Low-Altitude Drone Monitoring Using 5G Base Stations RF Digital Beamforming

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Motivation

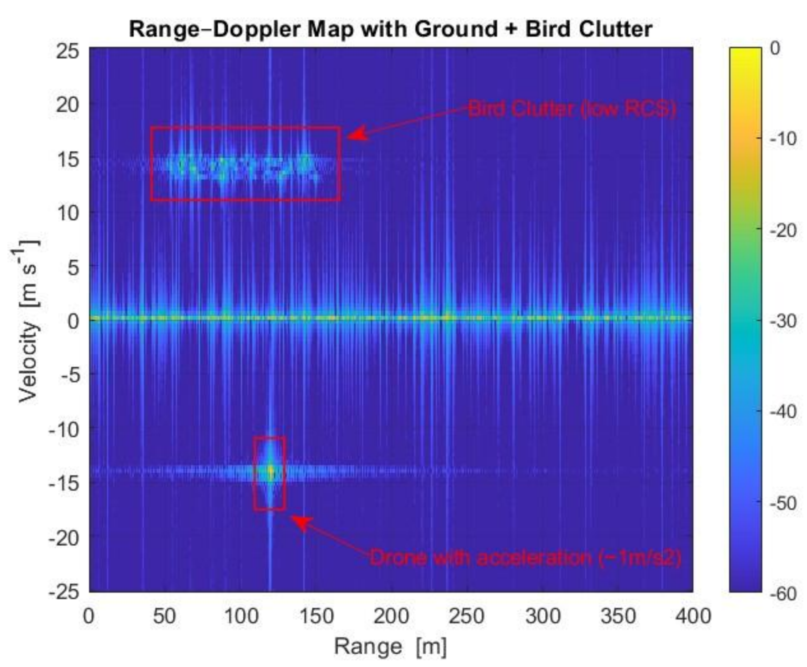
Low-altitude drones create safety and navigation risks, but monitoring them typically requires dedicated radar infrastructure. Meanwhile, 5G base stations are ubiquitous and already contain software-defined hardware that can be repurposed for sensing. In millimeter-wave FR2 (24–28 GHz), large bandwidths (up to 400 MHz) and directive massive-MIMO arrays enable sub-meter range resolution and multi-beam tracking from existing sites.

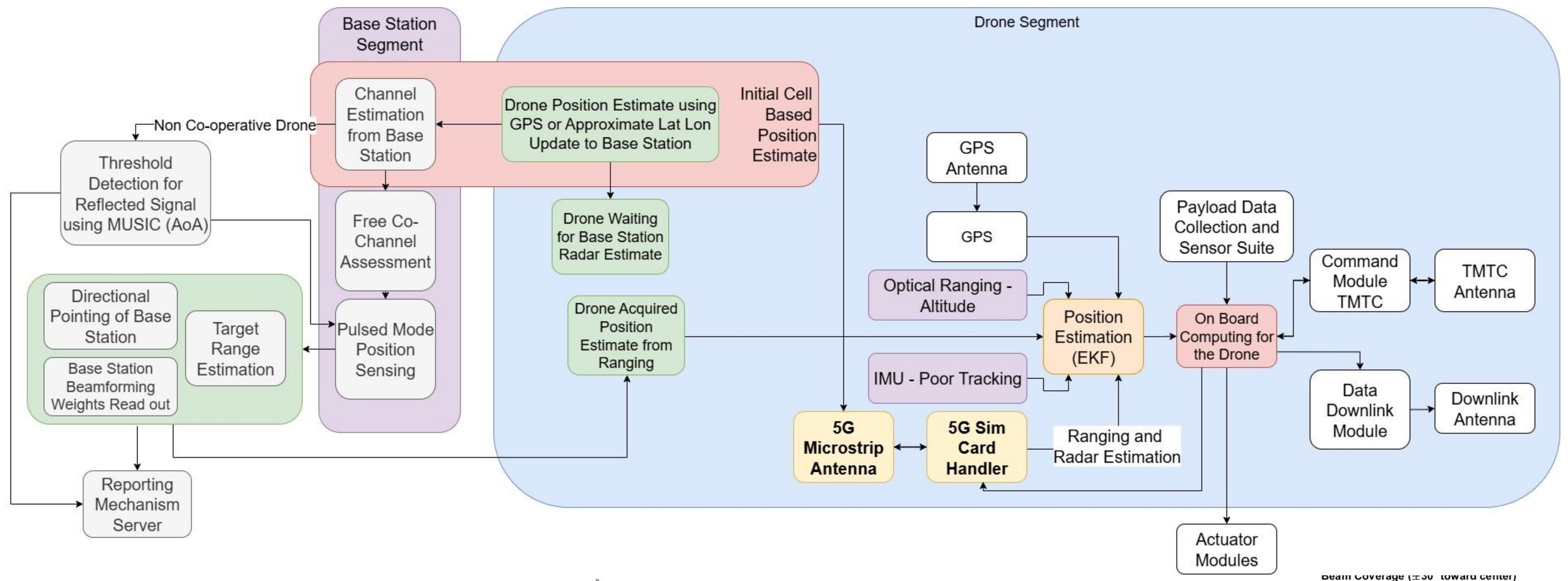
Problem & Key Idea

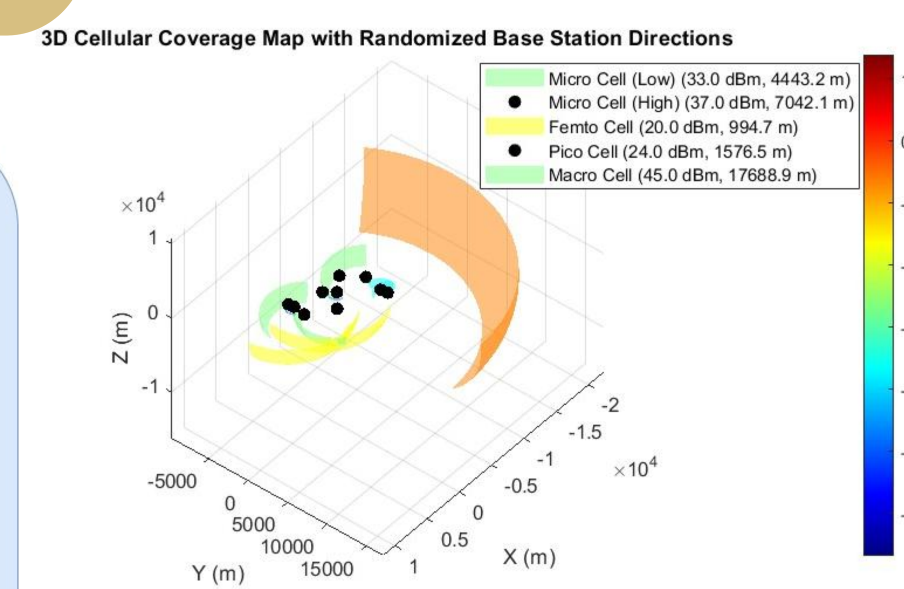
Can commercial 5G FR2 base stations be reused as a *distributed radar network* to detect and localize low-altitude UAVs in dense urban airspace? The Key idea is to leverage massive-MIMO beamforming and TDD slotting so sensing can coexist with communications, using multiple stations to provide complementary bearing/elevation/range views.

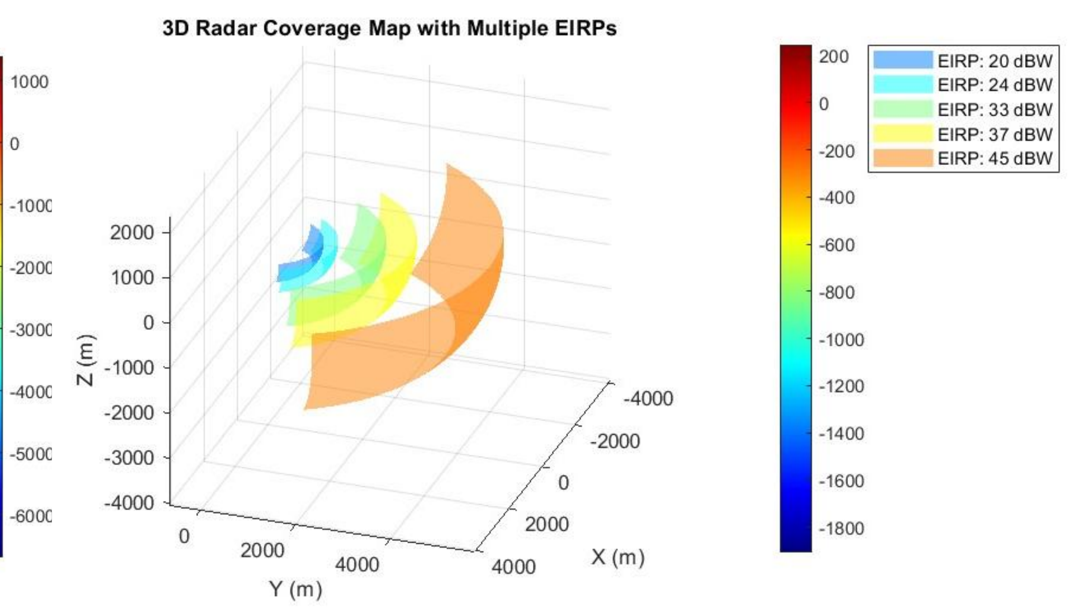
A Brief Summary

This poster evaluates feasibility by deriving power & SNR bounds, quantifying achievable spatial/temporal resolution, and characterizing clutter and Doppler behavior in dense urban scenes. We introduce a covariance-aware info fusion method that rotates local measurement covariances into a global Cartesian and accumulates information across stations with SNR-gating, variance floors, and Huber reweighting to suppress outliers.









Feasibility + Resolution

We map 5G FR2 bandwidths to radar range resolution and detection feasibility under LoS assumptions.

$$\Delta R = \frac{c}{2B}$$

Monostatic received power and SNR (per base-station snapshot) follow:

$$P_r = \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^3 r^4}, \mathrm{SNR} = \frac{P_r}{kT_0 B\, F}$$

Measurement model + covariance transport

Each station measures noisy spherical quantities $(\tilde{r}, \tilde{\phi}, \tilde{\theta})$ and maps them to ENU Cartesian:

$$\mathbf{z}_j = \mathbf{p}_j + \begin{bmatrix} \tilde{r}_j \cos\tilde{\theta}_j \cos\tilde{\phi}_j \\ \tilde{r}_j \cos\tilde{\theta}_j \sin\tilde{\phi}_j \\ \tilde{r}_j \sin\tilde{\theta}_j \end{bmatrix} = \mathbf{x} + \mathbf{v}_j$$

Transport covariance from local spherical errors into ENU via a rotation:

$$\mathbf{C}_j \approx \mathbf{R}_j\, \mathbf{C}_{loc,j}\, \mathbf{R}_j^{\top}$$

This is the core step that preserves cross-axis coupling after spherical to Cartesian mapping.

SNR-to-measurement uncertainty model (range + angles)

We parameterize per-station range/angle error from SNR using CRB-like scalings (with floors):

$$\sigma_r \approx \frac{c}{2B\sqrt{2\,\mathrm{SNR}}}, \sigma_\theta \approx \frac{\sigma_{\theta,0}}{\sqrt{\mathrm{SNR}}}$$

Spherical uncertainty is rotated into global ENU for proper cross-axis coupling:

$$\mathbf{C}_j \approx \mathbf{R}_j\, \mathrm{diag}\left(\sigma_{r,j}^2, \left(r_j\sigma_{\theta,j}\right)^2 \left(r_j\sigma_{\theta,j}\right)^2\right)\mathbf{R}_j^{\top},$$

Fusion estimator (information-space BLUE / MLE + robustness)

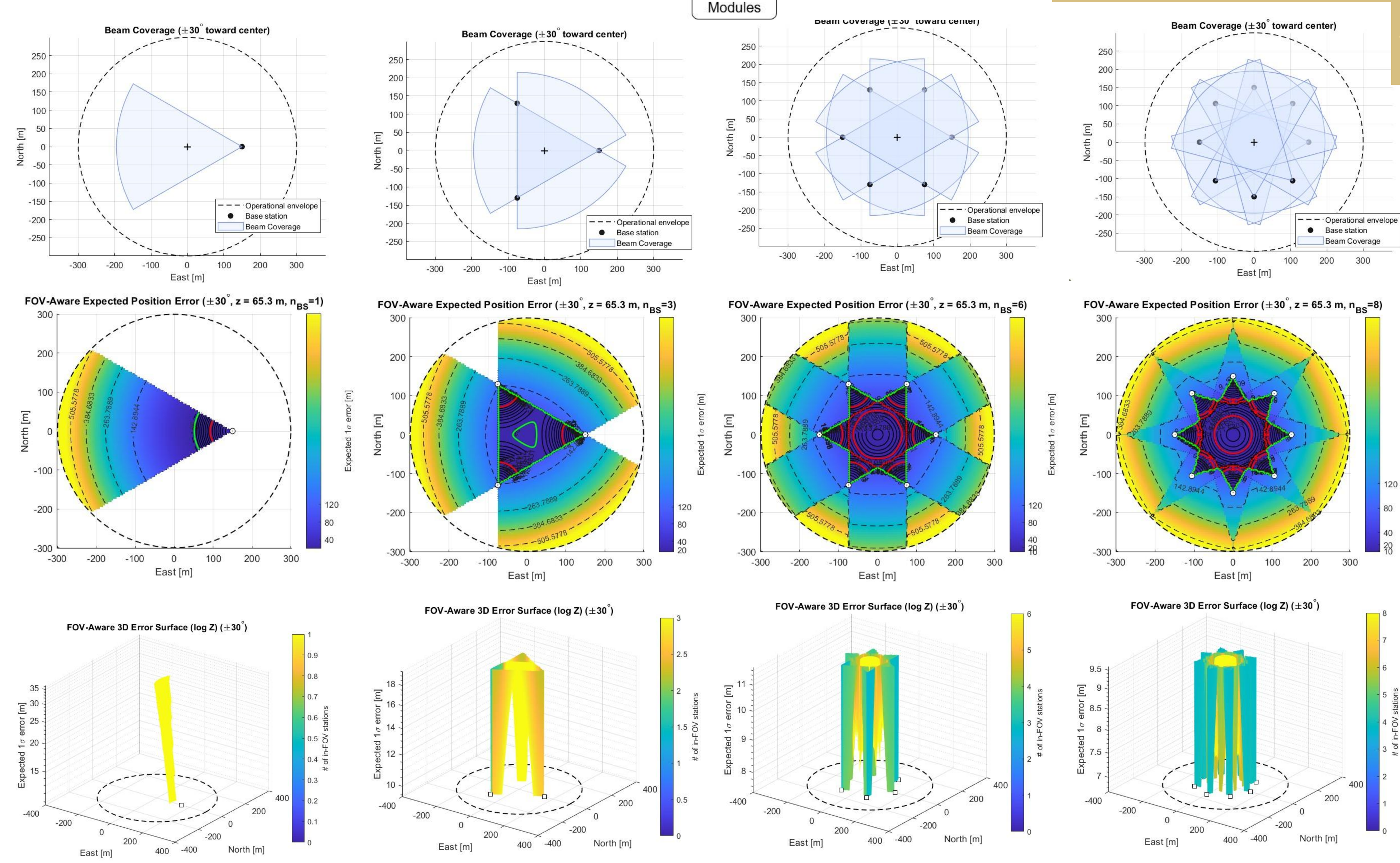
With m contributing stations, we fuse in **information form** (BLUE/MLE under Gaussian errors):

$$\boldsymbol{\Lambda} = \sum_{j=1}^{m} \mathbf{C}_j^{-1}, \boldsymbol{\eta} = \sum_{j=1}^{m} \mathbf{C}_j^{-1}\mathbf{z}_j, \hat{\mathbf{x}} = \boldsymbol{\Lambda}^{-1}\boldsymbol{\eta}$$

For urban bias/heavy tails, we add a **Huber reweighting** pass using the Mahalanobis residual:

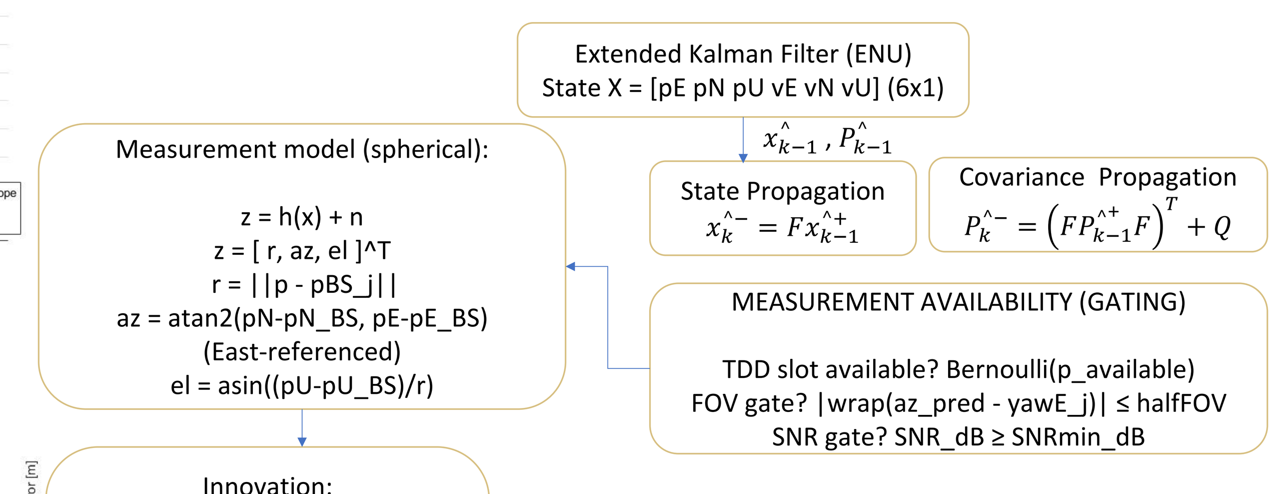
$$\rho_j = \sqrt{(\mathbf{z}_j - \hat{\mathbf{x}})^{\top}\mathbf{C}_j^{-1}(\mathbf{z}_j - \hat{\mathbf{x}})}, w_j = min\left(1, \frac{k}{\rho_j}\right)$$

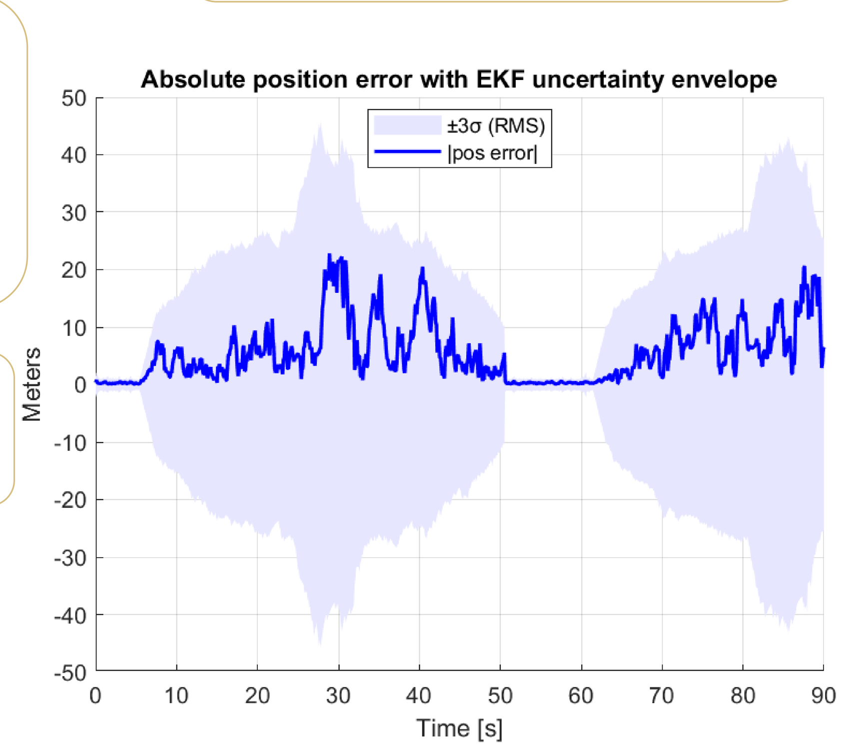
and inflate covariances $\mathbf{C}_j \leftarrow \mathbf{C}_j / w_j$ before refitting—down-weighting outlier stations.

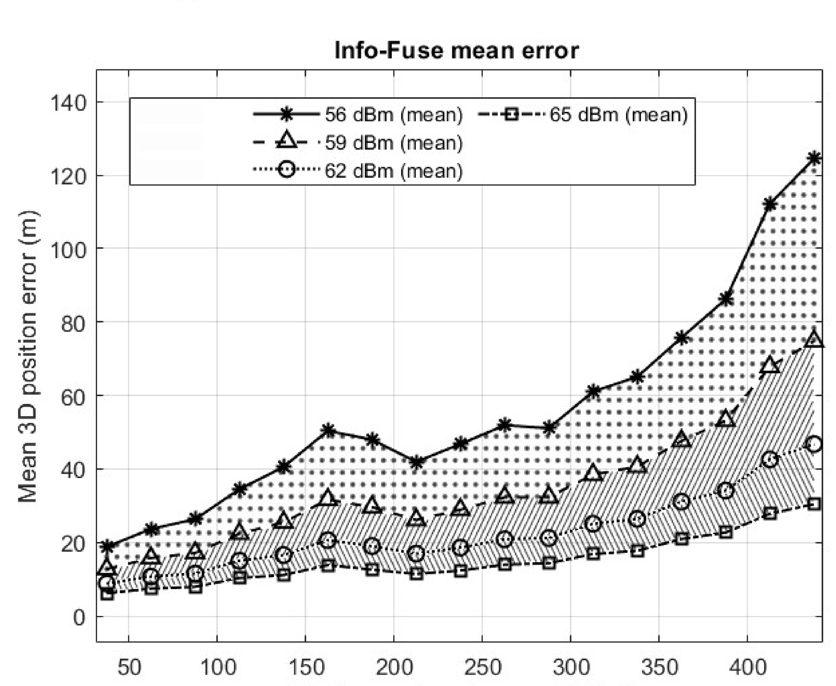


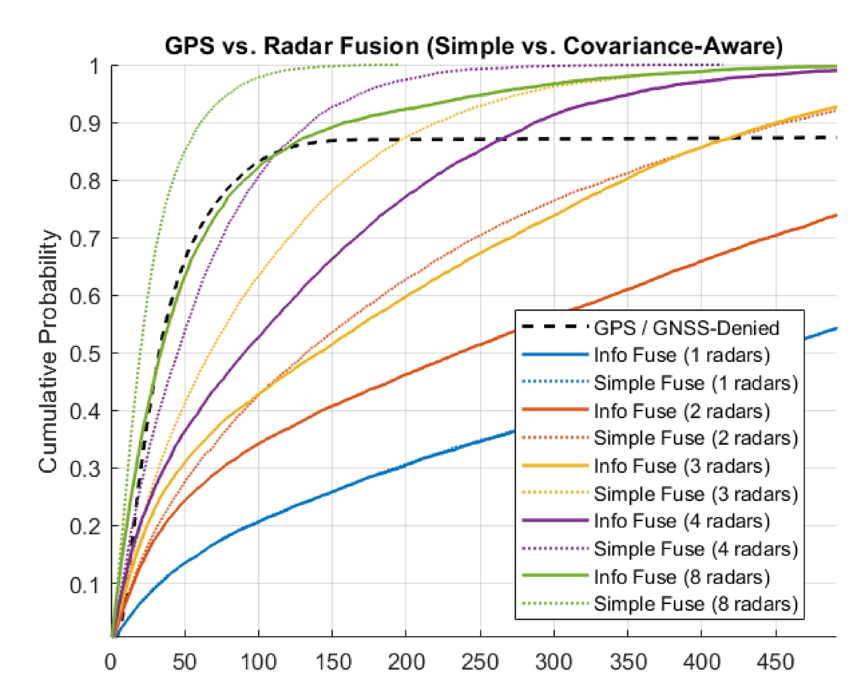
Continuous-Tracking using EKF

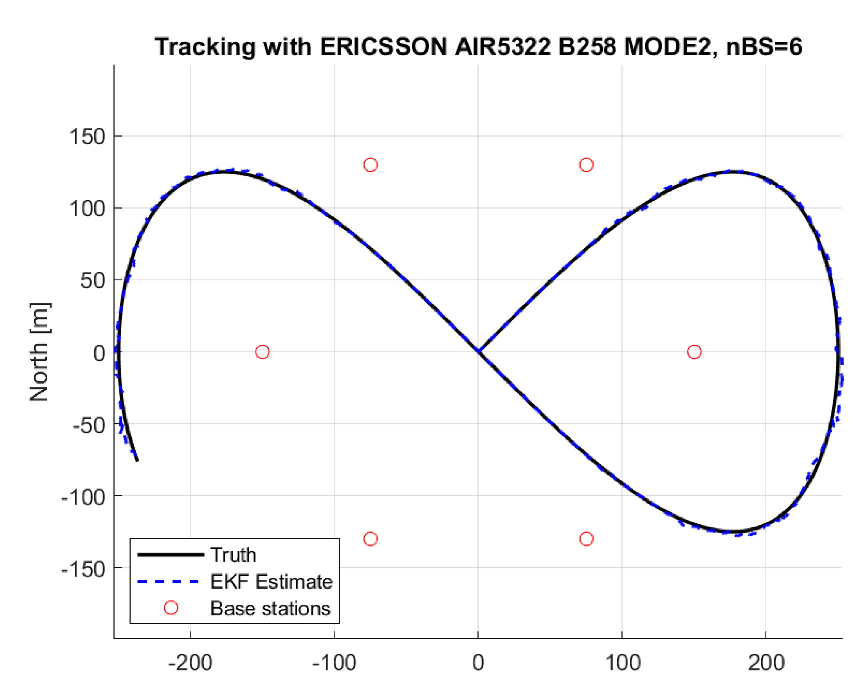
- We use an Extended Kalman Filter (EKF) to continuously track a low-altitude drone's 3D position and velocity using range, Az and El measurements from multiple 5G base stations.
- A constant-velocity motion model predicts the state forward in time, while each base station provides sporadic updates depending on TDD slot availability, field-of-view, and SNR.
- This produces a real-time trajectory estimate with uncertainty bounds, enabling robust tracking even when measurements are intermittent or some stations are unavailable.

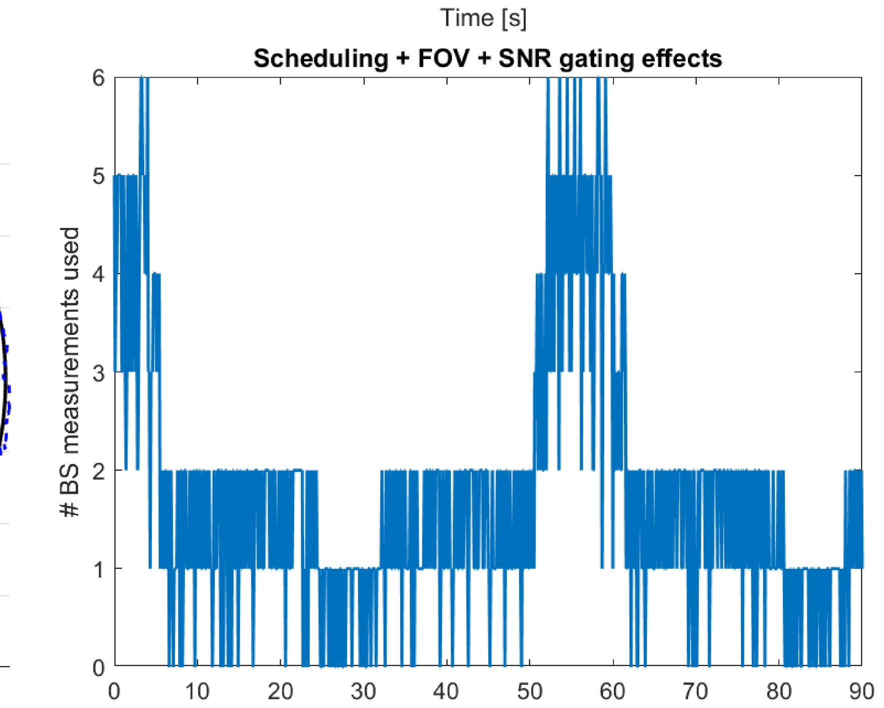












Results + integration concept

Monte-Carlo (LoS baseline) shows **error CDFs improve strongly with station count**; covariance-aware fusion consistently beats the per-axis baseline, and multi-station fusion can reach **GPS-competitive** regimes (especially GNSS-denied/urban-canyon baselines) depending on geometry/FoV overlap. System concept: radar bursts inserted into **TDD idle slots**, AoA/range/velocity processing in the FPGA/baseband chain, and a simple backhaul message carrying $\mathbf{z}_j$ and $\mathbf{C}_j$ per station to a fusion server.

$$\mathbf{C}_{post}(\mathbf{q}) = \left(\sum_{j\in\mathcal{V}(\mathbf{q})} \mathbf{C}_j^{-1}\right)^{-1}, \epsilon_{1\sigma}(\mathbf{q}) = \sqrt{\mathrm{trace}\left(\mathbf{C}_{post}(\mathbf{q})\right)}$$

Next Steps in Development

Next, we will incorporate LoS/NLoS urban-canyon propagation (blockage, diffraction, multipath) and translate these effects into range and angle bias and covariance inflation models. We will move from snapshot localization to continuous tracking by adding Doppler/radial-velocity measurements and an EKF tracking layer. We will explicitly model TDD/beam-sweep timing and perform time-tagged, asynchronous fusion across stations. Finally, we hope to validate on real 5G hardware and beam schedules using controlled UAV flights.

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