Intelligent Reflecting Surface Assisted Integrated Sensing and Communications for mmWave Channels
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Abstract—This paper proposes an intelligent reflecting surface (IRS) assisted integrated sensing and communication (ISAC) system operating at the millimeter-wave (mmWave) band. Specifically, the ISAC system combines communication and radar operations and performs, detecting and communicating simultaneously with multiple targets and users. The IRS dynamically controls the amplitude or phase of the radio signal via reflecting elements to reconfigure the radio propagation environment and enhance the transmission rate of the ISAC system. By jointly designing the radar signal covariance (RSC) matrix, the beamforming vector of the communication system, and the IRS phase shift, the ISAC system transmission rate can be improved while matching the desired waveform for radar. The problem is non-convex due to multivariate coupling, and thus we decompose it into two separate subproblems. First, a closed-form solution of the RSC matrix is derived from the desired radar waveform. Next, the quadratic transformation (QT) technique is applied to the subproblem, and then alternating optimization (AO) is employed to determine the communication beamforming vector and the IRS phase shift. For computing the IRS phase shift, we adopt both the majorization minimization (MM) and the manifold optimization (MO). Also, we derive a closed-form solution for the formulated problem, effectively decreasing computational complexity. Furthermore, a trade-off factor is introduced to balance the performance of communication and sensing. Finally, the simulations verify the effectiveness of the algorithm and demonstrate that the IRS can improve the performance of the ISAC system.

Index Terms—Integrated sensing and communications, intelligent reflecting surface, performance tradeoff, waveform design, MIMO radar.

I. INTRODUCTION

Recently several new applications have emerged for the new generation of wireless communication systems, i.e. beyond 5G (B5G) and 6G, such as vehicle-to-everything (V2X), ultra high-definition (uHD) video and virtual reality (VR) [1]. The B5G/6G network can provide powerful support for sensing people, things, environment, and the connection of virtual spaces. Meanwhile, the increased demand for various sensing services has led to the problem of scarce spectrum resources. The communication and radar spectrum sharing (CRSS) techniques alleviate such spectrum crunch challenges, and one primary research direction for the CRSS is integrated sensing and communication (ISAC) [2]. The main goal of the ISAC is to achieve effective interference mitigation on a common hardware platform to ensure spectral coexistence, improve spectral efficiency and reduce hardware costs. Also, the ISAC strives to realize a full integration and mutual benefit of the sensing and communication functions [3].

Stepping towards B5G/6G, achieving a high transmission rate is an imperative requirement for the ISAC system. In recent years, the millimeter wave (mmWave) communication has been considered as one of essential techniques for 5G cellular system deployment due to its ultra-wide spectrum resources [4]–[6]. However, owing to high attenuation and weak penetration in the mmWave band, a large number of antennas are normally needed to implement high gain directional beamforming, which will incur hardware costs [7]. Thus, a low-cost scheme to develop the ISAC system in the mmWave band is urgently needed.

Intelligent reflecting surfaces (IRS) have attracted extensive research interests from both academia and industry in the last few years, as an efficient and cost-effective way to enhance the performance of wireless network systems [8]–[11]. The IRS enables reconfiguration of the wireless propagation environment to support wireless communications and radar sensing [12]–[14]. The IRS consists of many low-cost passive reflecting elements and the desired signal phase can be adjusted without specialized RF processing [15], [16]. Notably, the IRS allows to reshape channel realization and bypass environment obstacles, by dynamically controlling the wireless signals’ amplitudes or phase shift [17]–[19]. Also, the IRS can provide an additional reflected link to the ISAC system from a different angle, potentially resulting in better sensing performance. The above advantages inspired us to investigate the effect of the IRS on the performance of the ISAC system in the mmWave band.

Two forms of radar and communication antenna deployment were proposed in [20], namely separated deployment and shared deployment. The former approach designs the radar signal in the downlink channel null space, while the communication beamforming is optimized so as to meet both the radar’s...
and communication’s performance requirements. In [21], the authors considered a joint communication and radar system incorporating base station (BS) and a multiple-input multiple-output (MIMO) radar that can provide communication services and simultaneously detect several targets. The ISAC system in the mmWave band for high-resolution imaging radar was investigated in [22] where the IRS-assisted wireless powered sensor network intelligently adjusts the phase shift of each reflecting element. The IRS was adopted in [23] to enhance the capability of a mmWave radar and communication system. The authors studied joint active and passive beamforming designs in IRS-assisted radar and communication systems [24], to mitigate multiuser interference. The IRS was employed in [25] to select a suitable phase shift to increase the received signal strength (RSS), and the increased RSS difference between adjacent positions leads to improved positioning accuracy. Also, a deep learning-based radar-assisted channel estimation scheme for uplink mmWave multi-user MIMO communication systems was presented in [26], to improve channel estimation accuracy and reduce the overhead incurred by the guard frequency band. Spectrum sharing among MIMO radar and multiuser multiple-input single-output (MISO) communication systems was discussed in [27], where the IRS is employed to improve the MIMO radar detection probability.

In this paper, we investigate an IRS-aided ISAC system for the multi-user downlink scenario in the mmWave band. The main contributions of this paper are summarised as follows:

- In an IRS-assisted ISAC system at the mmWave band, the radar module is used to sense the targets of interest and maintain continuous tracking, while the communication module provides high-speed communication services to users, and the IRS is deployed to improve the performance of the communication system.
- We evaluate the effectiveness of the IRS by maximizing the sum rate of the downlink users subject to the constraints of the desired waveform for radar, the communication beamforming vector, and the IRS phase shift. Multivariate coupling makes the proposed problem non-convex. To overcome its non-convexity, we decompose the original problem into two sub-problems that can be solved separately.
- As the desired beam pattern for radar is controlled by the radar signal covariance (RSC) matrix, we first derive a closed-form solution to the RSC matrix by relaxing the first sub-problem. The second sub-problem is then solved using the quadratic transformation (QT) technique, and its closed-form solutions are obtained iteratively by adopting the alternating iteration (AO) algorithm for the beamforming vector and the IRS phase shift. For computing the IRS phase shift, we employ the majorization minimization (MM) algorithm and the manifold optimization (MO) algorithm.
- Finally, we present extensive simulation results to verify that the advantages of the IRS in improving the transmission rate of the ISAC system in the mmWave band.

The remainder of the paper is organized as follows: We introduce the system model in Section II. The achievable solution is presented in Section III. We provide the numerical results in Section IV and conclude the paper in Section V.

Notations: Lowercase boldface and uppercase boldface indicate a vector and a matrix, respectively. A ≥ 0 means that A is a semi-positive definite matrix. A_H and vec(A) represent conjugate transpose and the vectorization of A, respectively. A^{-1} denotes matrix inverse. diag(a) equals a diagonal matrix whose diagonal elements are a vector a. conj(a) and arg(a) stand for the conjugate and the phase of a complex number a, respectively. ○ indicates the Hadamard product. |·| and ||·|| denote the absolute value and Euclidean norm, respectively. R(·) and Im(·) define the real and imaginary parts, respectively.

II. SYSTEM MODEL

We consider an IRS-assisted ISAC system with a BS with N communication antennas and M radar antennas, an IRS with L reflecting elements, and K single-antenna users as depicted in Fig. 1. The antennas are arranged in the BS as a unified linear array (ULA) pattern capable of transmitting statistically independent radar and communication signals to targets and K users. The IRS assists the BS in improving the signal strength in the communication coverage area.

A. MIMO Radar Signal

For the sensing purpose, we utilize a MIMO radar that transmits several probing signals with a higher degree of freedom and waveform diversity [28]. Here, we assume that the target’s prior position information has been obtained during the previous detection phase of the radar, and then is used to synthesize the desired beam pattern. The MIMO radar beamforming design aims to optimize the transmit power in a given direction or to match the desired beam pattern.

The RSC matrix R defines the spatial beam pattern of a radar [29], which can be expressed as

\[ R = \frac{1}{T} \sum_{t=1}^{T} r_t r_t^H, \]  (1)
where $T$ is the number of the total snapshots and $r_t$ represents the channel vector of the k-th user. The array steering vector is obtained as:

$$a(\theta) = \left[1, \exp\left(\frac{j2\pi d}{\lambda} \sin \theta\right), \ldots, \exp\left(\frac{j2\pi d(M-1)}{\lambda} \sin \theta\right)\right]^T$$

where $d$ is the spacing between adjacent antenna elements, and $\lambda$ indicates the wavelength. Then according to (20), the transmit beam pattern is written as

$$P_t(\theta) = a^H(\theta)Ra(\theta).$$

### B. MIMO Communication Signal

The signal received at the k-th user can be computed as:

$$x_k = \left(h_{r,k}^H \Theta_k h_{dr} + h_{d,k}\right) \sum_{k=1}^{K} w_kd_k + f_{d,k}r_t + n_k,$$

where $h_{r,k}$, $h_{d,k}$ and $h_{r,k}$ indicate the mmWave channels between the communication antennas and the IRS, between the communication antennas and the k-th user, and between the IRS and the k-th user, respectively. $f_{d,k}$ is the mmWave channel between the radar antennas and the k-th user, the $\Theta_k = \text{diag}(\exp(j\alpha_{k,1}), \ldots, \exp(j\alpha_{k,L}))$ for $k = 1, ..., K$ denotes the diagonal IRS phase shift matrix and $\alpha_{k,l} \in [0, 2\pi]$ ($l = 1, ..., L$) equals the phase shift of the l-th corresponding reflecting element, and $d_k$ and $w_k$ are the communication symbol and the beamforming vector of the k-th user, respectively. All channel status information (CSI) is assumed to be perfectly known by transmitting pilot symbols. Based on the channel model (20), the channel coefficient $h_{dr}$ can be expressed as

$$h_{dr} = \sum_{\ell = 0}^{N_p} v^\ell a_B(\theta_B^\ell) a_t(\theta_t^\ell),$$

where $v^\ell$ represents the $\ell$-th complex path gain, $N_p$ is the nonline-of-sight paths, $a_B(\theta) = \frac{1}{N_p} \left[\exp\left(-\frac{j2\pi d\theta}{\lambda}\right)\right]_{i \in I(N)}$ with $I(N) = \{n - (N - 1)/2, \ldots, n\}$ for $n = 0, 1, ..., N - 1$, $a_t(\theta)$ is defined in the same way as $a_B(\theta)$, and $\theta_B$ and $\theta_t$ indicate the $\ell$-th azimuth angle for the BS and the IRS, respectively. $\ell = 0$ denotes the line of sight (LoS) path and the IRS is generally deployed in a hotspot space resulting in a higher probability of LoS paths. Therefore, the channel between the IRS and the k-th user can be obtained as

$$h_{r,k} = \sqrt{V^\ell} \rho_1 a_{r,k}(\theta_k),$$

where $\rho_1$ and $\rho_2$ denote the gains of the transmit elements and receive elements respectively, and $a_{r,k}$ is the IRS steering vector. The channel coefficient $h_{d,k}$ is expressed by

$$h_{d,k} = \sqrt{V^\ell} \rho_2 a_{d,k}(\theta_k),$$

where $\rho_2$ and $a_{d,k}$ represent the transmit and the steering vector of the communication antennas, respectively. Similarly, the radar channel coefficient with the k-th user can be written as

$$f_{d,k} = \sqrt{V^\ell} \rho_3 a_{s,k}(\theta_k),$$

where $\rho_3$ and $a_{s,k}(\theta_k)$ indicate the transmit gains and the steering vector of the radar antennas, respectively. Thus, the signal to interference and noise ratio (SINR) of the k-th user can be derived as

$$\gamma_k = \frac{\left|h_{r,k}^H \Theta_k h_{dr} + h_{d,k}\right|^2}{\left|\sum_{i=1,i \neq k}^{K} \left(h_{r,k}^H \Theta_k h_{dr} + h_{d,k}\right) w_i + |f_{d,k}r_t|^2 + \sigma^2\right|^2},$$

where $h_{r,k} = h_{r,k}^H \Theta_k h_{dr} + h_{d,k}$.

### C. Problem Formulation

In this paper, our objective is to maximize the transmission rate of the ISAC system, and assess the effectiveness of the IRS in improving the communication and radar performance. This problem can be formulated as

$$\max_{\Omega} \sum_{k=1}^{K} \log \left(1 + \gamma_k\right)$$

s.t. $\sum_{k=1}^{K} w_k^H w_k \leq P_c,$

$$\text{diag}(R) = \frac{P_r}{M},$$

$$f_{d,k} R f_{d,k}^H = 0,$$

$$R \succ 0, R = R^H,$$

$$\Omega = \{\Theta_1, ..., \Theta_K, w_1, ..., w_K, R\},$$

where $P_c$ and $P_r$ denote the transmit power of communication antennas and radar, respectively. $\Omega$ is the maximum transmitting power limit of the communication system. $\Omega$ indicates that all radar antennas keep the same transmitting power level. $\Omega$ aims to eliminate interference from the radar to the downlink user via a zero-forcing operation.

**Proposition 1:** Problem (10a) is equivalent to

$$\max_{\Omega} \sum_{k=1}^{K} \log \left(1 + \gamma_k\right)$$

s.t. $\sum_{k=1}^{K} w_k^H w_k \leq P_c,$

$$\text{diag}(R) = \frac{P_r}{M},$$

$$f_{d,k} R f_{d,k}^H = 0,$$

$$R \succ 0, R = R^H,$$

$$\Omega = \{\Theta_1, ..., \Theta_K, w_1, ..., w_K, R\},$$

where $P_c$ and $P_r$ denote the transmit power of communication antennas and radar, respectively. $\Omega$ is the maximum transmitting power limit of the communication system. $\Omega$ indicates that all radar antennas keep the same transmitting power level. $\Omega$ aims to eliminate interference from the radar to the downlink user via a zero-forcing operation. **Proof:** Refer to Appendix A.

We can find that the k-th optimal auxiliary variable is obtained as $\rho_k = \gamma_k$ by taking a partial derivative with respect to $p_k$ in (11) and set to zero. Then given $p$, the optimization of $w_k$, $\Theta_k$ and $R$ in (11) can be formulated as

$$\max_{w_k, \Theta_k, R} f_1 = \sum_{k=1}^{K} \left(\ln(1 + p_k) - p_k + \frac{(1 + p_k)\gamma_k}{1 + \gamma_k}\right)$$

s.t. (10b), (10c), (10d), (10e),

where $\tilde{p}_k = 1 + p_k.$ By converting to (12) as
where
\[
\max_{\mathbf{w}_k, \theta_c, \mathbf{R}} f_2 = \sum_{k=1}^{K} \sum_{i=1}^{K} \frac{p_k}{\beta} \left| \mathbf{h}_k^H \mathbf{w}_k \right|^2,
\]

s.t. (10b), (10c), (10d), (10e),

the logarithm in (10a) can be handled in a more straightforward manner.

### III. Achievable Sum Rate Maximization

Problem (12) is non-convex due to multivariate coupling. To solve this problem, we split the problem into two sub-problems. First, we derive a closed-form expression for the RSC matrix. We then apply the QT variation and utilize the AO algorithm to derive closed form expressions for the beamforming vector and the IRS phase shift matrix.

#### A. Design for Radar Signal Covariance Matrix

The radar beam pattern plays a pivotal role in radar detection and tracking, which can be obtained by the RSC matrix \( \mathbf{R} \) and a constrained least-squares problem is formulated as

\[
\min_{\beta, \mathbf{R}} \sum_{c=1}^{C} \left| \beta P(\theta_c) - \mathbf{a}^H(\theta_c) \mathbf{R} \mathbf{a}(\theta_c) \right|^2
\]

s.t. \( \beta > 0 \), (10d), (10e),

where \( \beta \) is a scale factor, \( \{\theta_c\}_{c=1}^{C} \) with \( C = 181 \), which indicates the fine angular grid covers the detection angle range from \(-90^\circ \) to \(90^\circ \), and \( P(\theta_c) \) represents the desired beam pattern of the MIMO radar given by

\[
P(\theta) = \begin{cases} 
1, & \theta_p - \frac{\pi}{2} \leq \theta \leq \theta_p + \frac{\pi}{2}, \\
0, & \text{otherwise},
\end{cases}
\]

where \( \theta_p \) and \( \nabla \) represent the angle and beamwidth for each target. Motivated by the pseudo-covariance matrix synthesis algorithm in [32], we adopt a scheme that can significantly reduce the RSC matrix’s complexity. First, neglecting the constraint (10d), the objective function can be vectorized as

\[
f(\mathbf{R}, \beta) = \sum_{c=1}^{C} \left| \beta P(\theta_c) - \mathbf{V}(\theta_c)^H \mathbf{r}_c \right|^2,
\]

where \( \mathbf{V}(\theta_c) = \mathbf{a}(\theta_c) \mathbf{a}^H(\theta_c) \) and \( \mathbf{r}_c = \text{vec}(\mathbf{R}) \).

Denoting \( \mathbf{A}_{ij} \) as the \((i,j)\)th element of a matrix \( \mathbf{A} \), let us define \( \mathbf{v}_1 = [\text{Re}(\mathbf{v}_1^T) \text{Im}(\mathbf{v}_1^T)]^T \) and \( \mathbf{r}_1 = [\text{Re}(\mathbf{r}_1^T) \text{Im}(\mathbf{r}_1^T)]^T \), where \( \mathbf{v}_d = [\mathbf{V}_{12}, \ldots, \mathbf{V}_{1M}, \mathbf{V}_{23}, \ldots, \mathbf{V}_{(M-1)M}]^T \), and \( \mathbf{r}_d = [\mathbf{R}_{12}, \ldots, \mathbf{R}_{1M}, \mathbf{R}_{23}, \ldots, \mathbf{R}_{(M-1)M}]^T \). Also we define \( \mathbf{v}_2 = [\mathbf{V}_{11}, \ldots, \mathbf{V}_{MM}]^T = \mathbf{1}_M, \mathbf{r}_2 = [\mathbf{R}_{11}, \ldots, \mathbf{R}_{MM}]^T = \frac{P_r}{M} \mathbf{1}_M \), where \( \mathbf{1}_M \) represents an all one vector of length \( M \).

Thus, we can transform (16) to

\[
f(\mathbf{r}_x) = \sum_{c=1}^{C} \left( \left[ 2\mathbf{v}_1^T \mathbf{v}_2, \mathbf{r}_1 \right] - \beta P(\theta_c) \mathbf{r}_x \right)^2
\]

\[
= 4 \sum_{c=1}^{C} \left( \mathbf{v}_1^T - \frac{1}{2} P(\theta_c) \mathbf{r}_x \right)^2 + \left( \frac{1}{2} P_r \right)^2
\]

\[
= 4 \sum_{c=1}^{C} \left( \mathbf{v}_2^T (\theta_c) \mathbf{r}_x + \frac{1}{2} P_r \right)^2,
\]

where \( \mathbf{v}_x^T = [\mathbf{v}_1^T - \frac{1}{2} P(\theta_c)] \) and \( \mathbf{r}_x = \left[ \frac{\mathbf{r}_1}{\beta} \right] \). The optimal closed-form solution can be derived by obtaining the derivative for \( \mathbf{r}_x \) in (17) and setting it to zero as

\[
\mathbf{r}_x = -\frac{P_r}{2} \mathbf{V}_x^{-1} \mathbf{v}_u,
\]

where \( \mathbf{V}_x = \sum_{c=1}^{C} \mathbf{v}_x (\theta_c) \mathbf{v}_x^H (\theta_c) \) and \( \mathbf{v}_u = \sum_{c=1}^{C} \mathbf{v}_x (\theta_c) \). Then, we can rearrange the \( \mathbf{r}_x \) to construct the RSC matrix \( \mathbf{R}_{\text{rad}} \). However, \( \mathbf{R}_{\text{rad}} \) is not guaranteed to be a positive definite matrix here, and thus we apply eigenvalue decomposition (ED) as

\[
\mathbf{R}_{\text{rad}} = \mathbf{U} \text{diag}(\bar{\sigma}) \mathbf{U}^H,
\]

where \( \bar{\sigma} \) is a vector, which replaces negative eigenvalues of the original matrix with their absolute values or zeros, and \( \mathbf{U} = [\mathbf{u}_1, \ldots, \mathbf{u}_{N_r}] \) represents the corresponding eigenvectors [32].

Then, the null space of the interfering channel by considering the constraint (10d) is formed as

\[
\mathbf{Z}_{\text{proj}} = \mathbf{I} - \mathbf{F} (\mathbf{F}^H \mathbf{F})^{-1} \mathbf{F}^H,
\]

where \( \mathbf{F} = [\mathbf{f}_{d,1}, \mathbf{f}_{d,2}, \ldots, \mathbf{f}_{d,K}] \). With the classical null-space projection (NSP) approach, the RSC matrix for eliminating radar interference to downlink users is given by

\[
\mathbf{R}_n = \mathbf{Z}_{\text{proj}} \mathbf{R}_{\text{rad}} \mathbf{Z}_{\text{proj}}^H,
\]

where \( \mathbf{R}_n \) is a semi-definite positive Hermitian matrix, but it is not guaranteed that all its diagonal elements are \( \frac{P_r}{N_r} \). Therefore, we apply the diagonal normalization (DN) method to normalize its diagonal elements as

\[
\mathbf{R}_{\text{com}} = \mathbf{R}_n \mathbf{T} \mathbf{T}^H,
\]

where \( \mathbf{T} \) is a diagonal matrix whose diagonal elements equal the diagonal elements of \( \sqrt{\frac{P_r}{N_r}} \mathbf{R}_n \).

Remark 1: Note that as the operation (22) will affect the performance of interference elimination, it is necessary to alternate the NSP and DN operations until satisfactory performance is reached.

To trade off the performance between communication and radar, we introduce a factor \( \lambda_1 \in [0, 1] \) and the final design of the RSC matrix as

\[
\mathbf{R} = \lambda_1 \mathbf{R}_{\text{com}} + (1 - \lambda_1) \mathbf{R}_{\text{rad}}.
\]

If there is no downlink user, we assign \( \lambda_1 = 0 \) and consider a radar only [33]. Otherwise, the NSP method will be needed to eliminate interference, which will incur a radar performance loss [21]. Given the RSC matrix, a waveform design with realistic constraints can be further obtained in [32], and a design for the RSC matrix is summarized in Algorithm 1.

#### Algorithm 1 Design the RSC Matrix

Calculate \( \mathbf{R}_{\text{rad}} \) by the ED method in (19).

**repeat**

Update \( \mathbf{R}_{\text{com}} \) by the NSP method in (21).

Update \( \mathbf{R}_{\text{com}} \) by the DN method in (22).

**until** convergence

**Output** \( \mathbf{R}_f \) in (23).
B. Design Communication Beamforming

For a given RSC matrix, the problem (12) can be reformulated as

\[
\max_{\mathbf{w}_k, \Theta_k} f_3 = \sum_{k=1}^{K} \frac{\tilde{p}_k \left| \mathbf{h}_k^H \mathbf{w}_k \right|^2}{\sum_{i=1}^{K} \left| \mathbf{h}_i^H \mathbf{w}_i \right|^2 + \mathbf{f}_{d,k}^H \mathbf{R}_f \mathbf{f}_{d,k} + \sigma^2},
\]

subject to (10b). 

Thus, the final beamforming vector of the communication channel can be expressed as

\[
\mathbf{w}_k = \lambda_2 \mathbf{w}_k + (1 - \lambda_2) \mathbf{w}_k^{rad}. 
\]

C. Design for phase shift of the IRS

In this subsection, we proceed to optimize the IRS phase shift of the k-th user after deriving the optimal \( \mathbf{w}_k \). We express \( \mathbf{h}_k \) as

\[
\mathbf{h}_k = \mathbf{h}_k^H \Theta_k \mathbf{h}_{dr} + \mathbf{h}_{d,k} = \mathbf{e}_k \text{diag} \left( \mathbf{h}_k^H \right) \mathbf{h}_{dr} + \mathbf{h}_{d,k}
\]

where \( \mathbf{e}_k = [ \mathbf{e}_{k,1}, \ldots, \mathbf{e}_{k,L} ] \) is an auxiliary vector with \( \mathbf{e}_k = [ \exp(j \alpha_{k,1}), \ldots, \exp(j \alpha_{k,L}) ] \). Then, the problem (24) can be reformulated as

\[
\max_{\mathbf{e}_k} f_5(\mathbf{e}_k) = \sum_{k=1}^{K} \frac{\tilde{p}_k |\mathbf{e}_k^H \mathbf{A}_k \mathbf{w}_k|^2}{\sum_{i=1}^{K} |\mathbf{e}_k^H \mathbf{A}_i \mathbf{w}_i|^2 + \mathbf{f}_{d,k}^H \mathbf{R}_f \mathbf{f}_{d,k} + \sigma^2}
\]

Similarly, we apply the QT technique to (32) as

\[
\max_{\mathbf{e}_k} f_6(\mathbf{e}_k, \mathbf{b}) = \sum_{k=1}^{K} \frac{\tilde{p}_k |\mathbf{e}_k^H \mathbf{C}_k|^2}{\sum_{i=1}^{K} |\mathbf{e}_k^H \mathbf{C}_i|^2 + \mathbf{f}_{d,k}^H \mathbf{R}_f \mathbf{f}_{d,k} + \sigma^2}
\]

where \( \mathbf{b} = [ b_1, \ldots, b_K ] \) is an auxiliary vector for the QT technique, and \( \mathbf{C}_k = \mathbf{A}_k \mathbf{w}_k \). We can derive the optimal \( \mathbf{b}_k \) by the Lagrange multiplier method as

\[
\hat{\mathbf{b}}_k = \frac{\tilde{p}_k \mathbf{e}_k^H \mathbf{C}_k}{\sum_{i=1}^{K} |\mathbf{e}_k^H \mathbf{C}_i|^2 + \mathbf{f}_{d,k}^H \mathbf{R}_f \mathbf{f}_{d,k} + \sigma^2}
\]

Thus, for a given \( \mathbf{b}_k \), we further manipulate the mathematical derivation of (35) as

\[
\max_{\mathbf{e}_k} f_7(\mathbf{e}_k) = -\mathbf{e}_k^H \mathbf{E} \hat{\mathbf{e}}_k + 2 \Re \{ \mathbf{e}_k^H \mathbf{F} \},
\]

where \( \mathbf{E} = \sum_{k=1}^{K} |b_k|^2 \sum_{i=1}^{K} \mathbf{C}_i \mathbf{C}_i^H \), \( \mathbf{F} = \sum_{k=1}^{K} \tilde{p}_k b_k^* \mathbf{C}_k \) and \( d_1 = \sum_{k=1}^{K} |b_k|^2 (\sigma^2 + \mathbf{f}_{d,k}^H \mathbf{R}_f \mathbf{f}_{d,k}) \). The problem (35) is a quadratical constraint quadratic programming (QCQP) problem and its objective becomes

\[
\min_{\mathbf{e}_k} f_7(\mathbf{e}_k) = \mathbf{e}_k^H \mathbf{E} \hat{\mathbf{e}}_k - 2 \Re \{ \mathbf{e}_k^H \mathbf{F} \}.
\]

This problem remains intractable due to the constant modulus constraint. Next, we will solve the problem by applying the MM and MO methods.

1) MM method: We employ the MM algorithm and consider a series of solvable subproblems to address the problem (36) iteratively through approximating its objective function and constraint set (35).

Proposition 2: Let us denote \( \mathbf{\hat{e}}_k^{(m)} \) as the vector at the m-th iteration. The objective function (36) at the m-th iteration for any given \( \mathbf{\hat{e}}_k^{(m)} \) is approximated as

\[
f_7(\mathbf{e}_k) \approx \mathbf{e}_k^H \mathbf{P} \mathbf{\hat{e}}_k^{(m)} - 2 \Re \{ \mathbf{e}_k^H \mathbf{P} (\mathbf{E} - \mathbf{E} \mathbf{\hat{e}}_k^{(m)} + \mathbf{F}) \} + \mathbf{e}_k^H (\mathbf{P} - \mathbf{E}) \mathbf{\bar{e}}_k^{(m)}
\]

where \( \mathbf{\hat{e}}_k^{(m)} \) is an approximate solution to \( \mathbf{\hat{e}}_k \) derived in the previous iteration, \( \lambda_{\max}(\mathbf{E}) \) represents the maximum eigenvalue of \( \mathbf{E} \), and \( \mathbf{d} \) and \( \mathbf{P} \) are defined as \( \mathbf{d} = \mathbf{e}_k^H (\lambda_{\max}(\mathbf{E}) \mathbf{I} - \mathbf{E}) \mathbf{\hat{e}}_k^{(m)} + \mathbf{F} \)

Likewise, the weight \( \lambda_2 \) is introduced to trade off the performance of the communication and the radar \((0 \leq \lambda_2 \leq 1)\). Thus, the final beamforming vector of the communication system can be expressed as

\[
\mathbf{w}_k = \lambda_2 \mathbf{w}_k + (1 - \lambda_2) \mathbf{w}_k^{rad}.
\]
\( P = \lambda_{\text{max}}(E)I \), respectively. Adopting a surrogate function of \([36]\), the problem \([36]\) becomes
\[
\min_{\tilde{e}_k} \lambda_{\text{max}}(E) ||\tilde{e}_k||^2 - 2R(\tilde{e}_k \tilde{F}),
\]
where \( \tilde{F} = (\lambda_{\text{max}}(E)I - E)\tilde{e}_k^H + F \). We can find that \( ||\tilde{e}_k||^2 = L + 1 \) since \( ||\tilde{e}_k|| = 1 \) in the IRS. The term \( R(\tilde{e}_k \tilde{F}) \) can be maximized when the two vectors \( \tilde{e}_k \) and \( \tilde{F} \) are identical. Thus, defining \( c = [c_1, \ldots, c_N] = (\lambda_{\text{max}}(E)I - E)\tilde{e}_k^H + F \), the optimal solution to \([38]\) is derived as
\[
\tilde{e}_k = [\exp(j \arg(c_1)), \ldots, \exp(j \arg(c_{L+1}))].
\]

We summarize the MM algorithm as Algorithm 2 below.

Algorithm 2 MM Algorithm

**Initialization:** \( m = 0 \).

repeat

- Obtain \( \tilde{F}^{(m)} = (\lambda_{\text{max}}(E)I - E)(\tilde{e}_k^{(m)})^H + F \).
- Obtain the optimal phase shift \( \tilde{e}_k^{(m)} \).
- Update \( \tilde{e}_k^{(m+1)} = \tilde{e}_k^{(m)} \) and calculate \( f(\tilde{e}_k^{(m+1)}) \).
- Set \( m \leftarrow m + 1 \).

until convergence

2) **MO method:** We provide another method called the MO algorithm to obtain the optimal phase shift of the \( k \)-th user. The principal idea is to derive a gradient descent algorithm on the manifold space \([36]\), and the problem \([36]\) can be reformulated as
\[
\min_{\tilde{e}_k} f_0(\tilde{e}_k) = \tilde{e}_k^H (E + \kappa I)\tilde{e}_k - 2R\{\tilde{e}_k F\},
\]
where \( \kappa \) is a constant that controls convergence. Since \( \kappa\tilde{e}_k\tilde{e}_k^H = \kappa(L + 1) \), problem \([40]\) is equivalent to problem \([36]\).

We define the feasible set of problem \([40]\) as \( S^{L+1} \), which is \( L + 1 \) complex circles, and each complex circle can be characterized as \( \mathbb{S} = \{ z \in \mathbb{C} | ||z||^2 = 1 \} \).

The set \( \mathbb{S} \) can be viewed as a sub-manifold of \( \mathbb{C} \), and the product of \( L + 1 \) circles corresponds to a sub-manifold of \( \mathbb{C}^{L+1} \). Hence, the manifold of \([40]\) can be given as \( S^{L+1} = \{ z \in \mathbb{C}^{L+1} | z_{l} = 1, \ for \ l \in [1, L + 1] \} \), where \( z_{l} \) is the \( l \)-th element of a vector \( z \). Next, we characterize the steps of the MO algorithm for solving problem \([40]\) iteratively.

1) The search direction: We first define \( f_0(\tilde{e}_k^{(i)}) \) as the objective function of \([40]\) at the \( i \)-th iteration. Then, the search direction of problem \([40]\) is set to be opposite to the gradient in the Euclidean space of \( f_0(\tilde{e}_k^{(i)}) \) as
\[
z^{(i)} = -\nabla_{\tilde{e}_k} f_0(\tilde{e}_k^{(i)}) = -2(\tilde{e}_k + \kappa I)(\tilde{e}_k^{(i)})^H + 2F. \quad (41)
\]

2) Projection search direction on the tangent space: The optimization step on the manifold space finds the Riemannian gradient of \( f_0 \) at the point \( \tilde{e}_k^{(i)} \) in the current tangent space \( \mathcal{T}_{\tilde{e}_k^{(i)}} S^{L+1} \). The search direction \( z^{(i)} \) in the Euclidean space is projected onto \( \mathcal{T}_{\tilde{e}_k^{(i)}} S^{L+1} \) and the Riemannian gradient at \( \tilde{e}_k^{(i)} \) of \( f_0(\tilde{e}_k^{(i)}) \) is given as
\[
P_{\mathcal{X}} \left( z^{(i)} \right) = z^{(i)} - R\left\{ \text{conj}(z^{(i)}) \odot \tilde{e}_k^{(i)} \right\} \odot \tilde{e}_k^{(i)}, \quad (42)
\]
where \( \mathcal{X} = \mathcal{T}_{\tilde{e}_k^{(i)}} S^{L+1} \).

3) Updated descent on the tangent space: \( \tilde{e}_k^{(i)} \) on the tangent space \( \mathcal{T}_{\tilde{e}_k^{(i)}} S^{L+1} \) can be updated as
\[
\tilde{e}_k^{(i)} = \tilde{e}_k^{(i)} + \zeta \bar{P}_{\mathcal{X}} \left( z^{(i)} \right), \quad (43)
\]
where \( \zeta \) is a step size.

4) Retraction operation: As \( \tilde{e}_k^{(i)} \) is not in \( S^{L+1} \), \( \tilde{e}_k^{(i)} \) is mapped to the manifold \( S^{L+1} \) by a retraction operation, and we normalise each element of \( \tilde{e}_k^{(i)} \) to unity as
\[
\tilde{e}_k^{(i+1)} = \tilde{e}_k^{(i)} \odot \frac{1}{||\tilde{e}_k^{(i)}||}. \quad (44)
\]

The following theorem is applied to determine the range of parameters \( \kappa \) and \( \zeta \) to ensure the convergence of the MO algorithm.

**Theorem 1** \([36]\): Let us denote \( \lambda_{E} \) and \( \lambda_{E+\kappa I} \) as the largest eigenvalue of matrices \( E \) and \( E + \kappa I \), respectively. If \( \kappa \) and \( \zeta \) satisfy the following conditions,
\[
\kappa \geq \frac{L + 1}{8} \lambda_{E} + ||F||_2, \quad 0 < \zeta < 1/\lambda_{(E+\kappa I)},
\]
then the MO algorithm generates a non-increasing sequence until convergence.

Based on the above descriptions, we summarize MO algorithm as Algorithm 3.

Algorithm 3 MO Algorithm

**Initialization:** \( i = 0 \), and the feasible solution \( \tilde{e}_k^{(0)} \).

repeat

- Obtain the search direction \( z^{(i)} \) in \([41]\).
- Obtain the tangent space projection of \( z^{(i)} \) from \([42]\).
- Update \( \tilde{e}_k^{(i)} \) on the tangent space by \([42]\).
- Update \( \tilde{e}_k^{(i+1)} \) to the manifold \( S^{L+1} \) by \([43]\).
- Update \( i \leftarrow i + 1 \).

until convergence

D. **Overall Algorithm for Problem** \([12]\)

Based on the descriptions so far, we summarize the overall algorithm as Algorithm 4 below.

Algorithm 4 Overall Algorithm

**Initialization:** \( m = 0 \), and a feasible solution \( \tilde{e}_k^{(0)} \).

repeat

- Obtain the optimal communication beamforming vector \( w_k \) via \([27]\).
- Obtain the optimal IRS phase shift \( \tilde{e}_k^* \) by Algorithm 2 or Algorithm 3.
- Update \( m \leftarrow m + 1 \).

until convergence

We investigate the convergence of the AO in Algorithm 4. To be specific, for given the phase shift of the IRS, (i.e., \( \tilde{e}_k \)), we derive the beamforming vector \( w_k \) of the BS in a closed-form. Then we apply the Algorithm 2 and Algorithm 3 to obtain the phase shift of the IRS, (i.e., \( \tilde{e}_k \)), where both algorithms can yield a monotonically decreasing objective.
value of problem \(36\) compared to the phase solution of the previous iteration. For given the RSC matrix \(R\), the objective value of \(23\) has an upper bound so as to guarantee that Algorithm 4 converges.

In a design of the RSC matrix, the calculation of \(18\) incurs the most computational cost, where \(V_x\) is a square matrix with \(M^2 - M + 1\) dimension. Eigen-decomposition is available to approximate the inverse of \(V_x\) and then the computational complexity of \(18\) is \(O(\Gamma(M^2 - M + 1)^2)\), where \(\Gamma\) denotes the rank of \(V_x\). The complexity order of the ED in \(12\), the NSP in \(20\) and the DN in \(22\) equals \(O(M^3)\), \(16(M^3 + KM^2) + 8K^2 + O(K^3)\), and \(4M^2\) flops, respectively. We can conclude that the computational complexity for the RSC matrix is \(O(\Gamma(M^2 - M + 1)^2 + K^3) + 16M(M^2 + 16K + 4) + 8K^2\).

Next, we apply the AO algorithm for the communication beamforming vector and the IRS phase shift, and denote the iteration number of the AO algorithm as \(I_{AO}\). For the communication beamforming vector, there are three closed-form expressions in \(26\), \(27\) and \(29\), for which the complexity order is \(O_2 = K(O(N^3) + O(KN^2) + O(N^2))\). For the IRS shift phase, the complexity of the algorithm using the MM is \(O_3 = K((L + 1)^2 + I_{mm}(L + 1)^2)\) and the MO algorithm requires \(O_4 = K((L + 1)^2 + I_{mo}(L + 1)^2)\), where \(I_{mm}\) and \(I_{mo}\) are the iteration number for the MM and MO algorithms, respectively. In summary, the overall complexity of the MM algorithm is \(O(O_1 + I_{AO}O_2O_3)\), while that of the MO algorithm is \(O(O_1 + I_{AO}O_2O_4)\).

IV. PERFORMANCE EVALUATION

In this section, we carry out numerical simulations to verify the performance of the IRS assisted ISAC system. According to \(38\) and \(50\), the channel gain is given by \(r_k \sim CN(0, 10^{-0.1PL}\eta)\), where \(PL(\eta) = \sigma_a + 10\sigma_b \log_2 \eta + \varphi \sim N(0, \sigma^2)\). In the channel realizations, we set the noise power \(\sigma^2 = -50\) dBm, \(\sigma_a = 61.4\), and \(\sigma_b = 2\), \(\sigma = 5.8\) dB. The BS is equipped with \(N = 8\) communication antennas and \(M = 8\) radar antennas, which are deployed at \((-20\ m, 0\ m)\). Users \(K = 5\) are randomly deployed in a circle of radius \(5\ m\) centered at the origin, and is located at \((20\ m, 0\ m)\) with \(L = 10\) reflecting elements. The transmit power of the communication and the radar are \(P_c = 30\) dBm, and \(P_r = 30\) dBm, respectively. The trade-off between the communication and radar is fixed as to \(\lambda = \lambda_1 = \lambda_2 = 0.1\). We assume that there are five targets located at the angle \(-50^\circ, -25^\circ, 0^\circ, 25^\circ, 50^\circ\) with respect to the BS in the mesh grid with 1° gap from \(-90^\circ\) to \(90^\circ\).

The following benchmark schemes are considered for comparison with the proposed algorithm.

1) Discrete phase shifts: We adopt the scheme of a discrete phase shift for IRS, which is given as \(\mathcal{F}_d = \{e^{j\alpha d(l)}\} = \{e^{j2\pi k\alpha d(l)}\} \cap \{2\pi k\}^\mathbb{Z} = \{2\pi k\}^\mathbb{Z} \setminus \{\frac{2\pi k}{2^n-1}\}^\mathbb{Z},\)

where \(\mathcal{F}_d\) is the finite set of phase shifts and \(B\) represents the phase resolution in bits.

2) Random phase shifts: The phase shift is randomly generated, while the precoding vector and the radar RSC matrix are optimally derived.

3) Without IRS: The system considers the transmission between the ISAC BS and the user with no IRS, while the RSC matrix and the communication precoding vector are derived accordingly.

First, we demonstrate the convergence property of the proposed Algorithm 4 in Fig. 2. From the figure, one can see that the sum rate converges within three iterations, confirming the effectiveness of our proposed AO algorithm. At the same time, the proposed MO and MM algorithms show very close performance, which validates our derivation in Section III-C.

Next, we characterize the effect of the transmit power of communication \(P_c\) on the sum rate from 25 dBm to 40 dBm in Fig. 3. We can find that the scheme with the trade-off factor \(\lambda = 0.5\) performs better than the scheme with \(\lambda = 0.1\), because an increased \(\lambda\) will reduce the weight of the radar RSC matrix in \(R_j\) in \(23\). Also, the MM and MO algorithms achieve the same performance, verifying the effectiveness of the proposed scheme. Additionally, the proposed scheme is superior to random phase shifts, which validates the benefits of the optimal phase shifts of the IRS. Finally, the schemes with
the IRS show a significant increase in the sum rate compared to the case without IRS.

In Fig. 4, we unveil the effect of the IRS reflecting elements \( L \) in improving the sum rate. It can be observed that the sum rate increases with the IRS reflecting elements in all schemes. By comparing the schemes with \( \lambda = 0.1 \) and 0.5, the number of IRS elements is more effective than adjusting the trade-off factor without affecting the sensing performance. The reason for this is that by jointly designing the BS beamforming and the IRS phase shift matrix, the BS-user channels and the beamforming can be better matched to each other. When the number of the IRS reflecting elements grows, the sum rate with the IRS improves considerably compared to the scheme without IRS. This follows from the fact that a large \( L \) will introduce a stronger reflected signal to enhance the signal reception.

In Fig. 5, we present the sum rate with respect to the number of transmit antennas for communication. We can see that the increase in the number of communication antennas \( N \) improves the sum rate. By comparing with Fig. 4, a large number of IRS elements is more efficient to improve the sum rate.

In Fig. 6, we calculate the detection probability in [39] with the radar constant false-alarm probability \( P_{FA} = 10^{-5} \). Although a high \( \lambda \) can bring high transmission rate, it also has a serious impact on the detection performance of the radar detection probability \( P_D \). By comparing with Fig. 4, it can be concluded that increasing the number of reflecting elements of IRS is a preferable solution compared to sacrificing radar performance for a high transmission rate.

In Fig. 7, we present the \( P_D \) with respect to the radar signal to noise ratio (SNR) at different false alarm rate \( P_{FA} \). We find that the system weighting factor \( \lambda \) assignment has a serious impact on the radar detection probability \( P_D \) at small SNR, but when the SNR increases to 13 dB and above, the radar is not constrained by the system weighting factor \( \lambda \) assignment and maintains a high level of detection probability.

Finally, we show the impact of the discrete phase resolution of the IRS on the sum rate performance and evaluate the gap between continuous and discrete phase shifts using the MM and MO algorithms in Fig. 8. The continuous phase case
represents an upper bound of the discrete phase counterparts, and the gap between them gradually decreases as $B$ increases. This can be explained by the fact that the quantized phase shift results in an incomplete alignment, which leads to a loss of performance. The plot confirms that $B = 3$ bits are sufficient to achieve the optimal performance.

V. CONCLUSION

This paper has focused on the IRS-assisted ISAC system in the mmWave scenario and formulated a sum-rate maximization problem by jointly optimizing the radar RSC matrix, the communication beamforming vector, and the IRS phase shift. We have derived closed-form expressions for the radar RSC matrix, the communication beamforming vector of the IRS, and the IRS phase shift. The MM and MO algorithms have been deployed to solve the IRS phase shift, which can effectively reduce the computational complexity. We have also introduced a parameter to trade off the radar and communication performance. Finally, the numerical simulations have verified the effectiveness of our proposed scheme, and demonstrated proved that the IRS can be employed as an effective way to improve the ISAC system transmission rate.

APPENDIX

A. Proof to Proposition 1

When $\lambda_k$ is given, (11) is a concave differentiable function with respect to $p_k$. Taking the derivative of (11) with respect to $p_k$ and setting it to zero, we have

$$\frac{\partial f_1}{\partial p_k} = \frac{1}{\ln 2} \sum_{k=1}^{K} \left( \frac{1}{1 + p_k} - 1 + \frac{\gamma_k}{1 + \gamma_k} \right) = 0. \quad (46)$$

Then, we obtain $p_k = \gamma_k$. Taking $p_k$ back to (11) yields (10a). As such, the two problems have equal optimal objective values, ensuring their equivalence.

B. Proof to Lemma 1

(27) can be re-arranged as

$$\hat{W} = [w_1, \ldots, w_K] = (\mu I + K)^{-1}HS \quad (47)$$

where $K = |s_k|^2 \sum_{i=1}^{K} [\hat{h}_i \hat{h}_i^H]$, $H = [\hat{h}_1, \ldots, \hat{h}_K]$ and $S = \text{diag}([\sqrt{P_1} s_1, \ldots, \sqrt{P_K} s_K])$. We have $\text{tr}(\hat{W} \hat{W}^H) = \sum_{i=1}^{K} w_i^H w_i$ and then take the derivative of the transit power with respect to $\mu$ as

$$\frac{\partial}{\partial \mu} \text{tr}(\hat{W} \hat{W}^H) = \text{tr}\left( \frac{\partial}{\partial w_i} \left( \left( \hat{W} \hat{W}^H \right) \right)^H \frac{\partial w_i}{\partial \mu} \right)$$

$$= -2 \text{tr} \left( P^H (\mu I + K)^{-1} P \right), \quad (48)$$

which shows that (47) is monotonically decreasing with $\mu$. Thus the optimal solution $\hat{\mu}$ in the critical case of the power constraint (10b) is precisely its minimum value.

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