. In the next stage, we fix θ_n for the reflected channels in $\mathcal{S}_{\text{II}}$, and optimize those in $\mathcal{S}_{\text{I}}$ and $\mathcal{S}_{\text{III}}$ via CSM. The whole method is then completed. We summarize the above steps in Algorithm 1. The computational complexity of the algorithm is $O(N(T+K))$. Most importantly, the proposed method has provable performance, as stated in the following proposition.

Proposition 1: For the phase shift solution $\{\theta_n^{\text{A-CSM}}\}$ of Algorithm 1, there holds

$$\max_{a,b \in \{1,\ldots,N\}} |\alpha_a + \theta_a^{\text{A-CSM}} - \alpha_b - \theta_b^{\text{A-CSM}}| \leq \omega, \tag{23}$$

i.e., the reflected channels are clustered inside a sector with an angle of ω, so the solution of Algorithm 1 guarantees

$$\cos^2\left(\frac{\pi}{K}\right) \cdot \text{SNR}^\star \leq \text{SNR}(\boldsymbol{\theta}^{\text{A-CSM}}) \leq \text{SNR}^\star \tag{24}$$

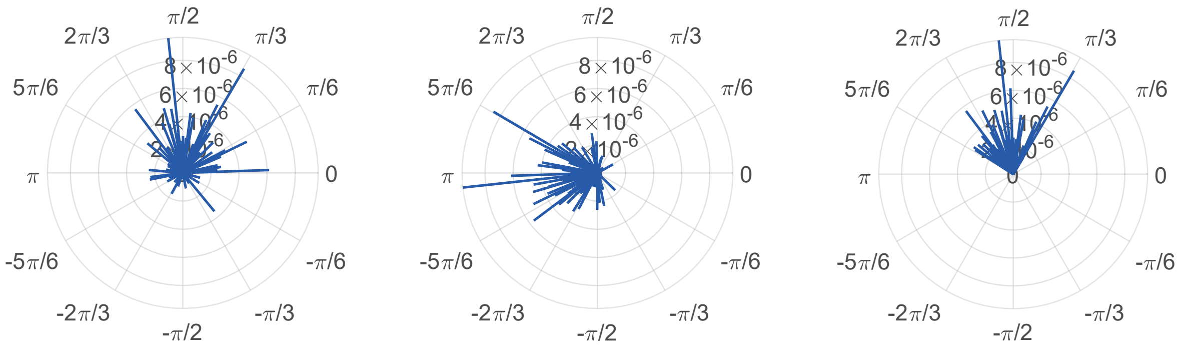
for the NLoS transmission case with $\beta_0 \to 0$.

Proof: For the 1st-time CSM in Algorithm 1, all those reflected channels of $\mathcal{S}_{\text{II}}$ are rotated to the closest possible position to the current virtual direct channel h_{I}, so they must lie inside the shaded sector as shown in Fig. 1(a). Clearly, their superposition h_{II} must lie in the shaded sector too. For the 2nd-time CSM, as shown in Fig. 1(b), all those reflected channels of $\mathcal{S}_{\text{I}}$ and $\mathcal{S}_{\text{III}}$ are rotated to the closest possible positions to h_{II}. Summarizing the above results gives (23). ■

V. Experiments

A. Field Tests

The field tests are carried out at the 3.5 GHz frequency band. The transmit power $P = -10$ dBm. The IRS prototype consists of $N = 400$ REs and provides $K = 4$ phase shift options for each RE. As shown in Fig. 2, the transmit and receive antennas are oriented such that the direct propagation



(a) CPP with Estimated CSI (b) Proposed Method (c) CPP with Perfect CSI

Fig. 4. Plots of the optimized reflected channels $h_n e^{j\theta_n}$ by the different methods when $N = 100$ and $K = 4$.

is nullified. The topology details of our testbed are shown in Fig. 3. Aside from the CSM method in Section III-B and the proposed adaptive blind beamforming method in Algorithm 1, the following benchmark methods are tested:

- *Zero Phase Shifts (ZPS):* Fix all phase shifts to be zero.
- *Random Max Sampling (RMS):* Try out T random samples $\boldsymbol{\theta}_t$ and choose the best.
- *CSM with Half of REs Fixed (CSM-Fixed):* Fix half of REs and optimize the other half by CSM.
- *Alternating CSM (CSM-Alternating):* Divide REs into two groups and optimize them alternatingly by CSM. Two iterations are used in our case.

For fairness, we use the same number $T = 1000$ of random samples for all the tested methods. We evaluate the SNR boost as compared to the baseline case without the IRS deployment.

TABLE I summarizes the SNR boost performance of the different methods. Because the direct channel is extremely weak, the deployment of IRS even without any phase shift optimization can already yield a remarkable SNR boost of almost 20 dB, as shown in the row of ZPS. Observe that the gain of RMS as compared to ZPS is marginal. The reason is that there are total 4^{400} possible solutions of $\{\theta_n\}$, so exploring merely 1000 of them may not provide many advantages over the all-zero trivial solution. Despite the NLoS setting, CSM still significantly outperforms the above two simple methods. Moreover, it can be seen that CSM is close to CSM-Fixed, although the latter just optimizes half of REs. This implies that the performance gain of CSM scales slowly with the number of REs in the NLoS environment. The proposed method can further double the SNR as compared to CSM. Observe also that CSM-Alternating attains similar performance. Nevertheless, CSM-Alternating does not guarantee convergence and hence it is difficult to decide when to stop iteration in practice, whereas the proposed method does not incur such concern.

TABLE I
SNR Boosts Achieved by the Different Methods

Method	SNR Boost (dB)
ZPS	19.955
RMS	21.671
CSM	28.954
CSM-Fixed	29.009
CSM-Alternating	31.389
Adaptive Blind Beamforming	31.892

B. Simulations

We further compare the proposed adaptive blind beamforming method with the CSI-based approach in simulations. Consider two benchmarks: (i) CPP with estimated CSI; (ii) CPP with perfect CSI. The DFT method [20] is used for channel estimation. The simulation setting follows the existing work [13]. The transmit power is 30 dBm and the background noise power is -70 dBm. The direct channel is modeled as $h_0 = 10^{-(\mathsf{PL}_0)/20} \cdot \zeta_0$ where $\mathsf{PL}_0 = 32.6 + 36.7\log_{10}(d_0)$ is the pathloss between the transmitter and the receiver which are d_0 meters apart, and ζ_0 is the Rayleigh fading component drawn i.i.d. from the Gaussian distribution $\mathcal{CN}(0, 1)$. The cascaded reflected channel h_n is modeled as $h_n = 10^{-(\mathsf{PL}_1+\mathsf{PL}_2)/20} \cdot \zeta_{n1}\zeta_{n2}, n = 1, \ldots, N$, where PL_1 and PL_2 are both based on the pathloss model $\mathsf{PL} = 30 + 22\log_{10}(d)$, with d in meters respectively denoting the transmitter-to-IRS distance and the IRS-to-receiver distance, while the Rayleigh fading components ζ_{n1} and ζ_{n2} are drawn from the Gaussian distribution $\mathcal{CN}(0, 1)$ independently across $n = 1, \ldots, N$. The locations of the transmitter, IRS, and receiver are respectively denoted by the 3-dimensional coordinate vectors $(50, -200, 20)$, $(-2, -1, 0)$, and $(0, 0, 0)$ in meters. The direct channel is fairly weak in this setting. Moreover, we assume $N = 500$ throughout the simulations.

Fig. 4 shows the optimized reflected channels $\{h_n e^{j\theta_n}\}$ by the different methods when the sample size $T = 1000$. It can be seen that the channels are more clustered together by the proposed method as compared to CPP with estimated CSI. The best result is achieved by CPP with perfect CSI, in which case the channels are clustered within a sector of an angle of $\pi/2$. Furthermore, we consider the cumulative distribution function of SNR boosts over the random channel realizations in Fig. 5 and Fig. 6. Fig. 5 shows the case of $T = 500$. Observe that the proposed method outperforms the CPP with estimated CSI in the low SNR boost regime, e.g., the former

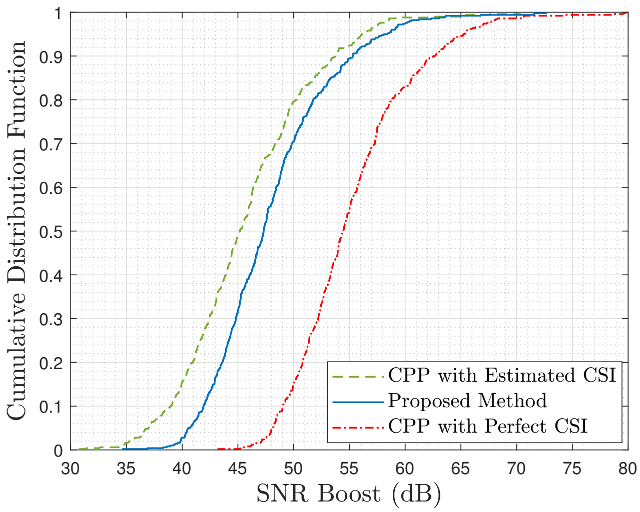


Fig. 5. Cumulative distribution of SNR boosts when $T = 500$.

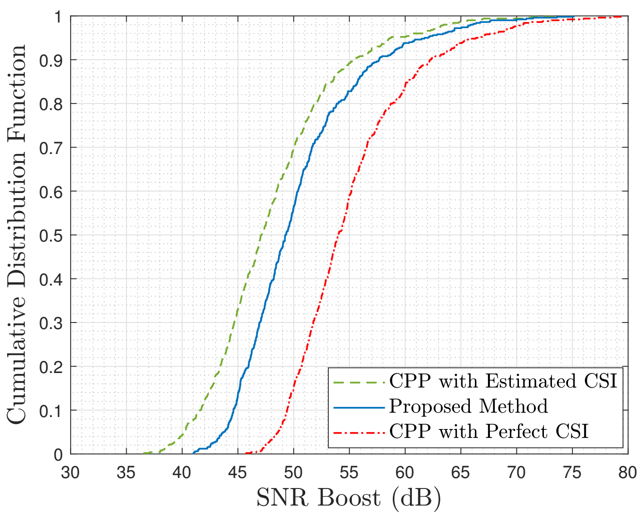


Fig. 6. Cumulative distribution of SNR boosts when $T = 1000$.

is around 3 dB higher than the latter at the 10th percentile. When T is raised to 1000, as shown in Fig. 6, the gap between the proposed method and the CPP with estimated CSI does not shrink, but the advantage of the CPP with perfect CSI becomes smaller. We remark that the CPP with estimated CSI takes much more time than the other two methods, mainly due to channel estimation.

VI. Conclusion

Blind beamforming is a promising approach to the practical optimization of IRS for its capability to bypass channel estimation. Nevertheless, as pointed out in this work, the existing blind beamforming methods in [1], [2] may fail in the NLoS environment. To address the above issue, we propose to fix a portion of reflected channels and treat them as a part of the virtual direct channel while optimizing the rest reflected channels, namely adaptive blind beamforming. It is shown that the proposed adaptive scheme guarantees an approximation ratio of $\cos^2(\pi/K)$ by requiring only a linear running time in the number of REs. Field tests show that the proposed method can be efficiently implemented in the real world.

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