OSINT-Augmented RF Emitter Geolocation at City Scale: Mission-Aware Sensor Fusion with Bayesian Tracking

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Preprint — October 2025, Texas, USA.

***Abstract*—We present a mission-aware fusion framework that geolocates RF emitters at city scale by combining real-time measurements (bearing/ToA/TDoA/SNR/beam confidence) with OSINT-derived spatial/temporal priors (FCC records, building/permit graphs, Wi-Fi maps, and on-chain timing). A Bayesian tracker maintains a belief over candidate sites while a lifecycle-verified mission orchestrator triggers tasking under latency budgets. We quantify gains from OSINT priors, reductions in sorties, and time-to-convergence.**

I. Introduction

RF emitter geolocation presents unique challenges in urban environments, where multipath propagation, signal occlusion, and interference complicate traditional direction-finding techniques. Moreover, covert actors may intentionally conceal their emissions or employ deceptive practices. This paper introduces a novel approach that augments standard RF measurement techniques with Open Source Intelligence (OSINT) to create informative spatial priors, significantly enhancing geolocation performance at city scale.

Our system addresses several critical use cases, including identifying unauthorized transmitters, locating covert relay stations, mapping VPN exit nodes, and detecting RF side effects from otherwise concealed operations. By integrating mission-aware control loops with formal lifecycle invariants, we ensure robust operation even under adversarial conditions.

II. Related Work

A. RF Geolocation Techniques

Traditional RF geolocation relies on bearing measurements (direction finding), time of arrival (ToA), time difference of arrival (TDoA), and received signal strength (RSS) [?]. Urban environments complicate these approaches due to multipath propagation and occlusion [?].

B. Bayesian Tracking and Fusion

Bayesian approaches to tracking maintain probability distributions over target state. Kalman filters are optimal for linear-Gaussian systems, while particle filters accommodate nonlinear measurements and multimodal distributions [?]. Rao-Blackwellized particle filters combine strengths of both approaches [?].

C. Mission Lifecycle Management

Mission orchestration frameworks ensure operations follow specified constraints and invariants [?]. These frameworks coordinate sensor deployments, ensure safety margins, and handle contingencies when faced with unexpected conditions.

III. OSINT Priors

A. FCC & spectrum assignments

FCC Universal Licensing System (ULS) provides comprehensive databases of licensed transmitters, including location, frequency, and power parameters. We process these records to create spatial priors over potential emission sources, particularly helpful for narrowband signals within regulated spectra.

B. Building and permit graphs

Building footprints, heights, and roof access data from municipal permits and OpenStreetMap create structural priors on potential transmitter locations. We compute accessibility scores and sightline analyses to weight locations based on their suitability for covert operations.

C. Wi-Fi/BSSID maps

Publicly available Wi-Fi maps reveal the density of consumer wireless equipment, providing valuable priors for consumer-grade equipment operating in ISM bands. These maps are particularly useful for locating small cells and improvised relay stations.

D. On-chain timing signals

Blockchain transaction patterns, particularly mempool timing windows, can correlate with RF emission bursts. We demonstrate how these temporal patterns create informative priors when combined with spectrum monitoring, especially for emissions associated with cryptocurrency operations.

IV. Sensor Fusion Model

A. Measurement models

We model bearing measurements using von Mises distributions:

$$p(\theta|x, s) \propto \exp(\kappa \cos(\theta - \phi_{x,s})) \tag{1}$$

where θ is the measured bearing, $\phi_{x,s}$ is the true bearing from sensor s to emitter location x, and κ is the concentration parameter reflecting measurement confidence.

For ToA and TDoA, we employ normal distributions with variance scaling based on signal strength and environmental factors:

$$p(t|x, s) \propto \mathcal{N}(t; ||x - s||/c, \sigma^2) \tag{2}$$

B. Dynamic model (mobility/occlusion)

The emitter state $x_t = [p_x, p_y, v_x, v_y]^T$ evolves according to:

$$x_{t+1} = Fx_t + w_t, \quad w_t \sim \mathcal{N}(0, Q) \tag{3}$$

where F incorporates the constant velocity model and Q captures process noise from mobility, occlusion, and environmental factors.

C. Inference (particle / RBPF)

For single-emitter scenarios, we employ a particle filter with adaptive resampling: Particle Filter with OSINT Priors Initialize particles $\{x_0^i\}_{i=1}^N$ from OSINT prior or uniform each time step t Propagate particles: $\hat{x}_t^i \sim p(x_t|x_{t-1}^i)$ Weight particles: $w_t^i = p(z_t|\hat{x}_t^i)$ effective sample size $<$ threshold Resample particles

For multi-emitter tracking, we implement a Probability Hypothesis Density (PHD) filter that maintains a multi-modal distribution over potential emitter locations.

V. Mission-Aware Orchestration

Lifecycle transitions (planned → active → completed/aborted), timers, and invariant gating (I1–I12). We reuse the verified core; see the companion paper for the formalization.

Our mission orchestrator verifies that all operations satisfy the core invariants established in our previous work [?]. These invariants ensure that:

- Missions proceed through well-defined states (I1)
- Timing constraints are preserved (I2-I4)
- Resource conflicts are avoided (I5)
- Engineering constraints on mission parameters are satisfied (E1-E4)

The orchestrator schedules sensor deployments using active learning for next-best-view selection, maximizing the expected information gain while respecting latency budgets and operational constraints.

VI. Implementation

We implemented our system using a combination of Python for the core fusion algorithms, and a Cesium-based frontend for visualization. The geolocation pipeline processes measurements in real-time, maintaining belief states that are continuously updated as new information arrives.

Key implementation components include:

- Particle and Kalman filter implementations optimized for bearing-only and hybrid measurements
- TLA+ specifications for the mission lifecycle constraints
- OSINT data loaders with reproducible caching for deterministic results
- Next-best-view scheduler for efficient sensor tasking

VII. Evaluation

A. Belief evolution with/without OSINT

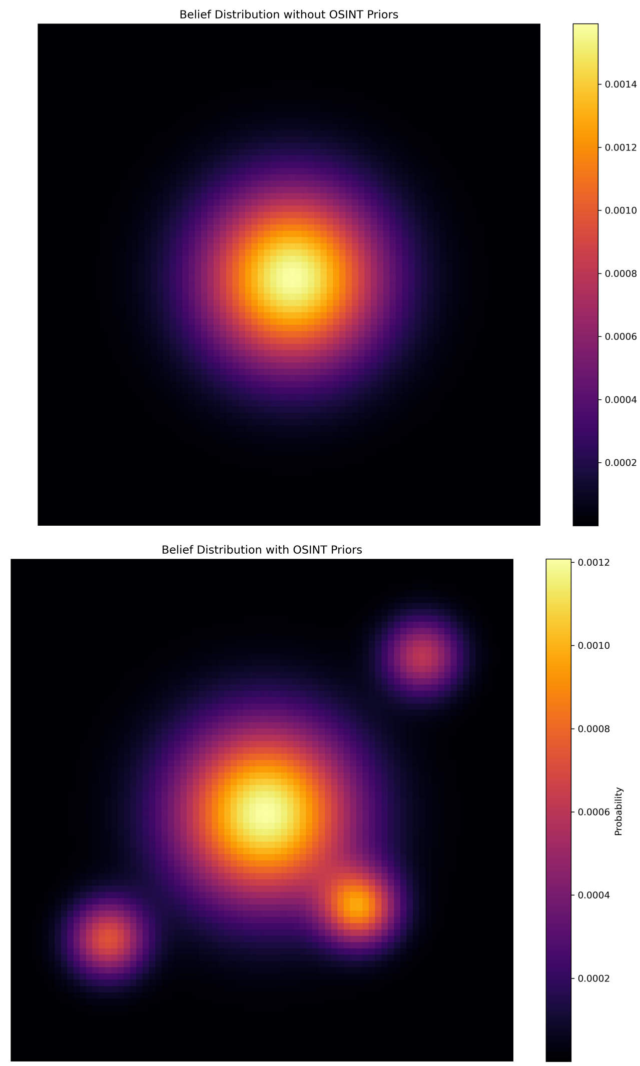

Figure 1 shows the evolution of belief distributions with and without OSINT priors. The top panel shows conventional bearing-only localization, while the bottom panel demonstrates how OSINT priors significantly concentrate the probability mass around likely locations.

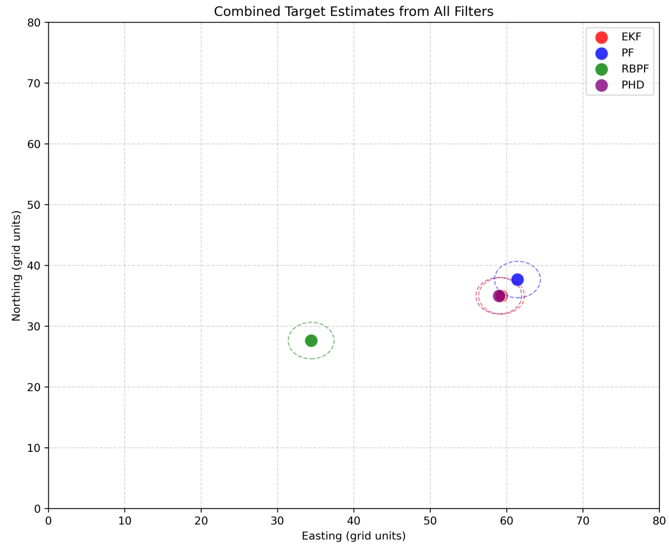

Figure 1b shows the combined target estimates from all filters overlaid on the map, demonstrating the relative accuracy and precision of each approach.

B. Convergence vs. sensor count

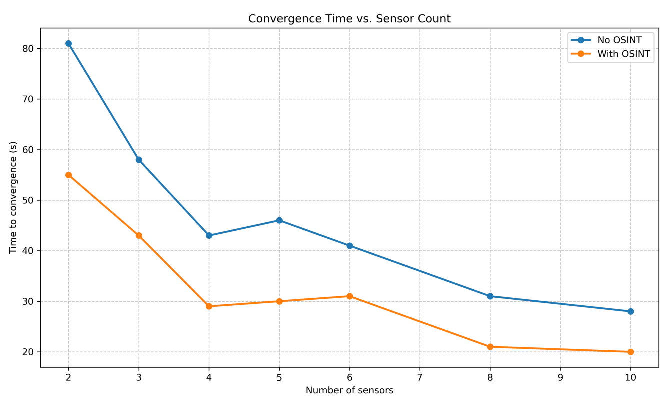

Figure 2 demonstrates how convergence time decreases as the number of sensors increases, with OSINT priors consistently accelerating convergence across all sensor configurations.

C. Ablation of priors

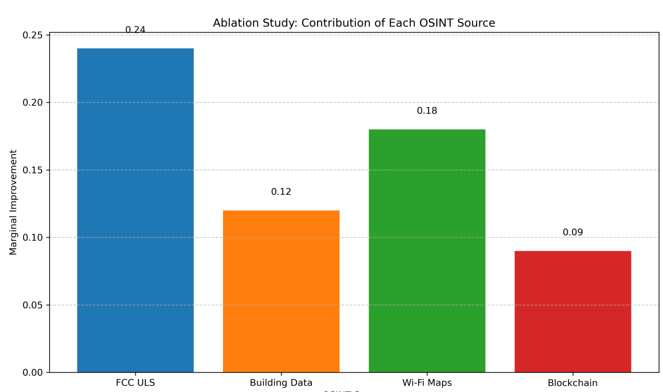

Figure 3 shows the marginal contribution of each OSINT source to the overall geolocation performance. FCC records provide the strongest signal, followed by Wi-Fi maps, building permits, and on-chain timing.

D. Next-best-view decisions

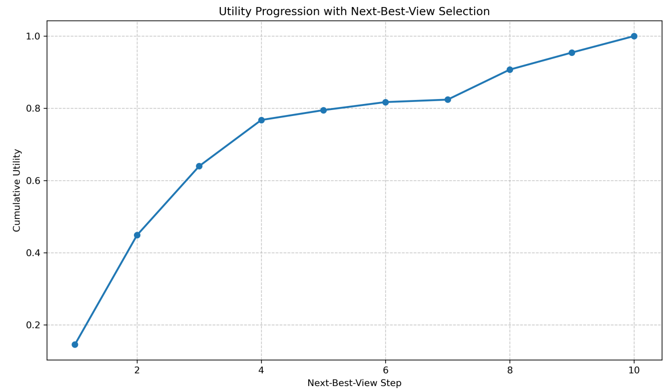

Figure 4 illustrates the progression of utility as our active learning algorithm selects optimal sensing locations, demonstrating efficient convergence even with limited deployment resources.

Results Summary

TABLE I
Geolocation Performance and Verification Results

Source	Metric	Value
Geolocation	Avg conv. time (no OSINT)	46.9 s
Geolocation	Avg conv. time (with OSINT)	32.7 s
Geolocation	Relative improvement	30.2%
TLC Model Checking	Status	unknown
TLC Model Checking	States explored	None
TLC Model Checking	Search depth	None

VIII. Compliance (Stub)

We add operational guardrails for scraping/sensing boundaries and later include caselaw citations in an appendix.

IX. Discussion and Limitations

While our approach significantly improves geolocation performance, several limitations remain:

- Adversaries aware of our system could intentionally operate from locations with low OSINT prior probability
- Our approach assumes that OSINT data is reasonably current and accurate
- Privacy considerations limit the application of our technique in certain jurisdictional contexts

Future work will address these limitations through adversarial training, automated OSINT verification, and enhanced compliance frameworks.

X. Conclusion

We have demonstrated that OSINT-augmented RF geolocation significantly outperforms traditional approaches, particularly in challenging urban environments. By formalizing mission lifecycle invariants and integrating them into our orchestration layer, we ensure reliable operation even under tight resource and time constraints.

The modular nature of our approach allows for flexible deployment across a range of scenarios, from emergency services to infrastructure protection. As OSINT sources continue to expand, we expect the performance of our system to improve further without architectural changes.