

RA-Enabled Multi-User Multi-Target ISAC Systems With Communication-Centric Optimization

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Abstract—Recently, rotatable antennas (RAs) have attracted widespread attention owing to their inherent simplicity and operational flexibility. In this paper, an RA-enabled integrated sensing and communication (ISAC) system is investigated, which can serve multiple communication users and sense multiple targets simultaneously. Specifically, a communication-centric optimization problem is formulated, where both the transmit beamforming and the rotation angle of the antennas are jointly optimized to improve the communication sum rate. To handle the nonconvex optimization problem, an alternating optimization (AO)-based algorithm is proposed. More specifically, a fractional programming approach is employed to optimize beamforming, while a successive convex approximation (SCA)-based algorithm is developed for optimizing the antenna rotation angles. Simulation results demonstrate the effectiveness of RAs in enhancing the ISAC performance, which confirm the superiority of our proposed optimization algorithm over existing state-of-the-art methods.

Index Terms—Integrated sensing and communication (ISAC), Rotatable antenna (RA), beamforming, rotation angle optimization

I. INTRODUCTION

Next generation wireless networks have been envisioned as key enablers for varied emerging application scenarios such as low-altitude economy [1], [2], embodied intelligence [3], etc. As such, the capacity of sensing environment and target is required [4], [5]. Against this background, integrated sensing and communication (ISAC) has emerged as one of the core technologies of upcoming sixth-generation (6G), which can realize both communication and sensing functionalities within the same spectrum and hardware [6], [7]. However, when the communication users and sensing targets lie in nearly orthogonal subspaces, it is difficult to guarantee the communication and sensing performance simultaneously for ISAC systems with fixed antenna [8]. Thus, it is urgent to introduce additional spatial degrees of freedom (DoFs) for enhancing the performance of ISAC systems [9].

To solve this problem, flexible antenna architectures exemplified by movable antennas (MAs) and fluid antenna systems (FAS) have been widely investigated [10], [11], which can improve the system's DoFs via regulating the geometric shape and physical position of the antennas. However, the performance of MAs or FAS is often constrained by limited

movement speed and considerable hardware response latency [9]. In addition, six-dimensional MA (6DMA) has attracted increasing research attention. The 6DMA architecture incorporates rotational adjustment in addition to antenna position adjustment, which greatly enhances the DoFs [12], [13]. Nevertheless, although 6DMA achieves significant performance improvement, it requires exorbitant hardware complexity and deployment costs, making it difficult for practical deployment [9].

As a simplification, rotatable antennas (RAs) architecture has been studied, which enhance the communication and sensing performance of the system while maintaining low hardware complexity and high feasibility [9]. Specifically, RA adjust the antenna beam direction by rotating the antennas while keeping antenna's positions fixed, thereby introducing new degrees of freedom and achieving flexible beam coverage [8]. For example, the authors in [8] formulated a multi-objective optimization problem to simultaneously maximize the sum rate of multiple communication users and minimize the Cramér-Rao bound (CRB) for target angle estimation, which jointly optimizes the transmit beamforming vectors and the array rotation angle at the BS. Moreover, the authors in [14] investigated an RA-enabled near-field ISAC system, where the transmit beamformers and the array rotation angle at the BS are jointly optimized to minimize the CRBs for angle and range estimation, thus guaranteeing a minimum SINR for communication users.

Although the effectiveness of RA in enhancing ISAC system performance have been demonstrated to some extent, only simplified scenario with single target is studied. Practical scenarios, however, usually involve multiple targets. Moreover, current research on the optimization of rotational angle still relies on search algorithms such as one-dimension search and particle swarm optimization (PSO). These algorithms typically entail high computational complexity yet yield suboptimal performance. Therefore, it is necessary to adopt convex optimization methods to solve the rotation angle problem.

Motivated by the aforementioned discussions, a more practical multi-user multi-target RA-enabled ISAC system framework is studied in this paper. as well as the joint design of beamforming and antenna rotation angle. To balance the

trade-off between communication and sensing performance, an optimization problem is formulated from communication-centric perspective. A new alternating optimization (AO)-based algorithm is proposed to solve the problem. Simulation results are provided to validate the convergence and effectiveness of the proposed algorithm. Moreover, the superiority of the proposed algorithms is confirmed through comparative simulations.

II. SYSTEM MODEL

We consider a RA-enabled ISAC system, which consists of a BS, K single antenna users, and T targets. Moreover, the BS is equipped with N_t transmit antennas and N_r receive antennas, forming a ULA with half-wavelength element spacing. To obtain better communication and sensing performance, the antenna can be rotated judiciously by mechanical or electronic methods.

A. Signal and Channel Model

In this work, a dual-functional signal is adopted, which can realize communication and sensing functionalities simultaneously. Therefore, the transmit signal from the BS can be modeled as

$$\mathbf{X} = \mathbf{W}\mathbf{s} = \sum_{k=1}^K \mathbf{w}_k s_k, \quad (1)$$

where $\mathbf{s} = [s_1, s_2, \dots, s_K]^T \in \mathbb{C}^{K \times 1}$ represents the information symbols, and $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_K] \in \mathbb{C}^{N_t \times K}$ represents the beamformer matrix with zero mean and unit power, i.e., $\mathbb{E}[\mathbf{s}\mathbf{s}^H] = \mathbf{I}_K$ with $\mathbb{E}[\cdot]$ denoting the expectation operation. Thus, the covariance matrix of transmit signal $\mathbf{X}$ is

$$\mathbf{R}_X = \mathbb{E}[\mathbf{X}\mathbf{X}^H] = \mathbf{W}\mathbf{W}^H. \quad (2)$$

Let $\mathbf{h}_k^H$ represents the channel between the BS and the k -th user, we have

$$\mathbf{h}_k^H = \alpha_k^l \alpha_{k,0}^s \mathbf{a}^H(\bar{\theta}_{k,0}) + \sum_{l=1}^L \beta_{k,l} \mathbf{a}^H(\bar{\theta}_{k,l}), \quad (3)$$

where $\theta_{k,l}, l \in \{0, 1, 2, \dots, L\}$ is the spatial angle corresponding to the l -th link between the k -th user and the BS, $\bar{\theta}_{k,l} = \theta_{k,l} + \phi$ denotes the effective spatial angle accounting for the RA's rotation, α_k^l denotes the large-scale fading of the k -th user, $\alpha_{k,0}^s \sim \mathcal{CN}(0, 1)$ denotes the small-scale fading of the line-of-sight (LoS) link for the k -th user, $\beta_{k,l}$ represents the complex path gains of the l -th non-LoS (NLoS) for the k -th user. α_k^l can be calculated as

$$\alpha_k^l = \sqrt{\frac{\lambda^2}{(4\pi)^2 d_k^2}} = \sqrt{\frac{c^2}{(4\pi)^2 f_c^2 d_k^2}}, \quad (4)$$

where d_k denotes the distance from the k -th user to the BS, λ denotes the wavelength, $f_c = 3\text{GHz}$ denotes the carrier frequency, and c denotes the speed of light.

Since the NLoS links is assumed to exhibit an additional attenuation of -20 dB compared with the LoS link [17], we define $\beta_{k,l} = 10^{(-20/10)} \alpha_k^l \alpha_{k,l}^s$. Here, $\alpha_{k,l}^s \sim \mathcal{CN}(0, 1), l \in$

$\{1, 2, \dots, L\}$ denotes the small-scale fading of the NLoS links for the k -th user.

Moreover, $\mathbf{a}(\bar{\theta}_{k,l}) \in \mathbb{C}^{N_t \times 1}$ denotes the channel steering vector accounting for the antenna rotation angle, given by

$$\mathbf{a}(\bar{\theta}_{k,l}) = [1, e^{j\pi \sin \bar{\theta}_{k,l}}, \dots, e^{j\pi(N_t-1) \sin \bar{\theta}_{k,l}}]^T. \quad (5)$$

Accordingly, the received signal of the k -th user y_k can be expressed as

$$y_k = \sum_{k=1}^K \mathbf{h}_k^H \mathbf{w}_k s_k + n_k, \quad (6)$$

where $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ denotes the additive Gaussian white noise (AWGN) of the k -th user with σ_k^2 representing the noise power.

For sensing, all targets are assumed to be point targets. Moreover, it is assumed that there exists a LoS link between the BS and each target. The spatial angle of the LoS link is given by θ_t . Then, the channel between the BS and the t -th target can be expressed as

$$\mathbf{H}_t = \beta_s \mathbf{a}_r(\bar{\theta}_t) \mathbf{a}_t^H(\bar{\theta}_t), \quad (7)$$

where β_s denote complex path gain accounting for radar cross section (RCS), $\bar{\theta}_t = \theta_t + \phi$ denotes the spatial angle of the t -th target accounting for the antenna rotation angle. Moreover, $\mathbf{a}_r(\bar{\theta}_t)$ and $\mathbf{a}_t(\bar{\theta}_t)$ denotes the receiving and transmitting steering vector, respectively, given by

$$\mathbf{a}_r(\bar{\theta}_t) = [1, e^{j\pi \sin \bar{\theta}_t}, \dots, e^{j\pi(N_r-1) \sin \bar{\theta}_t}]^T, \quad (8)$$

$$\mathbf{a}_t(\bar{\theta}_t) = [1, e^{j\pi \sin \bar{\theta}_t}, \dots, e^{j\pi(N_t-1) \sin \bar{\theta}_t}]^T. \quad (9)$$

Therefore, the reflected echo of t -th target received by the BS can be expressed as

$$\mathbf{Y}_t = \mathbf{H}_t \mathbf{X} + \mathbf{n}_t, \quad (10)$$

where $\mathbf{n}_t$ represents the noise matrix of t -th target which follows $\mathcal{CN}(0, \sigma_t^2 \mathbf{I}_T)$.

B. Performance Metric

For communication, the SINR at the k -th user can be expressed as

$$\gamma_k = \frac{|\mathbf{h}_k^H \mathbf{w}_k|^2}{\sum_{i \neq k} |\mathbf{h}_k^H \mathbf{w}_i|^2 + \sigma_k^2}, \forall k \in \{1, 2, \dots, K\}, \quad (11)$$

where the signals intended for other users are regarded as interference.

To evaluate the total transmission capacity, the achievable sum rate is adopted as the communication metric, which can be formulated as

$$R(\mathbf{W}, \phi) = \sum_{k=1}^K R_k(\mathbf{W}, \phi) = \sum_{k=1}^K \log_2(1 + \gamma_k). \quad (12)$$

For target sensing, the angle estimation CRB is adopted as the metric for sensing accuracy. According to [8], the CRB can be formulated as

$$\text{CRB}_t(\mathbf{W}, \phi) = \frac{1}{2M\gamma^s \|\dot{\mathbf{a}}_r(\bar{\theta}_t)\|^2 (\mathbf{a}_t^H(\bar{\theta}_t) \mathbf{R}_X \mathbf{a}_t(\bar{\theta}_t))}, \quad (13)$$

where $M = 100$ denotes the number of time slots, $\gamma^s = \frac{|\beta_s|^2}{\sigma_t^2}$ is assumed to be $\gamma^s = -10\text{dB}$, $\dot{\mathbf{a}}_r(\bar{\theta}_t)$ denotes the derivative of the receive steering vector with respect to $\bar{\theta}_t$, which can be calculated by

$$\dot{\mathbf{a}}_r(\bar{\theta}_t) = [0, j\pi \cos \bar{\theta}_t e^{j\pi \sin \bar{\theta}_t}, \dots, j\pi(N_r - 1) \cos \bar{\theta}_t e^{j\pi(N_r-1) \sin \bar{\theta}_t}]. \quad (14)$$

According to [8], the CRB of t -th target can be reformulated as

$$\text{CRB}_t(\mathbf{W}, \phi) = \frac{\chi}{\cos^2 \bar{\theta}_t (\mathbf{a}_t^H(\bar{\theta}_t) \mathbf{R}_X \mathbf{a}_t(\bar{\theta}_t))}, \quad (15)$$

where $\chi = \frac{3\lambda(N_r-1)}{\pi^2 M \gamma^s N_r(N_r+1)(N_r-1)}$.

III. AO-BASED OPTIMIZATION DESIGN

For our considered communication-centric design, communication performance is optimized while ensuring a certain sensing performance, which can be formulated as

$$\mathcal{P}_1 : \max_{\mathbf{W}, \phi} R(\mathbf{W}, \phi) \quad (16a)$$

$$\text{s.t. } \text{CRB}_t(\mathbf{W}, \phi) \leq \xi_t, \quad \forall t \in T \quad (16b)$$

$$\text{tr}(\mathbf{R}_X) \leq P_m, \quad (16c)$$

where ξ_t denotes the maximum CRB threshold for t -th target, P_m denotes the maximum transmit power of the system. Then, (16a) denotes the communication-centric optimization objective, (16b) represents the sensing constraint, and (16c) represents the power constraint. The optimization problem is rendered non-convex due to the strong coupling between the two optimization variables and the non-convexity of the functions. To address the complex non-convex problem, an AO-based algorithm is proposed to decouple $\mathbf{W}$ and ϕ .

A. Optimization of Transmit Beamforming $\mathbf{W}$

In this subsection, the transmit beamforming $\mathbf{W}$ of the ISAC signal is optimized with antenna rotation angle fixed. Although the angle is fixed, the problem remains non-convex due to the complex form of the objective function. Thus, methods such as fractional programming and semidefinite relaxation are introduced. We can find that (16a) is a typical multi-ratio FP problem. According to [15], quadratic transform is applied to (16a). By introducing an auxiliary variable $b_k, k \in \{1, 2, \dots, K\}$, (16a) can be reformulated as

$$R_1(\mathbf{W}, \phi) = \sum_{k=1}^K \log_2(1 + 2b_k \sqrt{\mathbf{h}_k^H \mathbf{W}_k \mathbf{h}_k} - b_k^2 (\sum_{i \neq k}^K \mathbf{h}_k^H \mathbf{W}_i \mathbf{h}_k + \sigma_k^2)), \quad (17)$$

where $\mathbf{W}_k = \mathbf{w}_k \mathbf{w}_k^H$, thus $\mathbf{W} \mathbf{W}^H = \sum_{k=1}^K \mathbf{W}_k$.

According to [15], the fixed b_k for fixed $\mathbf{W}$ can be calculated by

$$b_k = \frac{\sqrt{\mathbf{h}_k^H \mathbf{W}_k \mathbf{h}_k}}{\sum_{i \neq k}^K \mathbf{h}_k^H \mathbf{W}_i \mathbf{h}_k + \sigma_k^2}. \quad (18)$$

Then, $\mathbf{W}$ and b_k are updated iteratively. Moreover, (16b) and (16c) can be reformulated as

$$C_t = \cos^2 \bar{\theta}_t \left(\mathbf{a}_t^H(\bar{\theta}_t) \sum_{k=1}^K \mathbf{W}_k \mathbf{a}_t(\bar{\theta}_t) \right) \geq \frac{\chi}{\xi_t}, \quad (19)$$

$$\text{tr}(\sum_{k=1}^K \mathbf{W}_k) \leq P_m, \quad (20)$$

respectively. Through the above operations, $\mathcal{P}_1$ can be reconstructed as

$$\mathcal{P}_{1.1} : \max_{\mathbf{W}} R_1(\mathbf{W}) \quad (21a)$$

$$\text{s.t. } C_t \geq \frac{\chi}{\xi_t}, \quad (21b)$$

$$\text{tr}(\sum_{k=1}^K \mathbf{W}_k) \leq P_m, \quad (21c)$$

$$\mathbf{W}_k \succeq 0, \quad (21d)$$

$$\text{rank}(\mathbf{W}_k) = 1, \quad \forall k \in K, \quad (21e)$$

By neglecting (21e), $\mathcal{P}_{1.1}$ can be transformed into

$$\mathcal{P}_{1.2} : \max_{\mathbf{W}} R_1(\mathbf{W}) \quad (22a)$$

$$\text{s.t. } (19), (20), (21d).$$

Note that $\mathcal{P}_{1.2}$ is a convex semidefinite programming (SDP) problem, its global optimal solution can be directly obtained using tools such as CVX and MOSEK. However, the solution obtained by solving Problem $\mathcal{P}_{1.2}$ does not necessarily satisfy the rank-one constraint (21e). Therefore, methods such as eigenvalue decomposition or Gaussian randomization are required to construct a solution which satisfy (21e). Subsequently, $\mathbf{W}$ and b_k are alternately optimized. The aforementioned procedures are applied until convergence is reached. Thus yielding the optimized matrix $\mathbf{W}$. Furthermore, we define ϵ_1 as the convergence threshold for $\mathbf{W}$ optimization. Hence, convergence implies $|R^{(i)} - R^{(i-1)}| < \epsilon_1$, where $R^{(i)}$ denotes the sum rate after the i -th iteration.

B. Optimization of RA's Rotation

In this subsection, the RA's rotation ϕ is optimized with $\mathbf{W}$ fixed. Exploiting the structural symmetry of a ULA, a 180° rotation constitutes one full cycle. Thus $\mathcal{P}_1$ can be reformulated as

$$\mathcal{P}_{1.3} : \max_{\phi} R(\phi) \quad (23a)$$

$$\text{s.t. } -\frac{\pi}{2} \leq \phi \leq \frac{\pi}{2}, \quad (23b)$$

$$C_t \geq \frac{\chi}{\xi_t}. \quad (23c)$$

For ϕ , (23a) and (23c) are non-convex. Therefore, the SCA algorithm is adopted to convexify the non-convex problem $\mathcal{P}_{1.3}$ and obtain a local optimal solution to problem $\mathcal{P}_{1.3}$ in an iterative manner. Without loss of generality, the $(i+1)$ -th iteration in SCA algorithm is presented and denote $R^{(i+1)}$, $C_t^{(i+1)}$ and $\phi^{(i+1)}$ as R , C_t and ϕ in the $(i+1)$ -th iteration. The first-order Taylor expansion is adopted to convexify the non-convex (23a) and (23c). By using first-order Taylor expansion, (23a) and (23c) can be given as

$$R^{(i+1)} = R(\phi^{(i)}) + \dot{R}(\phi^{(i)})(\phi^{(i+1)} - \phi^{(i)}), \quad (24)$$

$$C_t^{(i+1)} = C_t(\phi^{(i)}) + \dot{C}_t(\phi^{(i)})(\phi^{(i+1)} - \phi^{(i)}) \geq \frac{\chi}{\xi_t}, \quad (25)$$

where $\dot{R}$ and $\dot{C}_t$ denote the first-order derivatives of R and C_t with respect to ϕ , respectively. Through calculation, $\dot{C}_t$ can be written as (26), where $\dot{\mathbf{a}}_t$ denotes the derivative with respect to ϕ of $\mathbf{a}_t$, given by

$$\dot{\mathbf{a}}_t(\bar{\theta}_t) = [0, j\pi \cos \bar{\theta}_t e^{j\pi \sin \bar{\theta}_t}, \dots, j\pi(N_t - 1) \cos \bar{\theta}_t e^{j\pi(N_t-1) \sin \bar{\theta}_t}]. \quad (27)$$

For $\dot{R}$, numerical differentiation is employed due to the excessive complexity of its analytical derivative with respect to ϕ . Hence, $\dot{R}$ can be calculated as

$$\dot{R}(\phi) = \frac{R(\phi + \delta) - R(\phi - \delta)}{2\delta}, \quad (28)$$

where δ denotes the step size for numerical differentiation.

Then, $\mathcal{P}_{1.3}$ can be rewritten as the following problem in the $(i+1)$ -th iteration, given by

$$\mathcal{P}_{1.4} : \max_{\phi} (24) \quad (29a)$$

$$\text{s.t. } -\frac{\pi}{2} \leq \phi^{(i+1)} \leq \frac{\pi}{2}, \quad (29b)$$

$$C_t^{(i+1)} \geq \frac{\chi}{\xi_t}. \quad (29c)$$

Moreover, as indicated in [16], oscillations may arise during the convergence process if a fixed stepsize is used. Therefore, diminishing stepsize is adopted in order to achieve fast convergence without oscillation. Given the diminishing coefficient $\varpi_i = \frac{1}{2^i}$, $\mathcal{P}_{1.4}$ can be reformulated as

$$\mathcal{P}_{1.5} : \max_{\phi} (24) \quad (30a)$$

$$\text{s.t. } \max\left(-\frac{\pi}{2}, \phi^{(i)} - \Delta * \varpi_{i+1}\right) \leq \phi^{(i+1)} \leq \min\left(\frac{\pi}{2}, \phi^{(i)} + \Delta * \varpi_{i+1}\right), \quad (30b)$$

$$C_t^{(i+1)} \geq \frac{\chi}{\xi_t}, \quad (30c)$$

where Δ represents the initial stepsize. It can be verified that $\mathcal{P}_{1.5}$ is a convex optimization problem, which can be solved by CVX and MOSEK. Upon completion of each optimization iteration, all relevant quantities in the optimization problem are updated. The optimization is then performed iteratively until convergence is achieved. Furthermore, we define ϵ_2 as the convergence threshold for ϕ optimization. Hence, convergence implies $|\phi^{(i)} - \phi^{(i-1)}| < \epsilon_2$.

Algorithm 1 AO-Based Optimization

Input: Initialize $i = 0, i_1 = 0, i_2 = 0, \mathbf{W}, \phi, \Delta$

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1: repeat
2:   Fix  $\mathbf{W}$ 
3:   while  $|\phi^{(i_1)} - \phi^{(i_1-1)}| \geq \epsilon_2$  and  $i_1 \leq I_{1max}$  do
4:     Get  $\phi^{(i_1)}$  by solving  $\mathcal{P}_{1.5}$ 
5:     Update  $R^{(i_1+1)}$  and  $C^{(i_1+1)}$  by (24) and (25)
6:     Update  $\varpi_{i_1+1}$ 
7:     Set  $i_1 = i_1 + 1$ 
8:   end while
9:   Update  $\phi$ 
10:  Fix  $\phi$ , calculate  $b_k$  by (18)
11:  while  $|R^{(i_2)} - R^{(i_2-1)}| \geq \epsilon_1$  and  $i_2 \leq I_{2max}$  do
12:    Get  $\mathbf{W}$  by solving  $\mathcal{P}_{1.2}$  and adopting eigenvalue decomposition or Gaussian randomization
13:    Update  $b_k$  by (18)
14:    Set  $i_2 = i_2 + 1$ 
15:  end while
16:  Update  $\mathbf{W}$ 
17:  Set  $i = i + 1$ 
18: until  $|R^{(i)} - R^{(i-1)}| < \epsilon$  or  $i \geq I_{max}$ 
Output:  $\mathbf{W}, \phi$ 

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C. Overall Optimization

The detailed overall optimization algorithm for solving $\mathcal{P}_1$ is shown in **Algorithm 1**. In each iteration, the computational complexity of computing $\mathbf{W}$ or ϕ using the interior-point method is given by $\mathcal{O}(K^{6.5} N_t^{6.5} \log \epsilon_i^{-1})$, where ϵ_i is the given solution accuracy [18]. Thus, the total computational complexity of **Algorithm 1** is $\mathcal{O}(I_{sum}(I_{FP} + I_{SCA}) K^{6.5} N_t^{6.5} \log \epsilon_i^{-1})$, where I_{sum} , I_{FP} , and I_{SCA} denote the iteration number of **Algorithm 1**, FP algorithm, and SCA-based algorithm, respectively.

IV. SIMULATION RESULTS

We consider a two-dimensional Cartesian coordinate system with the origin located at the BS. RAs can rotate freely in the $x - y$ plane and $N_t = N_r = 16$. It is assumed that $K = 4$ communication users are randomly distributed within the first and second quadrants, i.e., $\theta_{k,0} \sim \mathcal{U}(-\frac{\pi}{2}, \frac{\pi}{2})$. The distance between the k -th user and BS is assumed to be $d_k \sim \mathcal{U}(30m, 50m)$. Likewise, $T = 3$ sensing targets are assumed to be randomly distributed in the first or second quadrant, i.e., $\theta_t \sim \mathcal{U}(-\frac{\pi}{2}, \frac{\pi}{2})$. The distance between the t -th target and BS is assumed to be $d_{T,t} \sim \mathcal{U}(5m, 10m)$. The initial stepsize Δ for ϕ optimization in two proposed algorithms is $\frac{\pi}{6}$. The upper limit of iterations for every step within each algorithm is set to 20. σ_k^2, σ_t^2 are set to $\sigma_k^2 = \sigma_t^2 = -80\text{dBm}$. ξ_t is set to $\xi_t = 0.005\text{rad}$.

In Fig. 1, the convergence simulations of **Algorithm 1** under different maximum transmit power P_m are conducted. It can be observed that **Algorithm 1** converges within 1–2 iterations under all considered power constraints. Moreover, the communication sum rate is significantly improved under different power constraints. For example, at $P_m = 30\text{dBm}$, the sum rate

$$C'_t(\phi) = -2 \cos \bar{\theta}_t \sin \bar{\theta}_t (\mathbf{a}_t^H(\bar{\theta}_t) \sum_{k=1}^K \mathbf{W}_k \mathbf{a}_t(\bar{\theta}_t)) + \cos^2 \bar{\theta}_t (\mathbf{a}_t^H(\bar{\theta}_t) \sum_{k=1}^K \mathbf{W}_k \mathbf{a}_t(\bar{\theta}_t) + \mathbf{a}_t^H(\bar{\theta}_t) \sum_{k=1}^K \mathbf{W}_k \dot{\mathbf{a}}_t(\bar{\theta}_t)) \quad (26)$$

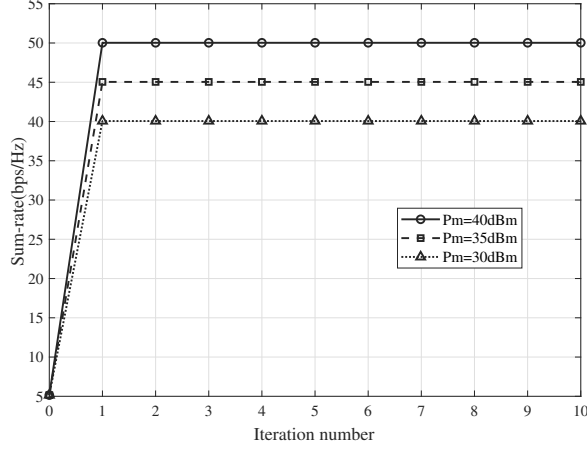
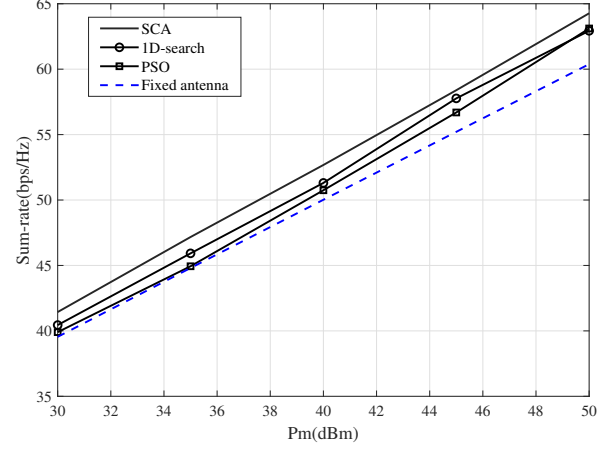
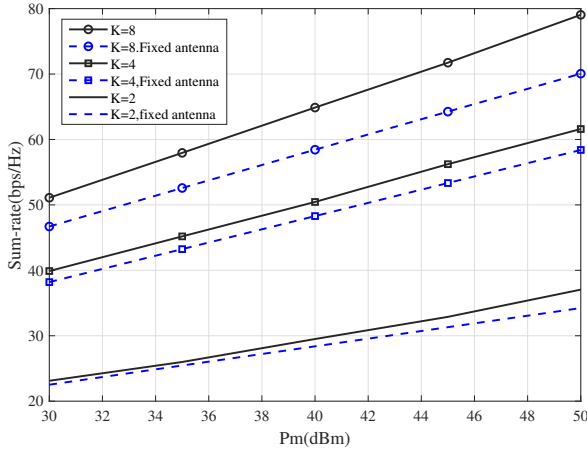


Fig. 1. Convergence of Algorithm 1.

Fig. 3. Sum-rate of different algorithms versus P_m .Fig. 2. Sum-rate of different algorithms under different K versus P_m .

after algorithm convergence is increased from approximately 5bps/Hz to 40bps/Hz. Thus, the effectiveness of **Algorithm 1** is also verified by the simulation results. In addition, the converged communication sum rate of **Algorithm 1** increases as the P_m increases, this phenomenon is also consistent with the theoretical analysis.

In Fig. 2, we set $T = 5$. The number of users K and P_m are varied, with the fixed antenna benchmark included for performance comparison. Based on the simulation results, it can be observed that RAs yield a performance improvement for the system under any parameter settings. Moreover, the

performance improvement brought by RAs becomes more pronounced as the number of users increases. This is because when the number of users is small, fixed antennas are sufficient to achieve relatively good beam coverage. In contrast, with a large number of users, antenna rotation facilitates superior beam coverage, thereby offering a higher upper bound for performance improvement. It is also observed that the sum rate shows an increasing trend with respect to both P_m and K . Notably, the growth of the sum rate from $K = 4$ to $K = 8$ is less pronounced compared to the increase from $K = 2$ to $K = 4$. This is caused by the increased inter-user interference as the number of users grows and the limited total transmit power.

In Fig. 3, the trends of the performance of **Algorithm 1** and three benchmark methods with the change in P_m are presented. The benchmarks PSO and 1D-search indicate that the rotation angle is optimized using PSO and one-dimensional search, respectively. It can be observed that all curves rise with the increase in P_m . Among them, the fixed-antenna scheme achieves the worst performance. The performance improvement of RAs for the ISAC system is thereby demonstrated. Of the three schemes with antenna rotation capability, **Algorithm 1** exhibits the best performance. The superiority of the SCA-based rotation angle optimization algorithm in **Algorithm 1** over other algorithms is thereby demonstrated. The simulation results are consistent with the theoretical analysis.

V. CONCLUSION

In this paper, a RA-enabled multi-user multi-target ISAC system was investigated. Considering both communication performance and sensing constraint, a communication-centric problem was formulated. For the communication-centric problem, the FP method was adopted for beamforming optimization, while the SCA-based algorithm was utilized to optimize the antenna rotation angle. The convergence and effectiveness of the proposed algorithm was verified through simulation. Simulation results demonstrated that the introduction of RA can improve the performance of ISAC system significantly.

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