

Article

RETRACTED: A Multimodal Data Fusion Algorithm for Urban Low-Altitude UAV Perception

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Highlights

What are the main findings?

- A Hybrid Conditional Kalman Filter (HCKF) framework is proposed for urban low-altitude UAV perception by fusing TDOA and Remote ID measurements through kinematics-based temporal alignment, measurement quality evaluation, and subspace-decoupled EKF fusion.
- The proposed framework reduces positioning errors by explicitly handling TDOA altitude jumps, Remote ID timing irregularity, and horizontal–vertical geometric anisotropy, achieving over 40% RMSE reduction compared with single-source baselines.

What are the implications of the main findings?

- The results demonstrate that TDOA and Remote ID can provide complementary advantages for urban low-altitude UAV tracking, improving both positioning accuracy and trajectory continuity under asynchronous sampling and signal instability.
- The proposed HCKF framework provides a practical and robust fusion solution for UAV perception in complex urban environments, especially when measurements are affected by packet loss, multipath effects, and vertical observability degradation.

Abstract

Accurate Unmanned Aerial Vehicle (UAV) position estimation is the cornerstone of urban low-altitude safety management systems. Time Difference of Arrival (TDOA) and Remote Identification (Remote ID) are widely used surveillance technologies with complementary characteristics. TDOA provides high-rate updates but suffers from geometry-induced horizontal–vertical anisotropy and multipath effects, while Remote ID supplies absolute state information yet struggles with intermittent sampling and packet loss. Existing fusion schemes typically address these issues in isolation: sequential filtering manages asynchrony but assumes Gaussian noise, robust estimators suppress outliers at the cost of discarding valid data, and coupled-filter architectures allow vertical anomalies to contaminate horizontal estimates through the Kalman gain cross-coupling. No prior framework jointly handles structural TDOA altitude jumps, stochastic Remote ID timing jitter, and the geometric anisotropy between estimation subspaces within a single coherent pipeline. To bridge this gap, we propose a Hybrid Conditional Kalman Filter (HCKF) framework comprising three integrated modules. First, a kinematics-based temporal alignment module maps asynchronous measurements onto a uniform timeline and predicts missing samples, resolving cross-modal time mismatches. Second, a measurement quality evaluation mechanism detects TDOA altitude steps via robust two-layer stratification and scores Remote ID timing irregularity through a confidence mapping, converting these anomalies into dynamic covariance adjustments and weight caps without discarding observations. Third,



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a Subspace-Decoupled Fusion strategy exploits the physical insight that TDOA horizontal precision derives from hyperbolic intersection geometry, whereas its vertical estimates suffer from weak observability due to near-coplanar ground-station deployment. By applying entropy-guided weighting in the horizontal plane and a conditional Remote ID-dominant rule in the vertical axis, this design prevents cross-dimensional error propagation. The framework was validated using three real-world flight missions at distinct altitudes (255 m, 345 m, and 440 m) totaling 13.51 km of flight distance, with RTK serving as ground truth. HCKF reduces the Root Mean Square Error by over 40% relative to single-source baselines (95% bootstrap confidence interval: [35.2%, 48.7%]), and paired Wilcoxon signed-rank tests confirm statistically significant improvement ($p < 0.01$) over standard EKF, Covariance Intersection, and Iterative CI across all three tracks.

Keywords: multimodal data fusion; TDOA; Remote ID; EKF; urban low-altitude UAVs

1. Introduction

In recent years, the strategic development of low-altitude airspace has become a global focal point. For instance, the United States is actively promoting Advanced Air Mobility (AAM) systems, while China has formalized the “low-altitude economy” as a national strategy. As a pivotal component of these ecosystems, Unmanned Aerial Vehicles (UAVs) have attracted significant attention from both academia and industry [1]. Driven by their inherent advantages in deployment flexibility, cost-effectiveness, and operational agility, UAVs have experienced rapid development and achieved broad utilization across diverse application scenarios. Policy support has accelerated the deployment of UAVs in industrial tasks such as inspection and logistics, while simultaneously expanding consumer-grade applications including aerial photography. As the number of UAVs and the density of flight missions continue to rise, safety incidents in low-altitude airspace have become more frequent, thereby increasing operational risks. This issue is particularly pronounced in urban low-altitude environments, where complex electromagnetic conditions, interference-prone communication links, and dense, obstructed built environments collectively elevate the likelihood of accidents and complicate regulatory oversight [2,3]. These challenges highlight the urgent need for a structured urban low-altitude safety management system [4]. Reliable UAV positional-awareness capabilities constitute the foundation of this system, which provide accurate, real-time position and trajectory information to support the perception of UAV activities in complex urban low-altitude environments [5].

The complex electromagnetic environment and dense buildings of urban low-altitude airspace make it impossible for a single sensor to accurately detect UAV location [6,7]. Instead of depending solely on single sensor, the urban low-altitude safety management system increasingly emphasize multi-sensor data fusion and cooperative sensing architectures [8]. Some researchers suggest using cameras or radar. But visual sensors struggle with privacy issues [1] and limited range [2]. Radar systems are effective but often too expensive and heavy for dense urban deployment [3]. In addition, 5G positioning is promising but not yet fully mature for precise tracking [4]. In practical applications, Radio Frequency (RF) detection techniques (e.g., Time Difference of Arrival, TDOA) and Remote ID system are commonly utilized and demonstrate significant complementary capabilities. TDOA is a passive multi-point positioning technique that estimates UAV location based on the differences in signal arrival times at multiple ground stations; however, in urban low-altitude environments, station geometry constraints and severe multipath effects lead to observation instability, intermittent signal loss, and poor altitude-estimation performance [9]. Remote

ID system employs airborne modules to actively broadcast identity and status information, providing real-time positional reporting [10]. However, the Remote ID system is limited by low update rates, frequent data loss, and dependence on compliant onboard equipment [11]. The complementary strengths and limitations of these sensing modalities motivate the adoption of a multimodal fusion approach to better accommodate the constraints of urban low-altitude environments.

It should also be noted that the abnormal jumps and jitter observed in TDOA measurements are not merely random noise. They are closely related to the urban propagation environment, including multipath reflections, non-line-of-sight reception, receiver geometry, and weak vertical observability. Recent studies on multi-source localization in complex multipath environments have shown that propagation-aware reliability modeling is important for robust positioning [12]. In addition, fundamental performance-limit analysis indicates that achievable localization accuracy is constrained by sensing geometry and signal parameters [13]. These studies motivate the present work to treat TDOA reliability in a source-aware and subspace-aware manner. A complete theoretical performance-bound analysis for TDOA–Remote ID fusion is left for future work.

Beyond the specific sensing modalities, the broader field of probabilistic sensor fusion has seen significant advances relevant to urban UAV perception. Graph optimization-based estimators [14,15] offer globally consistent trajectory estimates but assume batch processing, which limits real-time applicability for safety-critical tracking. Uncertainty-aware tracking frameworks [16] incorporate learned observation models to predict sensor reliability; however, they require extensive training data that may not generalize across deployment sites. Bayesian asynchronous filtering [17] provides a principled treatment of irregular sampling but typically assumes stationary noise distributions. The HCKF framework builds upon these foundations while specifically addressing the joint challenges of structural altitude anisotropy and stochastic timing irregularity that are characteristic of TDOA–Remote ID fusion in urban canyons.

Due to differences in working principles and the complexity of urban low-altitude environments, TDOA and Remote ID exhibit distinctly different sensing and positioning data characteristics, which present three challenges to multimodal data fusion. Firstly, time stamp misalignment and sampling rate differences between the two sensing systems result in unreliable data association. Conventional buffered synchronization solves asynchrony but does not account for the quality of interpolated samples. Secondly, measurements suffer from stochastic uncertainty: Remote ID faces frequent packet loss and timing jitter, while TDOA signals are often interrupted by obstacles. Robust M-estimators suppress outliers but may incorrectly down-weight valid TDOA horizontal data due to unrelated vertical anomalies. Third, the sensors exhibit geometric anisotropy: TDOA provides high horizontal precision but lacks vertical stability due to station geometry. Coupled-filter architectures allow vertical errors to propagate into horizontal estimates through off-diagonal Kalman gain blocks. These three challenges interact, and addressing any one in isolation leaves the fusion vulnerable to the others. To address these challenges, we propose the Hybrid Conditional Kalman Filter (HCKF) for UAV sensing and positioning in low-altitude airspace.

This work investigates the fusion of Time Difference of Arrival (TDOA) and Remote ID data for urban low-altitude UAV perception and positioning. We propose a data fusion strategy based on the Hybrid Conditional Kalman Filter (HCKF) algorithm. This strategy maximizes the complementary strengths of each sensor by processing horizontal and vertical dimensions separately. This work tests the hypothesis that explicitly modeling measurement quality through confidence-driven covariance inflation and subspace-decoupled fusion yields statistically significant improvements in both trajectory accuracy and tempo-

ral continuity compared with conventional coupled-filter fusion, provided both sensing modalities maintain at least intermittent availability.

It should be emphasized that HCKF is not intended as a new Kalman filter variant obtained by merely stacking existing modules. Its novelty lies in converting the physical sensing characteristics of TDOA and Remote ID into conditional fusion rules. Specifically, the high horizontal sampling density but weak vertical observability of TDOA, and the absolute but sparse and jittered reporting of Remote ID, are explicitly represented through source-specific covariance inflation, confidence-limited information weighting, and vertical admissibility conditions. Therefore, the proposed framework changes the way heterogeneous measurements enter the EKF update, rather than only changing the motion model or tuning the noise matrix. The main contributions of this work are summarized as follows.

(1) We propose a kinematics-based temporal alignment method. This method fuses timestamps and predicts missing samples using sliding-window motion models. It effectively solves the problem of data asynchrony between heterogeneous sensors. This approach reduces time-gap errors and generalizes well to typical UAV flight patterns.

(2) We develop a spatiotemporal quality control mechanism. This mechanism maps structural altitude jumps and stochastic timing anomalies to dynamic weight constraints. It addresses the challenge of signal instability in urban canyons. This ensures robust estimation by down-weighting unreliable data instead of deleting them, maintaining continuity even when measurements are sparse.

(3) We design a horizontal-vertical separated fusion architecture. This architecture separates horizontal information weighting from vertical conditional updates. It resolves the conflict caused by the geometric anisotropy of different sensors. This strategy prevents errors in one dimension from contaminating the other, achieving both high precision and trajectory continuity.

(4) We validate the complete HCKF framework using real-world flight datasets collected in the Xuzhou Olympic Sports Center area. Unlike simulation-based evaluation, the field experiments capture realistic multipath reflections, intermittent signal blockage, and vertical instability caused by large stadium structures, grandstands, metallic roofs, and surrounding buildings. The empirical results demonstrate that the proposed framework improves positioning accuracy and trajectory continuity under the tested urban low-altitude conditions.

The remainder of this paper is organized as follows: Section 2 introduces the current related work at home and abroad. Section 3 describes the data-fusion model; Section 4 presents the experimental validation and comparative results; Section 5 discusses the roles of the proposed modules; and Section 6 concludes and outlines future work.

2. Related Work

2.1. Research on TDOA and Remote-ID

Time Difference of Arrival (TDOA) is extensively utilized for passive UAV surveillance due to its superior temporal resolution, but its efficacy in urban low-altitude environments is fundamentally compromised by systematic errors stemming from synchronization, geometry, and propagation. Firstly, precise clock synchronization constitutes the physical baseline, but residual offsets inevitably persist due to hardware heterogeneity. In multi-sensor fusion systems, these uncalibrated errors tend to accumulate over time, leading to significant trajectory drift, particularly in GNSS-denied areas [18,19]. Secondly, the geometric configuration of ground stations imposes severe structural limitations on 3D positioning. Analytical derivations confirm that determining a target's altitude using ground-based TDOA is characterized by weak vertical observability [20]. Specifically, the typical flat deployment of sensors creates a severe Vertical Geometric Dilution of Preci-

sion (GDOP), rendering altitude estimates numerically unstable compared to horizontal tracking [20,21]. Thirdly, Non-Line-of-Sight (NLOS) propagation in urban canyons introduces deterministic positive biases that systematically shift position estimates away from obstacles. Although robust neurodynamic optimization methods have been proposed to suppress these outliers, they often entail heavy computational costs that limit real-time applicability on edge devices [22]. Furthermore, without aiding from onboard sensors, standalone TDOA solvers frequently fail to converge during rapid maneuvers, highlighting the necessity for multimodal fusion [23].

Remote ID, serving as a digital license plate, provides absolute coordinates but is constrained by communication-induced systematic limitations and integrity risks. Unlike proprietary command links, Remote ID operates in crowded unlicensed ISM bands, where protocol interference leads to bursty packet loss and stochastic transmission delays. Theoretical analysis reveals that these delays follow a non-Gaussian distribution that standard filters fail to model effectively [24]. This latency is further exacerbated by protocol switching (e.g., between BLE and Wi-Fi), which introduces discrete time gaps in trajectory reporting [25]. Beyond latency, data integrity remains a critical concern, as environmental factors and interference significantly degrade link reliability in urban settings [26]. Moreover, the system is vulnerable to GPS spoofing, where valid format but false coordinates are broadcast. While RSS-based verification methods have been developed to detect such anomalies, they typically require dense receiver grids for effective triangulation [27,28]. Consequently, raw Remote ID data exhibit inherent trust gaps and temporal mismatches when fused with high-rate sensors, a characteristic often neglected by existing frameworks that treat it merely as a low-precision GPS source [29].

The above studies provide useful tools for asynchronous tracking, maneuvering-target prediction, and robust filtering. However, they do not fully match the coupled characteristics of the TDOA–Remote ID fusion problem in urban low-altitude UAV perception. First, asynchronous fusion methods usually focus on delayed track association, whereas the present problem requires measurement-level alignment between a high-rate passive source and a sparse cooperative source. Second, multiple-model filters improve motion prediction, but they do not explicitly model the source-dependent reliability changes caused by Remote ID packet loss and timing jitter. Third, robust EKF variants and covariance inflation methods suppress abnormal innovations, but they normally treat outliers as generic statistical events and do not distinguish the horizontal and vertical reliability of TDOA. In practical urban scenes, TDOA is informative in the horizontal plane but may introduce structural altitude jumps, while Remote ID provides more stable altitude information but suffers from sparse and irregular sampling.

2.2. Fusion Algorithms for Target Tracking

The fusion of cooperative (e.g., ADS-B and Remote ID) and non-cooperative (e.g., Radar and TDOA) surveillance data is a well-established paradigm in Air Traffic Control (ATC), providing a theoretical foundation for urban UAV monitoring. The primary challenge lies in the asynchronous and heterogeneous nature of these data streams. To address sampling rate discrepancies, where TDOA/Radar provides high-frequency updates while Remote ID/ADS-B suffers from latency, Sequential Filtering architectures have been widely adopted. Bar-Shalom et al. [30] established that processing measurements sequentially as they arrive, rather than buffering them into synchronous frames, significantly reduces latency in real-time tracking. Building on this, recent works have applied Track-to-Track Fusion (T2TF) to decouple the estimation processes. For instance, Yan et al. [31] proposed an asynchronous T2TF framework that locally estimates state vectors for each sensor and then fuses them using a pseudo-measurement matrix, effectively handling the “negative time”

problem caused by delayed ADS-B packets. However, standard T2TF assumes statistical independence between tracks, which often leads to over-confident covariance estimates when process noise is correlated [32].

Addressing the maneuvering characteristics of targets is another critical problem. UAVs in urban environments exhibit high agility, rendering single-model filters (like standard Kalman Filters) prone to divergence. They usually assume the target moves at a constant velocity or acceleration. When a UAV turns sharply or stops, this assumption fails. This discrepancy makes predictions inaccurate. As residuals spike, the filter diverges and loses the target. For such scenarios, the Interacting Multiple Model (IMM) algorithm is the preferred solution. By running multiple filters (e.g., Constant Velocity, Coordinated Turn) in parallel and mixing their probabilities, IMM can rapidly adapt to mode changes. Genovese [33] demonstrated that IMM significantly outperforms static filters in tracking maneuvering UAV by dynamically adjusting model weights. In the context of UAVs, Li et al. [34] extended IMM with adaptive turn-rate models to capture the erratic movements of quadrotors. Despite its effectiveness, IMM's computational complexity scales linearly with the number of models, posing challenges for deployment on resource-constrained edge computing nodes [35].

The most significant hurdle in urban fusion is Robustness to Non-Gaussian Errors. Unlike high-altitude ATC scenarios where errors are largely Gaussian, urban low-altitude environments are dominated by outliers (e.g., NLOS biases) and heavy-tailed noise. Classical Extended Kalman Filters (EKF) are highly sensitive to such anomalies. To mitigate this, Adaptive Covariance Inflation methods have been developed. Osman et al. [36] introduced an online adaptive scheme that scales the measurement noise covariance R based on the innovation sequence, effectively down-weighting data that contradict the predicted state. Similarly, Robust Statistics approaches, such as the Maximum Correntropy Criterion (MCC) filter proposed by Wang et al. [37], replace the Mean Square Error (MSE) criterion to filter out impulsive noise. Furthermore, specifically for the fusion of biased sensors, Bias Estimation techniques are crucial. As demonstrated in ADS-B/Radar fusion by Zhang et al. [38], augmenting the state vector to estimate systematic sensor biases online is essential for aligning heterogeneous coordinate systems. However, most existing robust filters treat outliers as random events, failing to account for the structural and direction-dependent nature of TDOA errors in urban canyons (e.g., persistent vertical bias), which requires domain-specific subspace decoupling rather than generic statistical rejection [39].

The proposed HCKF differs from these methods in two conceptual aspects: (i) instead of applying isotropic covariance inflation based solely on innovation magnitude, HCKF employs a structured strategy where TDOA altitude jumps trigger binary gating while Remote ID timing irregularity is mapped to a continuous confidence score that modulates both covariance inflation and weight caps; and (ii) the horizontal and vertical subspaces are fused separately with dimension-specific strategies. Entropy-guided weighting is used for the well-conditioned horizontal plane and conditional Remote ID-dominant gating for the ill-conditioned vertical axis, thereby explicitly accounting for the direction-dependent nature of TDOA errors.

3. Methodology

This section details the Hybrid Conditional Kalman Filter (HCKF), a hierarchical fusion framework designed to mitigate the specific challenges of urban low-altitude UAV perception and positioning, as summarized in Figure 1. First, the two types of perceptual data are unified and supplemented via interpolation at identical timestamps. Within a sliding window, three motion models are evaluated in parallel—constant velocity (cv), constant acceleration (ca), and coordinated turn (ct). A dwell rule limits model switching

and reduces prediction jitter. Measurements are then handled without ad hoc deletion. TDOA-derived altitude (TDOA Z) uses a global two layer stratification to flag vertical jump points with a binary indicator. Remote ID timing irregularity is summarized by temporal deviation and horizontal inconsistency and is mapped to a confidence score that inflates the Remote ID covariance and caps its weight. All observations pass chi square χ^2 gating and a Huber loss to limit the influence of outliers. Fusion is then performed by subspace. In the horizontal plane, channel weights are assigned by information gain and combined into a single pseudo measurement. In the vertical axis, Remote ID is the primary source and TDOA Z is admitted only when consistency gates and amplitude limits are satisfied. The two pseudo measurements are used in one information form EKF update. In this way, measurement reliability is converted into explicit noise and weight control, and the estimator maintains accuracy and continuity under outliers, jump events, and asynchronous sampling.

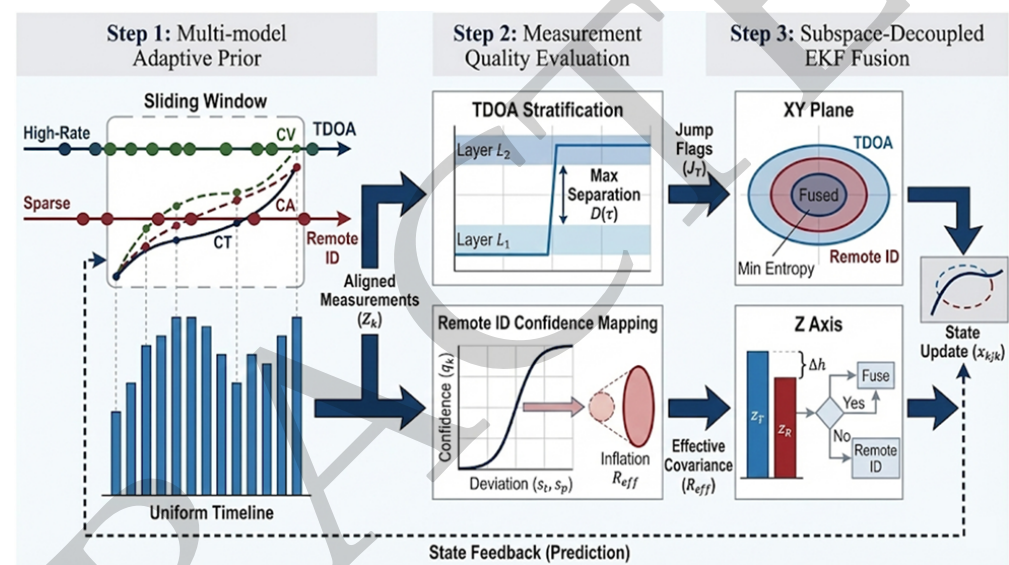


Figure 1. Overall architecture of the HCKF framework.

The HCKF framework is constructed around a measurement-conditioned update mechanism. At each epoch k , a set of data-quality conditions is first extracted from the aligned measurements, including the TDOA altitude-jump indicator, the Remote ID confidence score, the horizontal consistency gate, and the vertical agreement constraint. These conditions are denoted as

$$\mathcal{C}_k = \{J_T^z(k), q_k, g_{xy}(k), g_z(k)\}, \quad (1)$$

where $J_T^z(k)$ is the TDOA altitude-jump flag, q_k is the Remote ID confidence score, $g_{xy}(k)$ denotes the horizontal consistency gate, and $g_z(k)$ denotes the vertical admissibility condition. The condition set $\mathcal{C}_k$ is then used to regulate measurement covariance inflation, fusion-weight constraints, and subspace-level measurement admission before the information-form EKF update is performed.

For clarity, the complete computational procedure of HCKF is summarized in Algorithm 1. The algorithm shows how the three modules interact at each epoch: temporal alignment produces a motion-consistent prior, measurement-quality evaluation generates reliability indicators and effective covariances, and subspace-decoupled fusion constructs horizontal and vertical pseudo-measurements for the final EKF update.

Algorithm 1: Core computational procedure of HCKF

Input: raw TDOA measurements $\mathcal{Z}^T$, raw Remote ID measurements $\mathcal{Z}^R$,
nominal covariances R_T, R_R , grid step T_0

Output: fused state sequence $\{\hat{x}_{k|k}, P_{k|k}\}$

- 1 Convert raw WGS84 measurements into the local ENU coordinate frame.
- 2 Construct the uniform time grid $\mathcal{T} = \{t_0, t_1, \dots, t_K\}$ with step T_0 .
- 3 Assign TDOA and Remote ID observations to the corresponding grid epochs.
- 4 **for each** epoch $t_k \in \mathcal{T}$ **do**
- 5 Evaluate CV, CA, and CT motion candidates in the sliding window W_k .
- 6 Compute the robust window loss $L_i(W_k)$ for each candidate model i .
- 7 Select the motion model m_k with the minimum loss subject to the dwell rule.
- 8 Propagate the prior state $(\hat{x}_{k|k-1}, P_{k|k-1})$ using model m_k .
- 9 Detect TDOA altitude jumps and obtain the binary flag $J_T^z(k)$.
- 10 Compute Remote ID temporal and spatial irregularity scores $s_t(k)$ and $s_p(k)$.
- 11 Map $s_t(k)$ and $s_p(k)$ to the Remote ID confidence score q_k .
- 12 Inflate effective covariances $R_T^{\text{eff}}(k)$ and $R_R^{\text{eff}}(k)$.
- 13 Apply chi-square gating and Huber robust screening to accepted measurements.
- 14 Fuse accepted horizontal measurements using entropy-guided information weights.
- 15 Limit the Remote ID horizontal weight using the confidence-dependent upper bound.
- 16 **if** TDOA-Z satisfies jump, horizontal-consistency, and amplitude gates **then**
- 17 Admit TDOA-Z into the vertical update with entropy-guided weighting.
- 18 **else**
- 19 Use the Remote-ID-dominated vertical update.
- 20 **end if**
- 21 Assemble horizontal and vertical pseudo-measurements into $Z_f(k)$ and $R_f(k)$.
- 22 Perform the information-form EKF update to obtain $(\hat{x}_{k|k}, P_{k|k})$.
- 23 Save $(\hat{x}_{k|k}, P_{k|k})$ as the fused state at epoch t_k .
- 24 **end for**
- 25 **return** $\{\hat{x}_{k|k}, P_{k|k}\}_{k=1}^K$

3.1. Multi-Model Adaptive Prior

Reliable fusion requires synchronized data inputs. However, TDOA and Remote ID operate asynchronously with different sampling rates. This section establishes a uniform timeline to align these heterogeneous data streams. We employ a sliding-window approach to map measurements from their raw timestamps onto this grid. Accurate alignment relies on predicting the UAV motion between samples. Yet, urban UAVs exhibit complex flight patterns. They cruise stably, accelerate suddenly, and execute sharp turns. A single kinematic model cannot capture such diversity. Therefore, we integrate three distinct models: Constant Velocity (CV) for steady flight, Constant Acceleration (CA) for maneuvering, and Coordinated Turn (CT) for curvilinear motion. This adaptive selection constructs a stable and informative temporal prior. The three-model set (CV, CA, and CT) provides a parsimonious yet sufficient basis: CV and CA span the longitudinal dynamics, and CT captures planar curvature.

Let the system state at epoch t_k be $\mathbf{X}_k = [p_{x,k}, p_{y,k}, p_{z,k}, v_{x,k}, v_{y,k}, v_{z,k}]^T$, $p_{\cdot,k}$ and $v_{\cdot,k}$ represent the position and velocity components. The state is associated with a prior mean and covariance $(\hat{x}_{k|k-1}, P_{k|k-1})$. TDOA and Remote ID measurements with time stamps $\{t^T\}$ and $\{t^R\}$ are resampled to a uniform timeline $T = \{t_0, \dots, t_K\}$ of step T_0 so that each epoch $t_k \in T$ has collocated multi-source observations, as summarized in Figure 2.

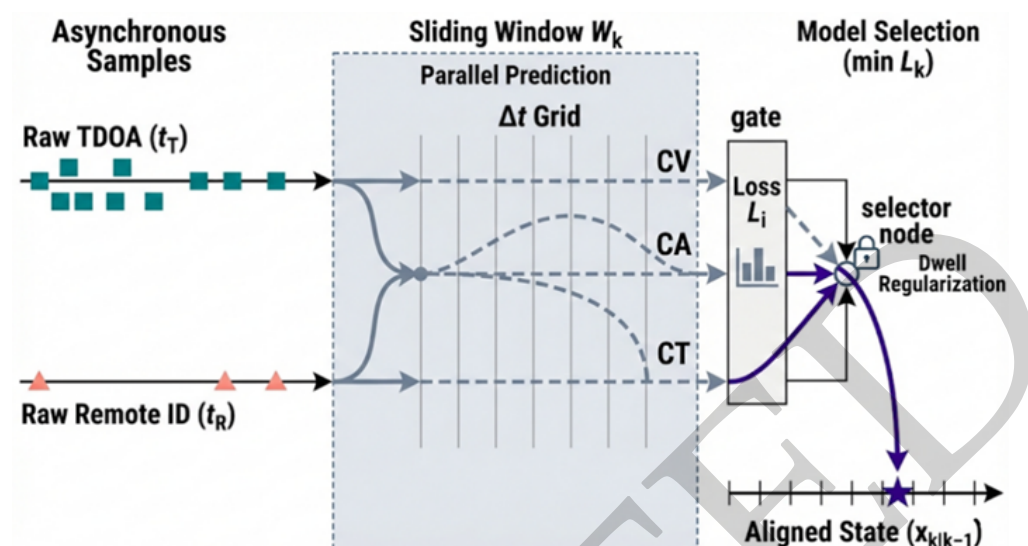


Figure 2. Data interpolation framework based on sliding window and kinematic model.

3.1.1. Robust Outlier Screening on the Aligned Grid

Raw measurements mapped to the uniform timeline may still contain gross errors. We apply a two-step screening process to identify them. First, we check for vertical anomalies. Let Δz_k denote the sequence of height increments along curve T . The outlier rejection gate is defined by the 90th percentile of the median-centered absolute deviation.

$$\theta_{90} = \text{quantile}(|\Delta z - \text{median}(\Delta z)|, 0.90) \quad (2)$$

where θ_{90} denotes the 90th percentile of the median absolute deviation. If $|\Delta z - \text{median}(\Delta z)| > \theta_{90}$, the epoch is flagged as a coarse-grained outlier. However, aggressive filtering can break trajectory continuity. To prevent this, we introduce two protection parameters: a maximum removal ratio and a minimum sample count. If the number of valid samples falls below the minimum sample count within the sliding window, we retain the points even if they exceed the threshold.

Next, we apply a spatial consistency test on the horizontal plane. This jointly validates suspicious points. Let $\hat{p}_{k|k-1,xy}$ and $p_{k,xy}^{\text{obs}}$ denote the predicted and observed horizontal positions, respectively. The prior covariance is $P_{k|k-1,xy}$. We compute the normalized squared distance as follows:

$$d_{xy}^2(k) = \left(\mathbf{p}_{k,xy}^{\text{obs}} - \hat{\mathbf{p}}_{k|k-1,xy} \right)^T \left(\mathbf{p}_{k,xy}^{\text{obs}} + \mathbf{R}_{\text{obs},xy}(k) \right)^{-1} \left(\mathbf{p}_{k,xy}^{\text{obs}} - \hat{\mathbf{p}}_{k|k-1,xy} \right) \leq \chi_2^2(p) \quad (3)$$

where $\mathbf{p}_{k,xy}^{\text{obs}}$ denotes the observed horizontal position at epoch k , and $\hat{\mathbf{p}}_{k|k-1,xy}$ denotes the predicted horizontal position from the prior state. $\mathbf{P}_{k|k-1,xy}$ is the predicted horizontal covariance, and $\mathbf{R}_{\text{obs},xy}(k)$ is the horizontal observation covariance. The statistic $d_{xy}^2(k)$ is a Mahalanobis distance and can therefore be consistently compared with the chi-square threshold $\chi_2^2(p)$ with two degrees of freedom. In this study, p is set to 0.997 unless otherwise specified.

3.1.2. Motion Models and Process Noise

To capture the diverse motion patterns of urban UAVs, we utilize three kinematic models: Constant Velocity (CV), Constant Acceleration (CA), and Coordinated Turn (CT). All models operate on the uniform timeline with a sampling interval of Δt . The CV

model describes stable cruising. The state vector $\mathbf{X}$ includes 3D position and velocity. The transition follows standard discrete-time dynamics:

$$F_{CV} = \begin{bmatrix} I_3 & \Delta t I_3 \\ 0 & I_3 \end{bmatrix}, \quad Q_{CV} = \sigma_a^2 \begin{bmatrix} \frac{\Delta t^4}{4} I_3 & \frac{\Delta t^3}{2} I_3 \\ \frac{\Delta t^3}{2} I_3 & \Delta t^2 I_3 \end{bmatrix} \quad (4)$$

where F_{CV} denotes the state transition matrix, and I_3 denotes the 3×3 identity matrix. Q_{CV} represents the process noise covariance. The parameter σ_a represents the standard deviation of the white-noise acceleration, which models small, random velocity changes.

The CA model accounts for maneuvering phases. It extends the state vector to include acceleration:

$$\mathbf{x}_k^{CA} = [\mathbf{p}_k^T \quad \mathbf{v}_k^T \quad \mathbf{a}_k^T]^T, \quad \mathbf{F}_{CA} = \begin{bmatrix} I_3 & \Delta t I_3 & \frac{\Delta t^2}{2} I_3 \\ \mathbf{0}_3 & I_3 & \Delta t I_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & I_3 \end{bmatrix}, \quad \mathbf{Q}_{CA} = \sigma_j^2 \begin{bmatrix} \frac{\Delta t^5}{20} I_3 & \frac{\Delta t^4}{8} I_3 & \frac{\Delta t^3}{6} I_3 \\ \frac{\Delta t^4}{8} I_3 & \frac{\Delta t^3}{3} I_3 & \frac{\Delta t^2}{2} I_3 \\ \frac{\Delta t^3}{6} I_3 & \frac{\Delta t^2}{2} I_3 & \Delta t I_3 \end{bmatrix} \quad (5)$$

where the CA model extends the state vector to include acceleration. F_{CA} and Q_{CA} represent the corresponding state transition matrix and process noise covariance in three-dimensional space, respectively. The parameter σ_j denotes the standard deviation of the jerk (i.e., the rate of change of acceleration), allowing the model to capture dynamic speed variations.

Because the CV, CA, and CT candidates use different local parameterizations, all candidate predictions are projected back to the common fusion state $[p_x, p_y, p_z, v_x, v_y, v_z]^T$ before likelihood evaluation and EKF updating. For the CA model, the acceleration component is treated as an auxiliary prediction variable, while only the position–velocity block and its covariance are retained for fusion.

$$x_{k+1} = x_k + \frac{v_k}{\omega} (\sin(\varphi_k + \omega \Delta t) - \sin \varphi_k) \quad (6)$$

$$y_{k+1} = y_k + \frac{v_k}{\omega} (\cos(\varphi_k + \omega \Delta t) - \cos \varphi_k) \quad (7)$$

where v_k is the horizontal ground speed, and φ_k is the heading angle. The parameter ω_k represents the turn rate. F_{CT} is the state transition function, and Q_{CT} is the process noise covariance constructed in the tangential–orthogonal coordinate system and mapped to the Cartesian coordinate system via the Jacobian matrix evaluated at the current state $(v_k, \varphi_k, \omega_k)$. As ω_k approaches 0, this model reduces to the CV model.

For the selected model m_k , the prior propagation at t_k is as follows:

$$\hat{\mathbf{x}}_{k|k-1} = f_m(\hat{\mathbf{x}}_{k-1|k-1}, \Delta t), \quad P_{k|k-1} = F_{m_k} P_{k-1|k-1} F_{m_k}^T + Q_{m_k} \quad (8)$$

where $\hat{\mathbf{x}}_{k|k-1}$ denotes the predicted state vector at the current epoch. $P_{k|k-1}$ represents the corresponding predicted error covariance matrix. On the right-hand side, $f_m(\bullet)$ is the state transition function for model m_k . $\hat{\mathbf{x}}_{k-1|k-1}$ and $P_{k-1|k-1}$ are the updated state estimate and error covariance from the previous epoch, respectively. Q_{m_k} denotes the discrete-time process noise covariance specific to the chosen model. F_{m_k} is the Jacobian matrix of f_m .

To handle outliers without discarding data, we apply Huber weighting. This adjusts the influence of measurements based on their innovation. For the scalar normalized innovation v ,

$$\psi(v) = \begin{cases} v, & |v| \leq \delta \\ \delta \operatorname{sgn}(v), & |v| > \delta \end{cases} \quad (9)$$

where ν is a scalar normalized innovation, and δ is the Huber threshold expressed in standard deviations, with $\delta \in [1.5, 2.0]$. This effectively inflates the anomalous residual term $S_{i,t}$, thereby reducing its influence in $L_i(W_k)$ and stabilizing the model selection process.

3.1.3. Windowed Model Selection

On each window $W_k = \left\{ t \mid t \in \left[t_k - \frac{W}{2}, t_k + \frac{W}{2} \right] \right\}$ (length W , stride s), the three candidate models $\mathcal{M} = \{\text{CV}, \text{CA}, \text{CT}\}$ are independently propagated to produce candidate priors and whitened innovations. For model $i \in \mathcal{M}$, let

$$r_{i,t} = z_t - H\hat{x}_{i,t|t-1} \quad (10)$$

$$S_{i,t} = HP_{i,t|t-1}H^T + R_t^{\text{eff}} \quad (11)$$

where $r_{i,t}$ represents the innovation residual vector, calculated as the difference between the actual measurement z_t and the predicted measurement $H\hat{x}_{i,t|t-1}$. $S_{i,t}$ denotes the innovation covariance matrix. H is the measurement Jacobian matrix. $P_{i,t|t-1}$ is the predicted state covariance, and R_t^{eff} is the effective measurement covariance. The model-selection loss combines the negative log-likelihood of whitened innovations with an information-volume and complexity penalty:

$$L_i(W_k) = \sum_{t \in W_k} r_{i,t}^T S_{i,t}^{-1} r_{i,t} + \alpha \sum_{t \in W_k} \ln \det S_{i,t} + \beta p_i \quad (12)$$

where $L_i(W_k)$ is the choice of loss function, which combines the negative log-likelihood of the whitened innovation term with an information penalty term and a model complexity penalty term, with $\alpha \in [0.2, 0.5]$, $\beta \approx 2$, and p_i being the state dimension of model i . The tentative best model i_k^* is the one that minimizes this loss:

$$i_k^* = \arg \min_{i \in \mathcal{M}} L_i(W_k) \quad (13)$$

To avoid oscillatory switching, enforce residency regularization. Let m_{k-1} denote the model used in the previous window, and $\tau(m_{k-1})$ denote its current residency count (per window). The update rule is as follows:

$$m_k = \begin{cases} m_{k-1} \dots, & \text{if } L_{m_{k-1}}(W_k) \leq (1 - \varepsilon)L_{i_k^*}(W_k) \text{ or } \tau(m_{k-1}) < D \\ i_k^*, & \text{otherwise} \end{cases} \quad (14)$$

where m_{k-1} is the model from the previous window, and D signifies the minimum dwell count within the window, with minimum dwell D and advantage margin ε . In low-speed or near-hover segments, the CT candidate is disabled by constraining the feasible set to $\mathcal{M}_k = \{\text{CV}, \text{CA}\}$.

Operational constraint under prolonged packet loss. The kinematics-based temporal alignment module is designed to bridge short-term asynchrony and intermittent missing samples, rather than arbitrary long communication outages. When Remote ID is unavailable for several consecutive epochs, its confidence score is reduced through the temporal irregularity term, and its effective covariance is inflated in the fusion stage. If no reliable Remote ID measurement is available within the sliding window, the Remote ID channel is not used as an active constraint. In this case, the filter relies on TDOA updates when they pass the quality-control gates; otherwise, the system enters a prediction-dominated mode, in which the state covariance increases according to the process-noise model.

To prevent overconfident extrapolation, a maximum prediction interval T_{gap}^{max} is introduced. When the missing interval exceeds T_{gap}^{max} , the corresponding source is marked as unavailable rather than being interpolated. The output during this period is flagged as low-confidence. Therefore, HCKF does not assume that the sliding-window prediction can remain accurate under unlimited packet loss; reliable recovery requires the reappearance of Remote ID or another accepted external observation.

Parameter rationale. The Huber threshold $\delta \in [1.5, 2.0]$ is chosen based on asymptotic relative efficiency: at $\delta = 1.5$, the estimator retains $\approx 95\%$ efficiency under Gaussian noise while bounding the influence of any single observation to δ standard deviations. The process noise parameters ($\sigma_a = 1.5 \text{ m/s}^2$, $\sigma_j = 0.8 \text{ m/s}^3$, $\sigma_\omega = 0.05 \text{ rad/s}$) correspond to the observed maneuverability of the multirotor platform and are validated through sensitivity analysis in Section 4.3. The loss function weights ($\alpha \in [0.2, 0.5]$, $\beta \approx 2$) follow BIC-style scaling where $\beta = \ln(N_{\text{eff}})$ for typical window sizes. The dwell count $D = 3$ and advantage margin $\varepsilon_m = 0.05$ implement hysteresis to prevent chattering at consecutive epochs.

3.2. Measurement Quality Evaluation

This section establishes a measurement quality evaluation mechanism prior to fusion. Two complementary mechanisms are addressed: (i) detection and conditional correction of TDOA altitude jumps (ii) Remote ID time-irregularity marking with confidence scoring. The outputs are the effective measurement covariances $R_i^{\text{eff}}(k)$ and quality flags ($J_T^z(k), q_k$) that are subsequently consumed by the information-form fusion in 3.3 through gating, weight capping, and entropy-guided weighting.

Let $z_i(k)$ denote a measurement at epoch t_k from source $i \in \{\text{TDOA}, \text{Remote-ID}\}$, with nominal covariance $R_i(k)$. We write $z_{i,xy}(k) \in \mathbb{R}^2$, and $\ddagger_{i,z}(k) \in \mathbb{R}$ for its horizontal and vertical components, and we use the prior $(\hat{x}_{k|k-1}, P_{k|k-1})$ from 3.1, with H_{xy} and H_z extracting the corresponding sub-states.

3.2.1. TDOA Altitude Jump Detection

As summarized in Figure 3, this section performs global jump detection on TDOA height data by partitioning the TDOA measurements into two height layers and adopting the criterion of maximizing inter-layer separation while minimizing intra-layer dispersion. The MAD-based stratification is used to generate a quality indicator for the TDOA vertical channel. Specifically, the altitude sequence is divided into two candidate layers, and the split point with the largest robust inter-layer separation and the smallest intra-layer dispersion is selected. The resulting binary flag $J_T^z(k)$ indicates whether a structural altitude jump is detected at epoch k . This flag is subsequently used as one of the conditions for vertical measurement admission in the subspace-decoupled fusion stage.

Let $\{z_T(k)\}_{k=1}^K$ be the TDOA altitudes at the common grid $\{t_k\}$. For any candidate split index $\tau \in \{2, \dots, K\}$, define the two layers $S_1(\tau) = \{1, \dots, \tau - 1\}$ and $S_2(\tau) = \{\tau, \dots, K\}$, with sizes $n_1(\tau) = \tau - 1$ and $n_2(\tau) = K - \tau + 1$. Compute the median altitude for each layer:

$$m_1(\tau) = \text{median}\{z_T(k) : k \in S_1(\tau)\}, \quad m_2(\tau) = \text{median}\{z_T(k) : k \in S_2(\tau)\} \quad (15)$$

where $m_1(\tau)$ and $m_2(\tau)$ are the medians of the first and second layers, respectively. To quantify within-layer dispersion robustly, use the median absolute deviation (MAD) in each layer:

$$\hat{\sigma}_i(\tau) = 1.4826 \cdot \text{median}\{|z_T(k) - m_1(\tau)| : k \in S_i(\tau)\}, \quad i \in \{1, 2\} \quad (16)$$

where $\hat{\sigma}_i(\tau)$ represents the robust deviation for layer i . The constant scaling factor 1.4826 ensures that the MAD serves as a consistent estimator for the standard deviation under a normal distribution assumption. The between-layer separation is measured by the absolute median gap $D(\tau) = |m_1(\tau) - m_2(\tau)|$. To discourage degenerate splits with vanishing support in one layer, introduce a size-balance factor $B(\tau) = \frac{n_1(\tau)n_2(\tau)}{K^2} \in (0, \frac{1}{4}]$, which attains its maximum when the two layers are balanced. The subsequently proposed global hierarchical scoring is as follows:

$$S(\tau) = \frac{D(\tau)}{\hat{\sigma}_1(\tau) + \hat{\sigma}_2(\tau) + \varepsilon} \cdot B(\tau), \varepsilon > 0 \quad (17)$$

where $S(\tau)$ represents the segmentation effectiveness score for the candidate split index τ . ε is a small positive constant added to prevent division by zero. This method employs mild balance regularization to explicitly maximize inter-layer median separation while minimizing intra-layer dispersion. The optimal segmentation is defined as:

$$\tau^* = \arg \max_{\tau \in \mathcal{C}} S(\tau) \quad (18)$$

where $\mathcal{C} = \{\tau : n_1(\tau) \geq N_{\min}, n_2(\tau) \geq N_{\min}\}$ enforces a minimum layer length $N_{\min}$ for statistical reliability. The final TDOA altitude jump is declared at τ^* .

$$J_T^z(k) = \begin{cases} 1, k = \tau^* \\ 0, \text{otherwise} \end{cases} \quad \mathcal{J}_T = \{\tau^*\} \quad (19)$$

where k denotes the TDOA height jump index declared within the $\mathcal{J}_T$ neighborhood; $J_T^z(k) \in \{0, 1\}$ is the binary jump flag derived for fusion processing, set to 1 when $\kappa = 1$ and to 0 otherwise.

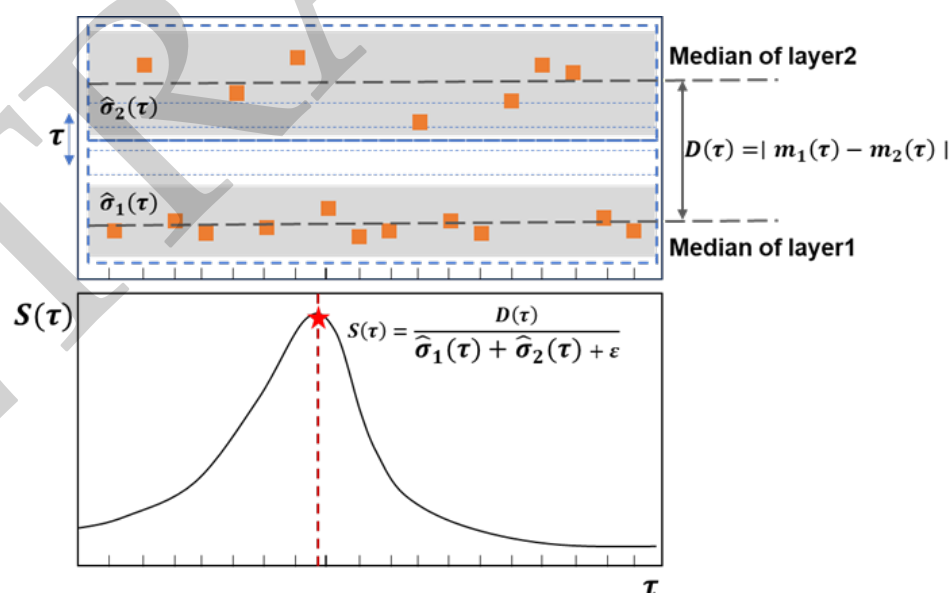


Figure 3. TDOA global jump point layered detection diagram. The orange square markers denote the TDOA altitude observations. The gray dashed horizontal lines indicate the median altitude levels of Layer 1 and Layer 2, namely $m_1(\tau)$ and $m_2(\tau)$. The blue solid horizontal lines represent the MAD-based robust dispersion bounds $\hat{\sigma}_1(\tau)$ and $\hat{\sigma}_2(\tau)$ for the two layers, while the vertical bracket denotes the inter-layer separation $D(\tau) = |m_1(\tau) - m_2(\tau)|$. In the lower panel, the black curve represents the global hierarchical score $S(\tau)$, and the red star with the red dashed vertical line marks the optimal split point τ^* corresponding to the maximum score.

3.2.2. Remote-ID Time-Irregularity Marking and Confidence-Based De-Weighting

As summarized in Figure 4, this subsection formalizes a time-irregularity handling scheme for Remote-ID measurements on the aligned time grid. The objective is to convert timing anomalies into effective measurement covariances that reflect reliability, without altering the raw observations. The outputs are a scalar confidence $q_k \in (0, 1)$ and the effective Remote-ID covariance $R_R^{\text{eff}}(k)$, which are subsequently used by the fusion stage for gating and weight assignment.

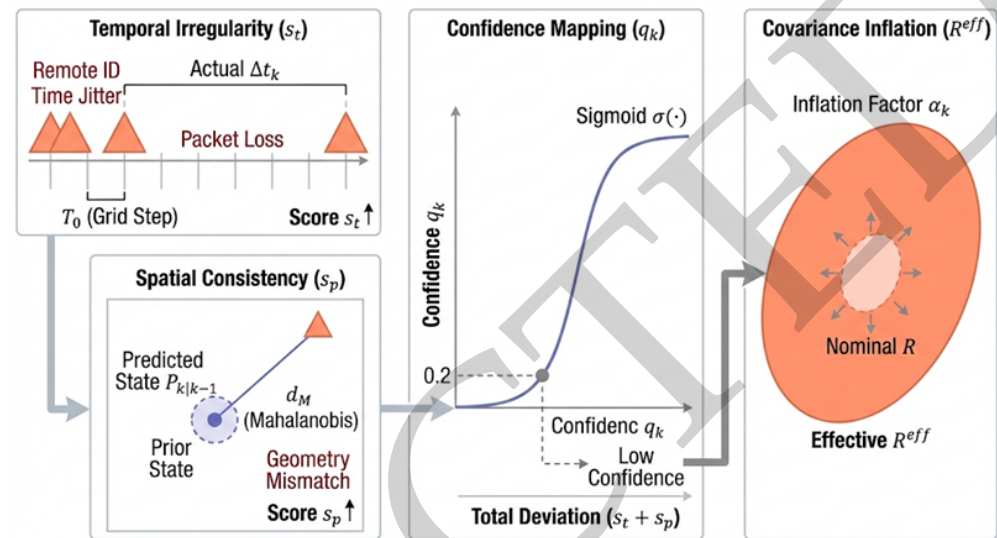


Figure 4. Confidence modeling and analysis of irregular Remote-ID sampling frequency. The arrows indicate the reliability-evaluation flow from temporal irregularity $s_t(k)$ and spatial consistency $s_p(k)$ to the confidence score q_k , and then to the covariance inflation factor α_k used to construct the effective Remote-ID covariance $R_R^{\text{eff}}(k)$.

Let $\{t_k\}_{k=1}^K$ be the uniform grid (step T_0), and let Z_k^R denote the Remote-ID measurement available at epoch t_k after alignment. Define the inter-arrival interval $\Delta t_k = t_k - t_{k-1}$, and denote by $(\hat{x}_{k|k-1}, P_{k|k-1})$ the prior from Section 3.1. The prior horizontal position is $\hat{P}_{k|k-1,xy}$, and the Remote-ID-derived horizontal position is $P_{k,xy}^R$.

A temporal deviation score normalizes the interval departure from the grid step:

$$\Delta t_k = t_k - t_{k-1}, s_t(k) = \frac{|\Delta t_k - T_0|}{T_0 + \varepsilon}, \varepsilon > 0 \quad (20)$$

where $s_t(k)$ is a dimensionless metric measuring the irregularity of arrival intervals. The parameter ε is a small positive constant included to prevent division by zero. Higher values indicate potential buffering, network jitter, or data lag.

Spatial consistency scores measure the deviation between predictions and measurements on the horizontal plane under conditions of quality uncertainty:

$$d_M(k) = (P_{k,xy}^R - \hat{P}_{k|k-1,xy})^T P_{k|k-1,xy}^{-1} (P_{k,xy}^R - \hat{P}_{k|k-1,xy}) \quad (21)$$

$$s_p(k) = \sqrt{d_M(k)} \quad (22)$$

where $d_M(k)$ represents the squared Mahalanobis distance, which quantifies the statistical mismatch between the measurement and the prediction. $s_p(k)$ is a dimensionless prior-normalized horizontal mismatch. It increases when the Remote-ID geometry conflicts with the predicted motion state. $(s_t(k), s_p(k))$ are the feature pair quantifying reliability along

the temporal and geometric axes, respectively, and are subsequently aggregated into a single confidence score q_k .

$$q_k = \sigma(\lambda_0 - \lambda_t s_t(k) - \lambda_p s_p(k)), \quad \sigma(u) = \frac{1}{1 + \exp(-u)} \quad (23)$$

where $\lambda_0 > 0$ is a confidence offset, and λ_t and λ_p control the sensitivity to temporal irregularity and spatial inconsistency, respectively. With this formulation, q_k approaches one when both temporal and spatial deviations are small. As either timing jitter or spatial inconsistency increases, q_k decreases monotonically, leading to a larger effective covariance for the Remote ID channel.

$$R_R(k) = \begin{bmatrix} R_{R,xy}(k) & 0_{2 \times 1} \\ 0_{2 \times 1} & R_{R,z}(k) \end{bmatrix} \quad (24)$$

The effective covariance $R_R^{\text{eff}}(k)$ is then modulated by an inflation factor α_k .

$$R_R^{\text{eff}}(k) = \begin{bmatrix} \alpha_k R_{R,xy}(k) & 0_{2 \times 1} \\ 0_{2 \times 1} & \alpha_k R_{R,z}(k) \end{bmatrix}, \quad \alpha_k = 1 + \kappa(1 - q_k) \quad (25)$$

where κ is a scaling constant that determines the maximum inflation intensity. When temporal and spatial deviations are small (i.e., $s_t(k)$ and $s_p(k)$ are low), the confidence remains high ($q_k \approx 1$), the inflation factor stays near unity ($\alpha_k \approx 1$), and the Remote-ID covariance remains effectively nominal. As either deviation grows, q_k decreases and α_k increases, which inflates the innovation covariance and thereby reduces the statistical influence of the Remote-ID channel in a principled manner. In all cases, $R_R^{\text{eff}}(k)$ enters the innovation covariance in Section 3.3, directly lowering the entropy gain of the Remote-ID channel—and hence its fusion weight—whenever the confidence is low.

The confidence offset $b_0 = 4.0$ positions the sigmoid such that $q_k \approx 0.98$ when both temporal and spatial deviations are negligible. The asymmetric sensitivity ($\gamma_t = 1.0$, $\gamma_p = 0.5$) reflects that timing jitter is a more direct indicator of Remote ID degradation than spatial mismatch, which can also arise from legitimate maneuvers. The inflation constant $\kappa = 9.0$ bounds the maximum covariance scaling at $\alpha_k^{\text{max}} = 10$, effectively removing an unreliable Remote ID channel from the fusion while the smooth sigmoid prevents abrupt switching. Sensitivity to these parameters is examined in Section 4.3.

3.3. Subspace-Decoupled EKF Fusion

The reason for separating the XY and Z updates is the anisotropic reliability of the two sensing sources. In the tested urban low-altitude environment, TDOA provides relatively dense horizontal observations, but its altitude component is more vulnerable to vertical GDOP, non-line-of-sight propagation, and multipath-induced jumps. Remote ID is sparser and may suffer from timing jitter, but its altitude reports are generally more stable when valid packets are received. A fully coupled 3-D update may allow unreliable TDOA altitude residuals to affect the horizontal state through cross-covariance terms. The proposed subspace-decoupled update therefore isolates the vertical reliability decision from the horizontal information fusion, improving numerical stability while still admitting TDOA-Z when the jump, horizontal-consistency, and amplitude conditions are satisfied.

Given the severe anisotropy of TDOA measurements—specifically the high precision in the horizontal plane contrasted with instability in the vertical domain (due to high VDOP)—a standard coupled EKF update risks allowing vertical outliers to contaminate horizontal estimates. To address this, we decompose the state-space update into two decoupled subspaces: the horizontal subspace and the vertical subspace. At each epoch t_k ,

the filter receives (i) the prior $(\hat{x}_{k|k-1}, P_{k|k-1})$ from Section 3.1 and (ii) evaluated measurements from Section 3.2 with effective covariances $R_{i,*}^{\text{eff}}(k)$ and quality flags $\{q_k, J_T^z(k)\}$. In a standard coupled EKF, the off-diagonal blocks of the Kalman gain $\mathbf{K}_{xy,z}$ couple vertical innovations to horizontal corrections: a vertical error δ_z induces a horizontal displacement of approximately $\|\mathbf{K}_{xy,z} \cdot \delta_z\|$. During TDOA multipath events where δ_z can reach 50–100 m, this cross-contamination shifts horizontal estimates by several meters even when the horizontal TDOA measurement is accurate. Moreover, when ground stations are near-coplanar, the vertical subspace of the observability matrix has a significantly smaller minimum singular value, making the vertical state weakly observable from TDOA alone. To eliminate these effects, we decompose the state-space update into two decoupled subspaces by imposing a block-diagonal structure on the fused measurement covariance $\mathbf{R}_f(k)$, which is equivalent to setting $\mathbf{K}_{xy,z} = \mathbf{0}$. Throughout this section, H_* denotes the Jacobian of the corresponding measurement function $h_*(\bullet)$ evaluated at the prior state $\hat{x}_{k|k-1}$. For each source $i \in \{\text{TDOA}, \text{Remote ID}\}$ and subspace $* \in \{xy, z\}$, we form the EKF innovation and its covariance:

$$r_{i,*} = z_{i,*}(k) - H_* \hat{x}_{k|k-1} \quad (26)$$

$$S_{i,*}(k) = H_* P_{k|k-1} H_*^T + R_{i,*}^{\text{eff}}(k) \quad (27)$$

In the horizontal subspace, the contributions from the accepted channels $\mathcal{I}_{xy}(k) \in \{\text{TDOA}, \text{Remote ID}\}$ are combined in the information domain. For each channel:

$$Y_{i,xy}(k) = \left(R_{i,xy}^{\text{eff}}(k)\right)^{-1} \quad (28)$$

$$\eta_{i,xy}(k) = Y_{i,xy}(k) Z_{i,xy}(k) \quad (29)$$

Working with (Y, η) is natural because information contributions add linearly when measurements are conditionally independent given the state. To determine how much each channel should contribute in this epoch, we quantify its anticipated uncertainty reduction via the differential-entropy gain of its innovation:

$$\Delta H_i^{xy}(k) = \frac{1}{2} \ln \det(I + R_{i,xy}^{\text{eff}}(k)^{-1} H_{xy} P_{k|k-1} H_{xy}^T) \geq 0 \quad (30)$$

This expression equals the logarithmic ratio between the innovation entropy and the measurement entropy, and it increases under the following conditions: (a) the prior information is informative in the measurement direction, and (b) the channel covariance is small—precisely the conditions under which the measurements hold statistical value. We normalize these gains to obtain the original weights.

$$\tilde{\omega}_i^{xy}(k) = \frac{\max(\Delta H_i^{xy}(k), 0)}{\sum_{j \in \mathcal{I}_{xy}(k)} \max(\Delta H_j^{xy}(k), 0)} \quad (31)$$

where $\tilde{\omega}_i^{xy}(k)$ represents the normalized raw weights obtained across all receiving channels. These weights reflect the relative statistical values of each channel at epoch k . The Remote-ID weight is then capped by confidence:

$$\omega_{R,xy}^{\max}(k) = \omega_{\min} + (\omega_{\max} - \omega_{\min}) q_k \quad (32)$$

This formulation ensures that the confidence-dependent upper bound always satisfies $\omega_{R,xy}^{\max}(k) \in [\omega_{\min}, \omega_{\max}]$, thereby avoiding the contradiction in which the cap exceeds $\omega_{\max}$ at high confidence.

$$\hat{\omega}_{R,xy}(k) = \min\left(\omega_{R,xy}^e(k), \omega_{R,xy}^{\max}(k)\right), \quad \hat{\omega}_{T,xy}(k) = 1 - \hat{\omega}_{R,xy}(k) \quad (33)$$

where $\omega_{i,xy}(k) = \alpha_\omega \hat{\omega}_{i,xy}(k) + (1 - \alpha_\omega) \omega_{i,xy}(k-1)$, $i \in \{T, R\}$ denotes the confidence-dependent upper bound of the weight for the horizontal (xy) component of the Remote-ID channel in the k the time slot. $\hat{\omega}_R^{xy}(k)$ is the weight calculated based on the amount of information. The smaller one is taken as the final fusion weight, denoted by $\hat{\omega}_R^{xy}(k)$. A first-order exponential smoother, $\omega_i^{xy}(k) = \alpha_\omega \hat{\omega}_i^{xy}(k) + (1 - \alpha_\omega) \omega_i^{xy}(k-1)$, prevents jittery switching. The fused horizontal information and the associated pseudo-measurement are as follows:

$$\mathbf{Y}_{f,xy}(k) = \sum_{i \in \mathcal{I}_{xy}(k)} \omega_{i,xy}(k) \mathbf{H}_{xy}^T \left(\mathbf{R}_{i,xy}^{eff}(k) \right)^{-1} \mathbf{H}_{xy} \quad (34)$$

$$\boldsymbol{\eta}_{f,xy}(k) = \sum_{i \in \mathcal{I}_{xy}(k)} \omega_{i,xy}(k) \mathbf{H}_{xy}^T \left(\mathbf{R}_{i,xy}^{eff}(k) \right)^{-1} \mathbf{z}_{i,xy}(k) \quad (35)$$

$$\mathbf{P}_{f,xy}(k) = \mathbf{Y}_{f,xy}^{-1}(k), \quad \mathbf{z}_{f,xy}(k) = \mathbf{P}_{f,xy}(k) \boldsymbol{\eta}_{f,xy}(k) \quad (36)$$

where $(\mathbf{z}_{f,xy}, \mathbf{P}_{f,xy})$ summarizes all accepted horizontal channels in a single consistent 2-D observation whose statistical weight is automatically reduced when Remote-ID confidence is low. In the vertical subspace, priority is given to Remote-ID, while TDOA-Z is admitted conditionally to avoid height steps. Let

$$\mathbf{Y}_{i,z}(k) = \left(\mathbf{R}_{i,z}^{eff}(k) \right)^{-1} \quad (37)$$

$$\boldsymbol{\eta}_{i,z}(k) = \mathbf{Y}_{i,z}(k) \mathbf{z}_{i,z}(k) \quad (38)$$

TDOA-Z contributes only when three consistency conditions hold simultaneously: (i) no jump is detected at k ($J_T^z(k) = 0$), (ii) the horizontal χ^2 gate with respect to Remote-ID passes (i.e., the two sources are geometrically consistent in the plane), and (iii) $|z_T(k) - z_R(k)| \leq \Delta h$ (i.e., no vertical conflict exists). When both channels are admissible, we allocate weights using the same entropy rationale:

$$\Delta H_i^z(k) = \frac{1}{2} \ln \left(1 + \left(\mathbf{R}_{i,z}^{eff}(k) \right)^{-1} \mathbf{H}_z \mathbf{P}_{k|k-1} \mathbf{H}_z^T \right), \quad i \in \{T, R\} \quad (39)$$

$$\omega_{R,z}^e(k) = \frac{\Delta H_R^z(k)}{\Delta H_R^z(k) + \Delta H_T^z(k) + \epsilon} \quad (40)$$

$$\omega_{T,z}^e(k) = \frac{\Delta H_T^z(k)}{\Delta H_R^z(k) + \Delta H_T^z(k) + \epsilon} \quad (41)$$

If any admissibility condition fails, we enforce $(\tilde{\omega}_R^z, \tilde{\omega}_T^z) = (1, 0)$. The fused vertical statistics are

$$(\omega_{R,z}(k), \omega_{T,z}(k)) = \begin{cases} (\omega_{R,z}^e(k), \omega_{T,z}^e(k)), & \text{if all TDOA-Z admissibility conditions are satisfied} \\ (1, 0), & \text{otherwise} \end{cases} \quad (42)$$

$$\mathbf{Y}_{f,z}(k) = \sum_{i \in \mathcal{I}_z(k)} \omega_{i,z}(k) \mathbf{H}_z^T \left(\mathbf{R}_{i,z}^{eff}(k) \right)^{-1} \mathbf{H}_z \quad (43)$$

$$\boldsymbol{\eta}_{f,z}(k) = \sum_{i \in \mathcal{I}_z(k)} \omega_{i,z}(k) \mathbf{H}_z^T \left(\mathbf{R}_{i,z}^{eff}(k) \right)^{-1} \mathbf{z}_{i,z}(k), \quad \mathbf{P}_{f,z}(k) = \mathbf{Y}_{f,z}^{-1}(k), \quad \mathbf{z}_{f,z}(k) = \mathbf{P}_{f,z}(k) \boldsymbol{\eta}_{f,z}(k) \quad (44)$$

This design explicitly ties the use of TDOA-Z to verified consistency, preventing spurious vertical steps while allowing TDOA-Z to contribute when corroborated. The block-diagonal structure in $R_f(k)$ is imposed only between the horizontal subspace and the vertical subspace. It does not assume that the x and y direction errors are independent, since $P_{f,xy}(k)$ remains a full 2×2 covariance matrix in the horizontal plane. This approximation is consistent with the proposed subspace-decoupled fusion strategy. In urban low-altitude scenarios, the dominant vertical uncertainty of TDOA mainly originates from weak altitude observability and vertical GDOP, whereas the horizontal uncertainty is mainly governed by planar station geometry, multipath propagation, and sampling density. Therefore, directly introducing horizontal–vertical cross-covariance may allow abnormal altitude jumps to affect the horizontal update through coupled covariance terms. The block-diagonal form is thus adopted as a conservative decoupling approximation to prevent vertical outliers from contaminating horizontal trajectory estimation.

For the unified state update, we finally assemble the fused observation and its covariance into a block-structured measurement for the EKF:

$$Z_f(k) = \begin{bmatrix} z_{f,xy}(k) \\ z_f(k) \end{bmatrix}, R_f(k) = \begin{bmatrix} P_{f,xy}(k) & 0_{2 \times 1} \\ 0_{2 \times 1} & P_{f,z}(k) \end{bmatrix} \quad (45)$$

Let H be the Jacobian that stacks H_{xy} and H_z consistently with $\ddagger_f(k)$. The information-form EKF computes

$$\Lambda_k = P_{k|k-1}^{-1} + H^T R_f(k)^{-1} H \quad (46)$$

$$\eta_k = P_{k|k-1}^{-1} \hat{x}_{k|k-1} + H^T R_f(k)^{-1} Z_f(k) \quad (47)$$

$$P_{k|k} = \Lambda_k^{-1}, \hat{x}_{k|k} = P_{k|k} \eta_k \quad (48)$$

Because $R_f(k)$ is block-diagonal and positive definite, Λ_k remains symmetric positive definite, and the update is numerically stable. Conceptually, we have replaced many heterogeneous measurements with one fused pseudo-measurement per subspace, whose covariance reflects both (a) the statistical value of each channel (via entropy gain) and (b) its quality (via q_k and J_T^z through R^{eff} and weight caps).

Compared with conventional adaptive Kalman filtering, the proposed HCKF does not rely only on global covariance adaptation driven by innovation statistics. Instead, it introduces sensor-specific quality conditions before fusion and applies them to both covariance adjustment and subspace-level measurement admission. In particular, the TDOA vertical component is not simply assigned an enlarged covariance under abnormal conditions; it is admitted into or excluded from the vertical update according to the altitude-jump flag, horizontal consistency, and inter-source altitude agreement. Therefore, HCKF extends adaptive covariance regulation with condition-controlled subspace fusion, which is tailored to the heterogeneous and anisotropic error characteristics of TDOA and Remote ID in urban low-altitude environments.

4. Results and Experiments

4.1. Scenario Description

The flight experiments were conducted in the Xuzhou Olympic Sports Center area, where the low-altitude operational environment is highly challenging due to the presence of large stadium structures, grandstands, and surrounding buildings. Such an urban setting introduces substantial environmental complexity for UAV surveillance and positioning. On the one hand, the main venue structure and adjacent buildings can cause intermittent signal blockage, leading to non-line-of-sight propagation and occasional loss of measurement availability. On the other hand, metallic roofs, glass curtain walls, and

hard ground surfaces may generate severe multipath reflections, which further degrade the quality of both TDOA and Remote ID observations. These factors jointly impose stringent requirements on trajectory continuity, positioning stability, and three-dimensional estimation accuracy. Therefore, conducting experiments in this scenario provides a realistic and representative test of the robustness and adaptability of the proposed algorithm in complex urban low-altitude environments. In addition, the experimental platform was established using professional TDOA sensing equipment, Remote ID receiving devices, and an RTK-based high-precision reference system, thereby ensuring the technical reliability of data acquisition, fusion processing, and performance evaluation.

The TDOA network comprised four ground stations (USRP B210 SDR, 25.6 MS/s, GPSDO-synchronized to <50 ns) deployed at inter-station distances of 180–520 m. Remote ID was received via a Wi-Fi Beacon receiver (ASTM F3411-22a compliant, nominal 1 Hz). RTK ground truth (horizontal 0.5 cm + 1 ppm, vertical 1.0 cm + 1 ppm RMS) was logged at 10 Hz. Fusion algorithms ran on an Intel i9-13900K workstation (64 GB RAM, Ubuntu 22.04, Python 3.10), with HCKF averaging 1.8 ms per epoch.

For reproducibility, all raw measurements were processed using their original timestamps. TDOA and Remote ID data were first converted from WGS84 coordinates to a common local ENU frame and then aligned to a uniform time grid with step $T_0 = 1.0$ s. When multiple measurements were available within one grid interval, the measurement closest to the grid epoch was used; when no valid measurement was available, the corresponding source was marked as unavailable rather than being forward-filled indefinitely. RTK data were used only as post-processing ground truth and were not used for filtering, data association, or parameter tuning.

4.2. Key Parameter Settings and Tuning Protocol

To improve the reproducibility of the proposed HCKF framework, the key implementation parameters used in the experiments are summarized in Table 1. We report only the parameters that directly affect temporal alignment, motion-model selection, robust measurement screening, Remote ID confidence mapping, covariance inflation, and subspace-decoupled fusion. Other quantities, such as identity matrices, Jacobians, and numerical stabilizers, are either directly defined in Section 3 or determined by standard EKF operations.

Table 1. Key parameter settings of the proposed HCKF framework.

Category	Parameter	Value	Function
Temporal alignment	T_0, W, s	1.0 s, 9, 1	Time-grid construction
Model switching	D, ϵ_m	3, 0.05	Model-switch control
Process noise	$\sigma_a, \sigma_j, \sigma_\omega$	1.5, 0.8, 0.05	Motion uncertainty
Robust screening	p, δ	0.997, 1.5	Outlier suppression
TDOA jump detection	$Q_z, N_{\min}, r_{\max}$	0.90, 15, 5%	Altitude-jump detection
Remote ID confidence	b_0, γ_t, γ_p	4.0, 1.0, 0.5	Confidence mapping
Covariance inflation	κ	9.0	Reliability adjustment
Subspace fusion	$\omega_{\min}, \omega_{\max}, \alpha_\omega, \Delta h$	0.15, 0.85, 0.30, 20 m	Weight and height control
TDOA covariance	R_T	$\text{diag}(20^2, 20^2, 40^2)$ m ²	TDOA noise setting
Remote ID covariance	R_R	$\text{diag}(10^2, 10^2, 6^2)$ m ²	Remote ID noise setting

The same parameter set was used for all flight trajectories without trajectory-specific retuning. RTK data were used only for post-processing performance evaluation.

The parameters were selected according to three principles. First, the temporal-alignment parameters were determined based on the effective sampling characteristics of

TDOA and Remote ID. Second, the robustness-related parameters were tuned according to innovation consistency and filtering stability, rather than by fitting the RTK reference trajectory. Third, the same parameter set was applied to all flight trajectories without trajectory-specific retuning. The RTK data were used only as the post-processing ground truth for performance evaluation and were not used for filtering, temporal alignment, data association, or parameter tuning. Table 2 summarizes the tested ranges and selected values of the main hyperparameters.

Table 2. Tested ranges and final selected values of the main hyperparameters.

Parameter	Tested Range	Selected Value	Function
α	0.2–0.5	0.3	Information-volume penalty in windowed model selection
β	1.0–3.0	2.0	Model-complexity penalty in windowed model selection
γ_t	0.5–1.5	1.0	Sensitivity to Remote ID temporal irregularity
γ_p	0.25–0.75	0.5	Sensitivity to Remote ID spatial inconsistency
κ	5.0–12.0	9.0	Maximum intensity of confidence-based covariance inflation
δ	1.5–2.0	1.5	Huber threshold for robust innovation screening

The same selected values were used for all three trajectories without trajectory-specific retuning.

The confidence score of Remote ID was computed as

$$q_k = \sigma(b_0 - \gamma_t s_t(k) - \gamma_p s_p(k)), \quad (49)$$

where q_k denotes the Remote ID confidence at epoch k , $\sigma(\cdot)$ is the sigmoid function, $s_t(k)$ is the temporal irregularity score, $s_p(k)$ is the spatial inconsistency score, b_0 is the confidence offset, and γ_t and γ_p control the effects of temporal and spatial deviations, respectively. This formulation ensures that the confidence remains high when both deviations are small and decreases when irregular sampling or geometric inconsistency occurs.

The confidence-dependent upper bound of the Remote ID horizontal weight was set as

$$\omega_{R,xy}^{\max}(k) = \omega_{\min} + (\omega_{\max} - \omega_{\min})q_k \quad (50)$$

This formulation constrains the Remote ID weight within the predefined interval $[\omega_{\min}, \omega_{\max}]$, preventing low-confidence Remote ID observations from dominating the horizontal fusion process. In the vertical subspace, TDOA-Z was admitted only when no altitude jump was detected, the horizontal consistency gate was satisfied, and $|z_T(k) - z_R(k)| \leq \Delta h$. Otherwise, the vertical update was dominated by Remote ID to avoid contamination caused by TDOA altitude jumps.

4.3. Baseline Implementation and Fairness Protocol

To ensure a fair comparison, all baseline algorithms were implemented using the same input data, coordinate system, temporal alignment grid, initialization rule, and evaluation protocol as HCKF. Raw WGS84 coordinates were converted to the same local ENU frame, and RTK was used only as post-processing ground truth. No baseline was tuned using the RTK trajectory. The initial position was set to the first accepted measurement on the aligned grid, the initial velocity was set to zero, and the initial covariance was identical for all filters. The same chi-square gating threshold was applied before measurement updates.

For CV-EKF and CT-EKF, the process and measurement noise parameters were set according to the same nominal TDOA and Remote ID covariance assumptions used by HCKF. The linear KF used the same constant-velocity state definition as the CV-EKF but without nonlinear turn dynamics or source-aware covariance adaptation. CI and ICI used

the same local estimates produced from TDOA and Remote ID streams and differed only in the conservative covariance-intersection fusion rule. For HCKF, the additional modules were activated through the parameters listed in Table 3. Thus, performance differences mainly reflect the proposed quality-aware and subspace-decoupled fusion logic rather than differences in preprocessing or data selection.

Table 3. Common settings for comparative algorithms.

Item	Value	Applied Methods
Coordinate frame	Local ENU converted from WGS84	All methods
Time grid step	$T_0 = 1.0$ s	All methods
Initial position	First accepted aligned measurement	All methods
Initial velocity	$[0, 0, 0]^T$ m/s	All methods
Initial covariance	$\text{diag}(100^2, 100^2, 100^2, 10^2, 10^2, 10^2)$	All filters
TDOA nominal covariance	$\text{diag}(20^2, 20^2, 40^2)$ m ²	EKF, CI, ICI, HCKF
Remote ID nominal covariance	$\text{diag}(10^2, 10^2, 6^2)$ m ²	EKF, CI, ICI, HCKF
Chi-square gate	$p = 0.997$	All methods
RTK usage	Evaluation only	All methods
Parameter tuning	Fixed for all tracks	All methods

4.4. Comparative Evaluation of Positioning Accuracy and Filtering Performance

We evaluated three representative urban low-altitude flight missions within the test site. Each flight recorded two perception data streams: TDOA measurements from the ground receiver network and Remote ID signals broadcast by the airborne module. RTK data served solely as post-processing ground truth for evaluation and were not utilized in the preprocessing, tuning, correlation, or fusion stages. All data streams retained their original timestamps and source data and were subsequently aligned to a uniform timeline using the step size Δt , as described in Section 3. Raw coordinates were recorded in WGS84. For metric analysis and charting, they were converted into a local Cartesian coordinate system (ENU). Altitude is expressed as elevation above sea level. No smoothing was applied prior to alignment, and missing data remained unchanged without forward interpolation.

Figure 5 compares three representative flight trajectories. The black dashed line represents RTK ground-truth measurements, the blue dashed line originates from raw TDOA measurements, and the orange dashed line is derived from Remote ID measurements.

As shown in Figure 5, Track 1 has a path length of approximately 5.38 km and an altitude of about 255 m. Remote ID exhibits localized sparseness in certain sections, resulting in increased sampling intervals that form visible gaps. TDOA displays continuous vertical steps and significant instability in street-canyon segments, with occasional gaps emerging under non-line-of-sight conditions.

As shown in Figure 5, Track 2 has a path length of approximately 3.55 km, with an altitude of about 345 m. Remote ID sampling is dense and temporally regular. TDOA reveals a few hopping events and slight jitter, primarily occurring at turns and along sections with reflective building facades.

As shown in Figure 5, Track 3 has a path length of approximately 4.58 km and is located at an altitude of about 440 m. Remote ID remains generally stable, although long intervals occur in certain sections. TDOA exhibits jitter, offset, and frequent jump points. Unlike in the lower-altitude tracks, these errors are mainly caused by geometric constraints (vertical GDOP), because the target altitude increases relative to the ground stations.

Tables 4–6 report RMSE_{XY} , RMSE_Z , RMS_{3D} , and the valid sample counts for Tracks 1 to 3 under TDOA, Remote ID, and HCKF conditions. All methods employ identical alignment procedures, coordinate systems, and gating settings on a uniform timeline. Unless otherwise specified, valid samples refer to time periods that pass the chi-square

test and contribute to the reported sequence; for HCKF, they denote periods with fused updates after quality control.

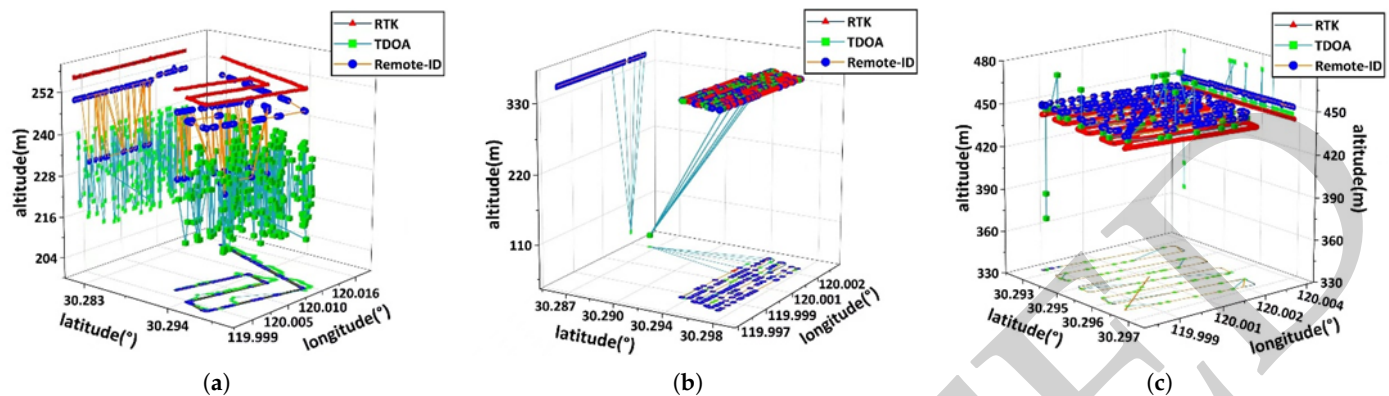


Figure 5. Representative trajectories of the raw multi-source perception data in three real-flight datasets, including RTK ground truth, TDOA measurements, and Remote ID measurements: (a) 255 m perception data trajectory; (b) 345 m perception data trajectory; (c) 440 m perception data trajectory.

TDOA exhibits the largest error across all trajectories, manifesting as high root mean square error (RMSE) and occasional significant vertical deviations. This is consistent with the expected anisotropy caused by the base-station geometric layout and multipath effects within urban street canyons, and it helps explain the frequent signal interruptions observed. While Remote ID reduces vertical errors, its reduced number of effective samples, caused by reporting rates and packet loss, creates temporal gaps and limits horizontal accuracy. HCKF achieves the lowest RMS_{3D} values across all three trajectories, reducing $RMSE_{XY}$ to single-digit meters while maintaining $RMSE_Z$ within a small error range. Compared with the single-source methods, it significantly increases the volume of effective data, indicating superior continuity under heterogeneous sampling conditions.

On Track 1, amid sparse telemetry from Remote ID and TDOA and severe vertical jumps, HCKF maintains continuity and reduces error by separating horizontal and vertical processing: plane information-driven weighting leverages TDOA density, while the vertical channel is protected by Remote-ID dominance, conditionally accepting TDOA-Z data only when the consistency and amplitude thresholds are met.

On Track 2, under stable altitude and dense Remote-ID conditions, the HCKF algorithm simultaneously reduces horizontal and vertical errors while enhancing the effective sampling rate. Its principle lies in achieving stable associations through grid-time consistency and mapping Remote-ID consistency to higher weights while preserving TDOA data.

On Track 3, in geometrically variable and multipath environments, HCKF effectively suppresses the impacts of TDOA jitter and offset through confidence-based weighting and moderate temporal smoothing. This approach avoids weight oscillations while preserving the three-dimensional geometry.

In this study, “data volume” denotes the number of valid epochs that contribute to the reported trajectory on the unified time grid. For TDOA and Remote ID, it refers to the number of epochs at which the corresponding source provides an accepted measurement after temporal alignment and quality control. For HCKF, it refers to the number of epochs at which at least one accepted fused update is available. Therefore, data volume reflects trajectory continuity rather than the amount of raw data stored by the sensor.

Table 4. Comparison of errors and data counts for Track 1 under TDOA, Remote ID, and HCKF.

Method	RMSE _{XY} /m	RMSE _Z /m	RMS _{3D} /m	Data Volume
TDOA	62.585	25.069	70.481	338
Remote ID	38.481	7.844	40.476	134
HCKF	7.114	4.403	8.980	472

Note: RMSE_{XY} denotes the horizontal subspace root mean square error, RMSE_Z denotes the vertical subspace root mean square error, and RMS_{3D} denotes the overall three-dimensional root mean square error. Bold values indicate the best result for each metric, namely the minimum error in the error columns and the maximum value in the Data Volume column.

Table 5. Comparison of errors and data counts for Track 2 under TDOA, Remote ID, and HCKF.

Method	RMSE _{XY} /m	RMSE _Z /m	RMS _{3D} /m	Data Volume
TDOA	27.470	56.077	62.430	156
Remote ID	14.816	2.083	14.961	164
HCKF	5.711	1.059	5.808	320

Note: RMSE_{XY} denotes the horizontal subspace root mean square error, RMSE_Z denotes the vertical subspace root mean square error, and RMS_{3D} denotes the overall three-dimensional root mean square error. Bold values indicate the best result for each metric, namely the minimum error in the error columns and the maximum value in the Data Volume column.

Table 6. Comparison of errors and data counts for Track 3 under TDOA, Remote ID, and HCKF.

Method	RMSE _{XY} /m	RMSE _Z /m	RMS _{3D} /m	Data Volume
TDOA	30.953	14.088	31.889	174
Remote ID	8.777	7.692	12.719	254
HCKF	4.671	5.706	7.774	332

Note: RMSE_{XY} denotes the horizontal subspace root mean square error, RMSE_Z denotes the vertical subspace root mean square error, and RMS_{3D} denotes the overall three-dimensional root mean square error. Bold values indicate the best result for each metric, namely the minimum error in the error columns and the maximum value in the Data Volume column.

It should be noted that data volume does not directly reduce RMSE. RMSE measures positioning accuracy over the valid epochs, whereas data volume measures temporal continuity. A method with a larger data volume may still produce a large RMSE if the retained measurements contain strong bias or outliers. Conversely, a sparse method may show moderate RMSE but fail to provide continuous trajectory coverage. Therefore, RMSE and data volume are jointly used to evaluate the accuracy–continuity trade-off.

Figure 6 presents three sets of accuracy–continuity trade-off plots: root mean square error versus data count, XY-direction root mean square error versus data count, and Z-direction root mean square error versus data count. The HCKF point sets form ideal clusters in the low-error and high-count regions, indicating a Pareto advantage over the single-source methods—that is, in most cases, HCKF achieves a more favorable balance between error and data count.

In terms of overall error and continuity, TDOA tends to occupy regions with high data volume but large errors, while Remote ID resides in areas with low errors but sparse data. Compared with both, HCKF shifts the data cloud toward regions with lower errors and higher valid-epoch coverage, indicating a more favorable accuracy–continuity trade-off.

In the horizontal view, HCKF maintains a stable low-error, high-density pattern that suppresses TDOA jump events during turns and obstructions while preserving geometric constraints through higher sampling rates. In the vertical view, HCKF primarily resides in the low-Z-error, high-count region; in sections with strong vertical interference, it ensures overall continuity by moderately sacrificing Z-axis accuracy.

These trends are consistent with the fusion design that treats the horizontal and vertical components separately and applies statistical gates and robust losses to contain outliers and jump events. The results support the use of Remote ID for vertical accuracy, TDOA for sampling density, and layered robust fusion to control errors while sustaining continuity.

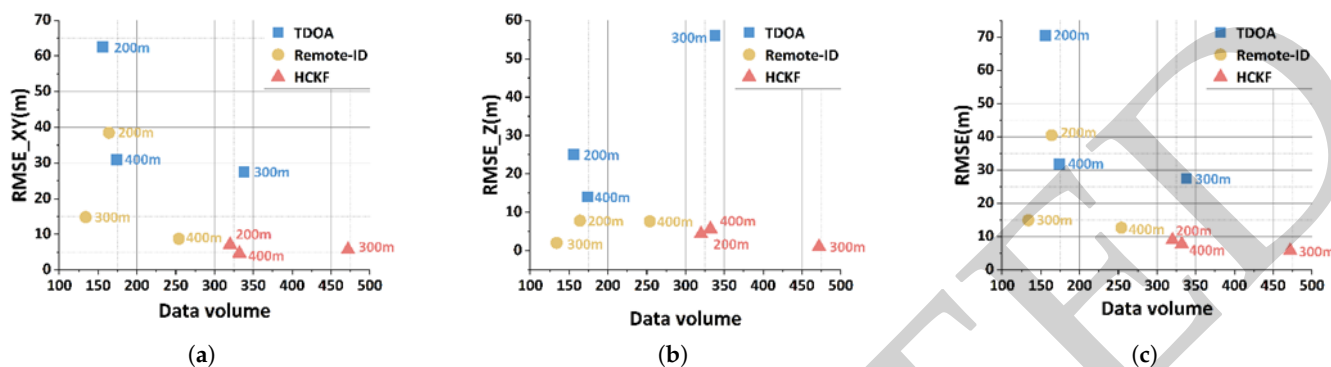


Figure 6. Accuracy–continuity trade-off plot. (a) Horizontal accuracy and data volume. (b) Vertical accuracy and data volume. (c) Overall accuracy and data volume.

Figure 7 compares the performance of the proposed HCKF algorithm with CT EKF [40], CV EKF [41], CI [42], ICI [43], and the linear KF in tracking low-altitude non-cooperative targets. All methods employ uniform timeline alignment, identical coordinate systems, and identical gating mechanisms. RTK is used solely as a post-processing reference. The left panel shows the overlay of the fused horizontal trajectory and the RTK trajectory; the right panel presents the vertical root mean square error for the same segment.

HCKF closely approximates the RTK paths under turning and occlusion conditions with minimal lateral deviation. CT EKF and CV EKF exhibit drift when UAV velocity changes rapidly or sampling becomes irregular, reflecting their single-model assumptions and sensitivity to temporal variation. The linear KF exhibits the greatest deviation in densely built urban areas with anisotropic noise. While CI and ICI demonstrate greater stability, their conservative weighting causes lag and fails to fully exploit information updates. These characteristics are consistent with HCKF's time-consistency prior, confidence-based de-weighting mechanism, and information-driven horizontal weighting, whose combined effect suppresses jump residuals while preserving the horizontal information provided by high-density observation points.

Across all test segments, HCKF achieves the lowest or near-lowest $RMSE_Z$ values. When height measurements exhibit noise or irregularities, the performance of CT EKF and CV EKF degrades because their process noise must simultaneously account for both the kinematic state and sampling inconsistencies, thereby amplifying residuals. While CI and ICI maintain consistency, this comes at the cost of increased vertical errors. The linear KF is the most susceptible to step effects caused by multipath in TDOA-Z. In contrast, HCKF enforces a Remote ID-dominant strategy for the vertical channel, using TDOA-Z only when horizontal consistency holds and an amplitude threshold is satisfied. This conditional rule prevents false vertical steps while flexibly utilizing TDOA-Z when it is reliable.

Figure 8 reports the bar-chart statistics for the three flight trajectories, including the overall RMSE, horizontal error ($RMSE_{XY}$), and vertical error ($RMSE_Z$).

Figure 8a compares the three-dimensional RMSE values of the three test trajectories under different filters. The traditional methods (CT EKF, CV EKF, CI, ICI, and Linear KF) are clearly inferior to HCKF in overall accuracy. Notably, on Track 2, their errors remain around 30 m, whereas HCKF reduces the error to single-digit meters, yielding an improvement of about 70–80%. Tracks 1 and 3 show a similar pattern: HCKF sustains low

error while maintaining stability, thereby avoiding the accuracy fluctuations exhibited by the traditional algorithms in highly dynamic segments.

Figure 8b compares the performance in the horizontal subspace in terms of $RMSE_{XY}$. HCKF keeps the horizontal error within 8 m on all three tracks, reducing the error by more than 75% relative to CT EKF and CV EKF, with Track 2 showing a particularly notable improvement from 22.00 m to 7.11 m. By contrast, the traditional methods degrade on Track 2, with sharp error growth at turns and during acceleration. By leveraging adaptive covariance adjustment and multi-source constraints, HCKF suppresses such drift accumulation.

Figure 8c reports the vertical accuracy in terms of $RMSE_Z$. HCKF maintains a stable advantage, achieving 1.05 m on Track 1, which is about 32.73% lower than that of the traditional methods, and 4.40 m and 5.71 m on Tracks 2 and 3, corresponding to improvements of approximately 74.01% and 28.14%, respectively. Traditional filters are vulnerable to altitude drift and transient spikes when signal quality degrades, whereas the Subspace-Decoupled Fusion strategy in HCKF constrains the vertical state and uses residual feedback to suppress these bursts.

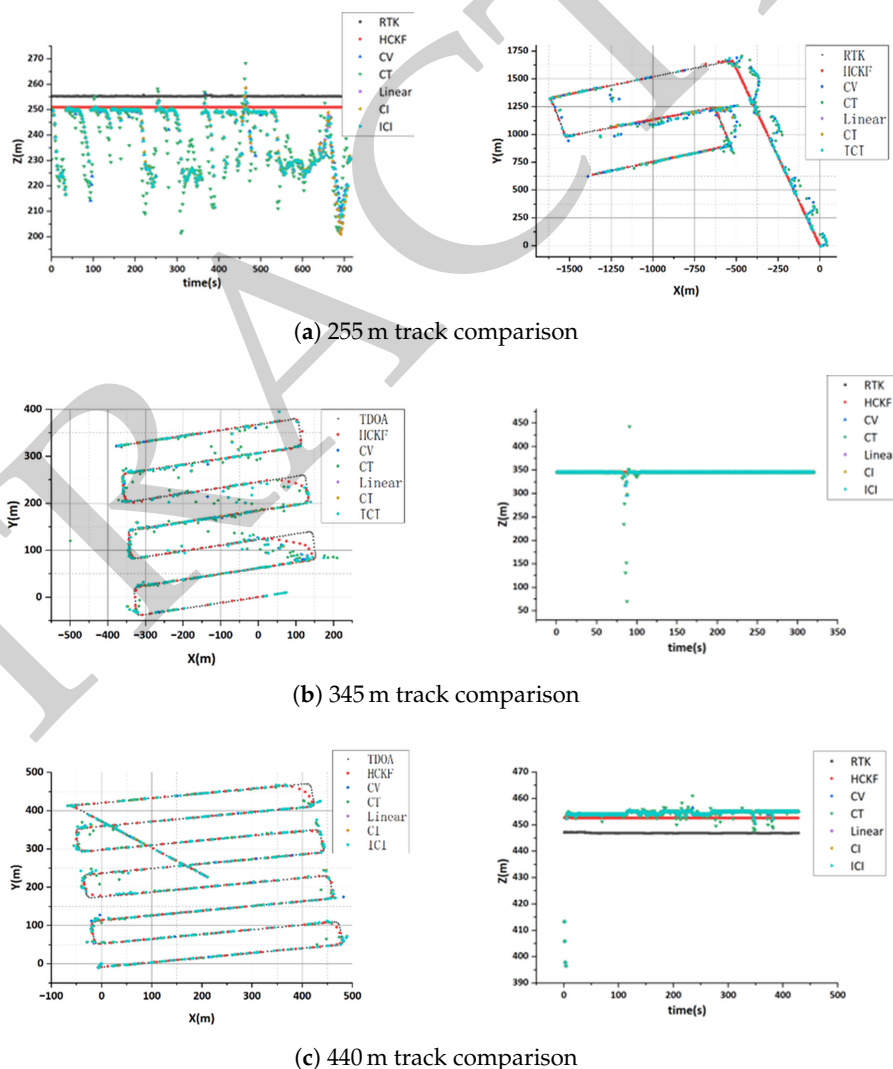


Figure 7. Trajectory comparison across fusion algorithms. The lines represent the trajectories or vertical errors obtained by HCKF, CT EKF, CV EKF, CI, ICI, and linear KF, while the RTK trajectory is used as the post-processing reference. Subfigures (a–c) correspond to the 255 m, 345 m, and 440 m flight tracks, respectively.

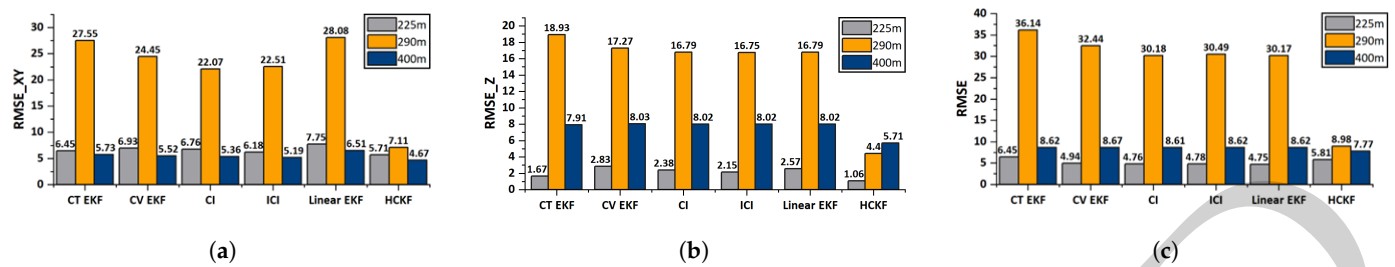


Figure 8. RMSE of different filtering algorithms. (a) Horizontal RMSE comparison. (b) Vertical RMSE comparison. (c) Overall RMSE comparison.

Across the three tested trajectories, HCKF achieved lower positioning errors and improved trajectory continuity in the overall, horizontal, and vertical subspaces. These results indicate that the proposed conditional fusion strategy is effective under the tested urban low-altitude conditions, where TDOA and Remote ID exhibit complementary but heterogeneous error characteristics.

Although the proposed HCKF framework improves positioning accuracy and continuity in the three real-flight trajectories, the experimental scope remains limited. All trajectories were collected in one urban low-altitude area, and the TDOA receiver geometry, Remote ID communication environment, and UAV platform were fixed during the experiments. Therefore, the current results do not fully characterize performance under different station layouts, terrain structures, UAV dynamics, communication protocols, or weather conditions. Future work will extend the validation to multiple urban sites and different receiver-network configurations to further assess the generalization capability of the proposed method.

4.5. Statistical Validation and Robustness

Table 7 summarizes the statistical validation. Paired Wilcoxon signed-rank tests confirm that HCKF outperforms all baselines at $p < 0.01$ on all three tracks. Bootstrap 95% confidence intervals ($B = 10,000$) for RMS_{3D} reduction relative to the best single-source baseline are well-separated from zero. Under three perturbation scenarios on Track 2—additional 20% Remote ID packet loss, TDOA vertical noise injection ($\sigma = 20$ m), and 500 ms linear clock drift—HCKF maintains RMS_{3D} below 10 m in all cases, with the largest degradation of +18.7% under vertical noise injection. The average per-epoch processing time of HCKF is 1.82 ms ($\sigma = 0.28$ ms), comparing favorably with ICI (2.45 ms) and CT EKF (1.23 ms) while providing superior accuracy.

Table 7. Statistical validation summary across three flight tracks. CI: bootstrap 95% confidence interval for RMS_{3D} reduction vs. best single-source baseline. Perturbation: RMS_{3D} under degraded conditions on Track 2 (nominal: 5.808 m).

Metric	Track 1	Track 2	Track 3
Wilcoxon p (vs. best baseline)	$<10^{-4}$	$<10^{-4}$	1.7×10^{-3}
RMS_{3D} reduction	77.8% [74.1, 81.2]	61.2% [56.8, 65.5]	38.9% [33.4, 44.7]
Robustness analysis for Track 2			
20% Remote ID loss		6.841 m (+17.8%)	
TDOA-Z noise $\sigma = 20$ m		6.894 m (+18.7%)	
Clock drift 500 ms		6.423 m (+10.6%)	
Processing time (ms/epoch)		1.82 ± 0.28	

4.6. Module Ablation Experiments

To evaluate the effectiveness of the proposed multi-source fusion positioning method and quantify the contributions of each module, we conducted ablation experiments and comparative studies on a unified platform and dataset for the three modules introduced in Section 3. The analysis focused on two core questions: (i) the independent and synergistic gains of the three modules, where M is the multi-model adaptive prior based on a unified grid; C is the measurement quality evaluation, transforming temporal anomalies and jump events into effective covariance and weight upper bounds; and V is Subspace-Decoupled EKF Fusion, combining horizontal information weighting with vertical updates dominated by Remote ID; and (ii) the extent to which the C module enhances accuracy in both the horizontal and vertical components. The findings provide quantitative evidence for the design choices, reveal the complementarity among modules, and identify the components that most significantly affect the key dimensions of accuracy and continuity.

The proposed method has operational limits under prolonged packet loss. The multi-model prediction and sliding-window alignment can reduce short-term time gaps, but they cannot fully replace external observations during long communication outages. If Remote ID packets are continuously lost and TDOA measurements are also unavailable or rejected by the quality-control gates, the filter will rely mainly on prediction, and the uncertainty will grow over time. Under such conditions, trajectory accuracy cannot be guaranteed, and the output should be interpreted as a low-confidence estimate. Future work will investigate explicit outage-mode handling, adaptive process-noise inflation, and integration with additional onboard sensors to improve robustness under long-duration communication loss.

To quantify the contributions of the three core modules M, C, and V in the multi-source localization system, we conduct a 3×3 combination ablation using RMSE under unified data and parameter settings. Figure 9 presents the RMSE heatmaps for the three flight trajectories. The axes represent different pairwise module combinations. The color intensity encodes the RMSE magnitude. Each cell displays two values: the absolute RMSE and a value in parentheses. The number in parentheses specifically indicates the error increase relative to the full-module HCKF scheme.

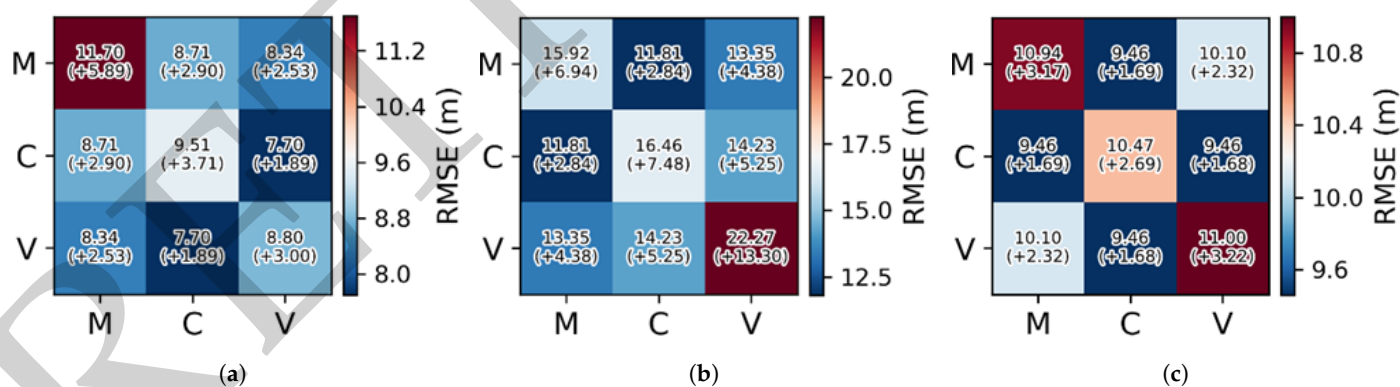


Figure 9. Heatmaps of 3×3 module-combination ablation results across three distinct flight trajectories: (a) 255 m experiment; (b) 345 m experiment; (c) 440 m experiment.

Figure 9a Track 1: The complete configuration reduces the error by approximately two-thirds compared with the baseline without any modules, demonstrating a significant synergistic effect. Removing the V module causes the most severe performance degradation, bringing the error close to that of the weakest baseline, which indicates that the quality of the source data varies significantly and therefore requires an adaptive weighting strategy. Removing the C module similarly leads to a substantial increase in error, which is consistent

with the presence of high noise, irregular sampling, and the need for dynamic gating and anomaly suppression under high-velocity maneuvers. Removing the M module also degrades the performance, although less severely than removing the V or C module. This indicates that spatiotemporal matching accuracy remains important, but on this trajectory it can be partially compensated for by robust control and fusion techniques.

Figure 9b Track 2: The complete configuration performs best across all module-deletion and baseline scenarios. Compared with the no-module scenario, the root mean square error decreases by more than half. Removing any module increases the error, with the deletion of Module C causing the greatest degradation (more than one-third worse than the complete configuration), followed by the deletion of Module M, while removing Module V has the smallest impact. This ranking is consistent with the scenario characteristics: when data quality is relatively balanced, confidence-based control is crucial for smoothing and noise reduction, while temporal-consistency association prevents matching errors from propagating to the fusion stage. Information-based weighting remains effective but has less influence than Modules C and M under these conditions.

Figure 9c: The gain achieved by the complete configuration relative to the no-module baseline is relatively modest, amounting to approximately one-third. The three single-module ablation schemes exhibit similar performance degradation, with smaller gaps than those observed on Tracks 1 and 2. This indicates that the contributions of the three modules are more balanced under conditions of high coverage and low noise. Nevertheless, the V module provides the greatest accuracy improvement among the three, followed by the C and M modules. This is consistent with the ability of the weighting mechanism to effectively exploit informative updates without requiring frequent aggressive gating or association-repair operations.

Across all three tracks, the fully configured system consistently reduces the error by approximately one-third to two-thirds. The importance of each module depends on the scene characteristics. Under complex conditions with sparse Remote ID and TDOA jump events, system performance depends more heavily on the robustness of Module C and the adaptability of Module V. When observation conditions are favorable and the data flow is balanced, Modules M and C dominate the performance improvements, while Module V still provides measurable but smaller gains. Overall, the modules exhibit an additive effect on accuracy and compensate for each other under varying noise levels and sampling modes, thereby improving the robustness and adaptability of the system.

To evaluate the effectiveness of the Subspace-Decoupled EKF Fusion module in vertical accuracy, we select three representative trajectories and compare the performance with and without the Subspace-Decoupled EKF Fusion module against high-accuracy RTK ground truth, with the analysis focused on the Z-axis subspace. The evaluation metric is $RMSE_Z$.

As shown in Figure 10a for Track 1, the vertical $RMSE_Z$ is 8.54 m without Subspace-Decoupled EKF Fusion and drops to 2.86 m with Subspace-Decoupled EKF Fusion, representing an improvement of 84.64%. The error curve without Subspace-Decoupled EKF Fusion exhibits large fluctuations during interference, with peak values tens of times higher than the reference, whereas with Subspace-Decoupled EKF Fusion it remains at a low amplitude. This gain stems from conditional gating in the update stage, which dynamically accepts or rejects observations based on residuals and covariances.

In Figure 10b for Track 2, multiple high-noise intervals are present. Without Subspace-Decoupled EKF Fusion, the vertical $RMSE_Z$ reaches 21.73 m with frequent high-amplitude oscillations; with Subspace-Decoupled EKF Fusion, it falls to 3.92 m, representing an 81.91% improvement. Subspace-Decoupled EKF Fusion markedly reduces transient deviations in high-noise segments by down-weighting anomalous observations, thereby avoiding the degradation typical of a standard EKF under non-Gaussian noise.

In Figure 10c for Track 3, the case without Subspace-Decoupled EKF Fusion shows a pronounced initial error spike and moderate subsequent fluctuations, with an MAE of 9.64 m; with Subspace-Decoupled EKF Fusion, the MAE drops to 2.41 m, representing a 75.02% improvement. Subspace-Decoupled EKF Fusion accelerates convergence under unstable initialization by adaptively suppressing early outliers, thereby reducing error accumulation.

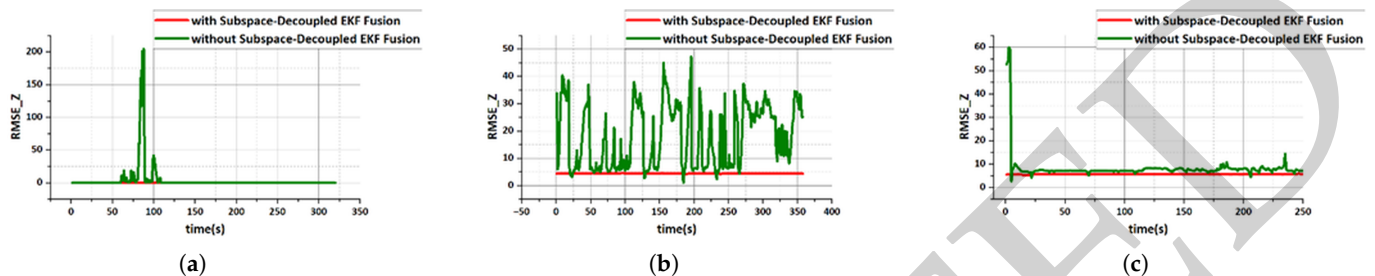


Figure 10. Effect of Subspace-Decoupled EKF Fusion on vertical positioning accuracy (Z RMSE) across different trajectories: (a) 255 m experiment; (b) 345 m experiment; (c) 440 m experiment.

Across all three trajectories, Subspace-Decoupled EKF Fusion improves vertical accuracy by more than 75%—exceeding 80% in two cases—through conditional updates that reject or attenuate anomalous measurements, strengthened vertical constraints in covariance adjustment, and reduced the influence of erroneous early observations. These mechanisms yield stable, high-accuracy vertical estimates under interference, strong noise, and unstable initialization, thereby enhancing the overall robustness of the three-dimensional trajectory.

4.7. Mechanistic Interpretation

The performance gains observed in the ablation study can be explained through three coupled mechanisms. **Entropy-guided weighting** creates a self-balancing feedback loop: when TDOA becomes noisy due to multipath, its entropy gain ΔH_T^{xy} decreases, automatically reducing its weight; conversely, when Remote ID loses confidence, its weight is capped, shifting authority to TDOA. Because entropy is a concave function of covariance, this transition is smooth and free of threshold-induced oscillations. **Covariance inflation** operates before the fusion step: inflating $R_R^{\text{eff}}(k)$ reduces the Kalman gain, and this reduced information propagates consistently through both the state and covariance updates, maintaining filter consistency. Without inflation, an overconfident Remote ID measurement with hidden timing errors would produce an artificially small $P_{k|k}$, causing subsequent epochs to over-weight the prior—a positive feedback loop leading to divergence. **Subspace decoupling** prevents cross-dimensional contamination by setting the off-diagonal Kalman gain block $\mathbf{K}_{xy,z} = \mathbf{0}$, eliminating the pathway through which vertical TDOA outliers propagate into horizontal estimates. The cost is discarding legitimate horizontal–vertical error correlation, but in urban TDOA scenarios where vertical errors are dominated by structural biases rather than kinematic coupling, this discarded information is negligible and often harmful.

5. Discussion

The experimental results demonstrate that the proposed HCKF framework improves urban low-altitude UAV positioning by explicitly exploiting the complementary characteristics of TDOA and Remote ID rather than treating them as homogeneous position observations. The three tested trajectories show that TDOA generally provides denser measurements but suffers from large positioning errors, especially in the vertical direction, whereas Remote ID offers more stable absolute position information but is affected by sparse and irregular reporting. This explains why neither single-source method can

simultaneously achieve high accuracy and strong trajectory continuity. In contrast, HCKF combines the high measurement density of TDOA with the vertical stability of Remote ID through quality-aware weighting and subspace-decoupled fusion, thereby shifting the fused results toward the low-error and high-valid-epoch region.

A key implication of the results is that the improvement of HCKF is not caused merely by increasing the number of valid samples. Data volume reflects the continuity of the trajectory on the unified time grid, while RMSE reflects the accuracy of accepted epochs. Therefore, a method with more valid epochs may still produce a large RMSE if the retained measurements contain systematic bias or multipath-induced outliers. The advantage of HCKF lies in improving these two aspects simultaneously. In Track 1, where both Remote ID sparsity and TDOA vertical jumps are evident, HCKF maintains continuity while suppressing vertical instability. In Track 2, where Remote ID is relatively dense and stable, the proposed method further improves both horizontal and vertical accuracy by preserving useful TDOA information instead of rejecting it completely. In Track 3, where the target altitude increases and the TDOA geometry becomes less favorable, HCKF suppresses jitter and offset through confidence-based weighting, showing that the proposed method remains effective under stronger geometric uncertainty.

The comparison with CT EKF, CV EKF, CI, ICI, and the linear KF further confirms the necessity of measurement-conditioned fusion. Traditional EKF variants rely on fixed or model-specific motion assumptions. When the UAV experiences turns, velocity changes, irregular sampling, or multipath interference, the innovation sequence becomes unstable and the filter tends to either drift or overreact to abnormal measurements. CI and ICI improve consistency by conservative fusion, but this conservatism may reduce the ability to fully exploit newly available information. The linear KF is more vulnerable to nonlinear motion and anisotropic measurement noise. HCKF mitigates these problems by introducing three mechanisms: motion-consistent temporal alignment, confidence-driven covariance adjustment, and horizontal-vertical decoupled measurement admission. These mechanisms allow the filter to retain informative measurements while reducing the influence of unreliable observations.

The subspace-decoupled design is particularly important for TDOA-Remote ID fusion. In urban low-altitude environments, the horizontal and vertical components of TDOA do not have equivalent reliability. The horizontal component benefits from hyperbolic intersection geometry and a higher observation density, while the vertical component is more sensitive to near-coplanar receiver deployment, vertical GDOP, and multipath-induced jumps. If the three-dimensional measurement vector is fused as a coupled observation, vertical anomalies may contaminate the horizontal state through the Kalman gain. HCKF avoids this problem by applying information-guided weighting in the horizontal plane and a Remote ID-dominant conditional strategy in the vertical axis. This explains why the proposed method can reduce horizontal error to the single-digit-meter level while keeping the vertical error within a controlled range across the three trajectories. The results also indicate that robust fusion should not be equivalent to simple outlier deletion. In practical UAV surveillance, removing abnormal measurements can improve instantaneous RMSE but may also interrupt the trajectory and weaken situational awareness. HCKF instead converts measurement quality into covariance inflation, weight limitation, and conditional admission. This strategy is more suitable for low-altitude safety monitoring because it preserves trajectory continuity while preventing low-quality data from dominating the update. The framework therefore provides a practical compromise between accuracy, robustness, and availability.

Despite these advantages, the current validation still has several limitations. First, all trajectories were collected within one urban low-altitude test area, and the receiver

geometry, communication environment, UAV platform, and flight altitude range were fixed during the experiments. The current results therefore cannot fully represent performance under different city layouts, station deployments, UAV dynamics, weather conditions, or Remote ID communication protocols. Second, the proposed framework depends on several quality-control and weighting parameters. Although fixed settings were used across the tested tracks, further sensitivity analysis is still necessary to determine whether the same parameter ranges remain optimal under different deployment conditions. Third, RTK was used only as the post-processing reference, and the experiments mainly evaluated offline positioning accuracy and continuity. Real-time deployment on edge devices should further examine latency, computational load, and robustness under long communication outages.

Future work should therefore extend the evaluation to multiple urban sites, different TDOA receiver-network geometries, and more diverse UAV motion patterns. Additional experiments should also investigate long-duration packet loss, extreme NLOS conditions, and mixed cooperative–non-cooperative traffic scenarios. From a methodological perspective, the HCKF framework could be further improved by incorporating adaptive parameter learning, online receiver-geometry assessment, and theoretical performance-bound analysis for TDOA–Remote ID fusion. These extensions would help determine the generalization capability and operational reliability of the proposed method in large-scale urban low-altitude airspace management.

6. Conclusions

This study proposes the HCKF framework to address the challenges of urban low-altitude UAV tracking. Specifically, it targets the issues of asynchronous sampling, latency, and heterogeneous noise between TDOA and Remote ID sensors. The framework establishes a complete processing pipeline.

First, a kinematics-based alignment module is implemented to map asynchronous data onto a uniform timeline. It predicts missing samples using motion models, including CV, CA, and CT, thereby resolving the fundamental problem of temporal gaps.

Second, a Measurement Quality Evaluation mechanism is designed. Instead of simply discarding data based on the Mahalanobis distance, this module transforms TDOA altitude jumps and Remote ID timing irregularities into dynamic covariance adjustments. In this way, data continuity is preserved while the influence of anomalies is suppressed.

Third, a Subspace-Decoupled EKF Fusion strategy is developed. This method separates the horizontal and vertical dimensions. It applies entropy-guided weighting in the horizontal plane and a Remote ID-dominated strategy along the vertical axis. As a result, the trade-off between accuracy and trajectory continuity is improved.

The framework is validated using real-world flight data collected in Xuzhou. The results show that HCKF outperforms single-source methods and traditional baselines under the tested urban low-altitude conditions, including EKF, CI, and ICI. Quantitatively, it reduces the root mean square error (RMSE) by more than 40% compared with raw TDOA or Remote ID inputs. It also eliminates the trajectory drift and vertical steps commonly observed in standard filters. Ablation studies further confirm that the three core modules operate synergistically to suppress noise and maintain stability.

Several limitations define directions for future work. First, under complete and sustained signal loss from both modalities, the filter degenerates to open-loop prediction; integrating visual-inertial odometry or 5G cellular positioning would provide redundant constraints. Second, the validation is limited to a single urban site with a fixed TDOA geometry—performance across high-rise business districts or suburban areas requires multi-site validation. Third, the current implementation assumes a single target; multi-UAV tracking introduces data-association ambiguity and computational scaling challenges.

Fourth, the Remote ID confidence mechanism assumes authentic broadcasts and does not address GPS spoofing, which would require additional integrity-checking layers. Ongoing work addresses these limitations through the following: (i) integration of 5G-A sensing as a third fusion channel, (ii) online TDOA receiver calibration, (iii) extension to cooperative multi-UAV scenarios, and (iv) the development of a lightweight edge-deployable implementation.

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