Optimized Design for IRS-Assisted Integrated Sensing and Communication Systems in Clutter Environments

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Abstract—In this paper, we investigate an intelligent reflecting surface (IRS)-assisted integrated sensing and communication (ISAC) system design in a clutter environment. Assisted by an IRS equipped with a uniform planar array (UPA), a multi-antenna base station (BS) is targeted for simultaneously sensing multiple targets in the non-light-of-sight (NLoS) region and communicating with multiple communication users (CUs). We consider the joint IRS-assisted ISAC design in the case with Type-I and Type-II CUs, where each Type-I CU and Type-II CU can and cannot cancel the interference from sensing signals, respectively. Under the perfect communication/sensing channel state information assumption, we aim to maximize the minimum sensing beampattern gain among multiple targets, where the sensing beampattern gain qualifies the achieved illumination signal power at the given location of the target of interest. We jointly optimize the BS’s communication-sensing beamformers and the IRS’s phase shifting matrix, subject to the signal-to-interference-plus-noise ratio (SINR) constraint for each Type-I/Type-II CU, the interference power constraint per clutter, the transmission power constraint at the BS, and the cross-correlation pattern constraint. Due to the design variable coupling, the joint IRS-assisted ISAC design problem is shown to be non-convex in the case with Type-I or Type-II CUs. To circumvent the non-convexity dilemma, we propose semidefinite relaxation (SDR) based alternating optimization algorithms in both cases, for which the computational complexity and convergence behavior are analyzed. In the case with Type-I CUs, we show that the dedicated sensing signal at the BS can help enhance the sensing performance gain. By contrast, the dedicated sensing signal at the BS is not required for the IRS-assisted ISAC designs in the case with Type-II CUs. Numerical results are provided to show that the proposed IRS-assisted ISAC design schemes achieve a significant gain over the existing benchmark schemes.

Index Terms—Integrated sensing and communication (ISAC), intelligent reflecting surface (IRS), phase shifting, interference mitigation, clutter environments, optimization.

I. INTRODUCTION

The advancement of the beyond-fifth-generation (B5G) and sixth-generation (6G) communication networks has led to various integrated sensing and communication (ISAC) applications, such as auto-driving, vehicle-to-everything, smart home, virtual/augmented reality, and edge intelligence [1], [2], [3], [4], [5]. In ISAC systems, the sensing and communication capabilities are tightly integrated to provide both sensing and communication services [6], [7], [8], [9], [10], [11], [12], [13], [14], [15]. The resources of communication and radar sensing can be shared in ISAC systems, thereby boosting the efficiency of utilization in terms of system spectrum, hardware, energy, and cost [16], [17], [18], [19].

The emerging intelligent reflective surface (IRS) (also known as reconfigurable intelligent surface (RIS)) has recently attracted a growing interest from academia and industry as a promising approach to improving the communication performance [20], [21], [22]. Motivated by the effectiveness of IRS-assisted communication systems, the IRS technology has been proposed to assist ISAC systems to further improve the system communication performance [23], [24], [25]. For example, the authors in [23] employed the IRS to mitigate multi-user interference to improve the communication performance, while matching the radar waveform. For the IRS-assisted system operating at the millimeter-wave band, the work [24] maximized the sum rate of communication users subject to the radar waveform constraint, by optimizing the IRS’s phase shifts, the communication beamformers, and the radar signal covariance matrix. The work in [25] investigated the joint constant-modulus waveform and discrete IRS phase shift design, so as to minimize the mean squared error (MSE) of communication users (CUs) under the Cramer-Rao bound (CRB) constraints for direction of arrival (DoA) estimation. The authors in [26] investigated IRS-enabled sensing designs to minimize the DoA estimation error in terms of CRB.

Note that the radar detection and sensing functionality is based on the channel condition of the direct link between the base station (BS) and the target of interest. Due to the non-availability of direct links, it is challenging to realize the ISAC performance for the sensing targets in the non-line-of-sight (NLoS) areas [27], [28], [29], [30], [31], [32]. Fortunately, by reconfiguring the wireless propagation environment, the IRS technology can help improve wireless communication rate, as well as to establish the sensing channel links between the BS and the target [27]. Specifically, the IRS...
can constructively enhance the reflected sensing signals and mitigate the malicious interference. Also, the IRS technology can provide additional degrees of freedom to combat the severe channel fading effect. The authors in [28] considered an IRS-assisted ISAC system, by leveraging IRS to create new channel links to achieve a high-quality communication and sensing performance. The work in [29] studied a hybrid IRS model comprising active and passive elements to assist the radar and communication, and aimed to maximize the worst-case target illumination power. The authors in [30] studied using IRS for further enhancing the capability of the target detection. Note that by minimizing the cross-correlation coefficient between radar signals, one can achieve a better radar detection performance [31]. The authors in [32] studied the IRS-assisted ISAC system design under the radar signal cross-correlation pattern constraints, where the IRS may introduce additional interference for sensing. Besides, the authors in [33] investigated IRS-assisted ISAC systems for preventing information leakage, leveraging IRS to create a virtual link for target sensing and preventing eavesdropping. Note that the aforementioned works [27], [28], [29], [30], [31], [32], [33] all considered clutter-free environments, and there lacks investigation of IRS-assisted ISAC designs in a clutter environment.

In a clutter environment, the radar sensing performance is often affected by various clutters, such as trees, tall buildings, and cars [34]. The reflected signal power from the clutter may be higher than the target’s reflected signal power, which can severely degrade the target detection reliability. How to detect and sense multiple targets in a clutter environment is a challenging issue for ISAC system designs [35], [36]. In [37], the authors employed multiple IRSs to help mitigate interference between radar and communication systems in a clutter environment. The clutter can be treated as a signal-dependent type of interference, which depends on a deterministic transmitted signal [38]. As such, one can adopt the clutter’s prior knowledge such as the clutter covariance matrix to achieve the suppression of clutter [39]. Subject to the communication quality of service requirement constraint in clutter environments, the works [40] and [41] proposed transmit beamforming solutions to maximize the radar signal-to-interference-plus-noise ratio (SINR) with the IRS assistance. Note that the impact of clutter on the blocking of the line-of-sight (LoS) link is ignored in [40] and [41]. The work in [34] studied the radar design with multiple IRSs in order to assist the sensing services in a clutter environment, where the effective sensing links were created by the IRSs for addressing the unavailability of the direct sensing link. In a clutter environment, the clutter interference to the radar system must be mitigated to achieve a desirable target sensing performance, which motivates our work in this paper. Table I summarizes the system model comparison with the existing state-of-the-art IRS-assisted ISAC works.

In this paper, we consider a joint IRS-assisted ISAC system in clutter environments, where the multi-antenna BS assisted by an IRS to simultaneously sense multiple targets are located in the BS’s NLoS region and communicate with multiple CUs. The IRS is equipped with a uniform planar array (UPA), and each CU is equipped with a single antenna. We consider two types of CUs, i.e., Type-I and Type-II CUs, where Type-I CU has the ability to eliminate the interference caused by sensing signals, and Type-II CU cannot eliminate the interference power caused by the sensing signals. Under the perfect communication/sensing channel station information (CSI) assumption, we pursue a joint IRS-assisted ISAC design framework in clutter environments to maximize the minimum sensing beampattern gain among multiple targets while assuring the quality of service for multiple CUs, where the interference effect of the clutter on sensing performance is mitigated.

The main contributions of this paper are summarized as follows.

- First, we propose an optimization framework for the joint IRS-assisted ISAC system design in clutter environments with Type-I or Type-II CUs. Specifically, we maximize the minimum sensing beampattern gain among multiple desired targets, subject to the BS’s transmission power constraint, the SINR constraint for each Type-I or Type-II CU, the power constraint of each clutter, and the cross-correlation pattern constraint between sensing signals. We jointly optimize the BS’s beamforming vectors for multiple CUs and sensing covariance matrix for multiple targets, as well as the IRS’s phase shifting matrix. Due to the variable coupling, the formulated max-min IRS-assisted ISAC design problem in clutter environments in the case with Type-I or Type-II CUs is non-convex, which is difficult to obtain the global solution.

- Second, based on the semi-definite relaxation (SDR) based alternating-optimization method, we propose low-complexity IRS-assisted ISAC design solutions in clutter environments in the cases with Type-I and Type-II CUs, respectively. The tightness of the SDR and the computational complexities for the obtained solutions are analyzed. It is shown that the dedicated sensing signal is always required at the BS to enhance the sensing performance in the case with Type-I CUs in clutter environments. By contrast, in the case with Type-II CUs, the dedicated sensing signal can be removed at the BS without loss of the system sensing performance. In addition, based on a quantization and selection procedure, we further optimize the IRS with discrete phase shifts.

- Finally, extensive numerical results are provided to show the effectiveness of our proposed max-min IRS-assisted ISAC design solutions in clutter environments. In the case with Type-I CUs or Type-II CUs, the proposed design scheme is shown to achieve a significant performance gain over the existing benchmark schemes, and the IRS can effectively help increase the robustness against the link blockage in clutter environments. It is also shown that the IRS-assisted ISAC system with Type-I CUs always outperforms that with Type-II CUs. In addition, as the discrete phase shift quantization levels continue to increase, the system performance of IRS with discrete phase shifts is getting closer to the performance of continuous IRS phase shifts.

It is worth noting that the previous work [8] investigated the max-min ISAC designs in a clutter-free environment, where multiple targets are located in the LoS region of the BS.
TABLE I
COMPARISON WITH STATE-OF-THE-ART SCHEMES

| Ref. | CU       | IRS     | Targets | Clutter | Radar paths | Cross correlation | Discrete phase | Design metric     |
|------|----------|---------|---------|---------|-------------|------------------|----------------|-------------------|
| [8]  | Multiple | No      | Multiple| No      | LoS         | ×                | ×              | Beampattern       |
| [25] | Multiple | Single  | Multiple| No      | LoS         | ×                | ✓              | CU’s MSE          |
| [28] | Single   | Single  | Multiple| No      | NLoS        | ×                | ×              | Beampattern       |
| [32] | Multiple | Single  | Multiple| No      | LoS         | ✓                | ×              | Transmit power    |
| [33] | Multiple | Single  | Multiple| No      | NLoS        | ×                | ×              | Beampattern       |
| [34] | Multiple | Multiple| Multiple| LoS, NLoS| ×           | ×                | ×              | CU’s SINR         |
| [37] | Single   | Multiple| Single  | Yes     | LoS, NLoS   | ×                | ×              | Radar SINR        |
| [40] | Multiple | Single  | Multiple| Multiple| LoS, NLoS   | ×                | ×              | Radar SINR        |
| [41] | Multiple | Multiple| Multiple| Multiple| NLoS        | ✓                | ✓              | Beampattern       |

This paper | Multiple | Single  | Multiple| Multiple| NLoS        | ✓                | ✓              | Beampattern       |

Fig. 1. The IRS-assisted ISAC system model in clutter environments, where multiple targets are located in the NLoS region.

By contrast, this paper considers a more complex IRS-assisted ISAC system design in clutter environments, where multiple sensing targets in the BS’s NLoS region. Different from [8], the additional clutter interference constraints and the cross-correlation pattern constraints between sensing signals are characterized in this paper so as to achieve a guaranteed ISAC performance.

The rest of this paper is organized as follows. Section II presents the IRS-assisted ISAC system model in a clutter environment and formulates the joint max-min design problems under consideration. Section III and Section IV propose low-complexity design solutions in the cases with Type-I CUs and Type-II CUs, respectively. Section V shows numerical results and solutions, respectively; |[·]|, tr([·]), diag([·]), and vec([·]) denote the rank, the trace, the diagonal, and the vectorization operations, respectively; [·]∗, [·]T, and [·]H denote the conjugate, transpose, and Hermitian transpose operations, respectively; ∥·∥ denotes the Euclidean norm.

Notations: Boldface letters refer to vectors (lower case) or matrices (upper case); rank(·), tr(·), diag(·), and vec(·) denote the rank, the trace, the diagonal, and the vectorization operations, respectively; |[·]|∗, |[·]|T, and |[·]|H denote the conjugate, transpose, and Hermitian transpose operations, respectively; ∥·∥ denotes the Euclidean norm.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider an IRS-assisted ISAC system in a clutter environment, where a multi-antenna BS is assisted by an IRS for sending unicast communication signals for a number of $K$ single-antenna CUs and dedicated radar sensing signals for a total of $L$ targets, and the IRS is deployed to help propagate communication and radar sensing signals. The BS is equipped with a uniform linear array (ULA) of $M > 1$ antennas, and the IRS is equipped with an UPA of $N > 1$ passive reflecting elements. A number of $Q$ clutters are located between the BS and the $L$ sensing targets, which incur an interference effect to the BS’s target sensing performance. Furthermore, we consider that the $Q$ clutters are located farther away from the $K$ CUs than the $L$ targets, and hence the interference effect of the CUs is negligible when compared to that on the $L$ targets. The CU set and the clutter set are denoted by $K \triangleq \{1, \ldots, K\}$ and $Q \triangleq \{1, \ldots, Q\}$, respectively. Denote by $C \triangleq \{1, \ldots, L\}$ the set of $L$ sensing targets. In this paper, we consider that the $L$ targets are located in the NLoS region of the BS, i.e., the BS-target direct channels between the BS and the $L$ sensing targets can be negligible due to the blockage of $Q$ clutters. The sensing beampattern gain brought by the direct BS-target channel is significantly smaller than that by the cascade BS-IRS-target channel created by the IRS [34]. Based on the pilot-training based channel estimation techniques, the global communication/sensing CSI can be obtained during the previous channel estimation and target detection phase [20], [21], [22]. As an initial investigation on joint IRS-assisted ISAC designs in clutter environments, in order to reveal some essential design insights and characterize the performance upper bound, it is assumed that the global CSI is perfectly available in this paper. Note that in some quasi-static scenarios (such as indoor offices and shopping malls) where the CUs/targets/clutters are static/slowly-moving objects, the CSI estimation is highly reliable, such that the CSI error is insignificant and can thus be ignored for ISAC system designs.

Denote by $s_k \in \mathbb{C}$ and $w_k \in \mathbb{C}^{M \times 1}$ the information symbol and transmit beamforming vector for CU $k \in K$, respectively. Without loss of generality, we assume that the transmit symbols $\{s_k\}$ are independent and identical distributed (i.i.d.) random variables with zero mean and unit variance, i.e., $s_k \sim \mathcal{CN}(0, 1)$, $k \in K$. Let $x_0 \in \mathbb{C}^{M \times 1}$ be the dedicated sensing signal of the BS with zero mean, i.e., $\mathbb{E}[x_0] = 0$, and the sensing covariance matrix $R_0 = \mathbb{E}[x_0 x_0^H]$ is with a general rank, i.e., $0 \leq \text{rank}(R_0) \leq M$. As a result, the ISAC transmit signal $x \in \mathbb{C}^{M \times 1}$ of the BS is modeled as

$$x = x_0 + \sum_{k=1}^{K} w_k s_k$$

sensing signal for $L$ targets

transmit signal for CU $k$
Based on (1), the transmit power constraint of the BS is expressed as
\[
\mathbb{E} [\|x\|^2] = \text{tr}(R_0) + \sum_{k=1}^{K} \|w_k\|^2 \leq P_0,
\]  
where the expectation \(\mathbb{E} [\cdot] \) is taken on the randomness of \(\{x_0, s_k\}\), and \(P_0\) denotes the maximum transmit power budget of the BS.

A. IRS-Assisted Communication Model for Type-I and Type-II CUs

Let \(G \in \mathbb{C}^{N \times M}\) denote the complex-valued channel matrix from the BS to the IRS, and let \(h_{bu,k} \in \mathbb{C}^{M \times 1}\) and \(h_{\text{cu},k} \in \mathbb{C}^{N \times 1}\) denote the complex-valued channel vectors from the BS and the IRS to CU \(k\), respectively. Denote by \(\phi_n \in (0, 2\pi]\) the phase shift value of each passive reflecting element \(n \in N' \triangleq \{1, \ldots, N\}\) at the IRS. Let \(\Phi = \text{diag}(e^{j\phi_1}, \ldots, e^{j\phi_N}) \in \mathbb{C}^{N \times N'}\) denote the IRS's phase shifting matrix, where \(j = \sqrt{-1}\) denotes the imaginary unit. In the IRS-assisted ISAC system under consideration, each CU \(k \in K\) receives the BS's signal via both the direct BS-CU link and the cascaded BS-IRS-CU link. Note that since the \(Q\) clusters under consideration are located far away from each CU, then the interference effect of the clutter on the \(K\) CUs is negligible in this paper. Accordingly, the received signal \(y_k \in \mathbb{C}\) of CU \(k \in K\) is modeled as
\[
y_k = h_{\text{cu},k}^H x + n_k = h_{\text{cu},k}^H (x_0 + \sum_{k=1}^{K} w_k s_k) + n_k, \quad \forall k \in K,
\]
where \(h_{\text{cu},k} \triangleq G_{\text{cu},k}^H \Phi h_{\text{tu},k} + h_{bu,k}\) is defined as the effective channel vector from the BS to CU \(k \in K\), and \(n_k \sim \mathcal{CN}(0, \sigma^2_k)\) denotes the additive white Gaussian noise (AWGN) at CU \(k\)’s receiver.

Depending on the ability of cancelling the sensing signal \(x_0\) or not, we consider two types of CUs, i.e., Type-I and Type-II CUs. In the case with Type-I CUs, the sensing signal \(x_0\) is globally known, and each Type-I CU can completely cancel the interference generated by the sensing signal \(x_0\). Denote by \(\gamma^I\) the SINR of Type-I CU \(k \in K\). Accordingly, we have
\[
\gamma^I_k = \frac{|h_{\text{cu},k}^H w_k|^2}{\sum_{j=1, j \neq k}^{K} |h_{\text{cu},k}^H w_j|^2 + \sigma^2_k}, \quad \forall k \in K.
\]

In the case with Type-II CUs, the sensing signal \(x_0\) is not globally known, and each Type-II CU cannot eliminate the interference power caused by the sensing signal \(x_0\). Denote by \(\gamma^II\) the SINR of Type-II CU \(k \in K\). Then, we have
\[
\gamma^II_k = \frac{|h_{\text{cu},k}^H w_k|^2}{\sum_{j=1, j \neq k}^{K} |h_{\text{cu},k}^H w_j|^2 + |h_{\text{cu},k}^H x_0|^2 + \sigma^2_k}, \quad \forall k \in K.
\]

B. IRS-Assisted Sensing Model for L Targets

In the IRS-assisted ISAC system, the IRS can reconfigure a sensing link (i.e., the BS-IRS-target cascaded channel link) to provide a direct target sensing service by properly adjusting the phases of its reflecting elements. In this paper, we consider a three-dimensional (3D) scenario, where the IRS equipped with an UPA to assist the BS to perform sensing and communication simultaneously. The direction of target \(l \in L\) is defined as \(\theta_l = (\theta_l, \varphi_l)\), where \(\theta_l \in (-\pi, \pi]\) and \(\varphi_l \in (-\pi, \pi]\) denote the azimuth and elevation angle of target \(l \in L\) with respect to the IRS, respectively. Let \(d_x\) and \(d_y\) denote the distances between two consecutive reflecting elements of the IRS in \(x\)-axis and \(y\)-axis, respectively. For each target \(l \in L\), the IRS’s array response with azimuth angle \(\theta_l\) and elevation angle \(\varphi_l\) is given by [42]
\[
\alpha(\theta_l) = \alpha_{l,x} \otimes \alpha_{l,y},
\]
where
\[
\begin{align*}
\alpha_{l,x} &= [1, e^{-j\frac{d_x}{\lambda}}, \ldots, e^{-j\frac{N_x-1}{\lambda}d_x}]^T, \\
\alpha_{l,y} &= [1, e^{-j\frac{d_y}{\lambda}}, \ldots, e^{-j\frac{N_y-1}{\lambda}d_y}]^T,
\end{align*}
\]
where \(d_x = 2\pi d_x / \lambda\) and \(d_y = 2\pi d_y / \lambda\) denote the carrier wavelength, the number of the IRS reflecting elements is \(N = N_x N_y\) with \(N_x\) and \(N_y\) being the numbers of the IRS reflecting elements along \(x\)-axis and \(y\)-axis, respectively, and \(\otimes\) represents the Kronecker product.

In ISAC systems, both the communication signals \(\{s_k\}_{k \in K}\) and the dedicated sensing signal \(x_0\) can be used to illuminate the \(L\) targets so as to meet the requirement of quality of service in sensing. In this paper, we use the sensing beampattern gain as a sensing performance criterion to characterize the achieved illumination power of the location of the target of interest. Accordingly, the beampattern gain \(\rho(\theta_l)\) for target \(l \in L\) located at the AoD angle \(\theta_l\) with respect to the IRS is given as [43]
\[
\begin{align*}
\rho(\theta_l) &= \mathbb{E} \left[ |h_{\text{target},l}^H (x_0 + \sum_{k=1}^{K} w_k s_k)|^2 \right] \\
&= h_{\text{target},l}^H R_0 + \sum_{k=1}^{K} w_k w_k^H h_{\text{target},l}, \quad \forall l \in L.
\end{align*}
\]
where \(h_{\text{target},l} \triangleq G_{\text{target},l}^H \Phi_{\text{target},l}\alpha(\theta_l)\) is defined as the effective LoS channel vector from the BS to target \(l \in L\).

Furthermore, we consider the cross-correlation pattern constraint for the ISAC signal to sense the \(L\) targets with different angles. Let \(P_{\text{cross}}\) denote the mean-squared cross-correlation pattern for the \(L\) targets. As in [44], we have
\[
P_{\text{cross}} = \frac{2}{L(L-1)} \sum_{l=1}^{L-1} \sum_{i=l+1}^{L} P(\theta_l, \theta_i),
\]
where \(P(\theta_l, \theta_i)\) denotes the cross-correlation coefficient between target \(l\) at angle \(\theta_l\) and another target \(i\) at angle \(\theta_i\), and we have
\[
P(\theta_l, \theta_i) \triangleq h_{\text{target},l}^H \left( R_0 + \sum_{k=1}^{K} w_k w_k^H \right) h_{\text{target},i}, \quad \forall l \neq i \in L.
\]
C. Clutter Model for \( Q \) Clutters

Note that the clutters cannot spontaneously emit signals to the targets and CUs, and they only receive the signals from the BS to reflect echo signals back to the BS; in this case, the BS’s received signal consists of the target echo signal and the clutter returns, which thus degrades the BS’s target sensing performance [34]. Compared to the interference effect of the clutter on the target sensing, the interference effect on the CUs is negligible [40]. As adopted in the existing ISAC literature [34], [37], [40], [41], we only consider the interference effect of each clutter \( q \in Q \) on the \( L \) targets, and ignore the interference effect of the clutter on the \( K \) CUs. Let \( g_{bc,q} \in \mathbb{C}^{M \times 1} \) denote the complex-valued channel vector from the BS to clutter \( q \in Q \), and let \( g_{c,q} \in \mathbb{C}^{N \times 1} \) denote the complex-valued cascaded channel vector from the BS to clutter \( q \) via the IRS. As a result, the interference power incurred by each clutter \( q \in Q \) is expressed as

\[
P_{\text{clutter}}^q = \mathbb{E} \left[ \left| g_{\text{clutter},q}^H \left( x_0 + \sum_{k=1}^{K} w_k s_k \right) \right|^2 \right] \tag{10a}
\]

\[
= g_{\text{clutter},q}^H \left( R_0 + \sum_{k=1}^{K} w_k w_k^H \right) g_{\text{clutter},q}, \quad \forall q \in Q, \tag{10b}
\]

where \( g_{\text{clutter},q} \triangleq G^H \Phi^H g_{bc,q} + g_{c,q} \) is defined as the effective channel vector from the BS to clutter \( q \in Q \).

D. Problem Formulation

In this paper, we are interested in maximizing the minimum sensing beam pattern gain among the \( L \) targets, by jointly optimizing the BS’s transmit beamforming vectors \( \{w_k\}_{k \in K} \) for communication and covariance matrix \( R_0 \) for sensing, as well as the IRS’s phase shifting matrix \( \Phi \). The constraints include the BS’s transmit power constraint, the SINR constraint for each Type-I or Type-II CU \( k \in K \), the interference power constraint for each clutter \( q \in Q \), and the mean-squared cross-correlation pattern constraint for the \( L \) targets.

In the case with Type-I CU, we formulate the following optimization problem as

\[
(P1) : \max_{\{w_k\}_{k \in K}, R_0 \succeq 0, \Phi} \min_{l \in L} \rho(\theta_l) \tag{11a}
\]

s.t. \[
\sum_{k=1}^{K} ||w_k||^2 + \text{tr}(R_0) \leq P_0 \tag{11b}
\]

\[
\gamma^l_k \geq \Gamma_k, \quad \forall k \in K \tag{11c}
\]

\[
P_{\text{clutter}}^q \leq \eta_q, \quad \forall q \in Q \tag{11d}
\]

\[
P_{\text{cross}} \leq \xi, \tag{11e}
\]

where \( \Gamma_k \) denotes the SINR threshold prescribed for each Type-I CU \( k \in K \), \( \eta_q \) denotes the given interference power threshold for clutter \( q \in Q \), and \( \xi \) denotes the predefined power threshold for the mean-squared cross-correlation pattern \( P_{\text{cross}} \).

In the case with Type-II CU, we have the following design optimization problem as

\[
(P2) : \max_{\{w_k\}_{k \in K}, R_0 \succeq 0, \Phi} \min_{l \in L} \rho(\theta_l) \tag{12a}
\]

s.t. \[
\gamma^l_k \geq \Gamma_k, \quad \forall k \in K \tag{12b}
\]

\[
(11b), (11d), \text{ and } (11e),
\]

where \( \Gamma_k \) denotes the predefined SINR threshold for each Type-II CU \( k \in K \).

Remark 1: Note that problems (P1) and (P2) correspond to two different joint IRS-assisted ISAC designs with different CU types in clutter environments. Due to the ability of canceling the interference from the sensing signals, each Type-I CU can achieve a SINR value higher than each Type-II CU, and thus the design problem (P1) admits a larger feasible domain than (P2), as will be specified in Sections III and IV.

In this paper, we consider problems (P1) and (P2) are always guaranteed to be feasible, by properly managing the admission of CUs and mitigating interference powers. Since the BS’s transmit beamforming vectors \( \{w_k\}_{k \in K} \), the BS’s sensing covariance matrix \( R_0 \), and the IRS’s phase shifting matrix \( \Phi \) are coupled, (P1) and (P2) are non-convex optimization problems. It is highly complicated to obtain the global solutions for problems (P1) and (P2). As a compromise, based on the SDR based alternating-optimization method, we next pursue to obtain the low-complexity sub-optimal solutions for problems (P1) and (P2).

III. PROPOSED SOLUTION FOR (P1) WITH TYPE-I CUS

In this section, we propose an efficient alternating-optimization-based solution for problem (P1) in the case with Type-I CUs, and then discuss the computational complexity.

A. Optimization of BS’s Transmission Design (\( \{w_k\}_{k \in K}, R_0 \)) for ISAC

In this subsection, under the fixed phase shifting matrix \( \Phi \) of the IRS, we optimize the BS’s transmit beamforming vectors \( \{w_k\}_{k \in K} \) for the \( K \) Type-I CUs and sensing covariance matrix \( R_0 \) for \( L \) targets.

To this end, we introduce a beamforming matrix \( W_k \triangleq w_k w_k^H \) for each Type-I CU \( k \in K \). It is clear that \( W_k \preceq 0 \) and \( \text{rank}(W_k) \leq 1 \), \( \forall k \in K \). By substituting \( w_k w_k^H \) with \( W_k \) for each \( k \in K \) and the fixed IRS’s phase shifting matrix \( \Phi \), the original max-min ISAC design problem (P1) in the case with Type-I CUs is equivalently transformed as

\[
(P1.1) : \max_{\{w_k\}_{k \in K}, R_0 \succeq 0} \min_{l \in L} h_{\text{target},l}^H \left( R_0 + \sum_{k=1}^{K} W_k \right) h_{\text{target},l} \tag{13a}
\]

s.t. \[
\text{tr}(R_0) + \sum_{k=1}^{K} \text{tr}(W_k) \leq P_0 \tag{13b}
\]

\[
\frac{1}{\Gamma_k} \text{tr}(h_{CU,k} h_{CU,k}^H W_k)
\]

\[
- \sum_{j=1,j \neq k}^{K} \text{tr}(h_{CU,k} h_{CU,j}^H W_j)
\]
\[
\sigma_k^2 \geq 0, \quad \forall k \in \mathcal{K}
\]
\[
g_{\text{cluster}, q}(R_0 + \sum_{k=1}^{K} W_k) g_{\text{cluster}, q} \leq \eta_q, \quad \forall q \in \mathcal{Q}
\]
\[
\frac{2}{L^2 - L} \sum_{l=1}^{L-1} \sum_{i=l+1}^{L} H_{\text{target}, l}(\sum_{k=1}^{K} W_k + R_0)
\]
\[
h_{\text{target}, l} \leq \xi
\]
\[
W_k \geq 0, \quad \text{rank}(W_k) \leq 1, \forall k \in \mathcal{K},
\]
where the design variables are \( \{W_k\}_{k \in \mathcal{K}} \) and \( R_0 \). Due to the rank-one constraints in (13f), problem (P1.1) is still non-convex. By employing the celebrated SDR technique [45] for problem (P1.1), we are ready to obtain a convex optimization with respect to \( \{W_k\}_{k \in \mathcal{K}}, R_0 \) by removing the rank-one constraints \( \text{rank}(W_k) \leq 1, \forall k \in \mathcal{K} \). As a result, the relaxed problem (P1.1) can be efficiently solved by using standard convex solvers such as the CVX toolbox [46].

Let \( \{W^\ast_k\}_{k \in \mathcal{K}}, R^\ast_0 \) denote the optimal solution to the relaxed problem (P1.1). In particular, if \( \text{rank}(W^\ast_k) \leq 1, \forall k \in \mathcal{K} \), then the relaxation of problem (P1.1) is tight, which implies that \( \{W^\ast_k\}_{k \in \mathcal{K}}, R^\ast_0 \) is the optimal solution to problem (P1.1). In this case, by implementing eigenvalue decomposition (EVD) for each \( W^\ast_k \), we have \( W^\ast_k = \lambda_k v_k v_k^H \), \( \forall k \in \mathcal{K} \), where \( \lambda_k \) denotes the maximal eigenvalue of \( W^\ast_k \), and \( v_k \) denotes the corresponding unit-norm eigenvector associated with the eigenvalue \( \lambda_k \). Then, we are able to obtain the optimal solution \( \{\sqrt{\lambda_k} v_k\}_{k \in \mathcal{K}}, R^\ast_0 \) to problem (P1.1) under the fixed phase shifting matrix \( \Phi \) of the IRS. On the other hand, if there exists rank \( \text{rank}(W^\ast_k) > 1 \) for a certain CU \( k \in \mathcal{K} \), then a reconstruction procedure for \( \{W^\ast_k\}_{k \in \mathcal{K}}, R^\ast_0 \) is required to obtain the optimal solution to problem (P1.1) (i.e., problem (P1) under the given \( \Phi \)), which is stated in the following lemma.

**Lemma 1:** In the case with rank \( \text{rank}(W^\ast_k) > 1 \), for a certain \( k \in \mathcal{K} \), an optimal solution \( \{W^\ast_k\}_{k \in \mathcal{K}}, R^\ast_0 \) to problem (P1) under the IRS’s fixed phase shifting matrix \( \Phi \) is obtained as
\[
\bar{w}_k^\ast = \frac{1}{\sqrt{h_{\text{CU}, k}^H W^\ast_k h_{\text{CU}, k}}} W^\ast_k h_{\text{CU}, k}, \quad \forall k \in \mathcal{K}
\]
\[
\bar{R}^\ast_0 = R^\ast_0 + \sum_{k=1}^{K} W^\ast_k - \sum_{k=1}^{K} \bar{w}_k^\ast (\bar{w}_k^\ast)^H.
\]

**Proof:** See Appendix A.

### B. Optimization of IRS’s Phase Shifting Matrix \( \Phi \)

In this subsection, under the fixed transmit beamforming vectors \( \{w_k\}_{k \in \mathcal{K}} \) for the K CUs and sensing covariance matrix \( R_0 \) for the L targets, we optimize the IRS’s phase shifting matrix \( \Phi \) of problem (P1).

We first define \( \phi \equiv \text{vec}(\Phi) = [e^{j\phi_1}, \ldots, e^{j\phi_N}]^T \) as the IRS’s phase shifting vector. By letting \( R \equiv R_0 + \sum_{k=1}^{K} w_k w_k^H \), we introduce the following definitions as
\[
R^\ast_{\text{CU}, j} \triangleq \text{diag}(h_{iu,k})^H G w_j w_j^H G^H \text{diag}(h_{iu,k}), \quad \forall k, j \in \mathcal{K}
\]
\[
R^\ast_{q} \triangleq \text{diag}(g_{ic,q})^H G R G^H \text{diag}(g_{ic,q}), \quad \forall q \in \mathcal{Q}
\]
\[
b^\ast_{CU, j} \triangleq \text{diag}(h_{iu,k})^H G w_j w_j^H h_{bu,k}, \quad \forall k, j \in \mathcal{K}
\]
\[
b_q^\ast \triangleq \text{diag}(g_{ic,q})^H G h_{gq,c}, \quad \forall q \in \mathcal{Q}
\]
Based on (15), we define the augmented matrices as
\[
\bar{R}^\ast_{\text{target}}(\theta_i) = [R^\ast_{\text{target}}(\theta_i), 0, 0, 0], \quad \forall \theta_i \in \mathcal{L}, \quad \bar{R}^\ast_{\text{CU}, j} = \left[ R^\ast_{\text{CU}, j}, b^\ast_{\text{CU}, j}, (b^\ast_{\text{CU}, j})^H, 0 \right], \quad \forall j, \theta_i \in \mathcal{K}, \quad \bar{R}^\ast_{q} = \left[ R^\ast_{q}, b^\ast_{q}, (b^\ast_{q})^H, 0 \right], \quad \forall q \in \mathcal{Q}
\]

Then, with the change of variable \( \phi \equiv \text{vec}(\Phi) \), problem (P1) in the case with Type-I CUs under the fixed \( \{w_k\}_{k \in \mathcal{K}}, R_0 \) is recast as
\[
\text{(P1.2):} \quad \max_{\bar{R}^\ast_{\text{target}}(\theta_i)} \min_{\phi \in \mathcal{L}} \phi^H \bar{R}^\ast_{\text{target}}(\theta_i) \phi
\]
s.t. \( \phi^H \bar{R}^\ast_{q} \phi \leq \eta_q - |g_{bc,q}^H R g_{bc,q}|, \quad \forall q \in \mathcal{Q} \)
\[
\phi^H \bar{R}^\ast_{\text{cluster}} \phi \leq \eta_q - |g_{bc,q}^H R g_{bc,q}|, \quad \forall q \in \mathcal{Q}
\]
\[
\phi \equiv [e^{j\phi_1}, \ldots, e^{j\phi_N}]^T, \quad \eta_q \in [0, 2\pi], \quad \forall q \in \{1, \ldots, N\},
\]
where \( \xi_k \equiv \sqrt{\sum_{j=1, j \neq k}^{K} |h_{bu,k}^H w_j|^2 - \frac{1}{\eta_q} |h_{bu,k}^H w_k|^2 + \sigma_k^2}, \quad \forall k \in \mathcal{K}, \quad \phi \equiv \phi^H \) is the design variable vector. Note that problem (P1.2) is non-convex, due to the non-convexity of both the SINR constraints (16b) and the unit-modulus constraints of (16c). To address this issue, we define \( V \equiv \phi \phi^H \). By removing the rank-one constraint \( r(V) = 1 \), we relax problem (P1.2) into the following SDP [47]:
\[
\text{(P1.3):} \quad \max_{\bar{R}^\ast_{\text{target}}(\theta_i)} \min_{\phi \in \mathcal{L}} \text{tr}(\bar{R}^\ast_{\text{target}}(\theta_i) V)
\]
s.t. \( \text{tr} \left( \left( \frac{1}{\Gamma_k} \sum_{j=1, j \neq k}^{K} \bar{R}^\ast_{\text{CU}, j} \right) V \right) \geq \xi_k, \quad \forall k \in \mathcal{K} \)
\[
\text{tr} \left( \bar{R}^\ast_{\text{cluster}} V \right) \leq \eta_q - |g_{bc,q}^H R g_{bc,q}|, \quad \forall q \in \mathcal{Q}
\]
\[
\text{tr} \left( \bar{R}^\ast_{\text{target}}(\theta_i) V \right) \leq \xi
\]
\[
V \geq 0, \quad V_{n,n} = 1, \quad \forall n \in \{1, \ldots, N + 1\},
\]
which can be efficiently solved via standard convex solvers. Let \( V^* \) denote the optimal solution to problem (P1.3). Note that the solution \( V^* \) is not always guaranteed to be of rank-one. In the case where rank \( \text{rank}(V^*) > 1 \), we employ a Gaussian randomization procedure [48] to generate a feasible rank-one matrix. We generate Gaussian randomization vectors
\( r \sim \mathcal{CN}(0, V^*) \) and we construct the candidate approximate solution to problem (P1.2) as \( v = e^{j \arg((\pi / N \pi / N, 1, 1, 1))} \), the objective value is approximated as the maximum one among all these random realizations. Thus, the randomization realization number is set to be sufficiently to ensure that there are enough times to guarantee that the objective value is non-decreasing over iterations.

**Algorithm 1** Proposed Alternating-Optimization Algorithm for Solving (P1)

1: Initialize the phase shifting matrix \( \Phi^{(0)} \) and the iteration index \( i = 1 \);
2: repeat
3:  
4: For the given phase shift matrix \( \Phi^{(i-1)} \), update the solution by solving problem (P1.1), and then reconstruct an equivalent optimal solution \( \hat{W}^{(i)} \) and \( \hat{R}^{(i)} \) based on Proposition 1;
5:  
6: until The objective value between two iterations is smaller than a tolerance level \( \epsilon \) or the maximum number of iterations is reached.

**C. Proposed Algorithm and Analysis for (P1) With Type-I CUs**

We now present the alternating-optimization-based design solution for (P1) with Type-I CUs, which is summarized in Algorithm 1. In the case with Type-I CUs, the above two subproblems (P1.1) and (P1.3) are alternately optimized. Note that problem (P1.1) is optimally solved due to its convexity, and we deal with high-rank solution of problem (P1.3) by setting a sufficiently large number of Gaussian randomizations to generate a sufficiently good rank-one solution. Hence, the IRS-assisted design objective value of problem (P1) is non-decreasing in the proposed Algorithm 1. The alternating optimization process is repeated until convergence is achieved. As a result, the convergence of the proposed Algorithm 1 is guaranteed.

Note that in each iteration of the proposed Algorithm 1, we need to solve two subproblems (P1.1) and (P1.3). Specifically, problem (P1.1) is solved by the primal-dual interior-point method [45], where the computational complexity is \( \mathcal{O}(K^4.5 M^4.5 \log(1/\epsilon)) \) and \( \epsilon \) is the error tolerance level. For problem (P1.3), the computational complexity of adopting the primal-dual interior-point method is \( \mathcal{O}(K^4.5(N+1)^{4.5} \log(1/\epsilon)) \). In addition, for each Gaussian randomization iteration, the computational complexity is \( \mathcal{O}(I(N+1)^2) \), where \( I \) denotes the Gaussian randomization number for (P1.3). As a result, the overall computational complexity of the proposed Algorithm 1 is \( \mathcal{O}(J(K^4.5 M^4.5) \log(1/\epsilon) + J(K^4.5(N+1)^{4.5}) \log(1/\epsilon) + (JI(N+1)^2)) \), where \( J \) denotes the iteration number.

**IV. PROPOSED SOLUTION FOR (P2) WITH TYPE-II CUS**

In this section, we propose an alternating-optimization-based scheme for problem (P2) in the case with Type-II CUs.

**A. Optimization of BS’s Transmission Design (\( \{w_k\}_{k\in\mathcal{K}}, R_0 \)) for ISAC**

In this subsection, we obtain the BS’s beamforming vectors \( \{w_k\}_{k\in\mathcal{K}} \) for the \( K \) Type-II CUs and sensing covariance matrix \( R_0 \) for the \( L \) targets.

By introducing \( \tilde{W}_k = w_k w_k^H \geq 0 \), \( \forall k \in \mathcal{K} \), problem (P2) under the fixed IRS’s phase shifting matrix \( \Phi \) is expressed as

\[
(P2): \quad \max_{\{w_k\}_{k\in\mathcal{K}} \geq 0} \min_{\forall l \in \mathcal{L}} h_{\text{target},l}^H (R_0 + \sum_{k=1}^K \tilde{W}_k) h_{\text{target},l}^T \\
\text{s.t.} \quad \frac{1}{\Gamma_k} \text{tr}(\tilde{h}_{\text{CU},k} \tilde{h}_{\text{CU},k}^H W_k) - \sum_{j=1,j\neq k}^K \text{tr}(\tilde{h}_{\text{CU},k} \tilde{h}_{\text{CU},j}^H (W_j + R_0)) - \sigma^2_k \geq 0, \forall k \in \mathcal{K}
\]

(18a), (13b), (13d), (13e), and (13f),

where \( \{W_k\}_{k\in\mathcal{K}} \) and \( R_0 \) are the optimization variables. Due to the rank-one constraints \( \text{rank}(W_k) \leq 1, \forall k \in \mathcal{K} \), problem (P2.1) is non-convex and difficult to solve. As in the case with Type-I CUs, we employ the SDR method to solve problem (P2.1) by removing the rank-one constraints.

Let \( \{\tilde{W}_k\}_{k\in\mathcal{K}}, \{R_0^\text{II}\} \) denote the optimal solution to the relaxed problem (P2.1). If it holds that \( \text{rank}(\tilde{W}_k) = 1, \forall k \in \mathcal{K} \), then \( \{\tilde{W}_k\}_{k\in\mathcal{K}}, \{R_0^\text{II}\} \) is the optimal solution to problem (P2.1). In this case, by performing the EVD for each \( \tilde{W}_k \), we have \( W_k = \lambda_k v_k v_k^H, \forall k \in \mathcal{K} \), where \( \lambda_k > 0 \) is the non-zero eigenvalue of \( \tilde{W}_k \) and \( v \) is the unit-norm eigenvector associated with the eigenvalue \( \lambda_k \).

We now obtain the optimal solution \( \{\sqrt{\lambda_k} v_k \}_{k\in\mathcal{K}}, \{R_0^\text{II}\} \) to the original problem (P2) under the given \( \Phi \). On the other hand, if there exists \( \text{rank}(\tilde{W}_k) > 1 \) for a certain \( k \in \mathcal{K} \), then we employ the rank-one solution construction procedure as in Lemma 1. In particular, the obtained solution to problem (P2) under the given \( \Phi \) is expressed as \( \{\tilde{W}_k\}_{k\in\mathcal{K}}, \{R_0^\text{II}\} \), where \( \tilde{W}_k = \sqrt{\lambda_k} v_k v_k^H, \forall k \in \mathcal{K} \), and \( R_0^\text{II} = R_0^\text{I} + \sum_{k=1}^K \tilde{W}_k^H - \sum_{k=1}^K \tilde{w}_k^H (\tilde{w}_k^H)^T \).

Note that the optimal solution \( \{\tilde{W}_k\}_{k\in\mathcal{K}}, \{R_0^\text{II}\} \) to problem (P2.1) is unique. Interestingly, it is shown that there exists an optimal solution to problem (P2.1) with \( \tilde{R}_0^\text{II} = 0 \), as stated in the following proposition.

**Proposition 1:** For problem (P2.1), there always exists an optimal solution \( \{\tilde{W}_k\}_{k\in\mathcal{K}}, \{R_0^\text{II}\} \), i.e., \( \tilde{R}_0^\text{II} = 0 \), which implies that the dedicated sensing signal \( x_0 \) can be removed at the BS without loss of optimality of problem (P2.1) in the case with Type-II CUs.

**Proof:** See Appendix B.

Note that the feasible region of (P2.1) is included by that of (P1.1). As expected, the beampattern gain achieved by (P1.1)
is guaranteed to be greater than that by (P2.1). This is because the dedicated radar signals cannot affect the communication performance of the Type-I CUs, but it is not true for the ISAC system with Type-II CUs. The ISAC system with Type-I CUs is shown to achieve a better or equal beampattern gain than the counterpart with Type-II CUs.

### B. Optimization of IRS’s Phase Shifting Matrix \( \Phi \)

In this subsection, we obtain the optimal phase shifting matrix \( \Phi \) of the IRS for problem (P2) under the given \((\{w_k\}_{k \in K}, R_0)\). We first define the following notations as

\[
\begin{align*}
F_{k,j} & \triangleq \text{diag}(h_{iu,j})^H G R_0 G^H \text{diag}(h_{iu,j}), \forall k,j \in K \quad (19a) \\
\epsilon_{k,j}^e & \triangleq \text{diag}(h_{iu,j})^H G R_0 h_{bu,k}, \forall k \in K.
\end{align*}
\]

Based on (19), we define the augmented matrices as \( F_{k,j}^{CU} = [F_{k,j}; \epsilon_{k,j}^{CU}; (\epsilon_{k,j}^{CU})^H; 0], \forall k,j \in K \).

By introducing \( V \triangleq \phi \Phi^H \geq 0 \) and rank \( (V) \leq 1 \), problem (P2) under the given \((\{w_k\}_{k \in K}, R_0)\) is recast as

\[
(P2.2) \quad \max_{V} \min_{\ell \in L} \text{tr}(\tilde{R}_k^{\text{target}}(\theta_l) V) \\
\text{s.t.} \quad \text{tr}\left( \left( \frac{1}{K} \tilde{R}_{k,j}^{CU} - \frac{1}{K} \sum_{j=1,j \neq k}^{K} \tilde{R}_{k,j}^{CU} - F_{k,j} \right) V \right) \\
\geq \gamma_{k,j}, \forall k \in K \\
(16c) - (16e),
\]

where \( \gamma_{k,j} \triangleq \sum_{j=1,j \neq k}^{K} |h_{iu,j}^H w_j|^2 - \frac{1}{K} |h_{iu,k}^H w_k|^2 + \sigma_k^2, \forall k \in K \), and the matrix \( V \) is the design variable. As in problem (P1.2), problem (P2.2) can be relaxed into a SDP by employing the SDR technique. In the case with a high-rank solution for the relaxed problem (P2.2), a Gaussian randomization procedure is adopted to generate a feasible rank-one solution for problem (P2.2).

### C. Proposed Algorithm and Analysis for (P2) With Type-II CUs

In Algorithm 2, we summarize the proposed method for solving problem (P2) in the case with Type-II CUs. Based on the alternating-optimization-based method, we obtain a low-complexity solution to problem (P2) by alternately solving problems (P2.1) and (P2.2). Similarly as the proposed Algorithm 1, problem (P2.1) is optimally solved, and we employ a Gaussian randomization procedure with a sufficiently large Gaussian randomization number to generate a sufficiently good rank-one solution based on the high-rank solution of problem (P2.2). Therefore, the IRS-assisted ISAC design objective function value of problem (P2) is non-decreasing over iterations in the Proposed Algorithm 2, and the convergence of Algorithm 2 is guaranteed. The computational complexity of the proposed Algorithm 2 is given as \( \mathcal{O}(J(K^{4.5}M^{4.5}) \log(1/\epsilon) + J(K^{4.5}(N + 1)^{4.5} \log(1/\epsilon) + (Jl(N + 1)^2)) \), where \( J \) denotes the iteration number, \( I \) denotes the number of Gaussian randomizations for (P2.2), and \( \epsilon \) denotes the error tolerance level.

### Algorithm 2 Proposed Alternating-Optimization Algorithm for (P2)

1. Initialize the phase shifting matrix \( \Phi_0^{(0)} \) and the iteration index \( t = 1 \);
2. repeat
   3. For given \( \Phi_0^{(t-1)} \), obtain the optimal solution \( W_k^{(t)} \) and \( R_0^{(t)} \) to problem (P2.1);
   4. For given \( W_k^{(t)} \) and \( R_0^{(t)} \), solve the relaxed problem (P2.2), and then obtain a rank-one solution \( \Phi_0^{(t)} \) based on the Gaussian randomization method;
   5. Set \( t = t + 1 \);
   6. until The objective value between two iterations is smaller than a tolerance level \( \epsilon \) or the maximum number of iterations is reached.

### D. Discussion on IRS With Discrete Phase Shifts

Consider the case where the IRS is with discrete phase shifts to be optimized. Denote by \( B \) the quantization bit number of the discrete phase shifts for each IRS reflecting element. The available phase set of each IRS element is defined as \( F = \{0, \Delta \phi, \ldots, \Delta \phi(2B - 1)\} \), where \( \Delta \phi = 2\pi/2^B \). Accordingly, the IRS’s discrete phase shift matrix is given by \( \Phi_d = \text{diag}(e^{j\phi_1}, \ldots, e^{j\phi_N}) \), where \( \phi_n \in F \) for \( n = 1, \ldots, N \).

Based on the obtained continuous IRS phase shift solutions for (P1.3) and (P2.2), we employ a quantization-based selection procedure to determine the discrete phase shifts of the IRS. Denote by \( \phi_d^* \) and \( \phi_d^{**} \) the obtained continuous IRS phase shift values for the \( n \)-th element for (P1.3) and (P2.2), respectively. As such, the IRS’s discrete phase shift value of the \( n \)-th element is given as \( \phi_d^D = \mathcal{E}_F(\phi_d^*) \) in the case with Type-I CUs or \( \phi_d^D = \mathcal{E}_F(\phi_d^{**}) \) in the case with Type-II CUs, where \( \mathcal{E}_F(x) \triangleq \arg \min_{\phi \in F} |\phi - x| \) denotes the nearest-neighbor based quantization function which maps \( x \) to the nearest element in set \( F \). Hence, based on the quantization function \( \mathcal{E}_F(\cdot) \), it is guaranteed to minimize the phase gap of each IRS reflecting element \( n \in N \) between the discrete phase shift and continuous phase shift, so as to maximize the minimum sensing beampattern gain among multiple targets.

### V. Numerical Results

In this section, numerical results are provided to evaluate the proposed IRS-assisted ISAC system design scheme in a clutter environment. We consider the Rician fading channel models for the BS-CU, BS-IRS, BS-clutter, IRS-CU, and IRS-clutter communication links, where the Rician factor is set as 0.5 in the radar field. The path-loss model is given by \( K_0 \left( \frac{d}{d_0} \right)^{-\alpha} \), where \( K_0 = -30 \) dB corresponds to the path-loss at the reference distance of \( d_0 = 1 \) meter (m), and the path-loss exponent \( \alpha \) are set to be 2.5, 2.5, 2.2, 3.5, and 3.5 for the IRS-clutter, IRS-CU, BS-IRS, BS-CU, and BS-clutter links, respectively. Unless otherwise stated, the following settings are assumed throughout our simulations. The number of the BS’s antennas is set to be \( M = 8 \), and the number of the IRS’s passive reflecting elements is set to be \( N = 64 \), where \( N_x = N_y = 8 \). As shown in Fig. 2, we consider a 3D coordinate setup measured in meters, where the BS and IRS...
For performance comparison, we consider the following four benchmark schemes for IRS-assisted ISAC system designs.

- **Information Beamforming Design Scheme:** In this scheme, the BS only employs the information beamforming vectors \( \{w_k\}_{k \in K} \) for both communication and sensing, which is equivalent to solving problem (P2) by setting \( R_0 = 0 \).
- **Separate Design Scheme:** In this scheme, the BS’s transmit design \( \{w_k\}_{k \in K}, R_0 \) and the IRS’s phase shifting matrix \( \Phi \) are optimized separately. In particular, the phase shifting matrix \( \Phi \) at the IRS is first optimized so as to make the IRS reach the desired angle, and the transmission design \( \{w_k\}_{k \in K}, R_0 \) at the BS is then optimized under the obtained phase shifting matrix \( \Phi \).
- **Joint Design with Discrete IRS Phase Scheme:** In this scheme, the BS’s transmit design \( \{w_k\}_{k \in K}, R_0 \) and the IRS’s phase shifting matrix \( \Phi \) are jointly optimized, where each IRS’s phase is selected from a discrete phase set \( \mathcal{F} \).
- **Joint Design with Random IRS Phase Scheme:** In this scheme, the BS’s phase shifting matrix \( \Phi \) is randomized generated, and then \( \{w_k\}_{k \in K}, R_0 \) is jointly optimized at the BS.
- **Joint Design without IRS Scheme:** In this scheme, the IRS design is removed, i.e., \( \Phi = 0 \), and \( \{w_k\}_{k \in K}, R_0 \) at the BS becomes the only design variables for ISAC.

A. Convergence Performance

Fig. 3 shows the fast convergence performance of the proposed Algorithms 1 and 2. In Fig. 3(a), \( Q = 2, L = 4, K = 3, \xi = \infty \), and the SINR threshold for each CU \( k \in K \) is set to be \( \Gamma_k = 10 \) dB. It is observed in Fig. 3(a) that the sensing beampattern gain achieved by the proposed Algorithms 1 and 2 increases with the number of iterations under different setups. As the number of the BS’s antennas increases, the convergence speed of both Algorithms 1 and 2 becomes slower. For example, the proposed Algorithm 1 (i.e., Type-I CUs) can cancel the interference of sensing signals but it is not true for the CUs in Algorithm 2 (i.e., Type-II CUs). In Fig. 3(b), we set \( M = 8 \) and \( N = 64 \). The convergence speed becomes slightly slow as the number \( K \) of CUs increases. In addition, the achieved sensing beampattern gain becomes smaller as \( K \) increases. This is because the max-min based ISAC system design scheme relies heavily on the BS with the worst channel quality so as to satisfy the communication and sensing requirements.
B. Achieved Sensing Beampattern Gain Profiles

Fig. 4 shows the normalized 3D sensing beampattern gain achieved at different angles, where $L = 4$, $K = 3$, $Q = 2$, and $\xi = \infty$. As expected, the proposed design solutions for (P1) and (P2) are observed to concentrate the BS’s transmit signal energy at the sensing angles of the $L = 4$ targets. The proposed design solution in the case with Type-I CUs is observed to outperform the solution in the case with Type-II CUs, i.e., a higher power gain profile at the angle of interest is achieved in the case with Type-I CUs than that with Type-II CUs. This shows the benefits of cancelling the sensing interference at Type-I CUs for improving the sensing performance.

Figs. 5 and 6 illustrate the sensing beampattern gain profile of the proposed scheme in the case with Type-I CUs under different sensing mean-squared cross-correlation pattern threshold $\xi$ values, where $K = 3$, $\Gamma_k = 10$ dB, $Q = 2$, and $L = 4$. With a smaller threshold $\xi$, a stricter cross-correlation coefficient is imposed between the illuminating signals towards any two neighboring targets, which enhances the multi-target detection performance [45]. As the threshold $\xi$ value increases, the proposed design scheme is observed to achieve increasingly large sensing beampattern gains at the target angles. This implies the importance of properly setting a cross-correlation pattern threshold $\xi$, so as to achieve a good trade-off between the multi-target detection performance and the multi-target sensing performance [49].

C. Achieved Minimum Sensing Beampattern Gain Evaluation

Fig. 7 shows the achieved minimum beampattern gain versus the SINR threshold $\Gamma$ of CUs, where $K = 3$, $Q = 2$, $L = 4$, and $\xi = \infty$. The proposed designs are observed to achieve a significant performance gain over the four benchmark schemes. Thanks to the ability of eliminating the sensing signals for Type-I CUs, the proposed design scheme in the case with Type-I CUs outperforms the other schemes. In Fig. 7, the proposed scheme in the case with Type-II CUs is observed to achieve the same performance as the information beamforming design benchmark scheme, which corroborates Proposition 1. For the proposed design scheme in the case with Type-I CUs, the minimum beampattern gain remains unchanged in the low SINR requirement regime (e.g., $\Gamma \leq -5$ dB), but it is not true in the high SINR requirement regime (e.g., $\Gamma \geq 5$ dB). This shows the IRS-assisted ISAC system design needs to balance the trade-off between high communication and sensing performance requirements. In addition, the separate design scheme is observed to outperform the benchmark scheme with random IRS phase matrix. This implies the importance of optimizing the IRS phase matrix in improving the sensing performance. Finally, due to the fact that there exist no direct LoS links between the targets and the BS, the benchmark scheme without IRS is observed to fail to sense the targets. The result also shows that the discrete phase shift scheme approaches the continuous scheme when with a high quantization level, e.g., $B = 4$, and the performance of the system decrease when the quantization level drops to $B = 2$. 

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Fig. 8. The achieved minimum beampattern gain versus the clutter number $Q$ with $K = 3$ and $\Gamma = 10$ dB.

Fig. 9. The achieved minimum sensing beampattern gain versus the BS’s transmit power with $K = 3$, $Q = 2$, $\Gamma = 10$ dB and $N = 64$. The proposed schemes are observed to outperform the other schemes as the clutter number $Q$ increases. This is because a more amount of energy is needed to counter against the increasing clutter interference value. All the IRS-assisted benchmark schemes are observed to outperform the scheme without IRS. This is because the IRS can help create a sensing link to effectively illuminate the $L$ targets.

Fig. 10. The minimum sensing beampattern gain versus the number $N$ of the IRS passive reflecting elements with $K = 3$, $Q = 2$, and $\Gamma = 10$ dB.

In Fig. 10, we show the achieved minimum sensing beampattern gain versus the number of the IRS passive reflecting elements $N$, where $K = 3$, $\Gamma_k = 10$ dB, $Q = 2$, $L = 4$, and $\xi = \infty$. As expected, the achieved minimum sensing beampattern gain of all the schemes increases as $N$ increases. This is because the IRS with a larger number of passive reflecting elements is able to provide a higher degrees of freedom to reconfigure the signal propagation environment, thereby improving the system sensing performance. The proposed design scheme in the case with Type-I CUs is observed to achieve a significant performance gain than the other schemes, and the proposed scheme in the case with Type-II CUs achieves the same performance as the information beamforming only design scheme.

VI. CONCLUSION

In this paper, we studied an IRS-assisted ISAC system design in a clutter environment, where the IRS is deployed to assist for simultaneously sensing multiple targets in the BS’s NLoS region and communicating with multiple CUs. We consider Type-I CUs and Type-II CUs, where Type-I CUs have the ability to eliminate the sensing interference and Type-II CUs cannot eliminate the sensing interfering. Under the perfect CSI assumption, we maximized the minimum beampattern gain among multiple targets by jointly optimizing the BS’s transmit beamforming vectors for multiple Type-I/Type-II CUs and covariance matrix for sensing multiple targets, as well as the IRS’s passive phase shifting matrix. For the formulated non-convex max-min ISAC design problems in the cases with Type-I CUs and Type-II CUs, we developed low-complexity algorithms based on the alternating-optimization and SDR techniques. It is shown that the dedicated sensing signals for targets are necessary to improve the system performance in the case with Type-I CUs. By contrast, the dedicated sensing signals can be removed for the ISAC system designs in the case with Type-II CUs. Numerical results demonstrated that the proposed IRS-assisted ISAC design in the case with Type-I CUs outperforms that in the case with Type-II CUs, and...
both the proposed joint design schemes achieve a significant performance gain than the existing benchmark schemes.

Note that in some high mobility scenarios, the communication/sensing CSI error cannot be ignored. It is important to further investigate robust IRS-assisted ISAC system designs in clutter environments based on imperfect/partial/statistical CSI, where the CSI error can be modeled in a stochastic or worst-case approach. Furthermore, in order to achieve a better balance between minimizing the channel estimation overhead and maximizing the system performance gain, it calls for a unified channel estimation and transceiver/IRS optimization design framework and low-complexity algorithms, which is left for our future work.

APPENDIX

A. Proof of Lemma 1

First, it follows from (14b) that \( \hat{R}_0^{\text{is}} + \sum_{k=1}^{K} \hat{w}_k^* (\hat{w}_k^*)^H = R_0^{\text{is}} + \sum_{k=1}^{K} W_k^{\text{is}} \).

Therefore, the solution of \( (\{W_k^{\text{is}}\}_{k \in K}, \hat{R}_0^{\text{is}}) \) satisfies the constraints (13b), (13d), and (13e). In addition, the objective function value of problem (P1.1) achieved by \( (\{\hat{W}_k^{\text{is}}\}_{k \in K}, \hat{R}_0^{\text{is}}) \) is exactly the same as that achieved by \( (\{W_k^{\text{is}}\}_{k \in K}, R_0^{\text{is}}) \).

Next, we show the solution of \( \{\hat{W}_k^{\text{is}}\}_{k \in K} \) satisfies the constraint (13c). Based on (14a), we have \( \hat{w}_k^{\text{is}} = \frac{1}{\sqrt{h_{\text{CU},W_k}^{\text{cu},k}}} W_k^{\text{is}} h_{\text{CU},k} \), and \( \hat{w}_k^{\text{is}} = \hat{w}_k^{\text{is}} (\hat{w}_k^{\text{is}})^H, \forall k \in K \).

For an arbitrary vector \( y \in \mathbb{C}^M \), it follows that

\[
y^H (W_k^{\text{is}} - \hat{W}_k^{\text{is}}) y = y^H W_k^{\text{is}} y - (h_{\text{CU},W_k}^{\text{cu},k})^{-1} |y^H W_k^{\text{is}} h_{\text{CU},k}|^2, \forall k \in K.
\]

In addition, from the Cauchy-Schwarz inequality, it yields that

\[
(y^H W_k^{\text{is}} y) (h_{\text{CU},W_k}^{\text{cu},k})^{-1} \geq |y^H W_k^{\text{is}} h_{\text{CU},k}|^2, \forall k \in K.
\]

Based on (21) and (22), we have

\[
y^H (W_k^{\text{is}} - \hat{W}_k^{\text{is}}) y \geq 0 \iff W_k^{\text{is}} - \hat{W}_k^{\text{is}} \succeq 0, \forall k \in K.
\]

Furthermore, it holds that

\[
h_{\text{CU},k}^{\text{cu},k} \hat{W}_k^{\text{is}} h_{\text{CU},k} = h_{\text{CU},W_k}^{\text{cu},k} \hat{w}_k^{\text{is}} = h_{\text{CU},W_k}^{\text{cu},k} \hat{w}_k^{\text{is}} h_{\text{CU},k}, \forall k \in K.
\]

By expressing (13c) as

\[
(1 + \frac{1}{\Gamma_j}) h_{\text{CU},j}^H W_j^{\text{is}} h_{\text{CU},j} - h_{\text{CU},j}^H (\sum_{k=1}^{K} W_k^{\text{is}}) h_{\text{CU},j} - \sigma_j^2 \geq 0, \forall k, j \in K,
\]

we are ready to have

\[
(1 + \frac{1}{\Gamma_j}) h_{\text{CU},j}^H W_j^{\text{is}} h_{\text{CU},j} = \geq (1 + \frac{1}{\Gamma_j}) h_{\text{CU},j}^H W_j^{\text{is}} h_{\text{CU},j}
\]

\[
\geq h_{\text{CU},j}^H (\sum_{k=1}^{K} W_k^{\text{is}}) h_{\text{CU},j} + \sigma_j^2
\]

\[
\geq h_{\text{CU},j}^H (\sum_{k=1}^{K} \hat{W}_k^{\text{is}}) h_{\text{CU},j} + \sigma_j^2, \forall k, j \in K.
\]

Therefore, the reconstructed rank-one solution \( (\{W_k^{\text{is}}\}_{k \in K}, \hat{R}_0^{\text{is}}) \) satisfies the SINR constraints of Type-I CUs in (13c). Until now, we have proved that the solution \( (\{\hat{W}_k^{\text{is}}\}_{k \in K}, \hat{R}_0^{\text{is}}) \) is an optimal solution to problem (P1.1), which completes the proof of Lemma 1.

B. Proof of Proposition 1

First, by setting \( R_0 = 0 \) in the relaxed problem (P2.1), we obtain the following optimization problem as

\[
\max_{\{W_k \geq 0\}} \min_{l \in \mathcal{L}} h_{\text{target},l}^H \left( \sum_{k=1}^{K} W_k \right) h_{\text{target},l}
\]

\[
s.t. \sum_{k=1}^{K} \text{tr}(W_k) \leq P_0
\]

\[
\frac{1}{\Gamma_k} \text{tr}(h_{\text{CU},k}^H h_{\text{CU},k}) W_k - \sum_{j=1, j \neq k}^{K} \text{tr}(h_{\text{CU},j}^H h_{\text{CU},j} W_j) - \sigma_k^2 \geq 0, \forall k \in K
\]

\[
g_{\text{cluster},q}(\sum_{k=1}^{K} W_k) g_{\text{cluster},q} \leq \eta_q, \forall q \in Q
\]

\[
\frac{2}{L^2 - L} \sum_{l=1}^{L-1} \sum_{i=l+1}^{L} h_{\text{target},l}^H \left( \sum_{k=1}^{K} W_k \right) h_{\text{target},i} \leq \xi.
\]

\[
(25e)
\]

Denote by \( (\{W_k^{*}\}_{k \in K}) \) the optimal solution to problem (25). In particular, it holds that \( W_k^{*} = W_k^{\text{II}*} + \beta_k R_k^{\text{II}*}, \forall k \in K \), where \( \sum_{k=1}^{K} \beta_k = 1 \) and \( \beta_k \geq 0, \forall k \in K \).

Next, we prove that \( (\{W_k^{*}\}_{k \in K}, 0) \) is an optimal solution to problem (P2.1). For each Type-II CU \( j \in K \), it follows that

\[
(1 + \frac{1}{\Gamma_j}) h_{\text{CU},j}^H (W_j^{*} + 0) h_{\text{CU},j}
\]

\[
\geq (1 + \frac{1}{\Gamma_j}) h_{\text{CU},j}^H (W_j^{\text{II}*} + \beta_j R_0^{\text{II}*}) h_{\text{CU},j}
\]

\[
\geq h_{\text{CU},j}^H (\sum_{k=1}^{K} W_k^{\text{II}*} + R_0^{\text{II}*}) h_{\text{CU},j} + \sigma_j^2
\]

\[
= h_{\text{CU},j}^H (\sum_{k=1}^{K} W_k^{*} + 0) h_{\text{CU},j} + \sigma_j^2, \forall k, j \in K.
\]

where the first inequality holds from the fact \( R_0^{\text{II}*} \succeq 0 \), and the second inequality holds from that the SINR constraint for Type-II CU \( j \). Therefore, \( (\{W_k^{*}\}_{k \in K}, 0) \) is shown to be a feasible solution to problem (P2.1).

Finally, it is readily to show that both \( (\{W_k^{*}\}_{k \in K}, 0) \) and \( (W_k^{*}, R_k^{*}) \) can achieve the same objective function value for problem (P2.1). Now, we have proved that \( (\{W_k^{*}\}_{k \in K}, 0) \) is an optimal solution to problem (P2.1), and we complete the proof of Proposition 1.
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