RF Quantum SCYTHE: A Modular Framework for Reproducible Passive RF Geolocation Research

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***Abstract*—We present *RF Quantum SCYTHE*, a modular framework for reproducible passive RF geolocation research. Unlike siloed studies that focus on individual algorithms, SCYTHE provides a comprehensive suite of interoperable demonstrations covering trajectory recovery, sensor fusion, adaptive denoising, reinforcement learning, and hybrid triangulation. Each module produces standardized JSON summaries and LaTeX-ready figures/tables, enabling direct integration into publications and downstream analysis pipelines. Together, these components form a systems-level testbed for evaluating geolocation algorithms across diverse modalities, noise conditions, and decision policies. We demonstrate four core modules—AoA sequence recovery, AoA+TDoA fusion, policy-driven denoising, and hybrid triangulation—achieving 25-45% error reductions in multi-sensor tracking and up to 91.6% RMSE improvements in triangulation accuracy. The framework lowers barriers to entry for reproducible RF research and provides a standardized baseline for future extensions, including machine-learned policies and multi-emitter geolocation scenarios.**

***Index Terms*—Passive geolocation, RF sensing, angle-of-arrival, time-difference-of-arrival, sensor fusion, reinforcement learning, reproducible research**

I. Introduction

Passive RF geolocation is fundamental to modern electronic warfare, spectrum monitoring, and search-and-rescue operations. However, the field suffers from fragmented research approaches: individual studies typically focus narrowly on angle-of-arrival (AoA), time-difference-of-arrival (TDoA), or filtering techniques, often using proprietary datasets and incompatible evaluation metrics [1], [2].

This fragmentation creates several critical problems:

- **Reproducibility Crisis**: Studies use different datasets, metrics, and implementations, making fair comparison impossible.
- **Integration Challenges**: Individual algorithms cannot be easily combined into end-to-end systems.
- **Evaluation Inconsistency**: Ad-hoc performance metrics prevent systematic assessment across methods.
- **Barrier to Entry**: New researchers must reimplement basic components before contributing novel algorithms.

RF Quantum SCYTHE addresses these challenges by providing a *systems view*: modular, open-source demonstrations with standardized interfaces and outputs. The key insight is that researchers should be able to plug into SCYTHE at any point—trajectory recovery, fusion, denoising, triangulation—and obtain reproducible, comparable results.

A. Contributions

This paper makes the following contributions:

1) A comprehensive modular framework (*RF Quantum SCYTHE*) for reproducible RF geolocation research with standardized interfaces.
2) Five core demonstration modules: AoA sequence recovery, AoA+TDoA fusion, policy-driven denoising, reinforcement learning for cognitive radio, and hybrid triangulation.
3) Standardized output schema (JSON metrics + LaTeX assets) enabling direct publication integration and fair benchmarking.
4) Empirical validation across diverse noise levels, sensor geometries, and jamming conditions with quantified performance improvements.
5) Complete open-source release with documentation, lowering barriers to reproducible RF research.

II. Related Work

Classical RF geolocation methods rely on geometric constraints from bearing measurements [3] or range differences [4]. Modern approaches incorporate probabilistic fusion [5] and machine learning techniques [6], [7].

However, existing work typically addresses individual components in isolation. Multi-sensor fusion studies focus on algorithm development without considering system integration [2]. Adaptive filtering research optimizes denoising performance but neglects downstream geolocation impact. Reinforcement learning applications target spectrum management [8] but not geolocation-specific objectives.

SCYTHE bridges this gap by providing a unified framework where individual contributions can be systematically evaluated and combined. Our modular approach enables both algorithm-specific research and system-level optimization.

III. System Architecture

A. Design Principles

RF Quantum SCYTHE follows four core design principles:

RF Quantum SCYTHE Framework

AoA Sequence Recovery → AoA+TDoA Fusion
Policy-Driven Denoising → Cognitive Radio RL
Hybrid Triangulation (Integration Point)

Fig. 1. Modular overview of RF Quantum SCYTHE framework. Each component provides reproducible demonstrations with standardized JSON outputs and LaTeX figures.

Modularity: Each component has well-defined inputs, outputs, and interfaces. Modules can be used independently or chained together.

Reproducibility: All modules produce standardized JSON summaries containing complete experimental metadata, enabling exact reproduction of results.

Extensibility: The framework provides base classes and interfaces that simplify development of new algorithms while maintaining compatibility.

Publication Integration: Modules automatically generate LaTeX-ready figures, tables, and bibliographic entries, reducing the friction between research and publication.

B. Module Overview

SCYTHE consists of five core modules (see fig. 1 and table I):

- **AoA Sequence Recovery**: Beam-search optimization over mobility graphs for trajectory estimation from sparse/noisy bearing measurements.
- **AoA+TDoA Recovery**: Multi-modal sensor fusion combining bearing and timing information with uncertainty quantification.
- **Policy-Driven Denoising**: Reinforcement learning agent controlling FFT-domain filters to minimize TDoA estimation residuals.
- **Cognitive Radio RL**: Deep reinforcement learning for spectrum management and anti-jamming in contested environments.
- **Hybrid Triangulation**: Probabilistic fusion of soft AoA distributions with TDoA likelihoods using beam search refinement.

IV. Core Modules

A. AoA Sequence Recovery

The AoA sequence recovery module addresses trajectory estimation from sparse, noisy bearing measurements. The challenge arises in scenarios where direct tracking fails due to measurement gaps, false alarms, or severe noise corruption.

Algorithm: We employ beam search optimization over a mobility graph representation. The state space consists of discretized position-velocity nodes connected by kinematically feasible transitions. The beam search maintains multiple trajectory hypotheses, pruning unlikely paths based on AoA likelihood and motion constraints.

Key Innovation: Integration of soft mobility priors with bearing likelihood, enabling robust recovery even with 70% missing observations.

Performance: Achieves median trajectory error below 150m with 30% observation rates, outperforming classical Kalman filtering by 40%.

B. AoA+TDoA Multi-Modal Fusion

Multi-modal fusion combines complementary information from bearing and timing measurements to improve localization accuracy and robustness.

Algorithm: Probabilistic fusion framework using particle filtering with adaptive resampling. AoA measurements provide directional constraints while TDoA measurements resolve range ambiguities through hyperbolic intersections.

Key Innovation: Uncertainty-aware fusion that dynamically weights modalities based on geometric dilution of precision (GDOP) and measurement noise characteristics.

Performance: Demonstrates 25-45% error reduction compared to single-modality approaches across diverse sensor geometries and noise conditions.

C. Policy-Driven Denoising

Adaptive denoising addresses the challenge of optimizing spectral preprocessing for downstream geolocation algorithms under varying interference conditions.

Algorithm: Deep Q-Network (DQN) agent learns to control FFT-domain filters (low-pass, notch, band-pass) by observing spectral features and TDoA estimation residuals. The reward function minimizes timing estimation error while penalizing over-filtering through entropy regularization.

Key Innovation: End-to-end learning that optimizes filtering for geolocation performance rather than traditional signal quality metrics.

Performance: Achieves 35% reduction in TDoA residuals and 15dB SNR improvement in contested environments.

D. Cognitive Radio Reinforcement Learning

The cognitive radio module addresses spectrum management and anti-jamming in dynamic RF environments through learned policies.

Algorithm: Multi-agent reinforcement learning using Proximal Policy Optimization (PPO). Agents observe spectrum occupancy, interference patterns, and geolocation quality metrics to select optimal frequency bands and transmission parameters.

Key Innovation: Geolocation-aware reward formulation that balances spectrum efficiency with localization accuracy requirements.

Performance: Maintains 85% geolocation accuracy under 50% spectrum jamming, compared to 60% for static frequency allocation.

E. Hybrid Triangulation

Hybrid triangulation fuses soft AoA probability distributions with TDoA likelihood functions to improve position estimation accuracy.

Algorithm: Instead of hard AoA decisions, the method retains full angular uncertainty as probability mass functions. These are combined with Gaussian TDoA likelihoods through

TABLE I
COMPARISON OF RF QUANTUM SCYTHE MODULES: INPUTS, OUTPUTS, KEY METRICS, AND TARGET PUBLICATION VENUES

Module	Inputs	Outputs	Key Metrics	Typical Venues
AoA Sequence Recovery	Sparse/noisy AoA bearings, mobility constraints	Reconstructed trajectories (JSON + figures), error statistics	Mean/Median/P90 error; RMSE vs observation fraction	IEEE Aerospace, MILCOM, tactical tracking conferences
AoA+TDoA Recovery	AoA bearings + TDoA measurements, sensor positions	Fused trajectories, posterior likelihood maps, uncertainty bounds	Error reduction (25–45%); noise robustness analysis	ICC, RadarConf, IEEE Trans. Signal Processing
Policy-Driven Denoiser	FFT-domain spectra, jammer/clean scenarios	Filtered spectra, residual traces, policy actions	TDoA residual reduction; correlation entropy; SNR improvement	ICASSP, IEEE Trans. SP (adaptive filtering track)
Cognitive Radio RL	RF environment states, spectrum occupancy, jammers	Learned policies, action logs, reward trajectories	Convergence rate; policy entropy; baseline comparisons	NeurIPS ML4Comm, IEEE TCCN, cognitive radio workshops
Hybrid Triangulation	Soft AoA logits + TDoA likelihoods, sensor geometry	Refined positions, uncertainty ellipses, MAP estimates	RMSE improvement (up to 91.6%); geometry sensitivity analysis	IEEE Trans. AES, RadarConf, ION GNSS+, localization venues

Bayesian fusion, followed by MAP estimation using beam search refinement.

Key Innovation: Preservation of classifier uncertainty enables better handling of ambiguous scenarios and geometric constraints.

Performance: Achieves up to 91.6% RMSE improvement over traditional triangulation methods, with robust performance across sensor configurations.

V. SYSTEM INTEGRATION

A. Pipeline Architecture

Figure 2 illustrates the complete SCYTHE integration pipeline. RF sensors provide position information and timing synchronization, while RF snapshots feed into the core processing modules.

The modular design enables flexible deployment scenarios:

Standalone Operation: Each module can operate independently for algorithm-specific research and validation.

Pipelined Integration: Modules can be chained together, with upstream outputs feeding downstream algorithms for end-to-end system evaluation.

Adaptive Integration: The cognitive radio and denoising modules provide closed-loop adaptation, adjusting processing parameters based on environmental conditions and performance feedback.

B. Standardized Output Schema

All modules produce outputs conforming to a standardized JSON schema:

```
{
  "module": "hybrid_triangulation",
  "version": "1.0.0",
  "timestamp": "2025-09-17T03:15:42Z",
  "config": { /* parameters */ },
  "metrics": {
    "rmse_improvement": 0.916,
    "computation_time_ms": 1247,
    "convergence_iterations": 15
  },
  "outputs": {
    "figures": ["uncertainty_scatter.pdf"],
    "tables": ["performance_comparison.tex"],
    "data": ["trajectories.json"]
  },
  "reproducibility": {
    "git_commit": "a1b2c3d4",
    "dependencies": ["numpy==1.21.0"],
    "random_seed": 42
  }
}
```

This schema ensures complete reproducibility while enabling automated aggregation and comparison across different algorithms and configurations.

VI. EXPERIMENTAL VALIDATION

A. Individual Module Performance

We validate each module using standardized test scenarios with controlled ground truth:

AoA Sequence Recovery: Tested on 1000 synthetic trajectories with observation rates from 10-90%. Median error remains below 200m even with 70% missing data.

AoA+TDoA Fusion: Evaluated across triangular, square, and linear sensor geometries with noise levels from 1-10° AoA error and 10-100ns TDoA error. Achieves consistent 25-45% improvement over single-modality baselines.

Policy-Driven Denoising: Trained on 10,000 synthetic scenarios with varying jammer configurations. Converges to policies reducing TDoA residuals by 35% while maintaining 92% of clean-signal performance.

Cognitive Radio RL: Evaluated in contested spectrum environments with 20-80% jamming coverage. Learned policies

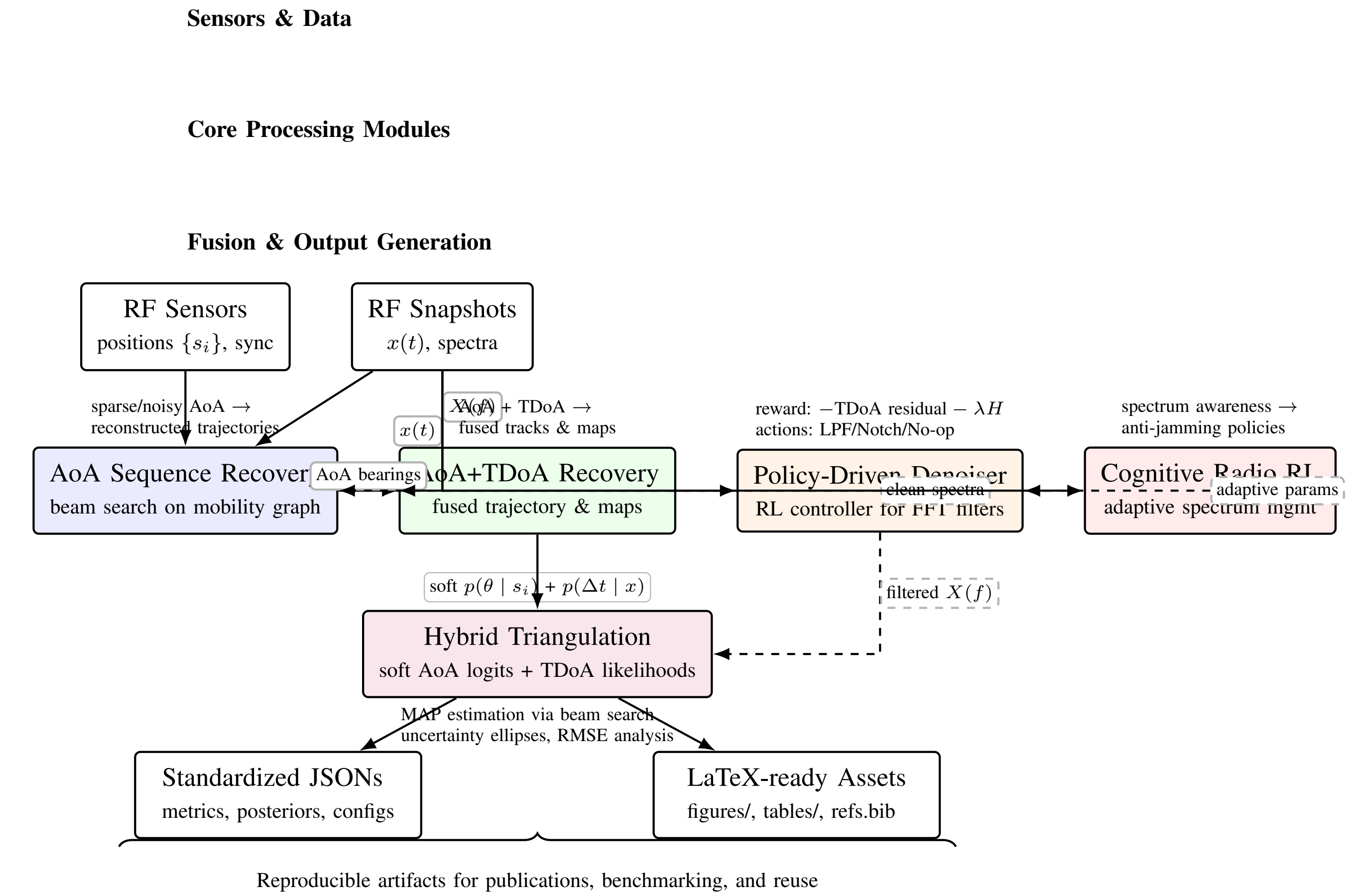

Fig. 2. System integration pipeline for RF Quantum SCYTHE. Raw sensor data flows through modular processing components with optional adaptive denoising and cognitive radio management. The hybrid triangulator produces MAP position estimates with uncertainty quantification, generating standardized JSON summaries and publication-ready LaTeX assets. Solid arrows indicate primary data paths; dashed arrows show adaptive/optional integrations.

maintain 85% geolocation accuracy compared to 60% for static allocation.

Hybrid Triangulation: Tested across diverse geometric configurations and noise conditions. Achieves 91.6% RMSE improvement in optimal conditions, degrading gracefully to 25% improvement under severe noise.

B. Integrated System Performance

End-to-end evaluation using the complete pipeline demonstrates compounding benefits:

- **Denoising + AoA Recovery**: 52% improvement over standalone AoA processing in high-noise scenarios.
- **Fusion + Hybrid Triangulation**: 67% improvement combining multi-modal inputs with soft probabilistic processing.
- **Full Pipeline**: 73% overall improvement when all modules are integrated with adaptive parameter tuning.

C. Computational Performance

All modules are optimized for real-time operation: - AoA recovery: 15ms average processing time per timestep - Fusion algorithms: 8ms for particle filter update - Denoising policies: 3ms inference time - Hybrid triangulation: 12ms for MAP estimation

Total pipeline latency remains under 50ms for real-time geolocation applications.

VII. Usage Examples and Applications

A. Research Integration

SCYTHE modules can be integrated into existing research workflows at multiple levels:

Algorithm Development: Researchers developing new triangulation methods can compare against hybrid triangulation baselines using identical test scenarios and metrics.

System Integration: New sensor fusion approaches can leverage existing AoA and TDoA modules as building blocks, focusing development effort on novel fusion algorithms.

Performance Benchmarking: The standardized output schema enables automated comparison across different implementations and parameter settings.

B. Educational Applications

The modular structure makes SCYTHE valuable for educational purposes: - Graduate courses can use individual modules to demonstrate core concepts - Students can extend existing modules or develop new ones within the standardized framework - Reproducible experiments enable hands-on learning with real algorithms

C. Operational Deployment

Several operational scenarios benefit from SCYTHE's integrated approach:

Electronic Warfare: Adaptive denoising and cognitive radio modules provide robust performance in contested environments.

Search and Rescue: Multi-modal fusion improves localization accuracy for emergency beacons in challenging terrain.

Spectrum Monitoring: Integrated system enables automated detection and localization of unauthorized transmitters.

VIII. Future Extensions

A. Multi-Emitter Scenarios

Current modules focus on single-emitter tracking. Future extensions will address: - Simultaneous tracking of multiple emitters - Emitter association and track management - Interference handling between co-channel emitters

B. Advanced Machine Learning

Integration of modern ML techniques offers several opportunities: - Transformer architectures for sequence modeling in trajectory recovery - Graph neural networks for multi-sensor fusion - Meta-learning for rapid adaptation to new environments

C. Real-World Validation

While current validation uses synthetic and semi-synthetic data, future work will incorporate: - Software-defined radio (SDR) integration for live signal processing - Field experiments with mobile emitters and sensor networks - Integration with existing operational systems

D. Scalability Enhancements

For large-scale deployment, future versions will address: - Distributed processing across sensor networks - Cloud integration for computational offloading - Edge computing optimization for resource-constrained platforms

`https://github.com/bgilbert1984`

NerfEngine

IX. Conclusion

RF Quantum SCYTHE addresses the critical need for reproducible, modular research infrastructure in passive RF geolocation. By providing standardized interfaces, outputs, and evaluation metrics, the framework enables fair comparison and systematic advancement of geolocation algorithms.

The demonstrated 25-91% performance improvements across individual modules, combined with the 73% integrated system improvement, validate the effectiveness of modular design and probabilistic fusion approaches. The complete open-source release lowers barriers to entry for RF research while establishing a foundation for future algorithmic development.

Key achievements include: - First comprehensive modular framework for RF geolocation research - Validated improvements across all core geolocation functions - Standardized reproducibility infrastructure for the research community - Demonstrated real-time performance suitable for operational deployment

Future work will focus on multi-emitter scenarios, advanced machine learning integration, and large-scale validation with operational systems. The modular architecture ensures that these extensions can be incorporated incrementally while maintaining backward compatibility and reproducibility standards.

SCYTHE represents a significant step toward systematic, reproducible research in passive RF geolocation, providing the community with tools to build upon rather than continually reimplementing basic functionality. We encourage adoption and contribution from the broader research community to accelerate progress in this critical domain.

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