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Robust High-Precision UAV Positioning in Urban Environments via Lightweight GPS/IMU EKF Fusion

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Abstract:

In dense urban canyons, multipath and occlusions significantly degrade standalone GPS accuracy or even cause loss of lock, while low-cost MEMS IMUs provide high-rate continuity but suffer from drift. To balance short-term stability and long-term accuracy, this paper presents a deployable and lightweight GPS/IMU tightly coupled fusion method based on the Extended Kalman Filter (EKF). The state vector includes position, velocity, attitude, and IMU biases. We employ IMU-driven prediction with Lie-algebra small-angle updates and quaternion normalization for numerical stability, and introduce measurement consistency tests and an adaptive quality-based weighting scheme that adjusts the GPS covariance using satellite count, HDOP, and residual statistics. A MATLAB/Simulink urban-block simulation with noisy measurements, intermittent occlusions, and 30 s continuous blackouts compares GPS-only, IMU-only, and the proposed fusion. Results show over 60% reduction in position RMSE compared with single-sensor baselines; during a 30 s blackout the maximum position deviation is contained within 3 m, and after recovery the error returns to <2 m in 4–6 s. The approach requires few parameters and low computation, making it suitable for real-time deployment on resource-constrained UAVs.

Keywords: GPS/IMU fusion, EKF, urban canyon, robust localization, UAV

1 Introduction

Urban environments exhibit rapidly varying satellite visibility and strong multipath/non-line-of-sight effects, causing non-Gaussian GPS measurement errors and outages. IMUs provide high-rate angular velocity and specific force that preserve short-term trajectory continuity, but their biases and scale-factor errors lead to time-accumulating drift. Single-sensor solutions therefore struggle to meet the combined requirements of high accuracy, robustness, and real-time performance. Fusing GPS with IMU leverages complementary strengths: IMU for short-term continuity and GPS for long-term global constraints. Motivated by practical deployment on resource-limited UAVs, we focus on a tightly coupled, lightweight EKF framework and evaluate it under representative urban conditions.

2 Related Work

GNSS/INS integration has evolved from loosely to tightly and deeply coupled architectures. EKF/UKF methods remain prevalent on embedded platforms due to their simplicity and real-time capability, though robustness can degrade under strong non-Gaussian noise and outliers. Sliding-window factor-graph optimization (e.g., visual/laser-inertial) achieves higher accuracy in complex environments but often requires higher-quality sensors and compute budget. Prior studies on urban weak-signal conditions propose adaptive measurement covariances driven by signal quality indicators, soft convergence during GPS recovery, and outlier suppression. In contrast, we deliberately target a low-cost, deployable solution using only GPS and IMU, integrating quality-aware weighting and statistical consistency checks within an EKF to balance compute, accuracy, and robustness.

3 Theoretical Background

3.1 GPS Positioning and Errors

GPS computes 3D position and clock bias using pseudoranges from at least four satellites. In urban canyons, multipath and occlusions substantially increase errors and introduce gross outliers.

3.2 IMU and Error Propagation

IMU measurements integrated over time produce velocity and position. Random walk and biases accumulate, causing divergence unless constrained by absolute references.

3.3 EKF for GPS/INS

EKF linearizes the nonlinear system to propagate state and covariance. IMU drives prediction, while GPS provides corrections, jointly achieving short-term continuity and long-term accuracy.

4 Method

4.1 State and Frames

We use world frame {W} and body frame {B}. The state is x = [p_W, v_W, q_WB, b_g, b_a]^T, where q_WB is the attitude quaternion and b_g/b_a are gyro/accelerometer biases.

4.2 Process Model (IMU Preintegration)

Debiased angular rates and specific forces drive prediction of attitude and velocity. Biases follow random walks. Lie-algebra small-angle updates and quaternion normalization ensure numerical stability.

4.3 Measurement Model (GPS)

Absolute position (and optionally velocity) are used as measurements with appropriate Jacobians for the EKF update.

4.4 Adaptive Measurement Weighting

We define a quality factor q = sat_num / HDOP and adjust the GPS covariance as R = α(q) R0, down-weighting weak-signal measurements rather than hard rejection to preserve observability.

4.5 Consistency and Robustness

Residuals are screened via chi-square tests and optionally Huber losses to reject or attenuate outliers. During GPS recovery after blackouts, small initial weights are used to avoid jumps.

4.6 Time Synchronization and Complexity

Timestamps are aligned by interpolation between IMU and GPS data. With a fixed-size state, each update solves a small linear system, suitable for real-time onboard implementation.

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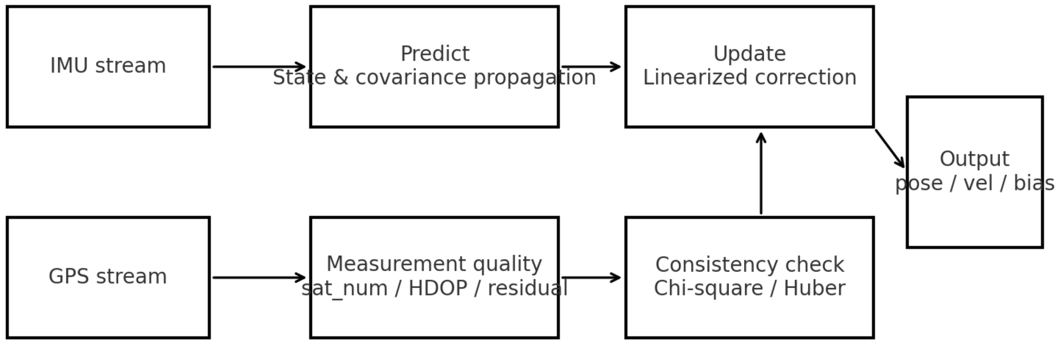

Figure.1. EKF flow with measurement quality evaluation, consistency checks, and recovery strategy.

5 Experiments and Evaluation

5.1 Scenario and Parameters

We build a 600 s urban-block trajectory in MATLAB/Simulink. IMU runs at 200 Hz and GPS at 5 Hz. IMU noise: accelerometer 0.02 m/s² and gyroscope 0.002 rad/s (white), with bias random walks. GPS noise is 3 m (inflated to 6 m in weak-signal periods). We include three 30 s continuous blackouts, totaling ~40% weak-signal duration.

5.2 Baselines and Metrics

Baselines: (A) GPS-only with hold/interpolation during blackouts; (B) IMU-only dead-reckoning; (C) Proposed EKF fusion with adaptive weighting and outlier rejection. Metrics: position/velocity RMSE, maximum deviation during blackouts (MaxE), recovery time after GPS returns (T_rec), and outlier rejection rate.

5.3 Key Parameters

Table 1 Key parameters and settings used in simulation experiments

Parameter	Symbol	Value/Unit	Notes
IMU sampling rate	f_IMU	200 Hz	Inertial prediction
GPS sampling rate	f_GPS	5 Hz	Measurement update
GPS noise (σ)	σ_GPS	3 m (6 m under weak signal)	Gaussian
Continuous blackout	—	3 × 30 s	Loss of lock
Adaptive factor	α(q)	1 + β·HDOP/sat_num	Quality weighting
Process noise	Q	Empirical	Sensor-level
Measurement noise	R	α(q)·R0	Dynamic adjustment

5.4 Results and Visualization

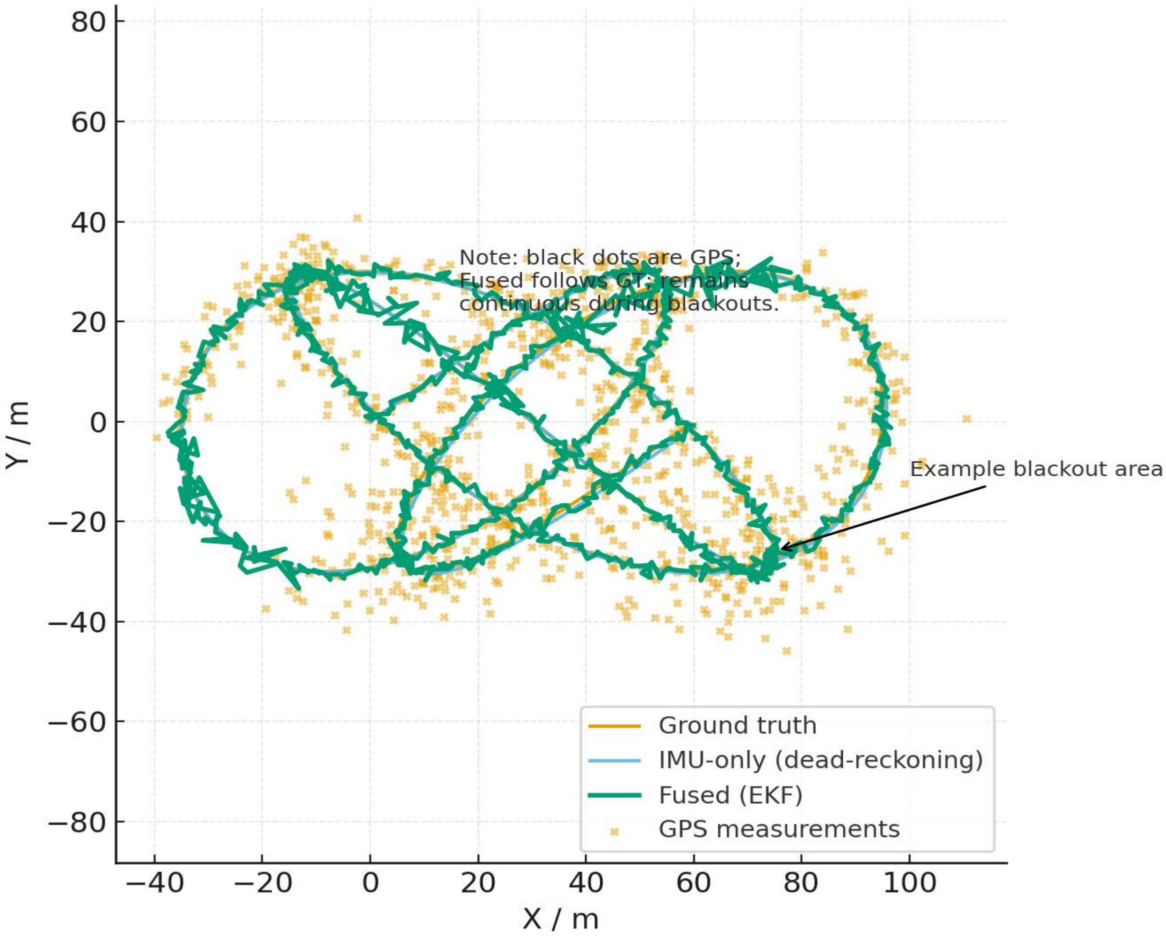

Figure. 2. Trajectory comparison (GPS dots, IMU-only drift, fused follows ground truth; continuous under blackouts).

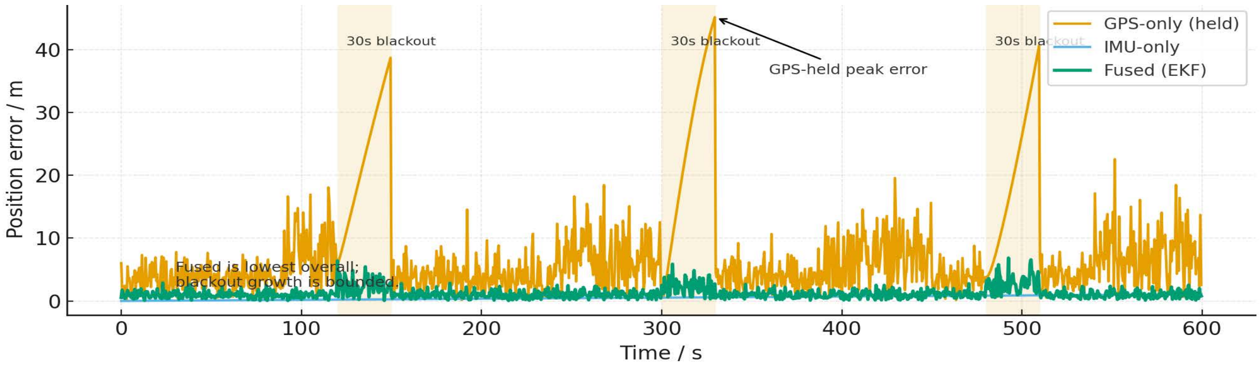

Figure. 3. Error vs. time with blackout spans: fused stays lowest; blackout growth is bounded.

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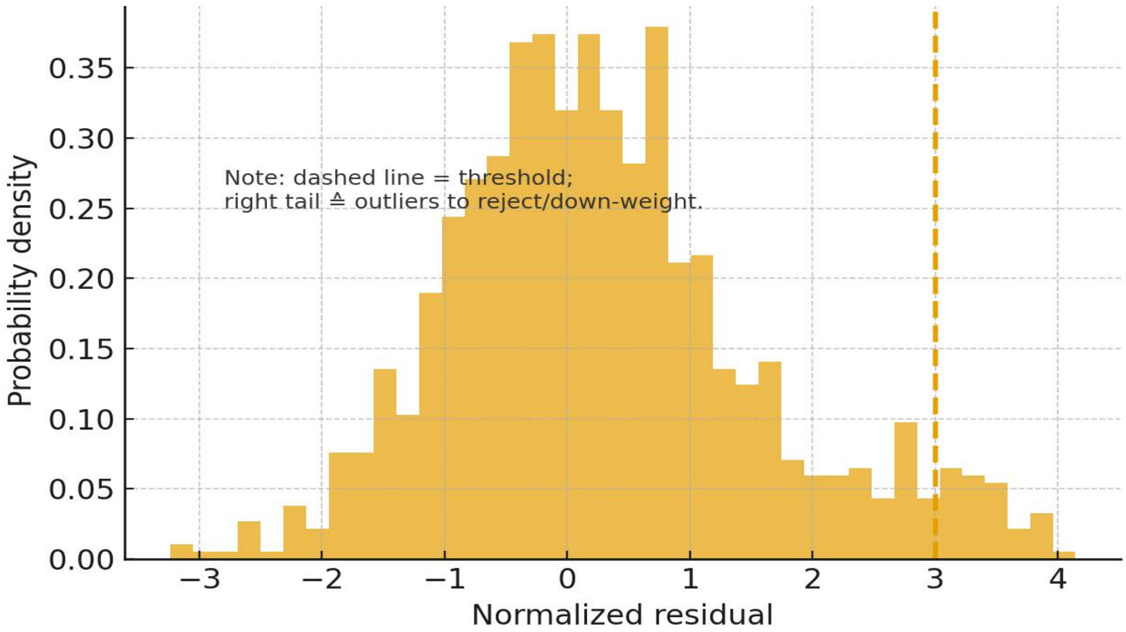

Figure.4. Residual histogram with chi-square/3σ threshold; right tail corresponds to outliers.

6 Discussion

Quality-aware weighting and chi-square/Huber screening effectively suppress non-Gaussian outliers in urban conditions while preserving observability. Compared to higher-complexity multi-sensor stacks (e.g., visual-inertial), the proposed EKF offers a practical accuracy–compute trade-off suitable for resource-limited UAVs. Limitations include drift growth under prolonged GPS-denied scenarios. Future work will consider online noise adaptation (e.g., adaptive R/Q, IMM) and periodic sliding-window factor-graph corrections.

7 Conclusion

We presented a lightweight tightly coupled GPS/IMU EKF for robust UAV localization in urban environments. Under noisy measurements and occlusions with 30 s blackouts, the method substantially outperforms GPS-only and IMU-only baselines in position RMSE, bounds deviations during outages, and rapidly reconverges upon GPS recovery. The algorithm's low parameter count and compute footprint make it attractive for real-time embedded deployment. Future validation will migrate to ROS 2/Gazebo hardware-in-the-loop and real flight tests.

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