Adaptive Resource Allocation for Multistatic ISAC UAV Detection and Tracking in Congested RF Environments

Cole Dickerson, Wahab Khawaja, Ismail Guvenc
North Carolina State University
Department of Electrical and Computer Engineering

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Motivation and Problem

- UAV presence near critical infrastructure is growing
- Conventional approaches for sensing drones have shortcoming
- Need robust, **multi-modal** tracking that works in real deployment

T. Prevot, J. Rios, P. Kopardekar, J. R. III, M. Johnson, and J. Jung, "**UAS traffic management (UTM) concept of operations to safely enable low altitude flight operations**," in *AIAA Aviation Forum*, Jun. 2016.

Approaches for Sensing Drones

Detection Technique	Advantages	Disadvantages
Ambient RF signals (e.g., [4, 6])	Low-cost RF sensors (e.g., SDRs), works in NLOS, long detection range. May allow deuthentication attacks for taking control of drone by mimicking a remote controller or spoofing GPS signal.	Need prior training to identify/classify different drones. Fails for fully/partially autonomous drone flights due to no/limited signal radiation from a drone/controller.
Radar (e.g., [7–10])	Low-cost FMCW radars, does not get affected from fog/clouds/dust as opposed to vision based techniques, can work in NLOS (more sophisticated). Higher (mmWave) frequencies allow capturing micro-Doppler/range accurately at the cost of higher path loss. Does not require active transmission from the drone.	Small RCS of drone makes identification/classification difficult. Further research needed for accurate drone detection/classification and machine learning techniques, considering different radar/drone geometries and different drone types which all affect micro-Doppler signatures. Higher path loss at mmWave bands limits drone detection range.
Acoustic signals (e.g., [11–13])	Low cost for simple microphones (cost depends on the quality of microphones). Can work in NLOS as long as the drone is audible.	Need to develop database of acoustic signature for different drones. Knowledge of current wind conditions and background noise is needed. May operate poorly under high ambient noise such as in urban environments.
Computer vision (e.g., [9, 14, 15])	Low cost for basic optical sensors. Pervasive availability of cameras even at most commercial drones that can be used as sensors.	Higher cost for thermal, laser-based, and wide FOV cameras. Requires LOS. Level of visibility impacted by fog, clouds, dust.
Sensor fusion (e.g., [9, 15])	Can combine advantages of multiple different techniques for wider application scenario, high detection accuracy, and long-distance operation.	Higher cost and processing complexity. Need effective sensor fusion algorithms.

Table 1. Comparison of advantages/disadvantages for different drone detection and tracking techniques.

I. Guvenc, F. Koohifar, S. Singh, M. L. Sichitiu and D. Matolak, "Detection, Tracking, and Interdiction for Amateur Drones," in *IEEE Communications Magazine*, vol. 56, no. 4, pp. 75-81, April 2018

Why Cellular ISAC?

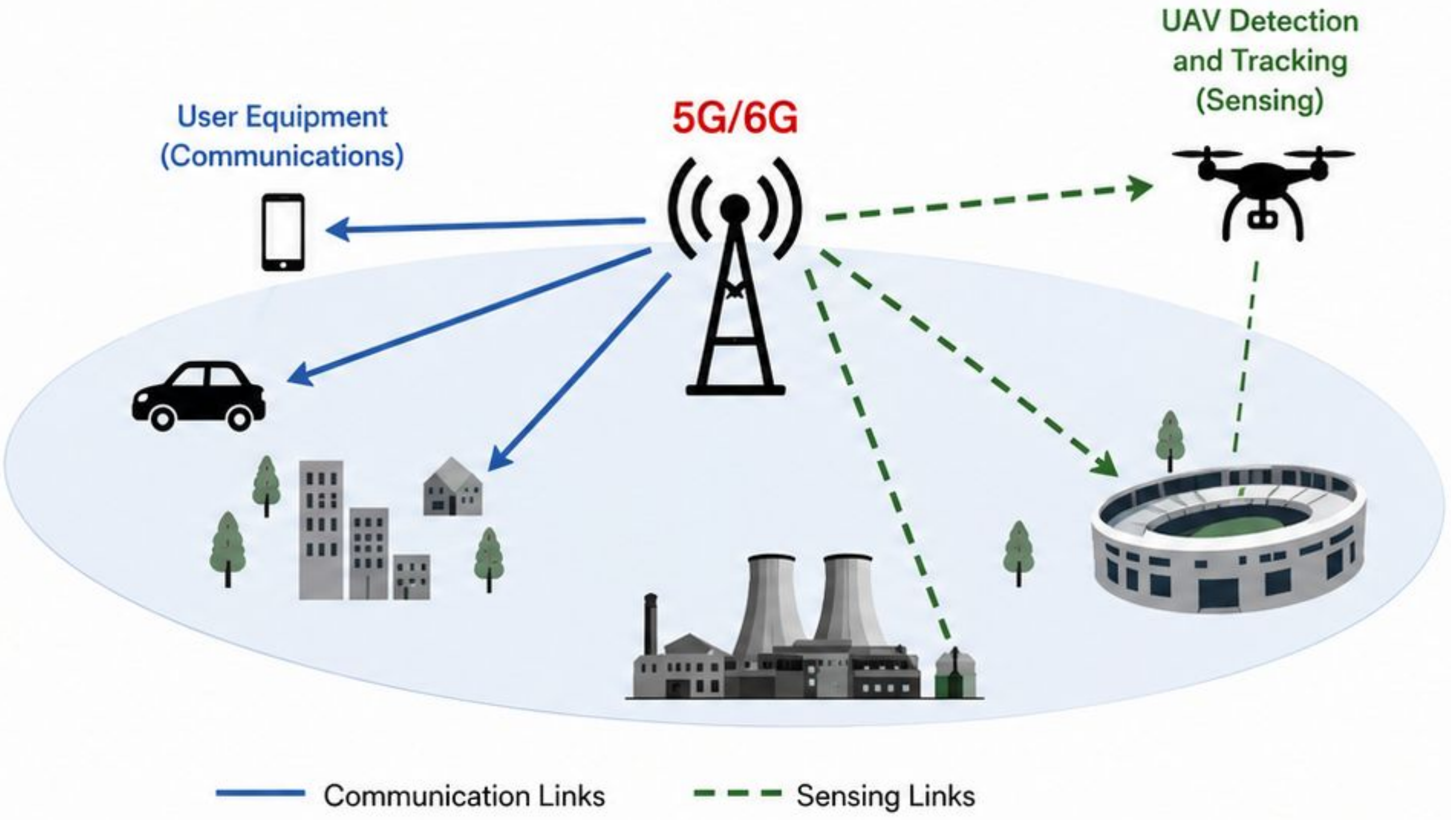
Cellular networks provide a compelling platform for integrated sensing and communications.

Ubiquitous Infrastructure
Leverages existing 5G/6G base stations for wide-area coverage.

Dual Functionality
Simultaneously supports communication for users and sensing of the environment.

Cost and Deployment Efficiency
Reuses spectrum, hardware, and backhaul —no need for dedicated sensing networks.

Built on Standards with Scalability Potential
Built on 3GPP standards with a path toward native 6G sensing capabilities.



Result: Cellular ISAC enables scalable, cost-effective, and spectrum-efficient UAV surveillance while maintaining high-quality communication services.

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Core Challenge: The Resource Allocation Problem

We must allocate limited time-frequency resources between **communication** and **sensing** under dynamic load.

Key Points

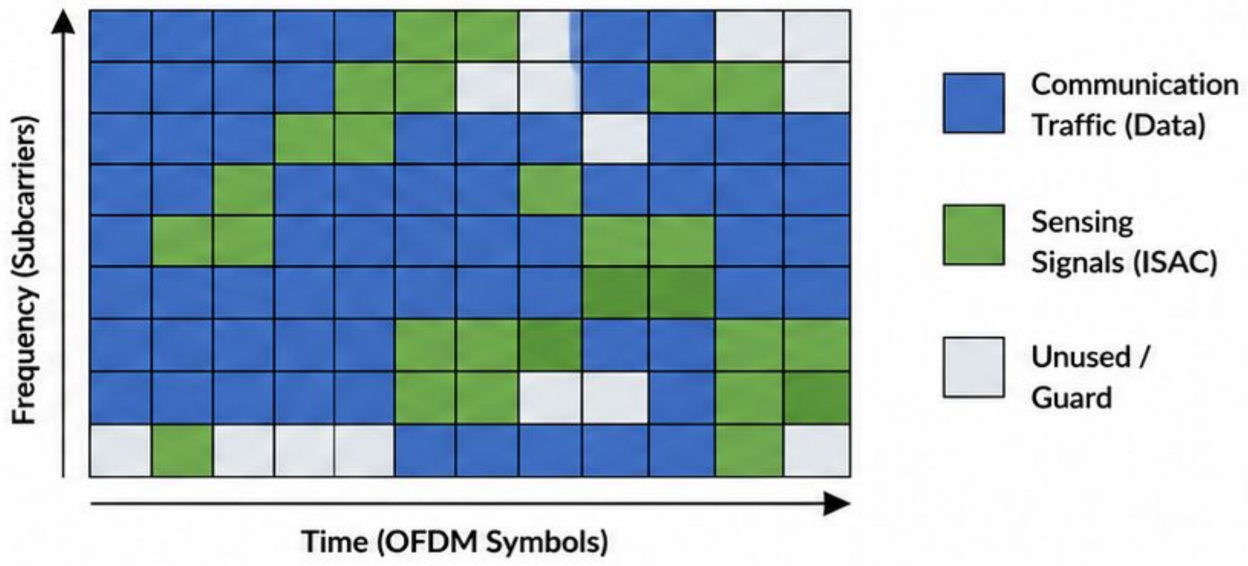
Sensing consumes time-frequency resources
Sensing transmissions occupy PRBs that could be used for communication.

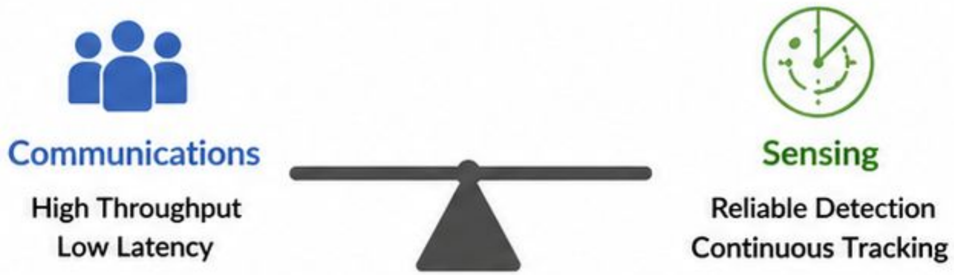
Traffic load changes over time
Network demand is highly dynamic, varying across time and frequency.

Static sensing reservation is inefficient
Fixed allocations waste resources during low load and limit sensing during high load.

Need adaptive policies
Allocate resources intelligently to balance throughput and sensing performance.

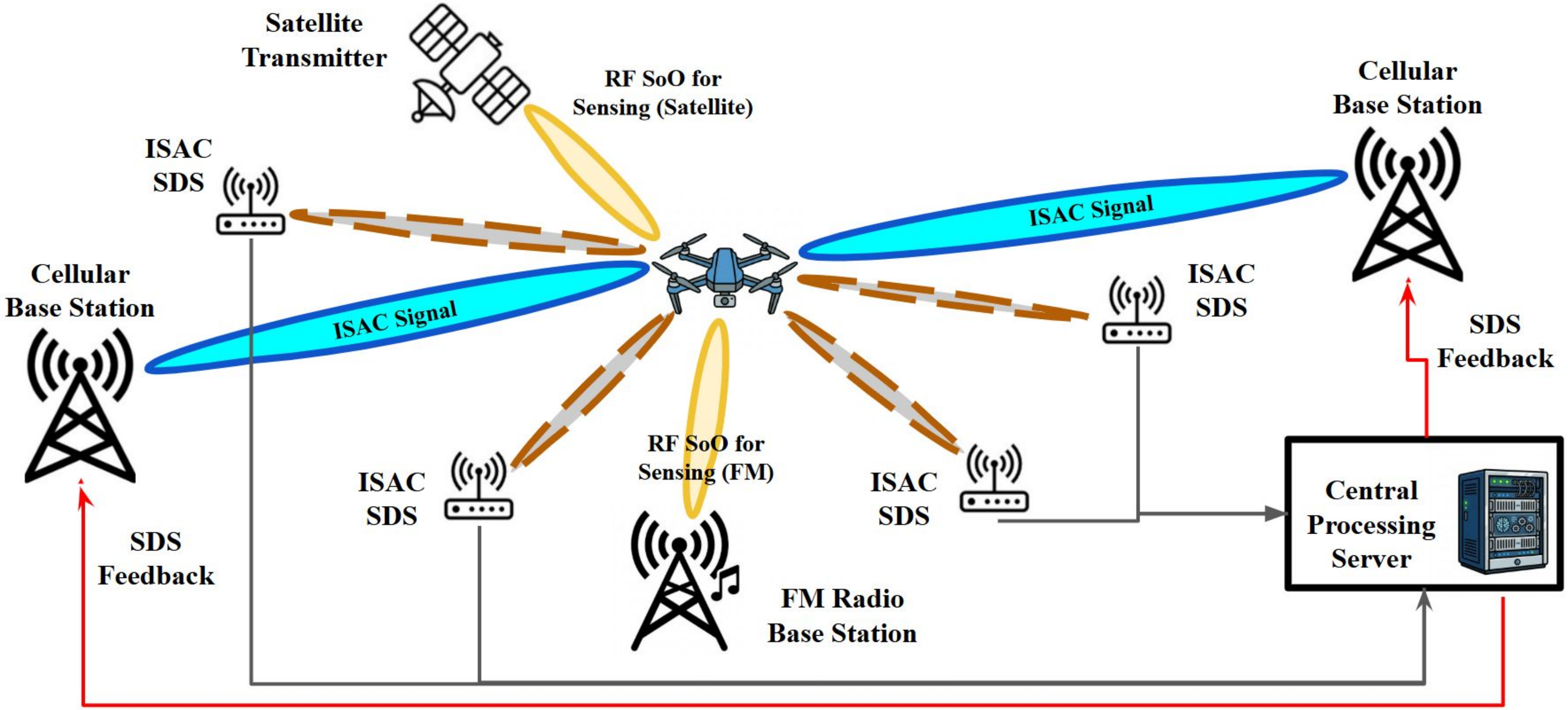
Example: PRB Grid at a Given Time





How much sensing should we allocate when the network is already busy?

Proposed Multistatic Architecture



Two Sensing Modes: Active + Passive Sensing

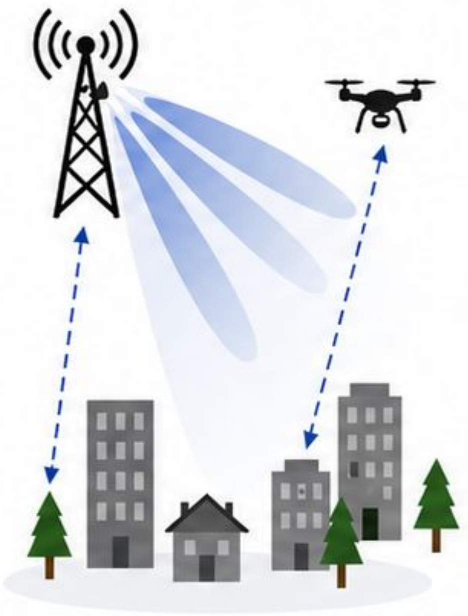
Our framework combines active sensing from the network with passive sensing from distributed sensors for resilient UAV detection and tracking.

Active Sensing (gNB)

Controlled Waveform
The gNB transmits dedicated sensing signals using designed waveforms (e.g., Zadoff–Chu).

Beamforming
Directional transmission focuses energy toward regions of interest to improve detection.

Adaptive Updates
Sensing resources (time, frequency, beams) are adapted based on network load and sensing needs.



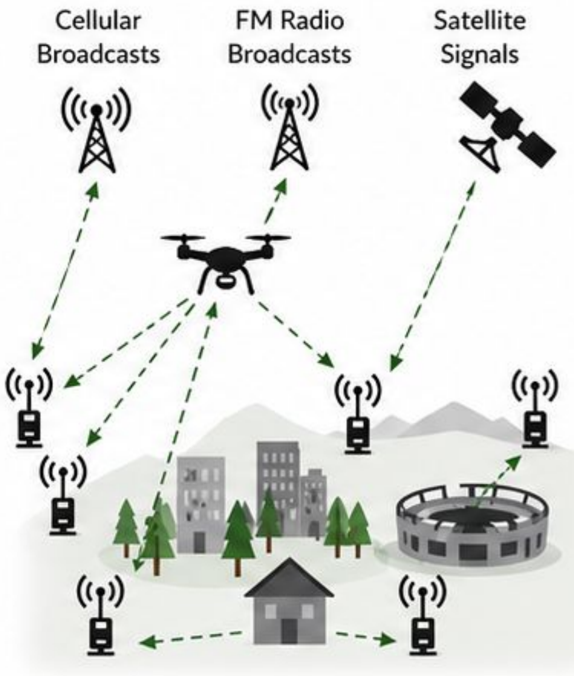
Active sensing provides high-quality measurements when resources are available.

Passive Sensing (SDS)

No Transmission Required
SDS nodes do not transmit; they only listen to ambient RF signals.

Uses Signals of Opportunity
Leverages existing broadcasts (e.g., cellular, FM, satellite) illuminating the environment.

Helps During Congestion
Provides supplemental sensing when network resources are limited or heavily loaded.



Passive sensing extends coverage and preserves awareness when active sensing becomes expensive.

Passive support preserves awareness when active sensing becomes expensive.

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SDS Coordination and Sensing Operations

The network coordinates Distributed ISAC Sensors (SDSs) by broadcasting system information and enabling efficient, wideband sensing operations.

1) SDS Hardware Configurations

SDSs may adopt different antenna architectures to perform sensing.

1 Antenna Switching based ISAC SDS

- Switched multi-antenna architecture
- Low-cost, energy efficient

2 Phased Array based ISAC SDS

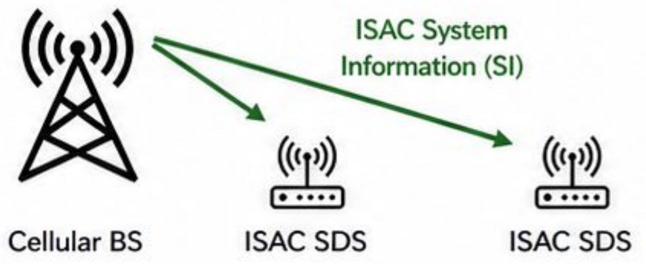
- Electronic beam steering
- Fast beam agility and higher gain

3 Rotational Antenna ISAC SDS

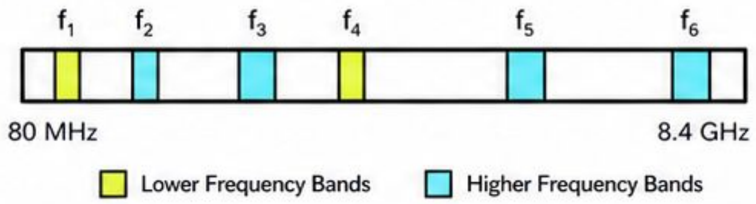
- Mechanical rotation (gimbal)
- 360° coverage capability

2) SDS Coordination via System Information (SI)

The cellular base station (gNB) periodically broadcasts ISAC system information to all SDSs within coverage.



Example: Bands to Scan (Advertised via SI)



SDSs use the advertised bands and operating parameters to perform sensing autonomously and coherently with the network.

3) ISAC SI Message Formats by Overhead Levels

SI Format	Field	Bits	Logic & Description
Low Overhead	Priority Level	8	1-bit per band (0: Off, 1: On)
	Total	**8**	Minimal overhead
Medium Overhead	Priority Level	16	2-bits per band (4 tiers of scheduling)
	UAV Loc. (Coarse)	12	6-bit Azimuth, 6-bit Elevation with respect to this BS
	Total	**28**	Directional tracking with coarse spatial data
High Overhead	Priority Level	24	3-bits per band (8 tiers of scheduling)
	UAV Loc. (Fine)	24	12-bit azimuth, 12-bit elevation with respect to this BS (or coarse tracking of 2 UAVs)
	Precoding Index	12	BS transmit Precoding Matrix Index (PMI)
	Total	**60**	Precision coherent multistatic sensing

Coordinated SDSs enable scalable, wideband, and efficient sensing across the network.

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Adaptive Waveform Design for Efficient ISAC Sensing

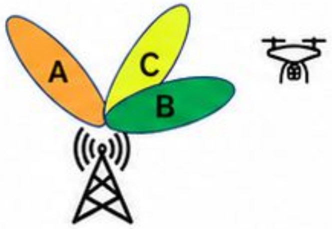
We adapt sensing beams, PRB allocation, and Zadoff–Chu waveforms to balance detection performance, resource efficiency, and coexistence with communications.

1) Adaptive Sensing Strategy

Two-stage sensing approach

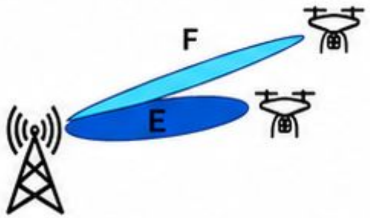
(a) Coarse Discovery

Use smaller bandwidth beams to scan wide area and discover potential UAVs.



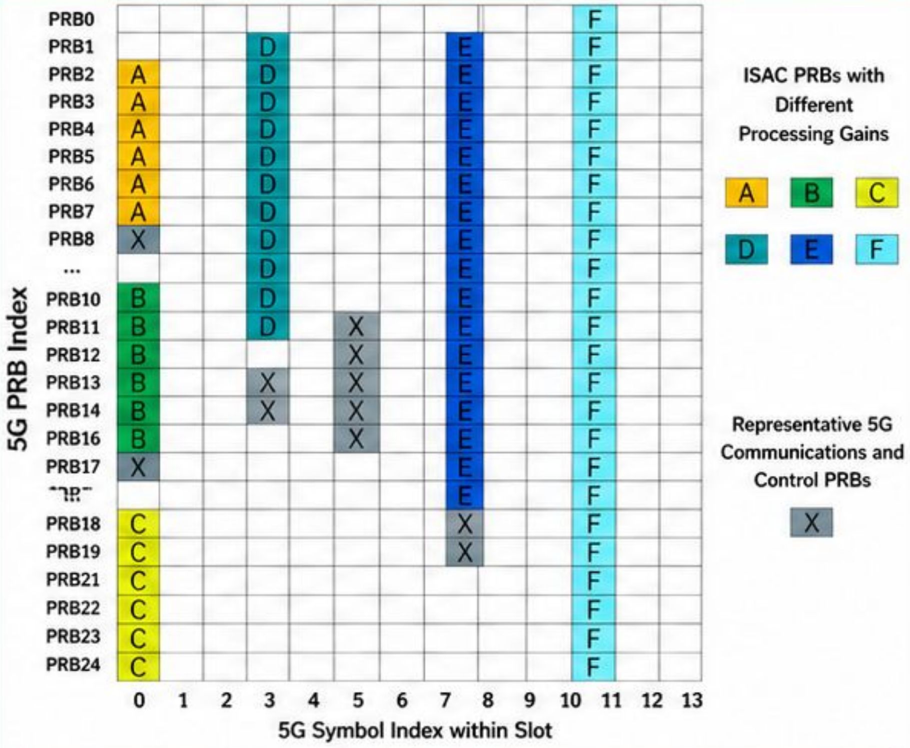
(b) Precision Tracking

Use narrower, higher gain beams to track and localize UAVs with high accuracy.



Start wide, then focus: adapt beams to improve efficiency and tracking accuracy.

2) Adaptive PRB Allocation in 5G NR



Higher gain PRBs (narrower bandwidth) are used for tracking (E, F), while lower gain PRBs are used for discovery (A–C). Communications and control PRBs (X) are protected.

3) Zadoff–Chu Waveform Design

Zadoff–Chu (ZC) Sequence

We use Zadoff–Chu sequences:

$$x_u(n) = \exp\left(-j\,\frac{\pi u n (n + d_{\mathrm{mod}})}{N_{ZC}}\right), \quad 0 \le n < N_{ZC}$$

where u is the root index, n is the sample index, and d_{mod} is a cyclic shift.

Choose sequence length N_{ZC} to maximize processing gain

Sequence Length (N_{ZC})	PRBs Required	Total Subcarriers	Wasted SCs (ω)	Gain (dB)
71	6	72	1	18.5
139	12	144	5	21.4
211	18	216	5	23.2
283	24	288	5	24.5
419	35	420	1	26.2
503	42	504	1	27.0
631	53	636	5	28.0
839	70	840	1	29.2
1063	89	1068	5	30.3
1291	108	1296	5	31.1

Larger sequence lengths → higher processing gain, but require more PRBs and may waste subcarriers. We adapt N_{ZC} to balance gain and overhead.

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Adaptive beams + smart PRB allocation + optimal Zadoff–Chu waveforms = efficient, accurate, and network-friendly ISAC sensing.

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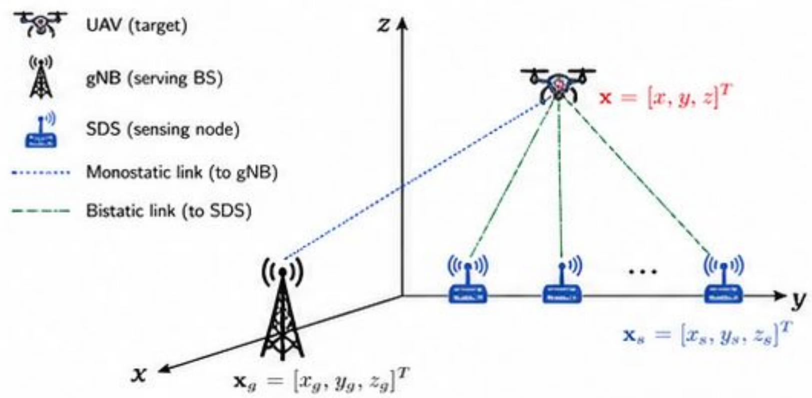
Geometry Model and CRLB Analysis

We model a 3D ISAC surveillance scenario with one UAV, one serving gNB, and N SDSs, and derive the Cramér–Rao Lower Bound (CRLB) to benchmark localization accuracy.

1) Geometry Model



Definitions

- Unknown UAV position: $\mathbf{x} = [x, y, z]^T$, estimate: $\hat{\mathbf{x}} = [\hat{x}, \hat{y}, \hat{z}]^T$
- gNB position (known): $\mathbf{x}_g = [x_g, y_g, z_g]^T$
- i-th SDS position (known): $\mathbf{x}_i = [x, y_i, z_i]^T$, $i = 1, \dots, N$
- One-way UAV–gNB range: $d_g \triangleq \|\mathbf{x} - \mathbf{x}_g\|_2$
- UAV–i-th SDS range: $d_i \triangleq \|\mathbf{x} - \mathbf{x}_i\|_2$
- For node at $\mathbf{x}_s$, define: $\Delta x_s = \mathbf{x} - \mathbf{x}_s$, $\Delta y_s = y - y_s$, $\Delta z_s = z - z_s$
  $\rho_s = \sqrt{\Delta x_z^2 + \Delta y_z^2}$, $r_s = \sqrt{\Delta x_z^2 + \Delta y_z^2 + \Delta z_z^2}$
- Azimuth: $\theta = \arctan2(\Delta y_s, \Delta x_s)$, Elevation: $\phi = \arctan2(\Delta z_s, \rho_s)$
- Monostatic (gNB): observing node $\mathbf{x}_s = \mathbf{x}_g$, range $r = d_g$
- Bistatic (i-th SDS): observing node $\mathbf{x}_s = \mathbf{x}_i$, range $r = d_g + d_i$

2) Measurement Model

Generalized observation model

$$\mathbf{z} = \mathbf{h}(\mathbf{x}) + \mathbf{n}$$

- $\mathbf{z} = [z_r, z_\theta, z_g]^T$: observed measurement vector
- $\mathbf{h}(\mathbf{x}) = [r, \theta, \phi]^T$: noiseless measurement vector
- $\mathbf{n} = [n_r, n_\theta, n_\phi]^T$: measurement noise
- $\mathbf{n} \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$: zero-mean Gaussian noise
- $\mathbf{R}$ depends on sensing link:
  - Monostatic: $\mathbf{R}_m$ (gNB)
  - Bistatic: $\mathbf{R}_{b,i}$ (i-th SDS)

Measurement functions h(x)

Monostatic (gNB) $\mathbf{x}_s = \mathbf{x}_g$

$$\mathbf{h}_m(\mathbf{x}) = \begin{bmatrix} r \\ \theta \\ \phi \end{bmatrix} = \begin{bmatrix} d_g \\ \arctan2(\Delta y_g, \Delta x_g) \\ \arctan2(\Delta z_g, \rho_g) \end{bmatrix}$$

Bistatic (i-th SDS) $\mathbf{x}_s = \mathbf{x}_i$

$$\mathbf{h}_{b,i}(\mathbf{x}) = \begin{bmatrix} r \\ \theta \\ \phi \end{bmatrix} = \begin{bmatrix} d_g + d_i \\ \arctan2(\Delta y_i, \Delta x_i) \\ \arctan2(\Delta z_i, \rho_i) \end{bmatrix}$$

Per-node covariance

Under independent Gaussian measurement errors,

$$\mathbf{R}_i = \mathrm{diag}(\sigma_{r,i}^2, \sigma_{\theta,i}^2, \sigma_{\phi,i}^2)$$

where $\sigma_{r,i}^2, \sigma_{\theta,i}^2, \sigma_{\phi,i}^2$ are the variances of range, azimuth, and elevation errors, respectively.

3) CRLB Analysis Framework

Fisher Information Matrix (FIM)

$$\mathbf{J}(\mathbf{x}) = \mathbf{H}^T(\mathbf{x})\mathbf{R}^{-1}\mathbf{H}(\mathbf{x}),$$

where $\mathbf{H}(\mathbf{x}) = \frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}}$ is the Jacobian matrix.

Jacobian – Monostatic (gNB)

$$\mathbf{H}_m(\mathbf{x}) = \begin{bmatrix} \frac{\partial r_g}{\partial x} & \frac{\partial r_g}{\partial y} & \frac{\partial r_g}{\partial z} \\ \frac{\partial \theta_g}{\partial x} & \frac{\partial \theta_g}{\partial y} & \frac{\partial \theta_g}{\partial z} \\ \frac{\partial \phi_g}{\partial x} & \frac{\partial \phi_g}{\partial y} & \frac{\partial \phi_g}{\partial z} \end{bmatrix} = \begin{bmatrix} \frac{\Delta x_g}{r_g} & \frac{\Delta y_g}{r_g} & \frac{\Delta z_g}{r_g} \\ -\frac{\Delta y_g}{\rho_g^2} & \frac{\Delta x_g}{\rho_g^2} & 0 \\ -\frac{\Delta x_g \Delta z_g}{r_g^2 \rho_g} & -\frac{\Delta y_g \Delta z_g}{r_g^2 \rho_g} & \frac{\rho_g}{r_g^2} \end{bmatrix}.$$

Jacobian – Bistatic (i-th SDS)

$$\mathbf{H}_{b,i}(\mathbf{x}) = \begin{bmatrix} \frac{\partial r_{b,i}}{\partial x} & \frac{\partial r_{b,i}}{\partial y} & \frac{\partial r_{b,i}}{\partial z} \\ \frac{\partial \theta_g}{\partial x} & \frac{\partial \theta_g}{\partial y} & \frac{\partial \theta_s}{\partial z} \\ \frac{\partial \phi_s}{\partial x} & \frac{\partial \phi_s}{\partial y} & \frac{\partial \phi_g}{\partial z} \end{bmatrix} = \begin{bmatrix} \frac{x - x_g}{d_g} + \frac{x - x_i}{d_i} & \frac{y - y_g}{d_g} + \frac{y - y_i}{d_i} & \frac{z - z_g}{d_g} + \frac{z - z_i}{d_i} \\ -\frac{\Delta y_g}{\rho_g^2} & \frac{\Delta x_i}{\rho_g^2} & 0 \\ -\frac{\Delta x_g \Delta z_i}{r_g^2 \rho_s} & -\frac{\Delta y_g \Delta z_i}{r_g^2 \rho_g} & \frac{\rho_g}{r_g^2} \end{bmatrix}$$

Total FIM and CRLB

$$\mathbf{J}_{\text{tot}}(\mathbf{x}) = \sum_{i=0}^{N} \mathbf{H}_i^T(\mathbf{x})\mathbf{R}_i^{-1}\mathbf{H}_i(\mathbf{x}),$$

- $i = 0$ corresponds to the gNB, and $i = 1, \dots, N$ to the SDSs.
- The position error covariance lower bound:
  $$\mathbf{C}_{\text{CRLB}}(\mathbf{x}) = \mathbf{J}_{\text{tot}}^{-1}(\mathbf{x})$$
- Position Error Bound (PEB): $\mathrm{PEB}(\mathbf{x}) = \sqrt{\mathrm{tr}\,(\mathbf{J}_{\text{tot}}^{-1}(\mathbf{x}))}$,
- This is the lower bound on achievable 3D RMSE for any unbiased estimator:
  $$\mathrm{RMSE}(\mathbf{x}) \geq \mathrm{PEB}(\mathbf{x})$$

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CRLB quantifies the best achievable localization accuracy for a given ISAC geometry and sensor configuration, serving as a fundamental performance benchmark.

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Communication Resource Model and Policy Comparison

We model the sensing overhead on 5G NR resources, define feasibility and throughput, and evaluate four resource-allocation policies under increasing communication load.

1) Sensing Overhead Model

The normalized sensing overhead (fraction of post-overhead shared resource budget) is

$$\alpha_{\text{sense}} = N_b \left(\frac{f_{\text{sense}}}{N_{\text{sym/sec}}}\right)\left(\frac{N_{\text{PRB,sense}}}{N_{\text{PRB,total}}}\right).$$

Sensing PRBs required by the waveform

$$N_{\text{PRB,sense}} = \left\lceil \frac{N_{ZC}}{12} \right\rceil \quad \text{(12 subcarriers / PRB)}$$

- N_b: number of sensing beams (or UAVs)
- f_{sense}: sensing update rate (Hz)
- $N_{\text{sym/sec}}$: number of OFDM symbols per second
- N_{ZC}: Zadoff–Chu sequence length (subcarriers)
- $N_{\text{PRB,total}}$: total 5G NR PRBs in a slot
- $N_{\text{PRB,sense}}$: PRBs occupied by sensing transmissions

Larger waveforms, faster updates, or more beams increase sensing overhead.

2) Feasibility and Throughput

Feasibility of Active Sensing

Active sensing is feasible only if

$$\alpha_{\text{sense}} \leq 1 - \eta \tag{7}$$

where $\eta \in [0, 1]$ is the offered communication load (normalized).

Adaptive Waveform Selection

The adaptive policy selects the largest feasible ZC sequence length under load η:

$$N^*_{ZC}(\eta) = \max\{N_{ZC} : \alpha_{\text{sense}} \leq 1 - \eta\} \tag{8}$$

Normalized Served Throughput

The normalized served throughput is

$$T(\eta) = \min\{\eta, 1 - \alpha_{\text{sense}}\} \tag{9}$$

- α_{sense}: fraction of post-overhead shared budget used by sensing
- $T(\eta)$: fraction of budget available for communications (after sensing) and served to users

3) Four Resource-Allocation Policies

Policy	Description
1) Communications-Oriented Policy	• Maintains a fixed low sensing reservation (α_{sense} small). • Prioritizes high communication throughput at the expense of sensing performance.
2) Sensing-Oriented Policy	• Maintains a fixed high sensing reservation (α_{sense} large). • Prioritizes sensing robustness at the expense of communication capacity.
3) Adaptive 5G ISAC Policy	• Selects the largest feasible ZC sequence length $N^*_{ZC}(\eta)$ under the current load η, satisfying $\alpha_{\text{sense}} \leq 1 - \eta$.
4) Adaptive ISAC with SDS Assistance	• Uses SDS (passive sensing) support to maintain tracking under heavy load when 5G sensing resources are limited. • Shifts sensing from active 5G resources to passive SDS.

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The communication resource model quantifies the tradeoff between communication load, sensing overhead, waveform design, and tracking performance.

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Detection and Tracking Model

We model how sensing waveform selection and sensing opportunities determine detection probability and tracking reliability under resource constraints.

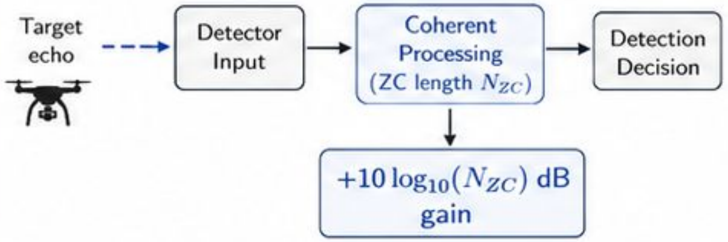
1) Effective Sensing SNR

- Let $\mathrm{SNR}_{\mathrm{in}}$ be the baseline target-echo SNR at the detector input prior to coherent processing gain.
- For a ZC sensing waveform of length N_{ZC}, the effective sensing SNR is

$$\mathrm{SNR}_{\mathrm{eff}} = \mathrm{SNR}_{\mathrm{in}} + 10\log_{10}(N_{ZC}) \qquad (10)$$

Interpretation

- Longer ZC sequences $\Rightarrow$ higher processing gain $\Rightarrow$ higher $\mathrm{SNR}_{\mathrm{eff}}$.
- N_{ZC} is selected by the resource-allocation policy (adaptive or fixed).



2) Detection Model

Probability of Detection (per sensing opportunity)

- Using the first-order Marcum Q-function:

$$P_d = Q_1\left(\sqrt{2\gamma}, \sqrt{-2\ln P_{\mathrm{fa}}}\right), \qquad (11)$$

where $\gamma = 10^{\mathrm{SNR}_{\mathrm{eff}}/10}$ and P_{fa} is the target false alarm probability.

- Probability of missed detection: $P_{\mathrm{md}} = 1 - P_d$.

Tracking Success with Active 5G Sensing

- In a tracking window, let N_{5G} be the number of active 5G sensing opportunities.
- Let M be the minimum number of successful detections required to maintain a track.
- If each opportunity is an independent Bernoulli trial with success probability P_d, then $K_{5G} \sim \mathrm{Binomial}(N_{5G}, P_d)$.
- Tracking success probability:

$$P_{\mathrm{cont}}^{5G} = \sum_{k=M}^{N_{5G}} \binom{N_{5G}}{k} P_d^k (1-P_d)^{N_{5G}-k} \qquad (12)$$

- Outage probability: $P_{\mathrm{out}}^{5G} = 1 - P_{\mathrm{cont}}^{5G}$.

Communication load affects tracking through the feasible sensing budget, which determines $N_{ZC}(\eta)$ and thus P_d.

3) SDS–Assisted Tracking Model

SDS Passive Sensing Support

- Let N_{SDS} be the number of passive sensing opportunities within the same observation window.
- Each SDS opportunity has detection probability $P_{d,\mathrm{SDS}}$.
- $K_{\mathrm{SDS}} \sim \mathrm{Binomial}(N_{\mathrm{SDS}}, P_{d,\mathrm{SDS}})$.
- Total successful detections:

$$K_{\mathrm{tot}} = K_{5G} + K_{\mathrm{SDS}}$$

SDS–Assisted Tracking Success

- Assuming independent active and passive outcomes,

$$P_{\mathrm{cont}}^{\mathrm{SDS}} = \Pr(K_{\mathrm{tot}} \geq M)$$

- Outage probability: $P_{\mathrm{out}}^{\mathrm{SDS}} = 1 - P_{\mathrm{cont}}^{\mathrm{SDS}}$, where the distribution of K_{tot} is obtained by convolving two binomial distributions.

Key Takeaway

SDS assistance increases the tracking success probability under heavy load by providing additional detections when active 5G sensing opportunities are limited.

Longer waveforms improve detection via processing gain. More sensing opportunities improve tracking via statistical diversity.

Adaptive policies balance communication load, sensing overhead, and tracking reliability.

Sensing Overhead Analysis

We evaluate the sensing-resource overhead for different waveform lengths, sensing rates, and number of beams in a 5G NR system to quantify the impact on communication resources.

1) Sensing Overhead Definition

Single-beam sensing overhead (% of post-overhead shared resources):

$$\alpha_{\text{sense}} = \underline{N_b} \left(\frac{f_{\text{sense}}}{N_{\text{sym/sec}}} \right) \left(\frac{N_{\text{PRB,sense}}}{N_{\text{PRB,total}}} \right),$$

Waveform resource usage

$$N_{\text{PRB,sense}} = \left\lceil \frac{N_{ZC}}{12} \right\rceil \quad \text{PRBs}$$

(12 subcarriers per PRB)

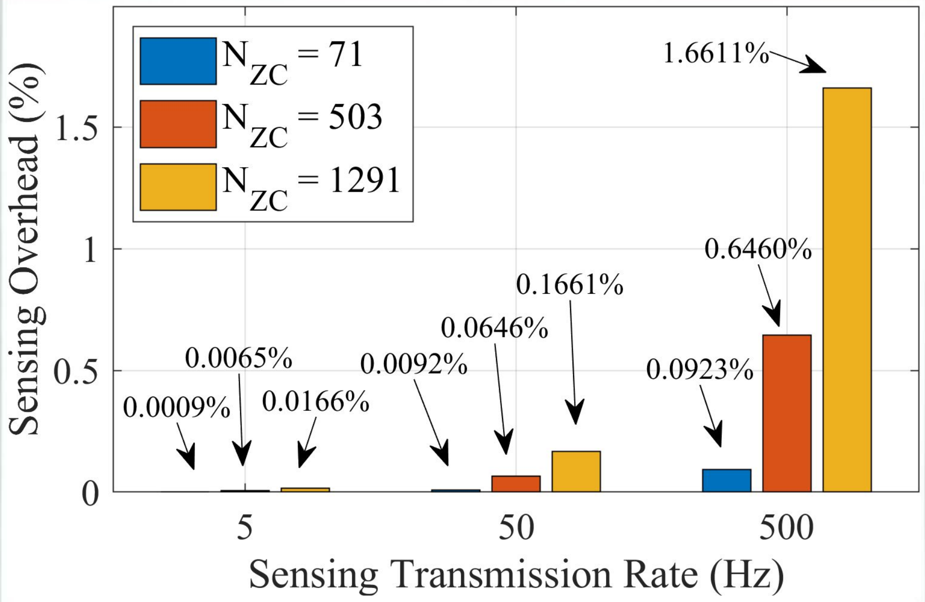
- N_b : number of sensing beams (targets)
- f_{sense} : sensing transmission rate (Hz)
- $N_{\text{sym/sec}}$: OFDM symbols per second
- N_{ZC} : Zadoff–Chu (ZC) sequence length
- $N_{\text{PRB,total}}$: total PRBs per slot

Larger waveforms, higher sensing rates, or more beams increase sensing overhead.

System Assumptions

- 5G NR FR1 @ 3.5 GHz (band n78)
- 50 MHz bandwidth, 15 kHz SCS, Normal CP
- $N_{\text{PRB,total}} = 270$ per slot, OH $= 0.14$
- $N_{\text{sym/slot}} = 14$, $N_{\text{sym/sec}} = 14{,}000$

2) Single-Beam Sensing Overhead vs. Sensing Rate



Even the most aggressive single-beam case ($N_{ZC} = 1291, f_{\text{sense}} = 500$ Hz) consumes only **1.66%** of the post-overhead shared resource budget.

3) Overhead Scaling with Number of Beams ($N_{ZC} = 1291$, $f_{\text{sense}} = 500$ Hz)

Number of Beams (N_b)	Sensing Overhead (%)	Remaining Schedulable Resources (%)
1	1.6611	98.3389
4	6.6444	93.3556
8	13.2888	86.7112

- Overhead grows linearly with the number of beams.
- Tracking multiple targets can rapidly consume available resources.
- For 8 beams, **13.29%** of usable resources are required.

Takeaway

Active sensing for a small number of targets has limited impact on communications, motivating load-aware adaptation of waveform length, sensing rate, and beam allocation.

Sensing overhead is small for a single beam, but scales linearly with the number of beams.

Adaptive policies are essential to balance sensing performance and communication throughput.

Detection Performance with Adaptive Waveforms

ROC-style performance: missed-detection probability P_{md} vs. false-alarm probability P_{fa} for representative ZC waveform lengths under different input SNR conditions.

Key Insights

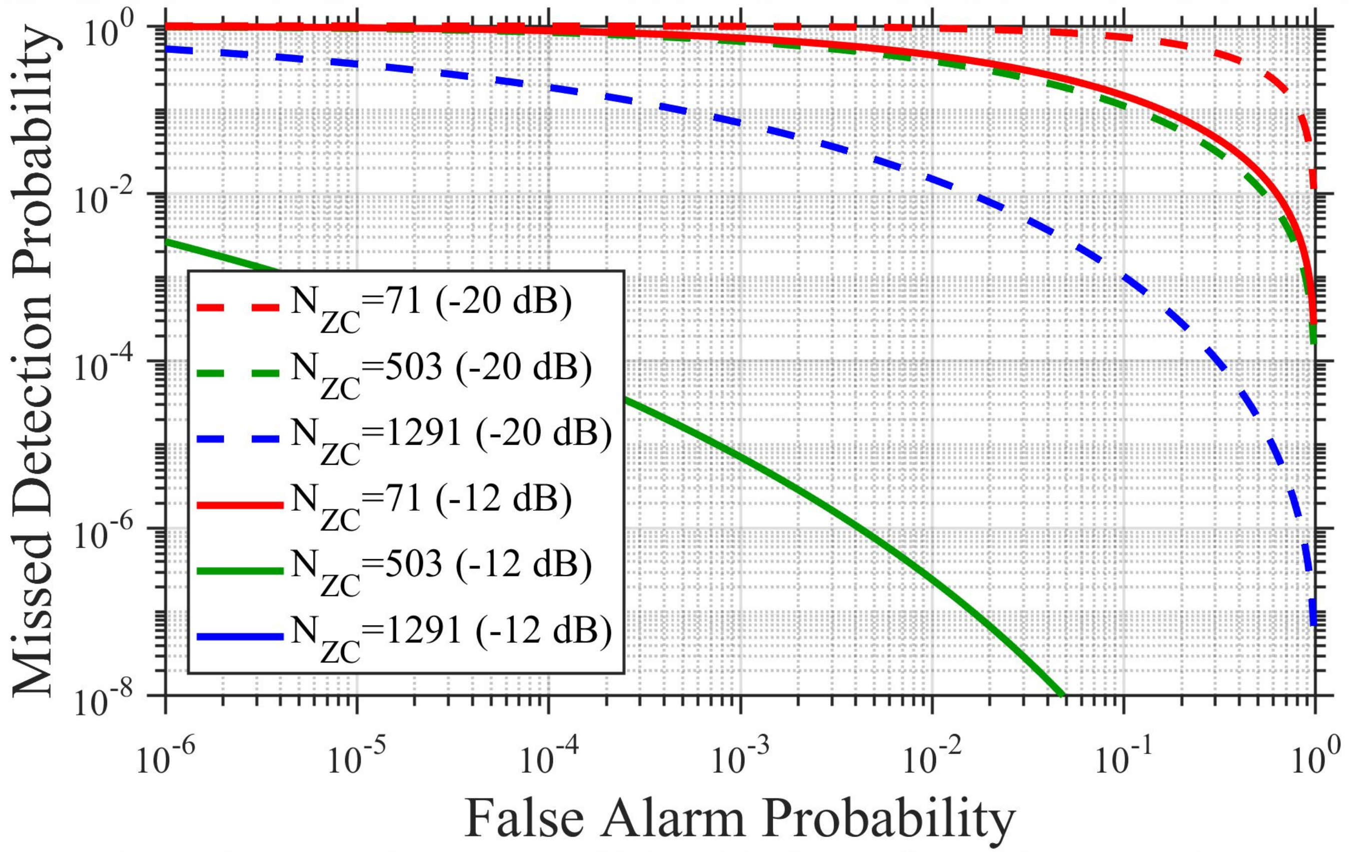
Longer waveforms improve detection
Increasing N_{ZC} increases coherent processing gain, thus lowering P_{md} for a fixed P_{fa}.

Higher SNR shifts curves downward
Better input SNR improves detection performance across all waveform lengths.

SNR-dependent benefit
Under favorable conditions (e.g., −12 dB), shorter waveforms may be sufficient.
Under degraded conditions (e.g., −20 dB), longer waveforms are needed to maintain reliability.

Severely degraded environments
Even the largest waveform provides limited improvement; complementary sensing (e.g., SDS or multi-sensor fusion) becomes valuable.

Missed-Detection Probability P_{md} vs. False-Alarm Probability P_{fa}



Larger ZC sequences reduce missed detections by providing higher processing gain.
Adaptive waveform selection balances detection reliability and sensing overhead under varying SNR conditions.

Tracking Reliability Under Challenging SNR

Tracking outage probability vs. input SNR for representative ZC waveform lengths under the $M = 3$-of-$N = 5$ tracking criterion with constant $P_{fa} = 10^{-6}$.

Key Insights

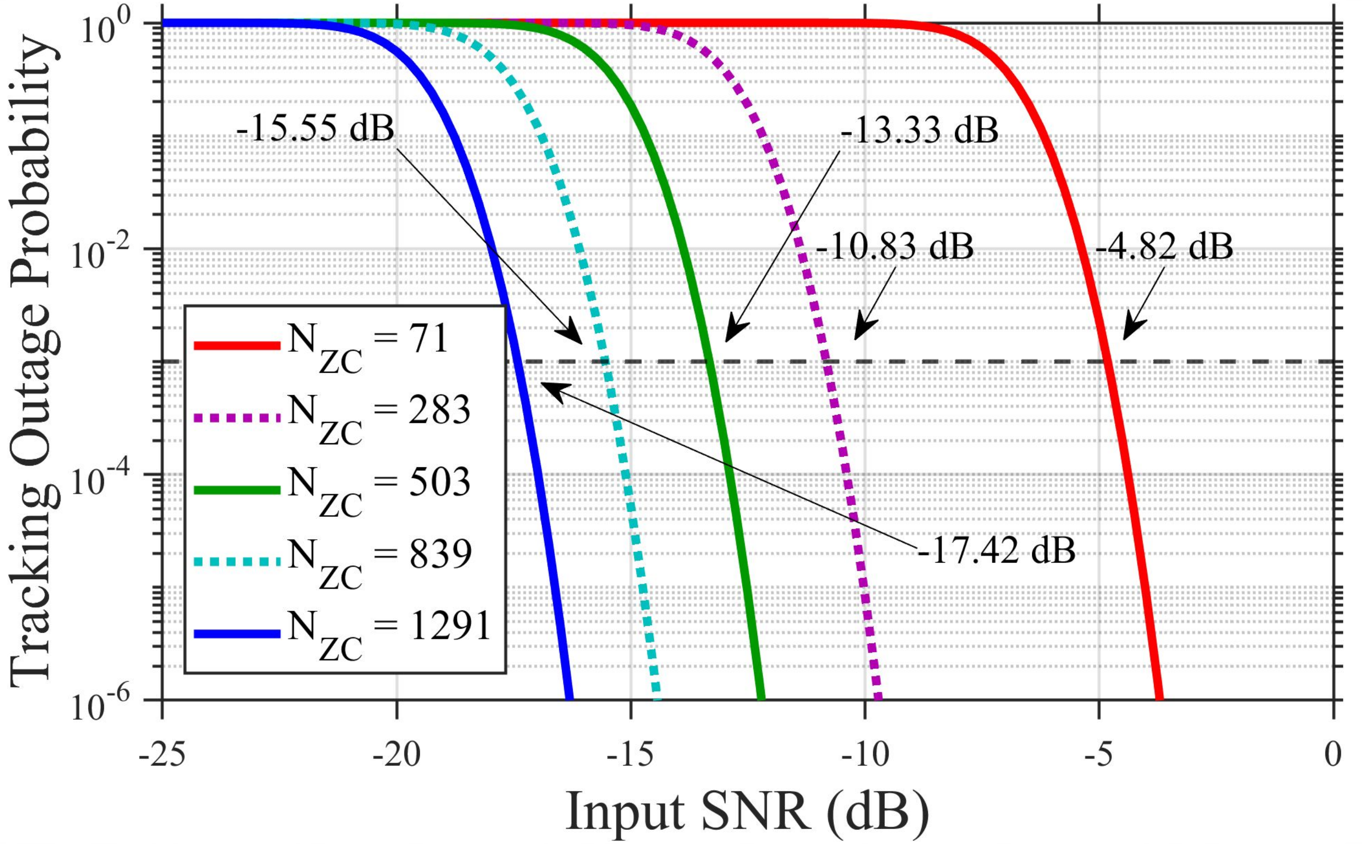
Larger waveforms extend reliable tracking
Increasing N_{ZC} shifts the outage curve left, enabling the same tracking reliability at lower input SNR.

Rapid outage reduction with SNR
Tracking outage probability drops sharply as input SNR increases.

Significant SNR gain
At $P_{\text{out}} = 10^{-3}$, required SNR improves from ~−4.8 dB ($N_{ZC} = 71$) to ~−17.4 dB ($N_{ZC} = 1291$), a gain of ~12.6 dB.

Adaptive waveform selection
Enables reliable tracking under lower-SNR conditions at the cost of higher sensing-resource consumption.

Tracking Outage Probability vs. Input SNR (M=3-of-N=5, $P_{fa} = 10^{-6}$)

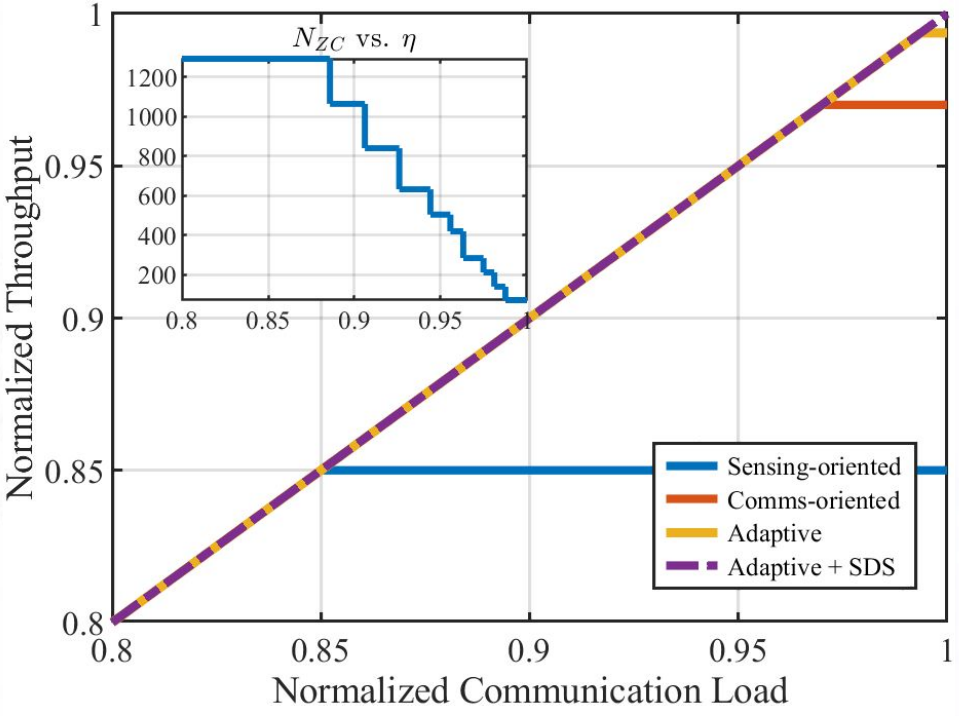


Larger ZC sequences provide substantial processing gain, shifting tracking outage curves left.
Adaptive waveform selection significantly extends reliable tracking into lower-SNR regimes.

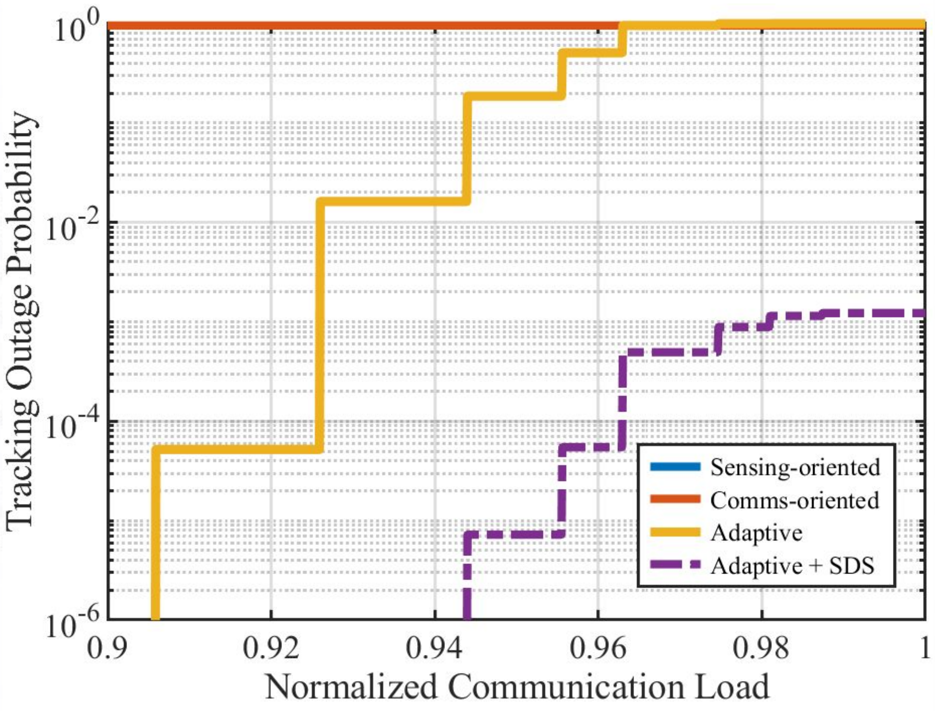
Throughput and Tracking Performance vs. Communication Load

Performance comparison of four resource-allocation policies under heavy communication load
with extreme sensing ($N_b = 8$ beams, $f_{\text{sense}} = 500$ Hz, $P_{fa} = 10^{-6}$, $SNR = -15$ dB, $M = 3$-of-$N = 5$).

(a) Normalized Throughput vs. Communication Load



(b) Tracking Outage Probability vs. Communication Load



Key Takeaways

Throughput Tradeoff

Communications-oriented maximizes throughput (0.97) but starves sensing. Sensing-oriented limits throughput (0.85) to protect sensing.

Adaptive Advantage

Adaptive policy tracks offered load closely by adjusting N_{zc}, with small loss only at extreme loads.

SDS Boosts Reliability

Adaptive + SDS maintains low outage by adding distributed sensing opportunities when 5G sensing resources are limited.

Bottom Line

Joint adaptation and distributed sensing sustain reliable tracking even as the network approaches full utilization.

Adaptive waveform selection balances communication throughput and tracking reliability.
Combining adaptation with SDS support preserves low outage even under fully saturated loads.

Localization Accuracy of Multistatic Sensing (CRLB)

We compare position error bounds (PEB) across sensing geometries using the CRLB framework.
Lower PEB (warmer colors) indicates better achievable localization accuracy.

Key Takeaways

Monostatic (gNB-only)
Best accuracy near the serving gNB but degrades toward the edges due to limited geometry.

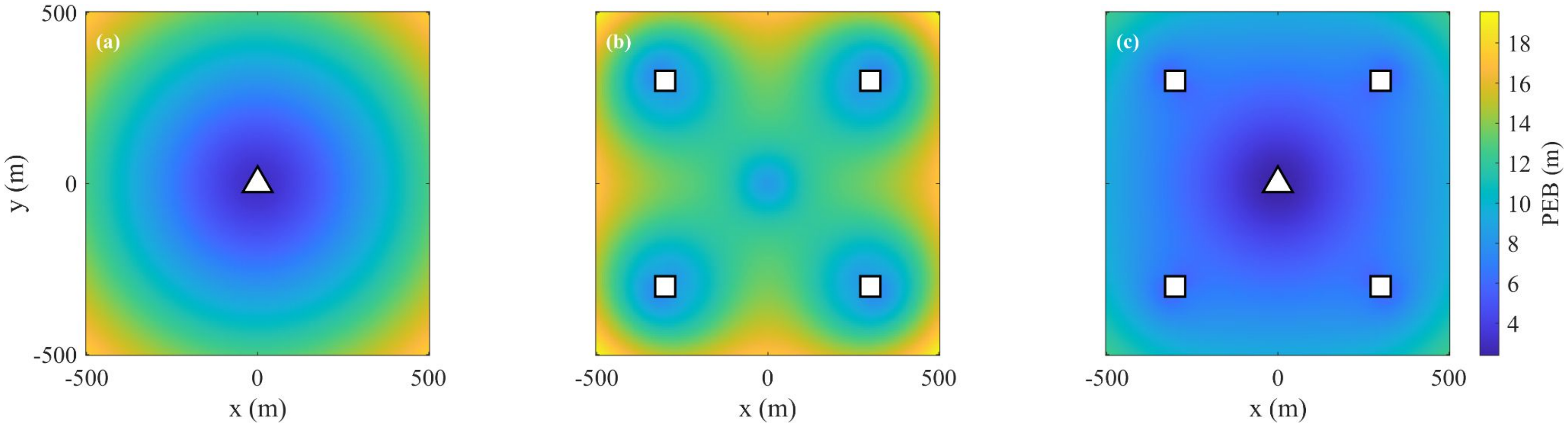
Multistatic (SDS-only)
Improved spatial diversity but nonuniform accuracy from bistatic geometry and higher noise.

Joint (gNB + SDS)
Combines strong monostatic reference with distributed SDS measurements, yielding lower PEB and more uniform accuracy across the region.

Simulation Setup

- 2D horizontal slice at $z = 100$ m over $[-500, 500] \times [-500, 500]$ m
- Serving gNB at $(0, 0, 50)$ m (single controlled illuminator)
- Four SDS nodes at $(\pm 300, \pm 300, 25)$ m (passive bistatic)
- CRLB framework from Section III-A
- Measurement noise (monostatic): $\sigma_r = 3$ m, $\sigma_\theta = \sigma_\phi = 1^\circ$
- Measurement noise (bistatic): $\sigma_r = 8$ m, $\sigma_\theta = \sigma_\phi = 4^\circ$
- External SoO transmitters excluded to isolate geometry effects
- Antenna patterns, propagation, LOS blockages, and beamforming adaptation are not explicitly modeled.

Position Error Bound (PEB) Heatmaps (meters)



△ Serving gNB (controlled illuminator)

□ SDS Nodes (passive bistatic)

Warmer colors (lower values) indicate better localization accuracy.

Distributed multistatic geometry substantially improves localization accuracy across the surveillance region.
Joint gNB + SDS sensing achieves the lowest and most uniform PEB, demonstrating the value of complementary sensing nodes.

Final Takeaways

Adaptive multistatic ISAC enables ***reliable UAV detection and tracking*** *under heavy load while* ***preserving communication performance*** *and* ***improving localization accuracy****.*

1. Adaptive Waveforms Boost Sensing under Load

- Adaptive selection of ZC sequence length maximizes sensing gain while satisfying communication constraints.
- Achieves near-linear throughput up to high offered loads with minimal loss.

2. Tracking Reliability Sustained with Adaptation

- Larger waveforms reduce missed detections via coherent gain.
- Adaptive policy maintains low outage over a wide load range.
- Distributed SDS support substantially suppresses outage as the network approaches full utilization.

3. Communication–Sensing Tradeoff Optimized

- Fixed baselines sacrifice either throughput or sensing.
- Adaptive ISAC balances the tradeoff by adjusting resource allocation in real time.
- Best overall performance achieved with adaptive ISAC + SDS under heavy load.

4. Multistatic Geometry Enhances Localization

- CRLB analysis shows lower position error bounds with multistatic sensing.
- Joint gNB + SDS configuration provides the lowest and most uniform PEB across the surveillance region.
- Benefits arise from improved spatial diversity and geometry.

5. Key Enablers & Path Forward

- Shared-resource framework captures the true ISAC tradeoffs in 5G NR systems.
- SDS nodes extend coverage and reliability at low cost.
- Future work: refine models and validate on the NSF AERPAW testbed.

Adaptive multistatic ISAC with distributed sensing delivers reliable detection, tracking, and localization in congested RF environments—**without sacrificing communication performance**.

Future Work: Real-World Validation on NSF AERPAW

Next step: *Validate adaptive multistatic ISAC policies on the NSF AERPAW testbed at NC State.*

1. Experimental Validation

Deploy adaptive waveform, sensing rate, and beam allocation policies in real-world outdoor experiments with UAV targets under dynamic load.

2. Integrated Sensing and Communication

Leverage AERPAW's 5G NR infrastructure and distributed passive sensors to collect joint RF and radar measurements.

3. End-to-End Performance Assessment

Evaluate detection, tracking, localization, and communication throughput under realistic propagation, interference, and mobility conditions.

4. Toward Operational Demonstrations

Demonstrate reliable UAV tracking and resource adaptation in congested RF environments, paving the way for real-world ISAC deployment.

AERPAW provides the ideal platform to bridge theory and practice—
advancing adaptive multistatic ISAC from simulations to real-world impact.

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Engineering

Thank you!

Questions?

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