

Signal-Driven AP Selection for Cell-Free mMIMO ISAC Systems in Clutter-Intensive Environments

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Abstract—Sixth-generation networks incorporate Integrated Sensing and Communication to support both high data rates and environmental awareness. In Cell-Free Massive MIMO systems, distributed access points enhance spatial diversity, but efficient distributed sensing under realistic propagation conditions remains challenging. This paper proposes the Dynamic Angle and Signal-driven Association (DASA) scheme, a two-step access point selection framework for clutter-intensive environments. DASA combines a post-convergence local SNR proxy with geometric angular refinement to identify reliable sensing access points. Simulations under the 3GPP UMa model show that DASA consistently outperforms conventional methods, achieving near-unity detection probability even under severe clutter.

Keywords—ISAC, cell-free, MIMO, AP selection, detection probability.

I. INTRODUCTION

The integration of Cell-Free (CF) [1] architectures with Integrated Sensing and Communication (ISAC) functionalities has recently attracted increasing research interest due to its potential to enhance sensing reliability, spatial diversity, and target coverage [2]. However, the distributed nature of CF systems introduces new challenges regarding the coordination and selection of Access Points (APs) participating in sensing tasks.

Existing literature focuses heavily on optimization aspects like power control [3], spectral efficiency [4], or beamforming [5]. The few proposed selection strategies are often inherited from communication scenarios and rely on large-scale metrics [1], graph neural networks [6], or idealized channel conditions [7]. Consequently, they fail to capture the unique geometric and signal-level demands of target detection under non-ideal propagation. In our previous work [8], the effectiveness of utilizing a local short-term Signal-to-Noise Ratio (SNR) proxy for AP selection was established. However, that analysis was limited to clutter-free environments. Under realistic deployments, strong static reflections and localized environmental clutter can easily mask the target's response, rendering both large-scale fading statistics and pure clutter-free signal metrics misleading.

To bridge this critical gap, this work proposes the *Dynamic Angle and Signal-driven Association (DASA)* scheme, a novel two-step AP selection framework designed for distributed sensing in CF-ISAC systems under adversarial propagation

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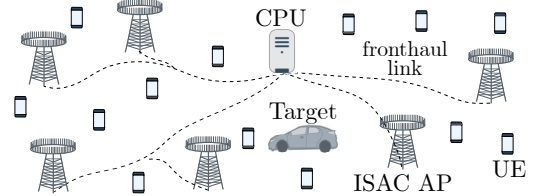


Fig. 1: CF-ISAC system representation.

conditions. The proposed approach is evaluated using the realistic 3GPP Urban Macrocell (UMa) channel model [9], which captures both line-of-sight (LOS) and non-line-of-sight (NLOS) propagation effects. DASA combines a post-convergence short-term SNR proxy, obtained from a local Modified Approximate Maximum a Posteriori Ratio Test (MAPRT) detector, with a geometric angular refinement stage. By jointly exploiting signal quality and spatial geometry, the proposed framework aims to provide robust AP selection in clutter-intensive sensing environments. Simulation results demonstrate that DASA successfully identifies and isolates blinded sensors, delivering superior robustness and scalable detection gains over state-of-the-art baselines that collapse under intense static reflections.

II. SYSTEM MODEL

We consider the CF-ISAC MIMO system represented in Fig. 1, operating in TDD with N_{tx} transmitting and N_{rx} sensing partly-informed APs. The APs serve N_{UE} users in the downlink while transmitting sensing signals toward the target. Reflected signals are collected by N_{rx} APs and forwarded to the CPU. Each AP is assumed to be perfectly synchronized and equipped with a uniform linear array (ULA) consisting of M half-wavelength-spaced antenna elements. The signal from the k -th AP at time t is $\mathbf{x}_k[t] \in \mathbb{C}^M$, as

$$\mathbf{x}_k[t] = \sum_{i=0}^{N_{UE}} \sqrt{\rho_i} \mathbf{w}_{i,k} s_i[t], \quad \text{for } k = 1, \dots, N_{tx}, \quad (1)$$

a linear combination of communication symbols, $s_i[t]$, a dedicated sensing symbol, $s_0[t]$, weighted by precoding vectors $\mathbf{w}_{i,k} \in \mathbb{C}^M$ and power allocation coefficients $\sqrt{\rho_i}$. Power control follows the Large-Scale Fading (LSF) model [1]. Under target-free conditions, the channel between the k -th transmitting and r -th sensing AP is assumed known to remove non-target signal components [7]. Thus, the signal at the r -th AP is

$$\mathbf{y}_r[t] = \sum_{k=1}^{N_{tx}} \sqrt{\beta_{r,k}} \alpha_{r,k} \mathbf{a}(\phi_r, \theta_r) \mathbf{a}^T(\varphi_t, \vartheta_t) \mathbf{x}_k[t] + \mathbf{v}_r[t] + \mathbf{n}_r[t], \quad (2)$$

with each AP collecting a sensing block of τ symbols. The noise is $\mathbf{n}_r[t] \sim \mathcal{CN}(\mathbf{0}, \sigma_n^2 \mathbf{I}_M)$. $\mathbf{v}_r[t] \sim \mathcal{CN}(\mathbf{0}, P_c g_r \mathbf{I}_M)$ is the clutter interference term with P_c denoting the base clutter power level, set to $P_c = \gamma \sigma_n^2$, where $\gamma \gg 1$ represents the clutter-to-noise ratio (CNR). The geometry-dependent clutter gain is given by $g_r = \exp\left(-\frac{\sin^2(\phi_r)}{\delta}\right)$, where ϕ_r is the elevation angle between the r -th and the target, and $\delta > 0$ is a shape parameter controlling the angular selectivity of the clutter. This model captures the well-known grazing-angle effect [10]: APs positioned at shallow angles relative to the ground ($\phi_r \approx 0^\circ$ or 180°) experience near-maximum clutter ($g_r \approx 1$) while APs with a broadside view of the target ($\phi_r \approx 90^\circ$) are largely unaffected ($g_r \approx 0$).

$\beta_{r,k}$ is the bi-static radar channel gain given by $\beta_{r,k} = \lambda^2 \sigma_{\text{RCS}}^2 / ((4\pi)^2 d_{\text{tx},k}^2 d_{\text{rx},r}^2)$ [10]. Following the Swerling-I model, $\alpha_{r,k} \sim \mathcal{CN}(0, \sigma_{\text{RCS}}^2)$ is the radar cross section (RCS) of the target, constant within each sensing block and Rayleigh-distributed in magnitude [10]. The azimuth and elevation angles from the target to receive AP r are ϕ_r and θ_r , with steering vector $\mathbf{a}(\phi_r, \theta_r) = [1 e^{j\pi \sin(\phi_r) \cos(\theta_r)} \dots e^{j(M-1)\pi \sin(\phi_r) \cos(\theta_r)}]$. Likewise, φ_t and ϑ_t denote the transmit-to-target angles [11].

To simplify notation, we collect the unknown RCS coefficients from all k APs into the vector $\boldsymbol{\alpha}_r \triangleq [\alpha_{r,1}, \dots, \alpha_{r,N_{tx}}]^T \in \mathbb{C}^{N_{tx}}$, and similarly, define the vector of scalars $\mathbf{c}_r[t] = [c_{r,1}, \dots, c_{r,N_{tx}}]^H \in \mathbb{C}^{N_{tx}}$. In addition, we define the scalars $c_{r,k}[t] \triangleq \sqrt{\beta_{r,k}} \mathbf{a}^T(\varphi_k, \vartheta_k) \mathbf{x}_k[t]$. Then $\mathbf{y}_r[t]$ can be rewritten as

$$\mathbf{y}_r[t] = \mathbf{a}(\phi_r, \theta_r) \mathbf{c}_r^H[t] \boldsymbol{\alpha}_r + \mathbf{v}_r[t] + \mathbf{n}_r[t]. \quad (3)$$

To reduce the fronthaul load, the CPU does not receive the scalars $\mathbf{c}_r[t]$, but only the statistics, so that $\mathbf{c}_r[t] \sim \mathcal{CN}(0, \mathbf{R}_r)$, where $\mathbf{R}_r$ denote the correlation matrix of $\mathbf{c}_r[t]$. The (k, p) -th entry $r_{r,kp}$ of the spatial correlation matrix can be derived as $r_{r,kp} = \sqrt{\beta_{r,k} \beta_{r,p}} \mathbf{a}^T(\varphi_k, \vartheta_k) \sum_{i=0}^{N_{\text{UE}}} \sqrt{\rho_i} \mathbf{w}_{i,k} \mathbf{w}_{i,p}^H \mathbf{a}^*(\varphi_p, \vartheta_p)$.

The effective noise-plus-clutter covariance at the r -th AP is therefore $\boldsymbol{\Sigma}_r = (\sigma_n^2 + P_c g_r) \mathbf{I}_M$ which replaces $\sigma_n^2 \mathbf{I}_M$ in the detector formulation. This spatially heterogeneous interference directly motivates the need for geometry-aware AP selection: a high channel gain $\beta_{r,k}$ does not guarantee effective sensing when $g_r \approx 1$ since the clutter can dominate the received signal even at strong APs.

As the communication and sensing symbols are independent, $\mathbb{E}\{s_i[t] s_j^*[t]\} = 0$, $i \neq j$, and otherwise $\mathbb{E}\{|s_i[t]|^2\} = 1$. The traditional approach for CF-ISAC Networks typically assumes centralized processing, where signals from the receivers are sent to the CPU. However, this methodology can result in excessive signalling overhead. Therefore, we adopt the distributed sensing approach presented in [7], known as the partially-informed MAPRT detector. To make this article self-contained, we will introduce the MAPRT detector before presenting our new AP selection metrics.

III. MAXIMUM A POSTERIORI RATIO TEST TARGET DETECTOR

To detect the target, each AP implements the MAPRT detector locally and performs the local test. In CF, these local

test statistics are then sent to the CPU for final decision making. Let $\mathcal{H}_0$ represent the hypotheses of absence and $\mathcal{H}_1$ the presence of the target. Thus, the set $\mathcal{H} \in \{\mathcal{H}_0, \mathcal{H}_1\}$ for receiver r is expressed as

$$\mathcal{H}_0 : \mathbf{y}_r^\tau = \mathbf{v}_r^\tau + \mathbf{n}_r^\tau \quad \text{and} \quad \mathcal{H}_1 : \mathbf{y}_r^\tau = \mathbf{g}_r^\tau + \mathbf{v}_r^\tau + \mathbf{n}_r^\tau, \quad (4)$$

where $\mathbf{y}_r^\tau$, $\mathbf{v}_r^\tau$, $\mathbf{n}_r^\tau$ and $\mathbf{g}_r^\tau \in \mathbb{C}^{M\tau}$ denote the concatenated vectors $\mathbf{y}_r[t]$, $\mathbf{v}_r[t]$, $\mathbf{n}_r[t]$, and $\mathbf{a}(\phi_r, \theta_r) \mathbf{c}_r^H[t] \boldsymbol{\alpha}_r$ at receive AP r through a sensing block τ , respectively.

In the partially-informed scenario, the receiving APs do not know the vector $\mathbf{c}_r[t]$. Thus, the goal is to estimate the test statistic T_r without the explicit knowledge of $\mathbf{c}_r[t]$, assuming a parametric model for signal reflection. Therefore, by maximizing the marginal likelihood with respect to the unknown variables $\boldsymbol{\alpha}_r$ and $\mathbf{c}_r[t]$, for $t = 1, \dots, \tau$, the local test statistic is expressed by:

$$\Lambda_r = \max_{\boldsymbol{\alpha}_r, \mathbf{c}_r[t]} \frac{p(\mathbf{y}_r^\tau | \boldsymbol{\alpha}_r, \mathbf{c}_r[t], \mathcal{H}_1) p(\boldsymbol{\alpha}_r | \mathcal{H}_1) p(\mathbf{c}_r[t] | \mathcal{H}_1)}{p(\mathbf{y}_r^\tau | \mathcal{H}_0)}, \quad (5)$$

where $p(\mathbf{y}_r^\tau | \boldsymbol{\alpha}_r, \mathcal{H}_1)$ is the likelihood term, $p(\boldsymbol{\alpha}_r | \mathcal{H}_1)$ is the prior term of $\boldsymbol{\alpha}_r$, given by the Swerling-I model and $p(\mathbf{c}_r[t]_{t=1}^\tau | \mathcal{H}_1)$ is the test statistic of $\mathbf{c}_r[t]$. (5) can be rewritten as a function of $\boldsymbol{\alpha}_r$:

$$\Lambda_r = \left(\frac{1}{\pi^{N_{tx}} \det(\mathbf{R}_r)} \right)^\tau \left(\frac{1}{\pi \sigma_{\text{RCS}}^2} \right)^{N_{tx}} \exp \left(-\frac{1}{\sigma_n^2} \min_{\boldsymbol{\alpha}_r, \mathbf{c}_r[t]} f(\boldsymbol{\alpha}_r, \mathbf{c}_r[t]) \right) \quad (6)$$

where

$$f(\boldsymbol{\alpha}_r, \mathbf{c}_r[t]) = \boldsymbol{\alpha}_r^H \left(M \sum_{t=1}^\tau \mathbf{c}_r[t] \mathbf{c}_r^H[t] + \mathbf{D}_r \right) \boldsymbol{\alpha}_r - 2 \Re \left\{ \boldsymbol{\alpha}_r^H \sum_{t=1}^\tau \mathbf{c}_r[t] \mathbf{a}_r^H \mathbf{y}_r[t] \right\} + \sigma^2 \sum_{t=1}^\tau \mathbf{c}_r^H[t] \mathbf{R}_r^{-1} \mathbf{c}_r[t], \quad (7)$$

$\mathbf{a}_r = \mathbf{a}(\phi_r, \theta_r)$ and $\mathbf{D}_r = \frac{\sigma_{\text{RCS}}^2}{\sigma_n^2 + P_c g_r} \mathbf{I}_{N_{tx}}$, where $P_c g_r$ is the geometry-dependent clutter power. To estimate $\boldsymbol{\alpha}_r$ and $\mathbf{c}_r[t]$ and solve the minimization problem, an iterative procedure based on alternating optimization is applied. Hence, we take the derivative of the function (7) with respect to $\boldsymbol{\alpha}_r$ and $\mathbf{c}_r[t]$. As a result, we have:

$$\hat{\mathbf{c}}_r[t](\hat{\boldsymbol{\alpha}}_r) = (M \hat{\boldsymbol{\alpha}}_r \hat{\boldsymbol{\alpha}}_r^H + \sigma_n^2 \mathbf{R}_r^{-1})^{-1} \hat{\boldsymbol{\alpha}}_r \mathbf{y}_r^H[t] \mathbf{a}_r^H \quad (8)$$

and

$$\hat{\boldsymbol{\alpha}}_r = \left(M \sum_{t=1}^\tau \hat{\mathbf{c}}_r[t] \hat{\mathbf{c}}_r^H[t] + \mathbf{D}_r \right)^{-1} \sum_{t=1}^\tau \hat{\mathbf{c}}_r[t] \mathbf{a}_r^H \mathbf{y}_r[t]. \quad (9)$$

Thus, the local test statistic at receive AP r , is obtained as $T_r = \ln \left[\left(\frac{1}{\pi^{N_{tx}} \det(\mathbf{R}_r)} \right)^\tau \left(\frac{1}{\pi \sigma_{\text{RCS}}^2} \right)^{N_{tx}} \left(-\frac{1}{\sigma_n^2} f(\hat{\boldsymbol{\alpha}}_r, \{\hat{\mathbf{c}}_r[t]\}) \right) \right]. \quad (10)$

As a common metric for an CF-ISAC detection, [7], [12] the final decision at the CPU is given by the summation of the local test statistics, as $T = \sum_{r=1}^{N_{rx}} T_r$.

The iterative algorithm at receive AP r [7], sets an arbitrary initial $\boldsymbol{\alpha}_r$ and a solution accuracy $\epsilon > 0$. Convergence

is declared when $|f_r^{\text{current}} - f_r^{\text{previous}}|^2 |f_r^{\text{current}}|^{-2} \leq \epsilon$. By leveraging the joint estimation of channel parameters and target RCS provided by the iterative detector, we derive specialized selection metrics to enhance the distributed sensing framework.

IV. PROPOSED DASA SCHEME AND STATE-OF-THE-ART BASELINES

Initially, the behavior of the baseline methods is investigated to establish a reference framework for the development and evaluation of the proposed technique. Each AP r first computes its local test statistic T_r from the received signal $\mathbf{y}_r$, which quantifies the scattered target energy. The AP selection schemes differ in the strategy used to select a subset of N_{sel} APs, whose local statistics T_r are forwarded and combined at the CPU for the final multi-static decision.

The first baseline scheme is *Random Selection (RS)*, which activates N_{sel} APs chosen uniformly at random from the available pool, without considering any sensing-quality criterion. This method serves as a lower-bound performance reference for the remaining strategies.

The second scheme, denoted *Smaller Distance (SD)*, leverages *a priori* knowledge of the network geometry. Based on the intuition that closer APs experience stronger channels, the selection criterion is the Euclidean distance between each AP and the known target position. This approach follows [7], where the CPU prioritizes the APs geographically closest to the target area.

To represent the state-of-the-art in joint radar and communication (JRC) user association, we consider a large-scale fading scheme with angular filtering, denoted *JRC*, inspired by the two-step framework in [13]. In the first step, APs are ranked based on their long-term LSF gain [1], approximated by $\text{tr}(\mathbf{R}_r)$, which represents the trace of the spatial covariance matrix at AP r . In the second step, a geometric filter excludes APs whose look angle ϕ_r falls outside a favorable bistatic sector, discarding shallow angles prone to elevated environmental clutter:

$$\mathcal{S}_{\text{JRC}} = \{r : \phi_r \in [\phi_{\text{th}}, 180^\circ - \phi_{\text{th}}]\}, \quad (11)$$

where the threshold is fixed at $\phi_{\text{th}} = 20^\circ$.

A. The Proposed DASA Scheme

While the JRC scheme provides solid geometric filtering, its initial tiering relies on LSF, a long-term metric that is inherently blind to local, instantaneous environmental clutter. To overcome this limitation in clutter-intensive scenarios, we propose the DASA scheme.

DASA reformulates the two-step selection process by replacing the long-term LSF ranking with a dynamic, short-term SNR proxy, defined as the ratio between the local MAPRT test statistic and its converged optimization cost, (T_r/f_r) . The underlying principle is that $\mathcal{M}_r$ acts as an anomaly-aware metric that captures signal integrity more comprehensively than raw energy. While T_r quantifies the captured reflected energy, the denominator f_r serves as a reliable indicator of model-fitting accuracy. In clutter-intensive scenarios, f_r

tends to increase significantly when the local detector fails to reconcile the received signal with the expected target model due to intense static reflections. Consequently, $\mathcal{M}_r$ effectively penalizes and filters out blinded APs that, despite having high channel gains, offer unreliable sensing data. The operation of DASA is structured as follows:

- **Stage 1 (Signal-Driven Screening):** Instead of selecting APs based on geographic proximity or average channel gains, the CPU ranks all available APs in descending order according to their instantaneous local detection SNR. This stage acts as an anomaly filter, immediately penalizing APs that are locally blinded by intense, static clutter reflections, which cause the denominator f_r to explode. The APs are thus arranged into a ranked candidate list $\mathcal{A}_{\text{init}}$, ordered by decreasing instantaneous SNR.
- **Stage 2 (Angular Refinement):** The CPU traverses $\mathcal{A}_{\text{init}}$ sequentially, admitting each AP into the final cluster only if its bistatic angle satisfies ϕ_{th} from [13], until N_{sel} APs are selected. This ensures that the final cluster possesses both high-integrity signal returns and robust angular diversity for multi-static target triangulation. Given the network density ($N_{\text{aps}} = 20$) and the wide angular sector allowed by (11), N_{sel} is consistently met in our evaluations; otherwise, the CPU would proceed with all available verified APs in $\mathcal{I}_{\text{verified}}$ for data fusion.

A target is declared present if the fused statistic T_{final} exceeds a threshold, which is numerically calibrated under H_0 to ensure the desired P_{fa} . The procedure is described in Algorithm 1.

V. NUMERICAL RESULTS

In this section, we evaluate the performance of the proposed DASA scheme alongside the state-of-the-art baselines through Monte Carlo simulations. The simulated CF-ISAC network covers a 500×500 m area where $N_{\text{tx}} = N_{\text{rx}} = 20$ APs are uniformly and randomly deployed, with a sensing target positioned at the coordinates center. User equipments (UEs) are also randomly distributed across the area.

The large-scale propagation effects, including LOS and NLOS transitions, follow the 3GPP UMa shadowing model [9], while the communication links experience independent and identically distributed (i.i.d.) Rayleigh fading. Power control is implemented based on the long-term LSF model [1]. Unless stated otherwise, the operational parameters are configured as follows: carrier frequency of 1.9 GHz, bandwidth of 20 MHz, antenna gain of 10 dBi, noise variance of -94 dBm, and a maximum AP transmit power of 1 W. The local detection thresholds are adjusted to ensure a constant $P_{\text{fa}} = 0.1$, with block lengths, $\tau = 100$, and $M = 4$ antennas per AP.

A. Detection Probability in Clutter-Free Environments

Fig. 2 evaluates P_d versus target RCS (σ_{RCS}^2) in a clutter-free environment for $N_{\text{sel}} = 4$. In this baseline scenario, the pure SNR metric achieves the highest detection sensitivity ($P_d \approx 1$ at the lowest RCS) and validating its signal-driven ranking. The conventional JRC scheme [13] closely follows, outperforming the geometry-based SD and the lower-bound

Algorithm 1 CPU Access Point Selection Process

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1: Inputs:  $N_{\text{aps}}, N_{\text{sel}}, N_{\text{cand}}$  (where  $N_{\text{cand}} > N_{\text{sel}}$ ),  $\phi_{\text{th}}$ ,
    $\{\mathbf{Y}_r, \mathbf{R}_r, \phi_r\}_{r=1}^{N_{\text{aps}}}$ ,  $\sigma_{\text{RCS}}^2, \sigma_n^2$ 
2: Step 1: Local Sensing and SNR Estimation at all APs
3: for  $r = 1 \rightarrow N_{\text{aps}}$  do
4:   Initialization: For receive AP  $r$ , set an initial random  $\alpha_r^{(0)}$ , convergence
     tolerance  $\epsilon = 10^{-5}$ , iteration counter  $i = 1$ , initial cost function
      $f_r^{(0)} = 10^5$ , and  $f_r^{(i)}$  as in (7).
5:   while  $|f_r^{(i)} - f_r^{(i-1)}|^2 |f_r^{(i)}|^{-2} > \epsilon$  do
6:     Compute  $\hat{\mathbf{c}}_r^{(i)}[t] \forall t \in \tau$  as in (8), keeping  $\hat{\alpha}_r^{(i-1)}$  constant
7:     Compute  $\hat{\alpha}_r^{(i)}$  as in (9), keeping  $\hat{\mathbf{c}}_r^{(i)}[t] \forall t \in \tau$  constant
8:     Update  $f_r^{(i)}$  as in (7)
9:     Update  $i \leftarrow i + 1$ 
10:  end while
11:  Compute local test statistic  $T_r$  as given by (10)
12:  Compute instantaneous local sensing SNR metric:  $\mathcal{M}_r \leftarrow T_r / f_r^{(i)}$ 
13: end for
14: Step 2: Two-Step Selection Framework at CPU (DASA)
    $\triangleright$  Stage 1: Signal-Driven Screening
15:  $\mathcal{A}_{\text{init}} \leftarrow \text{argsort}(\mathcal{M}, \text{'descend'})[1 : N_{\text{cand}}]$ 
    $\triangleright$  Stage 2: Angular Refinement (JRC Filtering)
16: Initialize verified group:  $\mathcal{I}_{\text{verified}} \leftarrow \emptyset$ 
17: for each  $r \in \mathcal{A}_{\text{init}}$  do
18:   if  $\phi_r \in [\phi_{\text{th}}, 180^\circ - \phi_{\text{th}}]$  then
19:      $\mathcal{I}_{\text{verified}} \leftarrow \mathcal{I}_{\text{verified}} \cup \{r\}$ 
20:   end for
    $\triangleright$  Final Cluster Sizing
21:  $\mathcal{I}_{\text{selected}} \leftarrow \text{Sort } \mathcal{I}_{\text{verified}} \text{ by } \mathcal{M} \text{ in descending order}[1 : N_{\text{sel}}]$ 
22: Step 3: Data Fusion and Final Decision
23:  $T_{\text{final}} \leftarrow \sum_{r \in \mathcal{I}_{\text{selected}}} T_r$ 
24: Output:  $T_{\text{final}} \triangleright$  Final multi-static test statistic for threshold comparison
    
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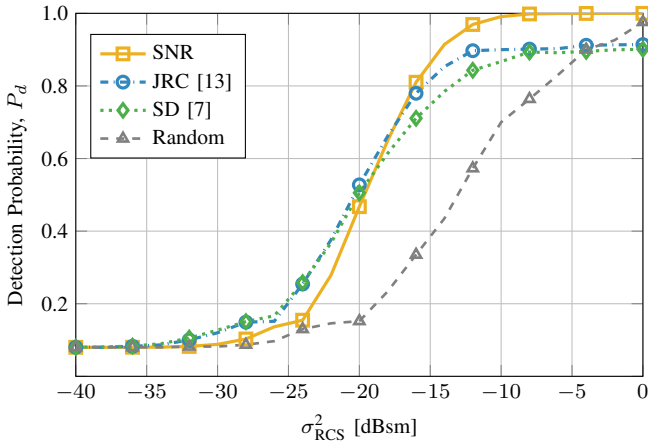


Fig. 2: Detection probability vs. target RCS under UMa channel model without clutter. Comparison of selection metrics with $N_{\text{sel}} = 4$.

RS. These results confirm that the short-term SNR proxy is inherently more informative than the long-term LSF, as it directly captures the local MAPRT model-fitting accuracy rather than a coarse average channel gain. Accordingly, DASA leverages this precise signal screening while retaining the geometrically sound angular filter from JRC ($\phi_{\text{th}} = 20^\circ$) to establish a robust foundation for more challenging, cluttered environments.

B. Detection Probability under Environmental Clutter

To rigorously test the scalability and resilience of the network, we inject localized static clutter into the environment, parameterized by the clutter-to-noise ratio (CNR) $\gamma \in \{50, 100, 500\}$. Fig. 3(a) illustrates the system performance under a constrained cluster size of $N_{\text{sel}} = 4$, featuring the proposed DASA, the conventional JRC [13], and the geometry-based SD baseline. Due to the presence of intense static reflections, the SD method performs extremely poorly across all clutter regimes, as its reliance on pure geometric distances makes it entirely blind to local clutter hotspots.

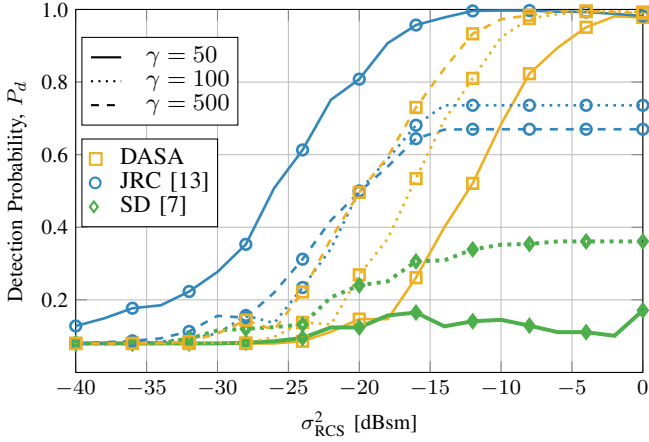
As the clutter intensity γ escalates, the performance gap between DASA and JRC widens drastically. DASA demonstrates resilience, maintaining near-unity P_d curves even at $\gamma = 500$. Conversely, the state-of-the-art JRC scheme experiences severe degradation, showcasing a pronounced performance drop at higher RCS regimes. This drop exposes the flaw of relying on long-term LSF rankings in cluttered environments; APs with strong average channel gains are often selected despite being completely blinded by instantaneous static reflections. Because DASA operates on the short-term local SNR proxy (T_r/f_r) computed after MAPRT convergence, it immediately penalizes blinded APs (where the optimization cost f_r explodes), successfully filtering them out during its initial screening stage. Due to its prohibitive degradation, the SD baseline is omitted in subsequent scalability analyses.

Comparing Fig. 3(a) with Fig. 3(b) and Fig. 3(c) reveals that increasing N_{sel} up to 10 yields diminishing performance returns for both schemes, demonstrating a spatial diversity saturation point. For DASA, expanding the cluster excessively forces the inclusion of uninformative, low-SNR APs that inject more noise variance than signal energy into the central decision, a phenomenon aligned with noise accumulation in distributed detection [14] and cluster limitations in user-centric communications [15]. Consequently, comparing the results of Fig. 3(b) and Fig. 3(c), the detection gains achieved are marginal, suggesting that operating the network at $N_{\text{sel}} = 8$ optimally balances distributed sensing accuracy with strict constraints on fronthaul signaling load and edge computational overhead.

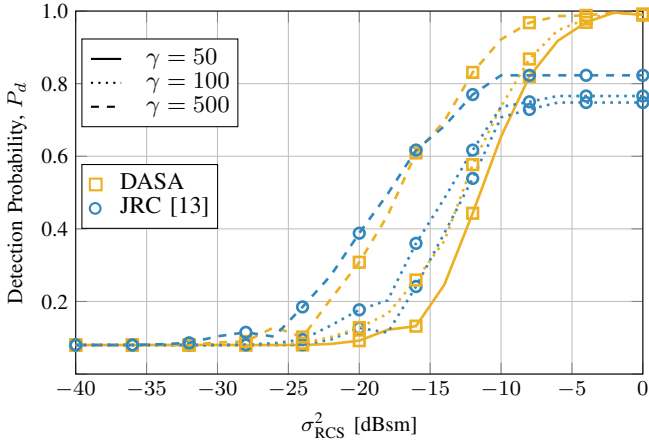
C. Computational cost and trade-offs

Regarding computational complexity, DASA shifts the local optimization framework from a post-selection execution to a distributed pre-screening stage at the network edge. Notably, both DASA and the conventional JRC baseline [13] share the exact same physical-layer channel estimation overhead, as both require computing channel correlation matrices to extract spatial statistics. The distinction lies in the orchestration: while JRC utilizes these large-scale metrics to restrict the iterative MAPRT local detector execution to a pre-selected cluster of size N_{sel} , DASA requires all available APs to run the local optimization to extract their instantaneous SNR metrics. Nevertheless, DASA's CPU-side coordination overhead remains negligible, restricted to simple sorting and linear angular filtering. This localized edge processing is fully justified by

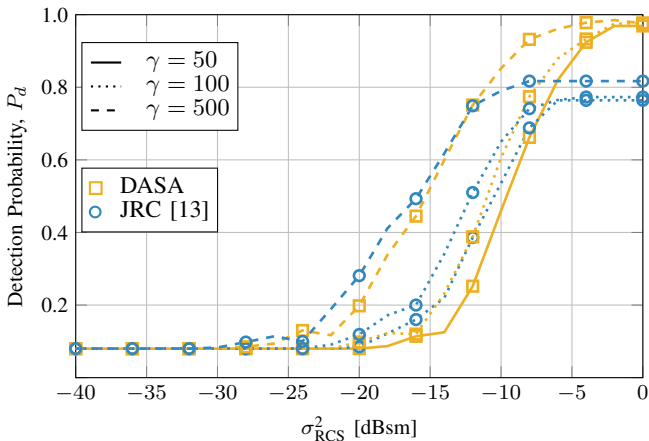
the massive detection robustness gains and subsequent fronthaul signaling savings, effectively preventing clutter-blinded sensors from corrupting the central data fusion center.



(a) $N_{sel} = 4$.



(b) $N_{sel} = 8$.



(c) $N_{sel} = 10$.

Fig. 3: Detection probability vs. target RCS under UMA channel model with different clutter values. Comparison of selection metrics with (a) $N_{sel} = 4$, (b) $N_{sel} = 8$, and (c) $N_{sel} = 10$.

VI. CONCLUSION

This paper evaluated AP selection for distributed sensing in CF-ISAC networks under a realistic 3GPP UMa channel model with geometry-dependent clutter. We introduced the two-step DASA scheme, which combines local instantaneous SNR screening with angular JRC filtering. Numerical results demonstrated that DASA consistently outperforms RS, SD, and conventional JRC baselines across all clutter severity levels, maintaining near-unity detection probability where competing methods severely degrade due to intense static reflections. Furthermore, our scalability analysis revealed a spatial diversity saturation point beyond $N_{sel} = 8$ APs, proving that a moderate cluster size balances detection accuracy with reduced fronthaul signaling and edge computational overhead. These findings confirm that sensing-oriented AP selection in realistic deployment scenarios must prioritize post-convergence signal-integrity metrics over coarse large-scale statistics. Future work will extend this framework to dynamic clutter environments and joint user-target association.

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