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Error Correction for Multi-Source Integrated Navigation in Unmanned Aerial Vehicles

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Abstract. Accurate and robust navigation of UAVs during approach and landing is challenging when GNSS is degraded and heterogeneous sensors are asynchronous. This paper studies error sources and correction methods for a multi-source integrated navigation system that combines SINS/GNSS with ground-based laser ranging and RF radar. First, error models are derived for attitude, velocity and position in strapdown inertial navigation, and major error sources of GNSS, laser ranging and RF radar are summarized. Second, two practical compensation strategies are introduced: a low-dynamic detector with complementary-filter-based angular-rate compensation to suppress attitude drift, and a GNSS latency compensation scheme that uses IMU short-term propagation to align delayed GNSS observations. Third, an adaptive federated unscented Kalman filter (AF-UKF) is developed. Innovation-consistency statistics drive online inflation of measurement covariance, reliability-based fusion weights, and fault isolation with state reset, enabling robust fusion under outliers and local sensor failures. Simulations on a fixed-wing landing trajectory (635 s, initial altitude 3000 m) show that multi-source fusion reduces mean position errors to about 0.42-0.47 m and mean velocity errors to about 0.02 m/s. Compared with UKF and federated UKF (F-UKF), AF-UKF further decreases mean latitude/longitude/altitude errors to 0.330/0.316/0.298 m and mean velocity errors to 0.012-0.015 m/s, demonstrating improved accuracy and robustness.

Keywords: UAV navigation, multi-source integrated navigation, error compensation, adaptive federated UKF, time synchronization.

1. Introduction

Reliable navigation during approach and landing is a core requirement for many UAV missions. Strapdown inertial navigation (SINS) provides high-rate motion propagation but suffers from bias-driven drift, while GNSS can bound long-term errors but is vulnerable to blockage, multipath and interference [1]. Ground-based laser ranging/angulation and RF radar can provide complementary observations, but their practical use introduces outliers, range-dependent noise, and spatiotemporal misalignment [2]. This paper reorganizes the provided content into a journal-style presentation focused on (i) sensor error analysis, (ii) compensation of low-dynamic attitude drift and GNSS time

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latency, and (iii) an adaptive federated unscented Kalman filter (AF-UKF) for robust multi-source fusion, validated by simulation [3].

2. Sensor error analysis

2.1. Strapdown inertial navigation errors

INS solution errors accumulate over time, so it is necessary to model the error propagation of attitude, velocity and position to support error-state filtering. The error-state typically includes attitude misalignment angles, velocity and position errors, and inertial sensor biases. Gyroscope and accelerometer biases are often modeled as first-order Markov processes driven by white noise [4].

2.2. GNSS error sources

Major GNSS error sources include satellite clock and orbit errors, ionospheric and tropospheric delays, multipath and satellite blockage (especially in urban canyons, dense buildings, or forests), receiver hardware and antenna effects, and satellite geometry (DOP). These factors jointly determine the accuracy and availability of GNSS positioning.

2.3. Laser ranging errors

Laser ranging can provide high accuracy but is limited by data rate when targets move fast, by target surface properties that affect reflectivity and signal-to-noise ratio, and by mixed-pixel effects where a footprint spans surfaces with different depths, producing ambiguous returns. Practical systems therefore require outlier rejection and robust filtering.

2.4. RF radar errors

RF radar ranging errors can be divided into systematic errors (fixed delays in the system chain) and random errors. Random errors arise from device instability (e.g., timing jitter, oscillator drift, reading errors) and external factors (e.g., random variations in propagation speed, atmospheric refraction, and target reflection center variations). Systematic errors can be reduced by calibration, while random errors are usually characterized statistically.

3. Compensation and spatiotemporal misalignment

3.1. Low-dynamic detection and angular-rate compensation

To improve attitude stability, a complementary-filter-based angular-rate compensation strategy is introduced. When the UAV is in a low-dynamic state, the specific force magnitude is close to gravity. A low-dynamic coefficient can be defined by the deviation between the measured acceleration magnitude and g:

$$coe = abs\left(\|a_{IMU} - b_a\| - \| g \|\right) \tag{1}$$

A binary low-dynamic flag is then obtained with a threshold N_{min} :

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$$state = \begin{cases} 1 & coe < N_{min} \\ 0 & coe \geq N_{min} \end{cases} \tag{2}$$

During low dynamics, roll and pitch are corrected using the gravity direction from the accelerometer, while yaw can be corrected using heading-related information derived from ground-based laser/radar observations. The correction is fed back to the gyroscope output through proportional-integral terms, suppressing long-term drift.

3.2. GNSS time-latency compensation

In embedded implementations, GNSS measurements can lag the latest IMU epoch due to serial reception and solution computation time. A time-latency compensation scheme predicts the state at the delayed GNSS time using short-term IMU propagation, and then applies a complementary correction to align GNSS and IMU in time. This exploits the short-term accuracy of IMU integration and the long-term stability of GNSS.

3.3. Spatiotemporal alignment discussion

Time misalignment arises from inconsistent sensor time bases, different sampling rates, and processing/transmission delays. A common engineering approach is to use GNSS NMEA messages and the 1-PPS signal as a unified time reference to periodically calibrate sensor clocks. Spatial misalignment is caused by inconsistent reference frames (e.g., inertial frame vs WGS-84 and other local frames), sensor lever arms, and installation offsets. Lever-arm calibration and consistent coordinate-frame transformations are required for high-accuracy fusion.

4. Fusion error-correction algorithms

4.1. Kalman filter and federated filtering

The Kalman filter provides a recursive minimum mean-square-error estimate for linear systems. For multi-sensor navigation, federated filtering introduces a global filter and multiple local sub-filters, offering modularity, reduced computation, and fault tolerance. A set of information-sharing factors β_i ($\sum \beta_i = 1$) distributes global prior information to sub-filters. The global estimate is obtained by fusing sub-filter estimates and then fed back to reset sub-filters [5].

4.2. Unscented Kalman filter

For nonlinear navigation models, the unscented Kalman filter (UKF) avoids Jacobian computation by propagating deterministically chosen sigma points through the nonlinear process and measurement models. The posterior mean and covariance are reconstructed from the transformed sigma points, providing improved accuracy over first-order linearization in many practical cases.

4.3. Adaptive federated UKF with innovation consistency

To enhance robustness under noise uncertainty, outliers, and local sensor failures, an adaptive mechanism is introduced into the federated UKF (F-UKF). For each sub-filter i, the innovation and the normalized innovation squared (INS) are computed as:

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$$v\left(\mathrm{i,k}\right) = z\left(\mathrm{i,k}\right) - \hat{z}\left(i,k\right) \tag{3}$$

$$\epsilon\left(\mathrm{i,k}\right) = \mathrm{v}\left(\mathrm{i,k}\right)^{T} S\left(i,k\right)^{-1} v\left(\mathrm{i,k}\right) \tag{4}$$

With confidence level p (e.g., 0.95 or 0.99), a chi-square threshold gamma_i is used for consistency checking. When epsilon(i,k) exceeds the threshold, the measurement covariance is inflated to down-weight unreliable observations. Sub-filter reliability weights are designed from consistency statistics:

$$\omega\left(\mathrm{i,k}\right) \leftarrow \exp\left(-\frac{\epsilon\left(\mathrm{i,k}\right)}{2}\right) \tag{5}$$

Persistent large epsilon(i,k) indicates sensor failure or severe outliers, and the corresponding sub-filter can be isolated by setting w(i,k)=0 and resetting its state to the global estimate. The global fusion is performed in information form:

$$P_f = \left(\sum \omega\left(i,k\right) P(i,k)^{-1}\right)^{-1} \tag{6}$$

$$\widehat{x}_f = P_f \sum_i \omega\left(i,k\right) P(i,k)^{-1} \widehat{x}\left(i,k\right) \tag{7}$$

After fusion, the global estimate is redistributed to sub-filters to form a closed-loop federated architecture that suppresses drift and improves robustness.

5. Simulation experiments

5.1. Simulation setup

The simulation considers a fixed-wing UAV landing trajectory with phases including level flight calibration, deceleration and descent, approach turning, and final approach. The initial altitude is 3000 m and the simulation duration is 635 s.

Table 1. Simulation parameters for the navigation system

Parameter	Reference value
Initial altitude	3000m
Gyro constant bias	0.03(°/h)
Accelerometer constant bias	100μg
Angle random walk	0.001(°/h)
Velocity random walk	10μg

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Table 1. (continued)

GNSS position accuracy	[3m3m5m]
GNSS velocity accuracy	0.5m/s
Laser wavelength	1535/1550nm
Laser aperture	60mm
Laser ranging frequency	5Hz
Laser ranging accuracy	$\leq$ 1m
RF radar slant range accuracy	1m
RF radar azimuth accuracy	0.03°
RF radar elevation accuracy	0.03°
Initial attitude error	[0.5'0.5'0.5']

5.2. Subsystem fusion results

Error curves are produced for pure inertial navigation and for different integrated navigation configurations. Tables 2–5 summarize maximum and mean errors (converted to meters for latitude/longitude).

Table 2. Error statistics for pure SINS and SINS/GNSS

Configuration	Metric	Max error	Mean error
Pure SINS	Latitude(m)	266.004	114.891
	Longitud(m)	41.597	11.908
	Altitude(m)	209.586	65.718
	v_E (m/s)	0.175	0.065
	v_N (m/s)	0.557	0.416
	v_U (m/s)	0.718	0.330
SINS/GNSS	Latitude(m)	3.106	0.974
	Longitud(m)	2.875	0.737
	Altitude(m)	5.516	1.064
	v_E (m/s)	0.170	0.037
	v_N (m/s)	0.100	0.035
	v_U (m/s)	0.164	0.028

Table 3. Error statistics for SINS/GNSS/laser fusion

Configuration	Metric	Max error	Mean error
SINS/GNSS/Laser	Latitude(m)	3.721	0.723
	Longitud(m)	1.813	0.687
	Altitude(m)	1.512	0.626
	v_E (m/s)	0.276	0.029
	v_N (m/s)	0.218	0.032
	v_U (m/s)	0.093	0.026

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Table 4. Error statistics for SINS/GNSS/RF radar fusion

Configuration	Metric	Max error	Mean error
SINS/GNSS/RF	Latitude(m)	1.251	0.645
	Longitud(m)	1.525	0.717
	Altitude(m)	1.132	0.586
	v_E (m/s)	0.130	0.031
	v_N (m/s)	0.098	0.025
	v_U (m/s)	0.043	0.023

Table 5. Error statistics for multi-source fusion

Configuration	Metric	Max error	Mean error
SINS/GNSS/Laser/RF	Latitude(m)	1.282	0.415
	Longitud(m)	0.930	0.474
	Altitude(m)	0.848	0.462
	v_E (m/s)	0.065	0.022
	v_N (m/s)	0.084	0.024
	v_U (m/s)	0.056	0.026

5.3. Filter comparison

Three filtering strategies are compared under loosely coupled fusion: UKF, federated UKF (F-UKF), and adaptive federated UKF (AF-UKF). Table 6 summarizes the statistics. AF-UKF achieves the lowest mean errors, while the peak error can increase for some components due to occasional outliers.

Table 6. Comparison of UKF, F-UKF, and AF-UKF

Filter	Metric	Max error	Mean error
UKF	Latitude(m)	1.672	0.562
	Longitud(m)	1.465	0.538
	Altitude(m)	1.854	0.506
	v_E (m/s)	0.063	0.025
	v_N (m/s)	0.089	0.017
	v_U (m/s)	0.053	0.021
F-UKF	Latitude(m)	1.438	0.482
	Longitud(m)	1.573	0.401
	Altitude(m)	1.019	0.438
	v_E (m/s)	0.092	0.019

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Table 6. (continued)

	v_N (m/s)	0.073	0.024
	v_U (m/s)	0.066	0.016
AF-UKF	Latitude(m)	2.237	0.330
	Longitud(m)	1.362	0.316
	Altitude(m)	1.064	0.298
	v_E (m/s)	0.047	0.012
	v_N (m/s)	0.075	0.015
	v_U (m/s)	0.039	0.012

6. Conclusion

This paper organized the document content into a journal-style report on multi-source UAV navigation error correction. Sensor error sources for SINS, GNSS, laser ranging, and RF radar were summarized, and practical compensation strategies were described for low-dynamic attitude drift and GNSS time latency. An innovation-consistency-driven adaptive federated UKF was presented, including online measurement-noise inflation, reliability-based weighting, and fault isolation with state reset. Simulation results on a landing trajectory show that multi-source fusion can substantially reduce SINS drift, and that AF-UKF achieves the lowest mean position and velocity errors among the compared filters.

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