

Article

Multi-UAV Adaptive Cooperative Localization Method Against Hybrid Abnormal Measurements

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Highlights

What are the main findings?

- An online diagnosis mechanism distinguishes normal, delayed, and lost cooperative measurements in weak communication environments.
- A novel framework adaptively combines multi-step delayed filtering with GWO-GRU virtual measurement reconstruction.

What are the implications of the main findings?

- The method improves cooperative localization robustness when random delays and intermittent data loss coexist.
- Simulation results show reduced horizontal RMSE and suppressed filter divergence during communication outages.

Abstract

To address the coexistence of random measurement delays and intermittent data loss in multi-UAV cooperative navigation under weak communication scenarios, an adaptive cooperative localization method based on online diagnosis is proposed. A timestamp-driven diagnosis mechanism first identifies the physical reachability and temporal validity of cooperative measurements and classifies the channel state as normal, delayed, or lost. The estimator then adaptively switches between timestamp-diagnosed multi-step augmented filtering for delayed packets and Gray Wolf Optimizer (GWO)-optimized Gated Recurrent Unit (GRU) virtual measurement reconstruction for complete dropouts. In a four-UAV hybrid-anomaly simulation with continuous random delays and a 10 s communication blackout, the proposed method reduces the mean east and north RMSE by 69.1% and 75.2%, respectively, and lowers the mean horizontal-channel RMSE from 2.200 m to 0.608 m. Ablation experiments isolate the contribution of each module (diagnosis and multi-step delayed filtering and GWO-GRU virtual reconstruction), and 20 paired Monte Carlo runs with paired significance tests confirm the improvement. Relative to the strongest delay-aware baseline, the full-trajectory mean accuracy is comparable, and the main advantage of the proposed method is its robustness during complete communication outages and fast post-outage recovery. The simulation scenarios are driven by flight data collected with the DJI Matrice 350 RTK platform; the communication anomalies are included in the simulation, and all evaluations are performed offline. These results indicate that the proposed diagnosis-driven scheduling strategy can improve cooperative localization robustness when delay and data loss occur simultaneously.



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Keywords: cooperative localization; hybrid abnormal measurements; delay filtering; online diagnosis; adaptive mechanism

1. Introduction

In recent years, the autonomous control of Unmanned Aerial Vehicle (UAV) systems has significantly improved, enabling widespread application in complex environments [1]. Multi-UAV cooperative systems further enhance task efficiency and robustness through information interaction and resource sharing [2,3]. However, reliable inter-vehicle communication is often compromised by limited bandwidth and multipath effects, causing random packet dropouts and time-varying delays. Dropouts lead to filter divergence due to missing updates [4], while random delays disrupt the temporal consistency of state estimation, resulting in severe biases [5]. Figure 1 illustrates the multi-UAV system and the link impairments considered in this study, including packet dropouts and transmission delays.

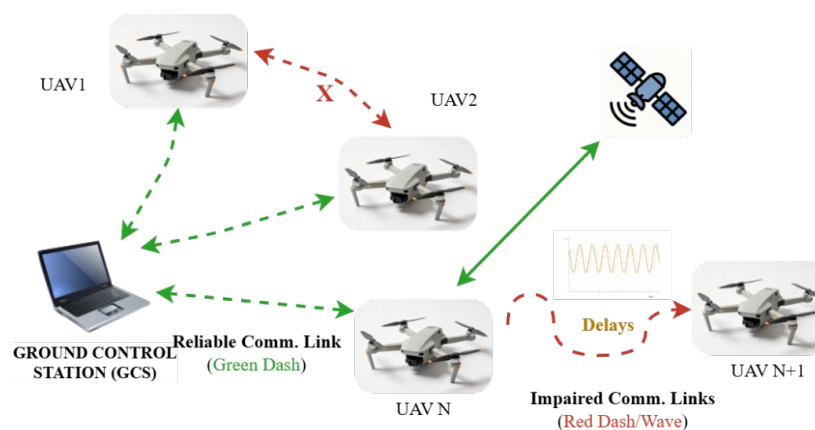


Figure 1. Multi-UAV system with link impairments.

Existing research primarily addresses these anomalies through independent frameworks. For measurement dropouts, “passive fault tolerance” strategies—such as Chi-square tests [6], robust estimation theories [7], and Strong Tracking Filters (STFs) [8,9]—improve algorithmic robustness but deteriorate rapidly during consecutive data losses. Conversely, “active prediction” methods utilizing deep learning (e.g., LSTM, GRU) successfully generate data to fill information gaps, but their generalization remains challenged by non-stationary noise and training data dependencies [10–12]. Regarding measurement delays, Bernoulli sequence-based state augmentation effectively handles one-step delays [13,14], with other studies exploring Variational Bayesian (VB) inference [15], stochastic cloning [16], and curve fitting compensation [17]. However, managing multi-step or out-of-sequence delays via Bayesian hybrid filtering or high-order Cubature Kalman Filtering (CKF) introduces severe computational burdens, making it difficult to meet the real-time requirements of cooperative navigation [18,19].

Recent work has moved cooperative localization closer to realistically impaired channels. Distributed state estimation with quality-aware update scheduling under both communication and navigation constraints has been proposed for multi-UAV localization [20]; consistent-innovation-aided distributed cooperative localization with GNSS-denied followers has advanced the fusion robustness under noisy links [21]; a UKF-based collaborative navigation scheme for UAV ad hoc networks has applied sequential quadratic programming to the GNSS-denied cooperative problem [22]; a learning-based measurement-validation approach that gates unreliable cooperative measurements before a Kalman

update has been demonstrated for multi-UAV navigation [23]; and GNSS-denied indoor UAV navigation has been realized with UWB-aided visual-inertial odometry [24]. On the estimation-theory side, filtering with randomly delayed measurements has been extended to adaptive Gaussian filters [25], risk-sensitive formulations [26], particle filters for multi-step randomly delayed measurements [27,28], and continuous-discrete trackers with out-of-sequence measurements [29]. Complementary results on multi-agent cooperative control under communication delays and packet loss show how strongly link quality shapes estimation-dependent behaviors [30]. These methods either assume a single anomaly type, operate on one pre-fixed delay order with limited depth, or compensate for loss without adapting the trust placed in the reconstructed data. None couples online timestamp-based state diagnosis with a multi-step delay filter and uncertainty-adapted virtual measurements within one switching estimator, which is the gap addressed here.

On the platform side, lightweight AI models are increasingly deployed on resource-constrained UAV payloads in real time. For example, a YOLO-based aircraft skin damage inspection system running on lightweight devices and UAVs shows how detection networks, real-time transmission, and onboard computing limits combine in practical aviation missions [31]. Although that system addresses visual defect recognition rather than navigation, it illustrates the same computational and real-time constraints that motivate our choice of a compact two-layer GRU optimized by GWO for measurement reconstruction.

While previous methods focus on resolving isolated anomalies (e.g., individual packet dropout compensation [32]), practical cooperative navigation environments exhibit intertwined, time-varying dropouts and delays. To overcome the limitations of single-mode solutions, this paper proposes an online diagnosis-based adaptive cooperative localization framework. By perceiving and quantifying real-time channel states (normal, delayed, or lost), the framework dynamically schedules a GWO-GRU-based prediction compensation module and a multi-step augmented filtering module, thereby achieving unified handling of time-varying hybrid anomalies.

The main contributions of this paper are threefold: (1) a timestamp-based online diagnosis mechanism is constructed to distinguish normal, delayed, and lost cooperative measurements under weak communication links; (2) delayed measurements and complete dropouts are handled within a single adaptive estimation framework by combining multi-step augmented filtering with GWO-GRU virtual measurement reconstruction; and (3) a hybrid-anomaly simulation with simultaneous random delays and bursty communication loss is used to quantify direction-dependent localization performance for multiple GNSS-denied follower UAVs.

The overall adaptive cooperative localization framework for handling hybrid abnormal measurements is shown in Figure 2.

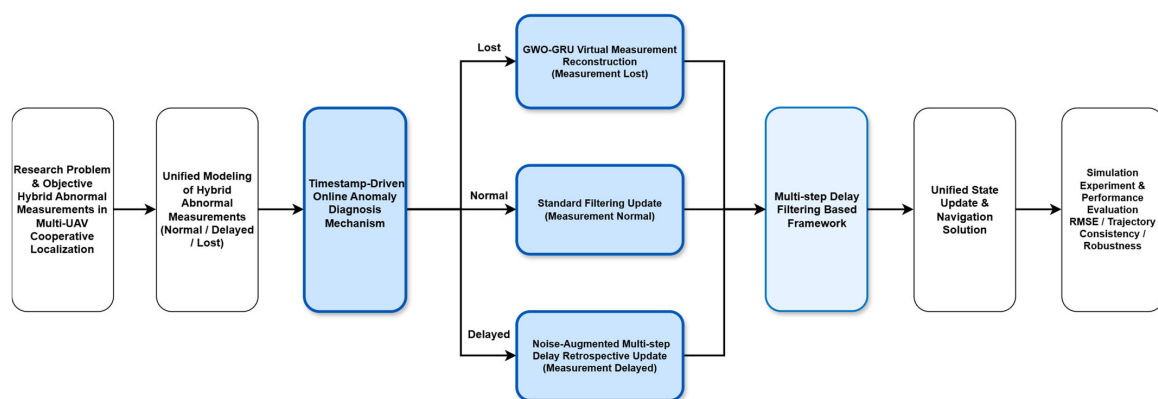


Figure 2. Adaptive cooperative localization Framework.

2. Modeling and Diagnosis of Abnormal Measurements

In practical multi-UAV cooperative mission scenarios, extreme operating conditions such as strong electromagnetic interference, long-distance low-altitude operations, and complex terrain obstructions all pose severe challenges to inter-vehicle communication links. Constrained by the finite bandwidth of airborne communication modules and channel multipath effects, physical-layer channel degradation mainly manifests as two typical transmission anomalies at the data link layer: random packet loss and random transmission delay. Specifically, random packet loss refers to the failure of measurement data to be completely transmitted to the filtering center at certain time steps, which is typically caused by either a sharp drop in the channel signal-to-noise ratio (SNR) leading to cyclic redundancy check (CRC) failures, or network congestion resulting in receiver buffer overflow, ultimately leaving the filter completely devoid of an observation update source at the corresponding moments. Random transmission delay arises from unpredictable time-varying latency introduced when data packets are transmitted through multi-hop ad hoc networks or when the underlying retransmission mechanism is triggered; when network load fluctuates, the delay may exceed one or even multiple sampling periods, causing the measurement sequence to arrive out of order (OOSM), meaning the data received at the current moment actually reflects the system state at a historical time.

Unlike ideal communication environments, the weak communication environment investigated in this paper exhibits a hybrid characteristic of “coexisting packet loss and delay”, with the channel state randomly switching among “normal transmission”, “multi-step delay” and “complete interruption”. This random switching feature severely violates the fundamental temporal consistency assumption that standard filtering algorithms rely on.

2.1. Hybrid Abnormal Measurement Modeling

To mathematically describe the aforementioned physical process, this paper first establishes a standard state-space model based on the sequential Kalman filter, and subsequently introduces Bernoulli variables to provide a unified description of the hybrid anomalies.

2.1.1. The System Dynamics Are Described by the Standard State-Space Model

The attitude error φ , the velocity error δv , the position error δp , the gyroscope bias ε_g and accelerometer bias ∇_a of the inertial solution, and the UWB range/elevation/azimuth residual biases b_r , b_{el} , and b_{az} are selected to construct the state vector $X_k = [\varphi^T, \delta v^T, \delta p^T, \varepsilon_g^T, \nabla_a^T, b_r, b_{el}, b_{az}]^T$, and the system state equation and ideal measurement equation are expressed as follows:

$$\begin{cases} X_k = \Phi_{k|k-1} X_{k-1} + W_{k-1} \\ Z_k = H_k X_k + V_k \end{cases} \quad (1)$$

Among them, $\Phi_{k|k-1}$ is the state transition matrix and W_{k-1} is the process noise. Z_k is the ideal observation residual generated at time k and V_k is the measurement noise.

2.1.2. Hybrid Anomaly Observation Model

Considering communication anomalies, the actual measurement y_k received by the fusion center at time k has high uncertainty: it may originate from the current time or from any time within the past N moments, or it may be empty due to loss.

Assume the maximum allowed delay steps is N ($N > 1$); introduce a set of indicator variables to construct a unified observation model:

$$y_k = \sum_{i=0}^N \gamma_{k,i} Z_{k-i}, k \geq N+1 \quad (2)$$

where Z_{k-i} denotes the true measurement generated at time $k-i$, as shown in Equation (2). $\gamma_{k,i} \in \{0, 1\}$ is a Bernoulli random variable, following the distribution characteristics below:

$$P(\gamma_{k,i} = 1) = p_{k,i}, \sum_{i=0}^N p_{k,i} \leq 1 \quad (3)$$

Under this model, the three channel states are precisely defined as follows:

- (1) Normal Measurement (Normal): When $\gamma_{k,0} = 1$, real-time data Z_k is received.
- (2) Measurement Delay (Delayed): When $\gamma_{k,i} = 1$ and $i > 0$, historical data is delayed by i steps, and Z_{k-i} is received.
- (3) Measurement Loss (Lost): When $\sum_{i=0}^N \gamma_{k,i} = 0$, it indicates that no valid data has been received at the current time ($y_k = \emptyset$).

This model transforms the communication interference at the physical layer into a mathematical probability distribution problem, clarifies the input uncertainty faced by the filter, and provides a theoretical foundation for subsequent design.

2.2. Adaptive Scheduling Mechanism Based on Online Diagnosis

The temporal state of the measurement data directly determines the choice of the subsequent filtering strategy. This paper designs a real-time diagnosis mechanism based on the comparison between the generation timestamp t_g and the system's current time t_k . This mechanism aims to filter out invalid data (measurement loss, temporal logic errors, outdated data) and quantify the delay steps d_k of valid data.

Let the system filtering period be T , and the current time be $t_k = k \cdot T$. For any arriving data packet $P_k = Z_k, t_g$ the diagnosis logic includes two stages:

- (1) Physical layer detection

If the receiving buffer is empty at time t_k , the system directly determines that the measurement is lost and uses the prediction module.

- (2) Logic layer verification

If a data packet is received, the transmission delay $\Delta t_k = t_k - t_g$ is first calculated. Transmission delay computation and tolerance are determined as follows:

$$\Delta t_k - \Delta t_g, \quad t_k = kT, \quad \tau = \frac{T}{2}, \quad N_{\max} = 4 \quad (4)$$

The diagnosis then reads as follows:

$$S_k = \begin{cases} \text{NORMAL}, & d_k = 0 \\ \text{DELAYED}, & d_k = \text{round}\left(\frac{\Delta t_k}{T}\right) \\ \text{Lost}, & \end{cases} \quad \begin{cases} |\Delta t_k| \leq \tau, \\ \tau < \Delta t_k < \left(N_{\max} + \frac{1}{2}\right)T, \\ \text{otherwise} \end{cases} \quad (5)$$

The tolerance $\tau = \frac{T}{2}$ absorbs only timestamp jitter; the delay step is quantized by the sampling period T , so a packet delayed by exactly one period yields $d_k = 1$, consistent with the experimental definition. Packets with $\Delta t_k < -\tau$ are logically future data and fall into the Lost branch, and any computed $d_k > N_{\max}$ is likewise reclassified as Lost; the upper limit $\left(N_{\max} + \frac{1}{2}\right)T$ corresponds exactly to the boundary above which the quantized delay exceeds $N_{\max}$, so the three branches are mutually exclusive and exhaustive. The classification rules of the timestamp-based diagnosis are illustrated through numerical examples in Table 1.

Table 1. Numerical example of the diagnosis.

Δt_k (s)	Classification	Reason/ d_k
−0.15	LOST	Future data ($\Delta t_k < -\tau$)
−0.05	NORMAL	$ \Delta t_k \leq \tau$
+0.09	NORMAL	inside the jitter tolerance
+0.15	DELAYED	$d_k = \text{round}(0.75) = 1$
+0.20	DELAYED	$d_k = 1$ (one sampling period)
+0.50	DELAYED	$d_k = 3$
+0.85	DELAYED	$d_k = 4$ (maximum 0.8 s lag)
+0.90	LOST	$d_k = 5 > N_{\max}$

The processes of timestamp acquisition and synchronization are as follows. The generation timestamp t_g is appended by the anchor at the UWB module and the current time t_k is taken from the fusion-center clock at reception. In the simulation, all nodes share one ideal clock. In a practical deployment, the anchor and the fusion center are time-disciplined by GNSS one-pulse-per-second signals, and follower links are corrected to the anchor clock by the same mechanism, so the residual error between t_g and t_k is dominated by inter-node clock drift and protocol jitter rather than by absolute offsets. The tolerance $\tau = T/2$ is precisely the budget allocated to this residual error: as long as the cumulative synchronization error stays below τ , the diagnosis absorbs it without misclassification. Section 4.3.2, by superposing systematic clock biases of 0.05–0.15 s on the timestamps, quantifies how the performance degrades once this budget is exceeded.

3. Adaptive Cooperative Localization Method Based on Anomaly Diagnosis

Addressing the aforementioned abnormal measurements, this paper proposes an adaptive processing architecture with multi-step augmented filtering as its core benchmark. The design of this architecture follows the “delay tolerance” principle: considering the prevalent lag in data transmission under weak communication environments, the system default incorporates all arriving measurement data into a multi-step augmented filtering model for unified spatiotemporal alignment and updating. On this basis, a timestamp-based anomaly diagnosis module is introduced as a pre-decision unit: only when the diagnosis determines a complete measurement loss does the designed GWO-GRU neural network module generate virtual measurements for compensation. This design organically integrates single prediction compensation with delay processing, forming a closed-loop solution that covers the full spectrum of anomaly modes—“normal, delayed, and lost”.

To further elaborate the sequential execution steps, spatiotemporal alignment logic, timestamp-based anomaly diagnosis decision-making process, and seamless switching mechanism between multi-step augmented filtering and GWO-GRU virtual measurement compensation of the proposed architecture in an intuitive and structured manner, the complete operational flowchart of the full framework—which covers the entire processing chain from raw measurement data reception to final filter state update under all three anomaly modes (normal, delayed, and lost)—is shown in Figure 3.

3.1. Adaptive Compensation and Unified Filtering Strategy

Based on the anomaly diagnosis result S_k determined in Section 2.2, this section proposes a cooperative localization framework with adaptive data source switching. This framework improves upon the separate processing paradigm in traditional methods, which uses independent filter structures for packet loss and delay, by establishing a multi-step augmented filter as the sole underlying state estimator.

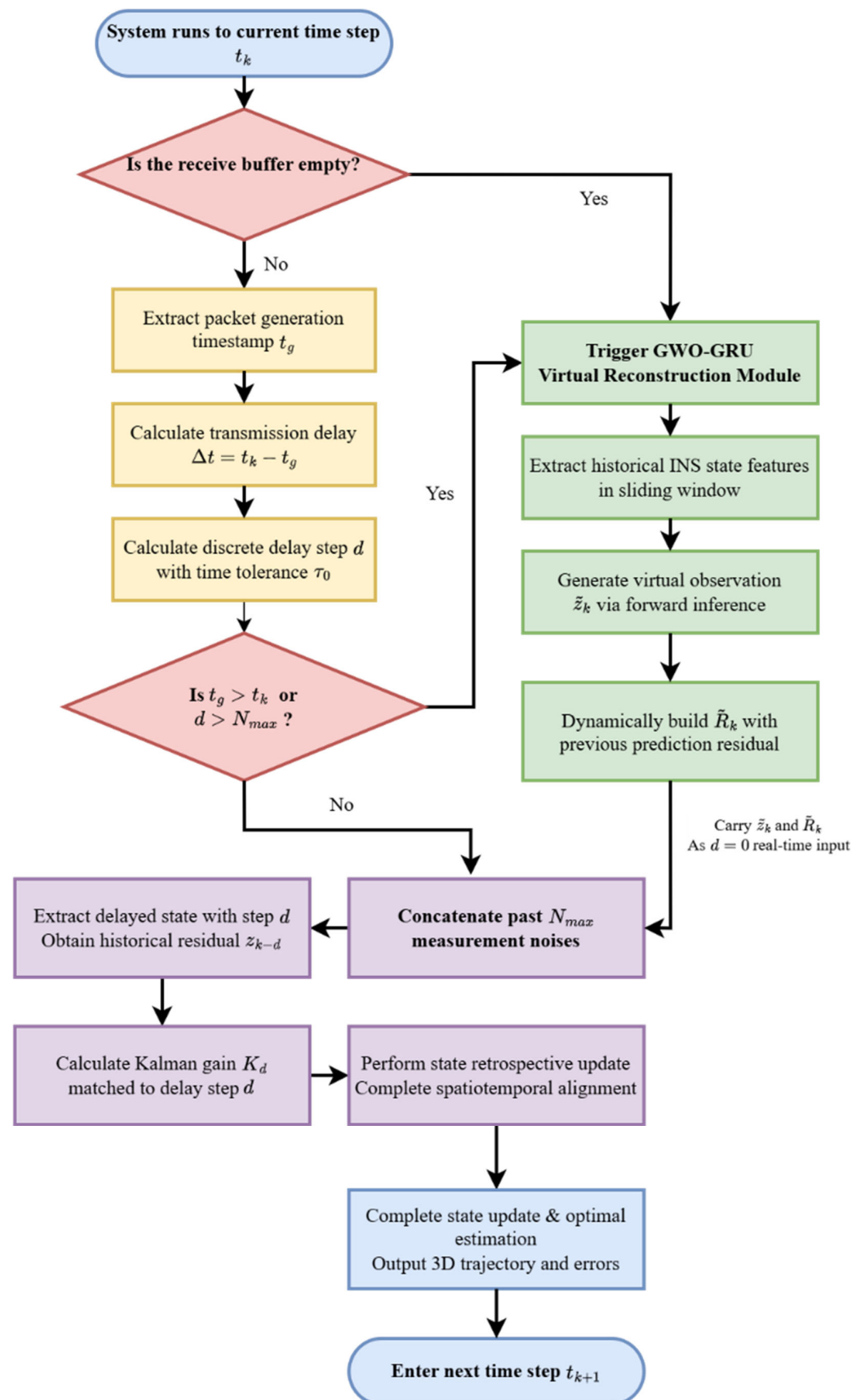


Figure 3. Flowchart of adaptive cooperative localization based on online diagnosis.

Through the scheduling of the anomaly diagnosis module, the system adaptively constructs the filter's input vector $Z_{in,k}$ and delay parameter $d_{in,k}$, thereby unifying hybrid anomaly processing into a standard filtering iteration process.

3.2. GWO-GRU Virtual Reconstruction Under Measurement Loss

When the anomaly diagnosis result is $\gamma_k = 0$, it indicates that the measurement is completely lost at the current time. To suppress the divergence caused by the filter lacking observation updates for a long time, the system adopts a GWO-GRU prediction module. This module utilizes the historical inertial state sequence (position, velocity, and attitude) within the sliding window to construct the input vector. By mining the temporal features of the carrier's motion, it maps to the virtual measurement $\tilde{Z}_k$ at the current time. The GWO-GRU module is introduced primarily to reconstruct missing measurements and reduce peak errors during prolonged communication loss; it is not intended to improve the full-trajectory accuracy under normal and delayed-measurement conditions, where the timestamp diagnosis and the multi-step delayed update dominate.

3.2.1. Construction of the GRU Prediction Model

Compared with LSTM, the Gated Recurrent Unit (GRU) reduces parameter redundancy and lowers computational complexity by simplifying the gate control structure, making it more suitable for cooperative positioning scenarios with high real-time requirements. GRU introduces an update gate z_t and a reset gate r_t to control the information flow, and the specific calculation process is as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (6)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (7)$$

Among them, x_t is the input at the current moment, h_{t-1} is the hidden state at the previous moment, σ is the Sigmoid activation function, W_z, W_r are weight matrices, and b_z, b_r are bias vectors. Based on this, the hidden state h_t at the current moment is updated as follows:

$$\tilde{h}_t = \tanh(W_h \cdot [r_t \odot h_{t-1}, x_t] + b_h) \quad (8)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (9)$$

In the formula, $\tilde{h}_t$ is the candidate hidden state, and $\odot$ denotes the Hadamard product. The reset gate r_t determines the extent to which historical information is forgotten, while the update gate z_t controls the proportion of the previous state information carried into the current state, thereby achieving effective capture of nonlinear motion characteristics.

3.2.2. GWO-Based Hyperparameter Optimization

The hyperparameters of traditional GRU networks are usually fixed based on empirical values or determined through simple grid search, which struggles to adapt to the dynamic characteristics of drones under complex maneuvers, making it prone to falling into local optima or causing overfitting. To address this, this study introduces the Gray Wolf Optimizer (GWO) to adaptively optimize the network structure.

The GWO simulates the social hierarchy (α, β, δ wolves) and hunting behavior of gray wolf populations. The algorithm maps the key hyperparameters of the GRU to the position vectors of the gray wolves. The optimization targets include the learning rate (LR, the number of hidden neurons in two layers (L1, L2), and the batch size (Batch). The optimization process uses the root mean square error (RMSE) of the prediction results as the fitness function.

In the iterative process, gray wolf individuals update their own positions according to the locations of the top three alpha wolves in the social hierarchy. Its mathematical description is as follows:

$$D = |C \cdot X_p(t) - X(t)| \quad (10)$$

$$X(t+1) = X_p(t) - A \cdot D \quad (11)$$

Among them, X_p is the prey (optimal solution) position, $X(t)$ is the current gray wolf position, and A and C are the coordination coefficient vectors. By controlling the convergence factor of A to decrease linearly from 2 to 0, GWO can perform global exploration in the early stages of iteration and local exploitation in the later stages, thereby achieving a dynamic balance in the solution space and finding the optimal network configuration.

Through the above mechanism, the GWO-GRU module can automatically search for the best hyperparameter configuration found within the prescribed search budget during the offline training phase. In the online operation phase, when a measurement loss occurs, the network uses the optimal parameters to generate a high-precision virtual measurement $\tilde{Z}_k$ in real time, thereby ensuring the continuity and robustness of the cooperative localization system.

The GWO search optimizes five hyperparameters—the learning rate (bounded 0.001–0.1), hidden units of the two GRU layers (3–200 each), number of training epochs (1–200), and mini-batch size (8–256)—using a lightweight population of 5 wolves over 3 iterations (15 candidate trainings). Training uses the Adam optimizer (gradient threshold 1, full-data shuffle per epoch, validation every 20 iterations) with random seed 20260105. The best configuration found is a learning rate of 0.01905, two GRU layers with 35 and 64 hidden units, 60 training epochs, and a mini-batch of 54, yielding a 26,202-parameter network.

3.2.3. Adaptive Adjustment of Virtual Measurement Noise Covariance

When introducing the virtual measurement $\tilde{Z}_k$, since its essence is an a priori prediction based on historical state sequences, its error characteristics are completely different from the physical measurement noise of real sensors (such as UWB or GNSS). If the original sensor's constant measurement noise covariance matrix R is directly used, it will lead to incorrect Kalman gain calculation, thereby destroying the rigor of the filtering.

To address this, this paper designs a covariance inflation strategy based on prediction uncertainty. When a measurement loss occurs, the system will adaptively construct the virtual measurement noise covariance matrix $\hat{R}_k$.

$$\hat{R}_k = R + \alpha \cdot \text{diag}(e_k \cdot e_k^T) \quad (12)$$

where R is the sensor nominal noise covariance, α is the penalty coefficient, and e_k is the one-step prediction residual (innovation) of the virtual measurement defined with respect to the filter's own one-step state prediction.

$$e_k = \tilde{z}_k - H_k \hat{x}_{k|k-1} \quad (13)$$

Because e_k is formed from the filter prediction rather than from a physical observation, it remains computable at every loss epoch, including throughout arbitrarily long communication blackouts. At the first loss epoch, the stored previous residual is zero ($\hat{R}_k = R$); as the outage continues, the covariance grows with the accumulated prediction error, progressively reducing the weight of the virtual measurements in the update and shifting the estimate toward the kinematic-model prediction whenever the network becomes unreliable.

3.3. Augmented State Filtering Under Measurement Delay

When $S_k = \text{DELAYED}$, $1 \leq d_k \leq N_{\max}$, it indicates that the received measurement Z_{k-d_k} is valid but delayed by d_k steps. At this time, direct filtering will cause estimation bias due to the correlation between process noise and measurement noise; therefore, this paper adopts a multi-step augmented filtering algorithm based on noise augmentation.

In the delay-order-weighted (mixture) form, the update weights several candidate delay orders instead of a single diagnosed one. Let $w_{k,i}$ denote the weight assigned to candidate delay order i at epoch k , with $\sum_i w_{k,i} = 1$. The fused delayed-measurement prediction, its innovation covariance, and the state–measurement cross-covariance are formed as weighted sums over the candidate orders, and the Kalman gain is computed from these weighted quantities. The weight vector is supplied by the online diagnosis of Section 2.2: in the timestamp-diagnosed configuration, the weight is concentrated on the diagnosed order ($w_{k,d_k} = 1$, a single diagnosed delay order), which is the form described below; in the statistical-mixture configuration, the weights equal the channel delay distribution ($w_{k,i} = p(i)$), which keeps the update stable when the timestamps are unreliable, e.g., under synchronization bias, or when the delay exceeds the designed horizon. The two configurations are therefore two weight settings of the same estimator and the same equations, not two different filters.

3.3.1. State Vector Augmentation

To explicitly describe the historical noise term V_{k-d_k} contained in the delayed measurement Z_{k-d_k} , we construct an augmented state vector X_k^a . This vector not only includes the current system state X_k but also concatenates the measurement noise sequences from the past $N_{\max}$ time instants:

$$X_k^a = \left[X_k^T, V_k^T, V_{k-1}^T, \dots, V_{k-N_{\max}+1}^T \right]^T \quad (14)$$

Under this definition, the system state equation is extended to an augmented form, and the augmented state transition matrix $\psi_{k/k-1}$ exhibits a sparse block-diagonal structure. The key lies in the maintenance of the augmented covariance matrix P_k^a , which dynamically records the cross-covariance between the current state error and historical measurement noise, expressed as $E[\tilde{X}_k \tilde{V}_{k-i}^T]$. This is the core of achieving precise retrospective updates.

3.3.2. Delayed-Measurement Update

Using the precise delay steps d_k calculated by the diagnostic module, the filter first extracts the corresponding delayed-measurement prediction $Y_{k|k-1}$ from the augmented state via the selection matrix H_{k,d_k}^a :

$$Y_{k|k-1} = H_{k-d_k} X_{k-d_k|k-1} + V_{k-d_k|k-1} \quad (15)$$

Subsequently, the Kalman gain K_k^a corresponding to this delay step is calculated, and the state update is performed:

$$\begin{cases} K_k^a = P_{XY}^{k|k-1} (P_{YY}^{k|k-1})^{-1} \\ X_{k|k}^a = X_{k|k-1}^a + K_k^a (y_k - Y_{k|k-1}) \end{cases} \quad (16)$$

Through the coupling relationship of augmented dimensions, this algorithm essentially realizes the “delayed” utilization of information from the historical time instant $k - d_k$ at the current time k , while theoretically maintaining the minimum mean square error criterion. At this point, the system input is set as $Z_{in,k} = y_k$ and $d_{in,k} = d_k$.

4. Experiments

4.1. Experimental Platform and Simulation Settings

The UAV platform shown in Figure 4 was used to collect the flight data for this study. It consists of DJI Matrice 350 RTK vehicles (SZ DJI Technology Co., Ltd., Shenzhen, China), a ground control station, and communication modules. Real flight data (trajectories, IMU

measurements, and UWB cooperative measurements) were recorded with this platform in an outdoor environment and were used to construct the simulation scenarios and train the GWO-GRU network. The communication anomalies (random delays, packet losses, and the 80–90 s blackout) were then injected in the simulation, and all filtering and localization evaluations were performed offline. No hardware-in-the-loop experiment and no onboard real-time flight validation of the proposed algorithm was conducted in this study.



Figure 4. (a) Physical diagram of the UAV platform and supporting equipment; (b) on-site outdoor field test environment. Flight data were collected with this platform and used to build the simulation scenarios; the algorithm evaluation was performed offline in the simulation.

A multi-UAV cooperative simulation environment was constructed on the basis of the flight data collected with the platform to reproduce random communication delays and complete link interruptions under identical maneuvering and sensor conditions. This controlled setting allows the baseline and adaptive methods to be compared using the same flight trajectories, sensor noise realizations, and abnormal-measurement sequence.

The simulation scenario is defined as a heterogeneous cooperative multi-UAV system consisting of one GNSS-equipped anchor node (UAV 1) and three GNSS-denied follower nodes (UAVs 2–4). Figure 5 presents the actual initial positions in the local ENU frame referenced to UAV 1. The followers form a triangular horizontal geometry 60 m below the anchor, and each follower receives UWB range and angle observations from UAV 1.

- (1) **Node Configuration:** The anchor node is equipped with a high-precision GNSS receiver, serving as the global spatiotemporal reference of the system. The target nodes to be localized operate in a GNSS-denied environment, relying only on the onboard IMU and UWB ranging/angle measurement modules for dead reckoning and cooperative correction.
- (2) **Trajectory Planning:** To fully excite the nonlinear dynamic characteristics of the system, a high-dynamic flight mission with a total duration of 243 s is designed. The anchor node (UAV 1) executes an independent maneuvering trajectory including rapid acceleration, constant-speed cruise, standard turns, and large-amplitude pitch climbing/descending. The target nodes (UAVs 2–4) maintain their respective cooperative maneuvering trajectories.

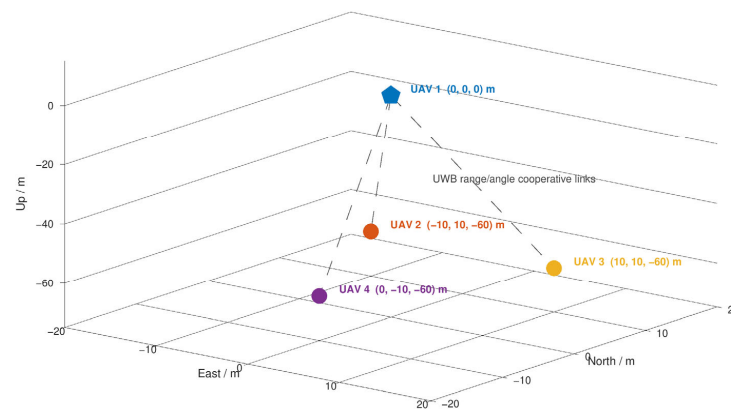


Figure 5. Initial ENU positions and cooperative formation of the UAVs.

To reproduce the link characteristics in real communication-constrained environments, a hybrid abnormal channel model was also constructed, which included “persistent random delay” and “sudden complete interruption”:

- (1) The channel parameters were chosen to represent a congested but functional multi-hop UAV link. Because packets traverse several hops and the link layer retries transmissions at the access period, the delay arrives as an integer number of 0.2 s measurement epochs.

The distribution $p = [0.2 \ 0.3 \ 0.2 \ 0.2 \ 0.1]$ has an expected delay of 1.9 epochs (0.38 s); 80% of the packets are delayed by at least one epoch, 30% are delayed by two or more, and 10% reach the maximum of $N_{\max} = 4$ epochs (0.8 s). The 10 s blackout placed on the most dynamic maneuver phase (80–90 s) models a complete link failure. Delay step i follows the non-uniform distribution $p_i, i = 0, \dots, 4$.

$$p = [p_0 \ p_1 \ p_2 \ p_3 \ p_4] \quad (17)$$

- (2) Bursty Communication Interruption: To test the robustness of the algorithm under extreme conditions, a 10 s communication blackout zone was set during the high-maneuver phase of the flight mission (80–90 s). During this period, the cooperative links were completely disconnected, the target nodes to be localized could not obtain any external observation information, and the system entered a pure prediction and dead reckoning mode.

In the simulation, the INS propagation interval was 0.01 s and cooperative measurements were updated at 5 Hz. UWB range and angle standard deviations were set to 5.0 m and 0.5 degrees, respectively, while the anchor GNSS position standard deviation was 5.0 m. The principal sensor parameters are summarized in Table 2.

Table 2. Specification of onboard sensors.

Sensor Type	Parameter Indicator	Parameter Value
IMU (Target Node)	Sampling Rate	100 Hz
	Gyroscope Bias Instability	$0.2^\circ/\text{h} \sim 0.4^\circ/\text{h}$
	Gyroscope Random Walk	$0.08^\circ/\sqrt{h}$
	Accelerometer Bias	800~1000 μg
UWB Module (Cooperative Link)	Data Update Rate	5 Hz
	Ranging Error (1σ)	5.0 m
	Angular Error (1σ)	0.5°
GNSS (Anchor Node Only)	Data Update Rate	5 Hz
	Positioning Accuracy	5.0 m

4.1.1. Cooperative Measurement Model

With regards to the cooperative measurement model, the anchor broadcasts its GNSS position; each follower forms the anchor-to-follower vector $\Delta r = r_a - r_f$ in LLA coordinates and maps it to the local ENU frame with the meridian/prime-vertical curvature map $M(r_f)$ in the follower body frame $\rho_b = C_{bn}^T M(r_f) \Delta r$. The nonlinear UWB measurement equations are

$$d = \|\rho_b\|, \quad el = \arcsin(\rho_{b,3}/d), \quad az = a \tan 2(\rho_{b,1}, \rho_{b,2}) \quad (18)$$

with independent Gaussian noises $\sigma_d = 5.0$ m and $\sigma_{el} = \sigma_{az} = 0.5^\circ$. The noise propagates into the body frame through the analytic Jacobian,

$$J = \begin{bmatrix} \cos el \sin az & -d \sin el \sin az & d \cos el \cos az \\ \cos el \cos az & -d \sin el \cos az & -d \cos el \sin az \\ \sin el & d \cos el & 0 \end{bmatrix} \quad (19)$$

giving

$$R_{body} = J \text{diag}(\sigma_d^2, \sigma_{el}^2, \sigma_{az}^2) J^T \quad (20)$$

The filter innovates in Cartesian relative-position coordinates and linearizes about the one-step predicted follower position, with $r_k = \Delta \hat{r} - \Delta r_{meas}$ and

$$H_k = \begin{bmatrix} [-\text{skew}(\Delta r_{meas})], & 0, & -M(\hat{r}), & 0, & 0, & (\text{UWB-bias block}) \end{bmatrix} \quad (21)$$

The covariance combines the anchor GNSS uncertainty ($\sigma_G = 5.0$ m) and the rotated body-frame term

$$R_k = \sigma_G^2 I + C_{bn} R_{body} C_{bn}^T \quad (22)$$

plus a small regularization floor. The azimuth from atan2 already lies in its principal range $(-\pi, \pi]$ and in the elevation from the asin in $[-\pi/2, \pi/2]$; because the innovation is formed in Cartesian coordinates, the update accounts for the local tangent geometry and no separate angular wrapping step is required in the tested envelope.

Two comparative schemes are evaluated in the experiment:

1. Baseline method: Standard Kalman filter. This method does not include an explicit abnormal measurement processing module. Delayed measurements are treated as current measurements, and missing measurements are handled by skipping the measurement update and retaining only the time update. It therefore provides a conventional reference for evaluating the benefit of the proposed diagnosis and compensation strategy.
2. Adaptive method: The proposed unified method applies GWO-GRU virtual measurement reconstruction during complete loss and timestamp-diagnosed multi-step augmented filtering for received delayed measurements.

The experiment adopts the position Root Mean Square Error (RMSE) as the core evaluation metric to quantify the positioning accuracy over a long time scale:

$$\text{RMSE} = \sqrt{\frac{1}{M} \sum_{k=1}^M \|\hat{p}_k - p_k^{\text{true}}\|^2} \quad (23)$$

Here, the estimated and true position vectors at sample k are used, and M denotes the number of sampled time instants in the complete simulation run.

4.1.2. Training Protocol and Dataset Partition

The network is trained on sliding windows comprising 50 time steps (equivalent to 10 s of data at a 5 Hz update rate), with a 26-dimensional feature vector at each step. The features include timestamp–angle pairs, the position/velocity/attitude states of both the anchor and follower UAVs, and relative geometric quantities expressed in both the ENU frame and the body frame. The network outputs one-step-ahead predictions of the range, elevation, and azimuth measurement triple. A total of 3498 sliding windows are generated from the flight data of the three follower UAVs, forming the complete dataset.

Three distinct data partitioning schemes are employed for different purposes:

- (1) Deployment training: The deployed network was trained on the 3498 windows with the 82/18 train/validation split of the original protocol, and GWO hyperparameter selection used the validation partition only. To additionally rule out temporal leakage, a stricter time-block partition—windows ending at or before 180 s for training (2553 windows) and the remaining 945 windows for validation—was applied to the fixed-hyperparameter GRU baseline, so that for that model, no validation window overlapped any training window in time. The leave-one-UAV-out generalization test below provides a strictly independent check on a completely unseen follower.
- (2) GWO hyperparameter tuning: Hyperparameter optimization via the GWO algorithm is performed exclusively using validation-set performance, which acts as both the model selection metric and the early stopping criterion.
- (3) Leave-one-UAV-out generalization test: The identical network architecture is trained solely on data from UAVs 2 and 3, and evaluated on the completely unseen UAV 4. This yields test RMSE values of 12.65 m for range, 0.109° for elevation, and 1.71° for azimuth.

The training windows and the localization evaluation are derived from the same nominal flight trajectories of the three followers; they are not independent simulation realizations. The communication anomalies (random delays, packet losses, and the 80–90 s blackout) are imposed only in the filtering evaluation and never appear in the network's training or tuning data, the inputs of which are kinematic states and the targets of which are the true range/elevation/azimuth geometry. The 80–90 s blackout is therefore an evaluation-time channel condition rather than a training scenario.

The following is a discussion on the leave-one-UAV-out error. The leave-one-UAV-out range RMSE of 12.65 m is larger than the nominal UWB ranging error (5.0 m, 1σ) used in the simulations, which is expected for the hardest generalization protocol considered here. Three factors contribute: (i) the predictor must extrapolate the anchor–follower relative geometry of a completely unseen UAV whose maneuver profile and formation position differ from those of the two training followers; (ii) the one-step-ahead range/elevation/azimuth prediction is formed over a 50-step (10 s) history window, so any motion-model mismatch accumulates along the window; and (iii) the range channel is the most sensitive output because it depends on the full three-dimensional relative geometry. This raw prediction error does not, however, translate directly into the final localization error. First, virtual measurements are injected only during loss epochs, i.e., exactly when no physical measurement is available; under normal and delayed-measurement conditions, the filter relies on the physical channel. Second, the adaptive covariance inflation of Section 3.2.3 progressively down-weights virtual measurements, the prediction residual of which grows, shifting the estimate toward the kinematic model whenever the reconstruction becomes unreliable. The localization-level results in Tables 3–6 and Section 4.4 (the mean horizontal RMSE of the proposed method around 0.6 m) therefore reflect the end-to-end performance of the framework rather than the raw prediction accuracy of the network alone; the leave-one-UAV-out figure should be interpreted as a worst-case generalization bound of the reconstruction module, not as the operating error of the complete framework.

Table 3. Position root mean square error for UAV 2.

Method	East RMSE (m)	North RMSE (m)	Vertical RMSE (m)
Baseline	2.113	2.372	1.078
Adaptive	0.560	0.492	0.620

Table 4. Position root mean square error for UAV 3.

Method	East RMSE (m)	North RMSE (m)	Vertical RMSE (m)
Baseline	2.244	2.637	1.538
Adaptive	0.562	0.672	0.986

Table 5. Position root mean square error for UAV 4.

Method	East RMSE (m)	North RMSE (m)	Vertical RMSE (m)
Baseline	1.772	2.061	1.790
Adaptive	0.769	0.591	0.748

4.2. Simulation Result Analysis

To comprehensively evaluate the proposed adaptive cooperative localization method under hybrid measurement anomalies, the simulation results are analyzed using position-error curves, overlaid 3D trajectory visualizations, and quantitative RMSE metrics.

Two approaches are compared in the experiments: the baseline method (standard Kalman filter) and the proposed adaptive method.

The northward errors are shown in Figures 6b, 7b and 8b. The adaptive method reduces the north RMSE from 2.372 m to 0.492 m for UAV 2, from 2.637 m to 0.672 m for UAV 3, and from 2.061 m to 0.591 m for UAV 4. The improvements are consistent across all follower nodes, indicating that timestamp diagnosis and delayed-measurement alignment effectively suppress the bias caused by persistent random communication latency.

The eastward errors are shown in Figures 6a, 7a and 8a. The adaptive method reduces the east RMSE by 73.5%, 75.0%, and 56.6% for UAVs 2, 3, and 4, respectively. Over all followers, the mean east RMSE decreases from 2.043 m to 0.630 m. These results demonstrate that timestamp-diagnosed multi-step augmented filtering effectively limits the bias caused by continuously delayed measurements.

The up-direction errors are shown in Figures 6c, 7c and 8c. The adaptive method also improves the vertical component for all three follower nodes, reducing the up RMSE from 1.078 m to 0.620 m for UAV 2, from 1.538 m to 0.986 m for UAV 3, and from 1.790 m to 0.748 m for UAV 4. The mean up RMSE decreases from 1.469 m to 0.785 m, which indicates that the virtual measurement reconstruction does not sacrifice vertical stability under the reproduced hybrid-anomaly scenario.

The overlaid 3D trajectory comparison is shown in Figure 9, where the true, baseline KF, and adaptive trajectories of all four UAVs are presented in a single coordinate system. The adaptive estimates remain continuous through the hybrid-anomaly scenario and track the true trajectories more closely than the baseline estimates do. The trajectory view is consistent with the quantitative RMSE improvements reported in Tables 2–4.

Table 6. Multi-method comparison under the nominal hybrid-anomaly channel.

Method	UAV2 E/N/U (m)	UAV3 E/N/U (m)	UAV4 E/N/U (m)	Mean Horiz (m)	Peak (m)	BO Mean/Peak (m)	Rec (s)	Wall (s)
Standard KF	2.113/2.372/1.078	2.244/2.637/1.538	1.772/2.061/1.790	2.200	6.124	2.834/3.711	114.2	6.1
Gated STF	3.876/4.048/1.257	2.305/2.022/1.865	2.051/1.464/1.598	2.628	12.263	6.366/11.609	16.8	6.0
OneDel-KF	0.554/0.393/0.767	0.668/0.671/1.112	0.685/0.569/0.855	0.590	2.663	0.753/1.801	64.4	6.1
Fixed-hyperparam. GRU-KF	2.460/2.567/1.142	2.541/2.565/1.595	2.029/2.360/1.643	2.421	6.919	2.688/4.062	117.2	6.1
Multi-step-delay filter only	0.586/0.389/0.597	0.591/0.814/0.964	0.694/0.594/0.740	0.611	2.615	0.926/2.414	114.4	7.0
Proposed	0.560/0.492/0.620	0.562/0.672/0.986	0.769/0.591/0.748	0.608	2.221	0.757/1.508	18.4	7.0

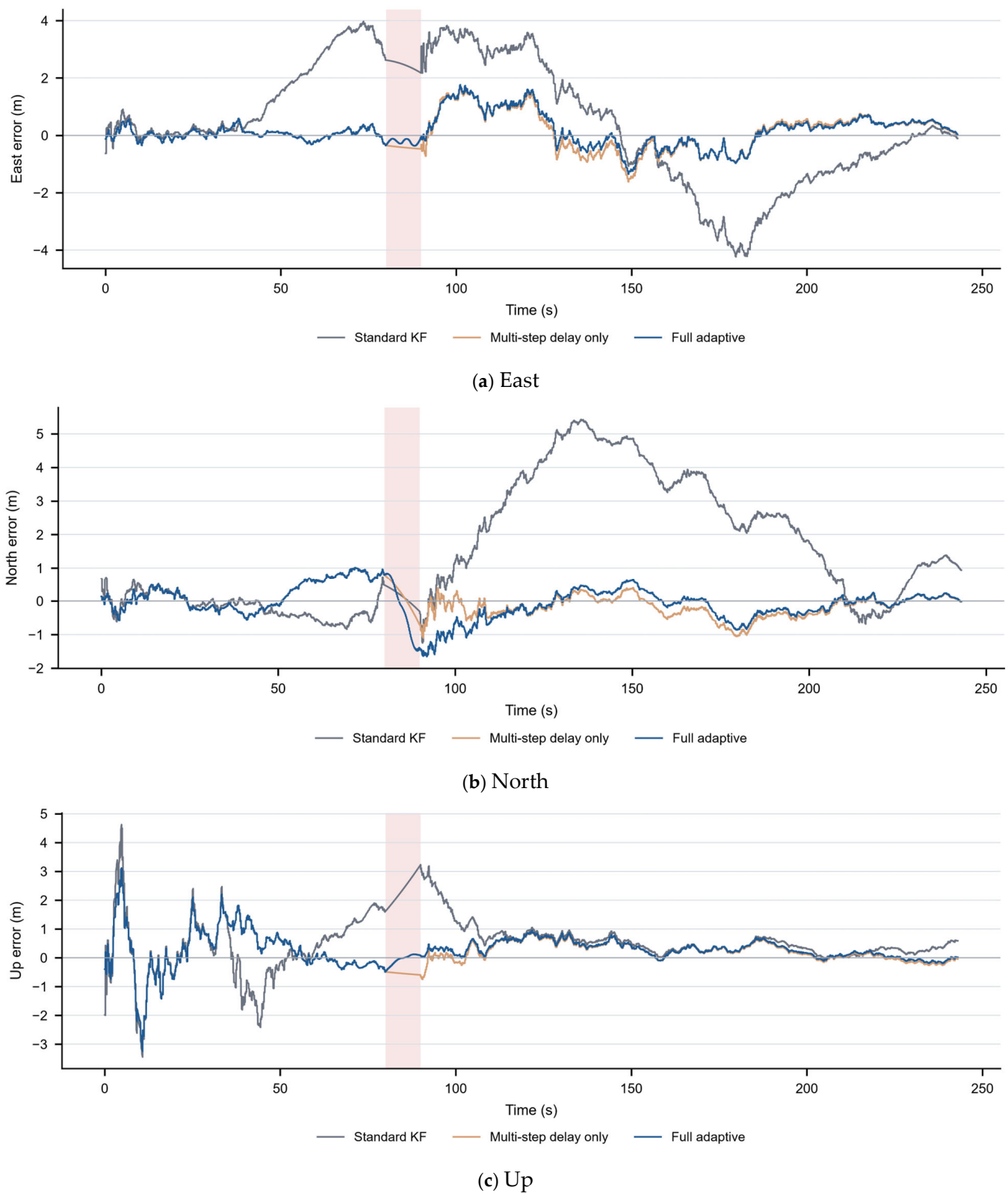


Figure 6. Position-error components for UAV 2: (a) east, (b) north, and (c) up. The pink-shaded vertical band marks the 80–90 s communication blackout window.

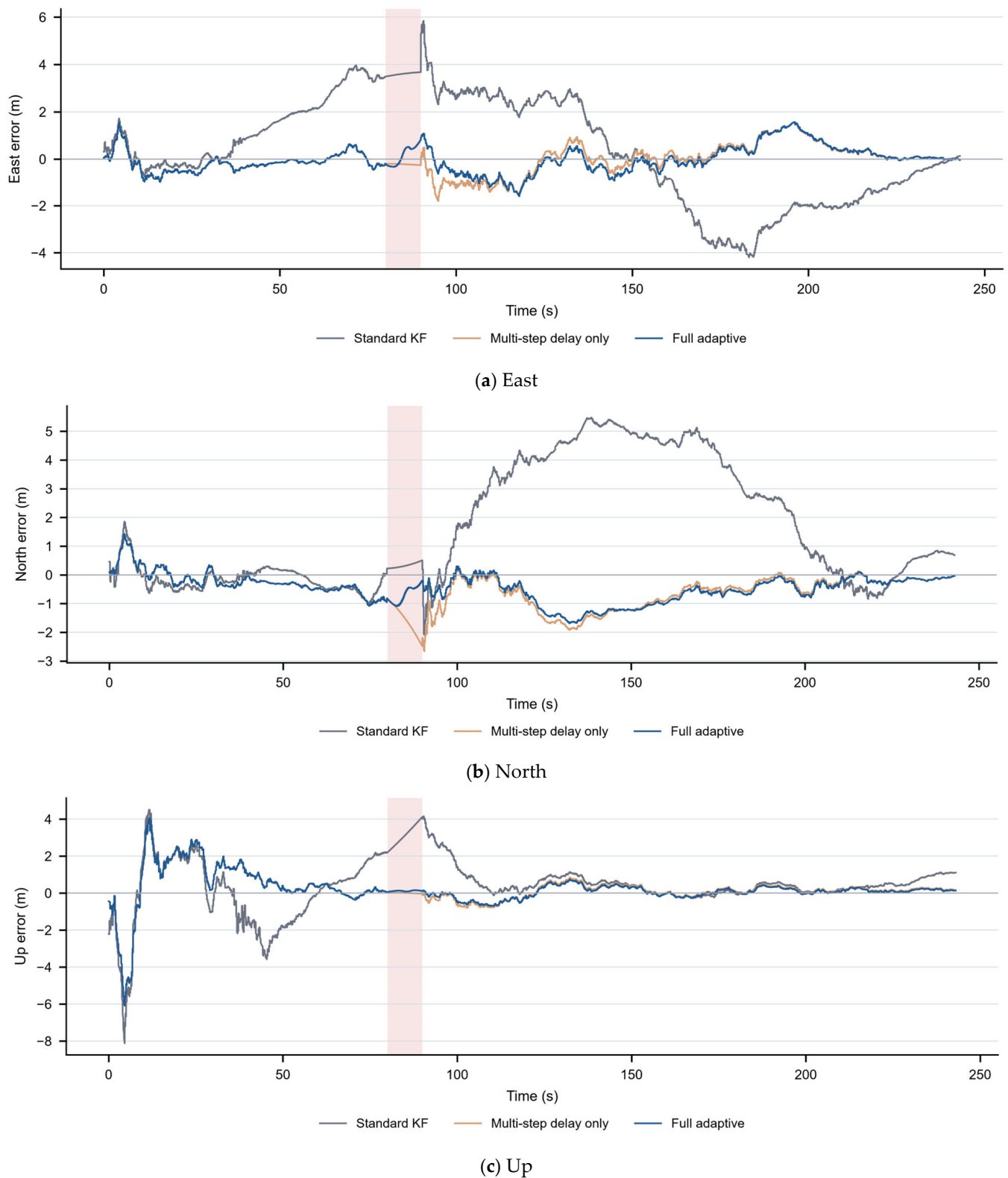


Figure 7. Position-error components for UAV 3: (a) east, (b) north, and (c) up. The pink-shaded vertical band marks the 80–90 s communication blackout window.

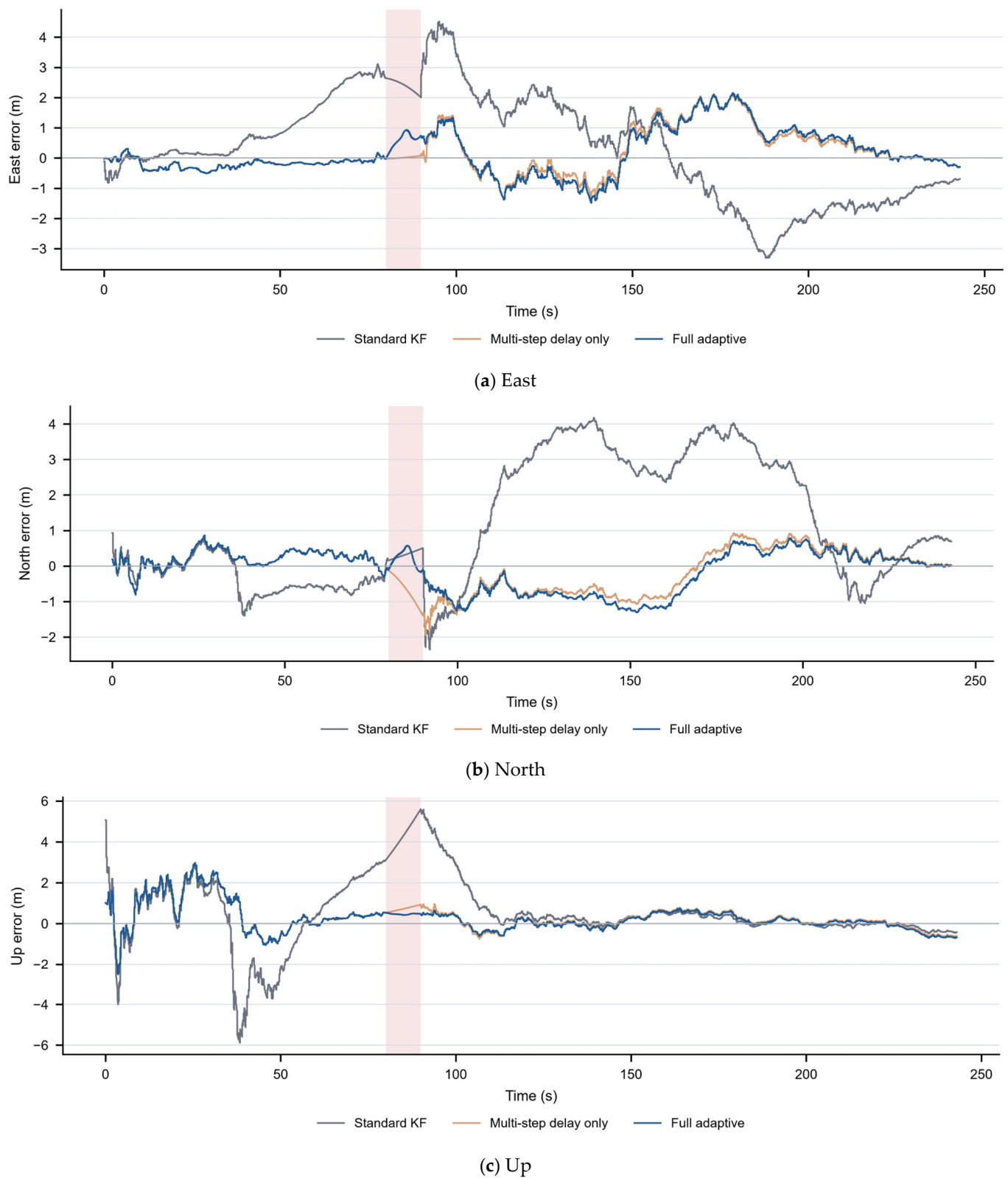


Figure 8. Position-error components for UAV 4: (a) east, (b) north, and (c) up. The pink-shaded vertical band marks the 80–90 s communication blackout window.

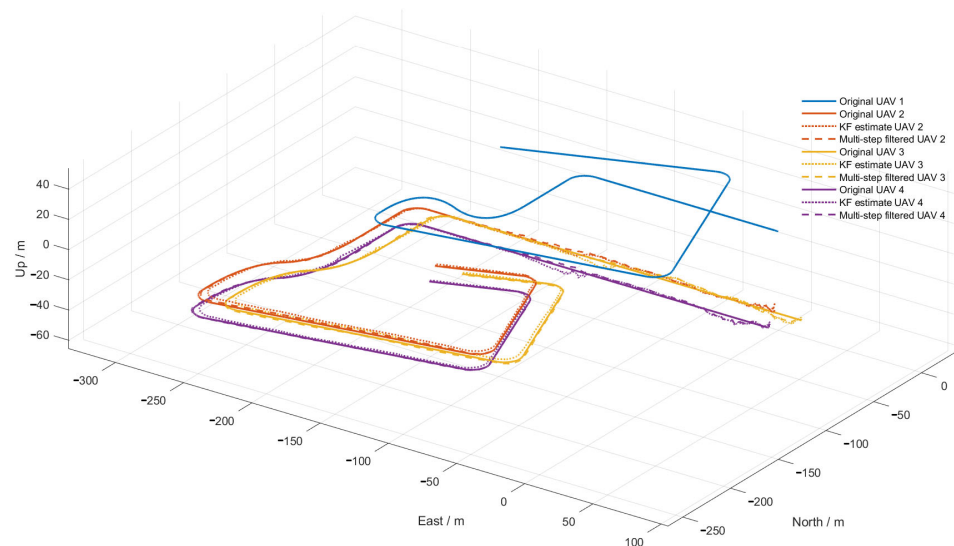


Figure 9. Overlaid true, baseline KF, and adaptive trajectories of all UAVs.

Tables 3–5 present the position-estimation RMSE values for the three GNSS-denied follower UAVs under the reproduced hybrid-anomaly scenario. East, north, and up components are reported separately to reveal the direction-dependent performance of each method.

According to Tables 3–5, the adaptive method reduces the mean east RMSE from 2.043 m to 0.630 m (69.1%) and the mean north RMSE from 2.357 m to 0.585 m (75.2%). Consequently, the mean horizontal-channel RMSE decreases from 2.200 m to 0.608 m, corresponding to an overall improvement of 72.4%. All six follower horizontal channels outperform the baseline KF.

Vertical accuracy also improves under the adaptive strategy. The up RMSE decreases for UAVs 2, 3, and 4, resulting in a mean reduction from 1.469 m to 0.785 m (46.6%). Because the cooperative formation is nearly coplanar, the vertical component remains a more demanding direction than the horizontal components; nevertheless, the proposed switching between delayed-measurement updating and GWO-GRU virtual measurement reconstruction does not introduce vertical instability in the tested scenario.

To further quantitatively evaluate the proposed method under hybrid channel anomalies, a comprehensive multi-index performance comparison with several classic and advanced filtering algorithms is conducted, including positioning accuracy, peak error, baseline offset error, and real-time performance. The detailed comparative results are presented in Table 6.

Collectively, the comparative results under the hybrid-anomaly channel corroborate that the proposed adaptive strategy achieves substantial improvements in both localization accuracy and robustness for multi-UAV cooperative systems subject to sustained random measurement delays and an abrupt 80–90 s communication blackout. The GWO-GRU virtual measurement module preserves uninterrupted filter state updates during complete measurement outages, whereas the timestamp-diagnosed multi-step augmented filtering scheme reinstates the temporal consistency of state estimation upon the arrival of delayed packets. Quantitatively, the proposed method yields a 72.4% reduction in mean horizontal-channel RMSE and a 46.6% reduction in mean up-direction RMSE relative to the standard Kalman filter under the controlled simulation setting, and exhibits the most favorable blackout-window peak error and post-outage recovery performance among the compared delay-aware methods, while its full-trajectory mean accuracy is comparable to that of the strongest delay-aware baseline (no statistically significant difference; Section 4.4). The deterministic ablation isolates the GWO-GRU module including its adaptive covariance inflation as a whole; the individual contributions of the GWO hyperparameter search and of the covariance inflation are not separately attributed, and the claims above are worded

at the module level. The role of the adaptive covariance inflation is further evidenced by the robustness and Monte Carlo analyses (Sections 4.3 and 4.4).

4.3. Robustness and Sensitivity Analysis

4.3.1. Scenario Matrix

Fifteen channel conditions were evaluated with the standard KF, the one-step delay-augmented baseline, and the proposal (the statistical-mixture configuration of the delay-order-weighted update of Section 3.3): the three delay distributions and the extended six-step channel; the added independent per-epoch loss rates of 10% and 25%; the burst losses of the 10%/25% average rate; a correlated (sticky) delay channel; blackout durations of 5/10/15/20 s placed at 80 s; the blackout relocated to 40–50 s and 140–150 s; and time-varying channel switching to the heavy distribution at 120 s. The proposal keeps the mean horizontal RMSE at 0.456–1.183 m across the fifteen conditions (standard KF 1.663–3.532 m), and its blackout-window peak stays at or below 2.6 m in every condition except the heavy-delay distribution (4.345 m), while the one-step baseline reaches 5.3 m at the 20 s blackout (2.1 m for the proposal). Two transparent findings are reported: (i) under the heavy-delay distribution, the one-step baseline remains a strong specialist on the full-trajectory mean (0.634 m vs. 1.183 m), because the proposal's mixture model spreads its probability mass across the delay orders and is therefore less sharp on that artificial distribution; (ii) the proposal is more accurate than the one-step baseline on the correlated-delay channel (0.456 m vs. 0.568 m) and on the moderate-loss, moderate-burst and blackout-relocation conditions, while it degrades on the high-loss and high-burst conditions (0.826 m at 25% loss and 0.858 m at 25% burst).

Figure 10 extends this comparison across the fifteen channel conditions. Panel (a) reports the mean horizontal RMSE: the proposal stays between 0.456 m and 1.183 m across all conditions (standard KF 1.663–3.532 m), and the one-step baseline is the sharper specialist only on the extreme heavy-delay distribution (0.634 m vs. 1.183 m). Panel (b) reports the blackout-window peak, which the proposal holds at or below 2.6 m everywhere except the heavy-delay distribution (4.345 m), against a 5.3 m peak for the one-step baseline at the 20 s blackout (2.1 m for the proposal).

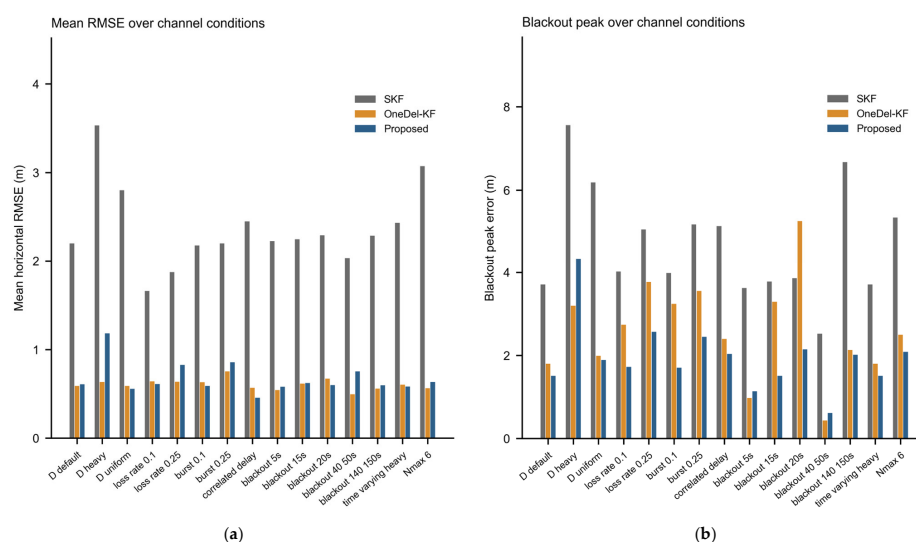


Figure 10. Performance comparison under different scenarios: (a) mean RMSE across channel conditions; (b) blackout peak across channel conditions.

4.3.2. Synchronization-Bias Sensitivity

Superposing systematic clock biases of 0.05/0.10/0.15 s on every timestamp shows that the statistical-mixture delay update is insensitive to the bias: it yields 0.608 m at every

bias, because the update weights the candidate delay orders by the delay distribution rather than betting on a single timestamp-diagnosed delay order. By contrast, the timestamp-diagnosed single-order configuration loses numerical stability once the bias reaches the tolerance $\tau = 0.1$ s (epoch-misaligned innovations), which is reported as such. The statistical-mixture configuration is therefore the framework's robustness default, and the tolerance design together with the admissible-error bound follow from these two rows of evidence.

4.4. Monte Carlo Statistical Validation

Twenty paired Monte Carlo runs are performed, with all compared methods sharing identical trajectories, sensor noise realizations, and anomaly sequences under each random seed to ensure a controlled paired comparison.

For each metric, we report the sample mean and its 95% confidence interval (CI) calculated as a mean. The 95% CI of the sample mean is computed as follows: $\pm t_{0.975,19} \cdot \frac{s}{\sqrt{20}}$, together with the 95% CI of paired differences, paired two-sided t -test p -values, Wilcoxon signed-rank test p -values, and Cohen's $d_z = \text{mean}(\text{diff})/\text{SD}(\text{diff})$ for inter-method comparisons.

Across 20 seeds, the mean horizontal RMSE is 2.373 m (95% CI [2.286, 2.460] m) for the standard KF, 2.824 m ([2.622, 3.025] m) for the gated STF, 0.605 m ([0.585, 0.626] m) for the one-step delay-augmented KF (OneDel-KF), and 0.618 m ([0.592, 0.644] m) for the proposed method.

Compared with the standard KF, the proposed method reduces the mean horizontal RMSE by 1.755 m (95% CI [−1.833, −1.677] m, paired- t $p = 3.7 \times 10^{-21}$, Wilcoxon $p = 1.9 \times 10^{-6}$, $d_z = -10.6$), while its full-trajectory difference from the strongest delay-aware baseline OneDel-KF is not statistically significant (+0.013 m, 95% CI [−0.006, +0.032] m, $p = 0.18$, $d_z = +0.31$). Within the communication blackout window on the same seeds, the mean RMSE difference between the proposed method and OneDel-KF remains not significant (−0.115 m, $p = 0.13$, $d_z = -0.35$), whereas the peak error is significantly reduced by −0.742 m (95% CI [−1.117, −0.367] m, $p = 5.6 \times 10^{-4}$, $d_z = -0.93$); relative to the standard KF, the improvements in blackout mean and peak RMSE reach 2.323 m and 2.741 m, respectively (both $p < 1 \times 10^{-9}$). These paired statistical results are visualized in Figure 11.

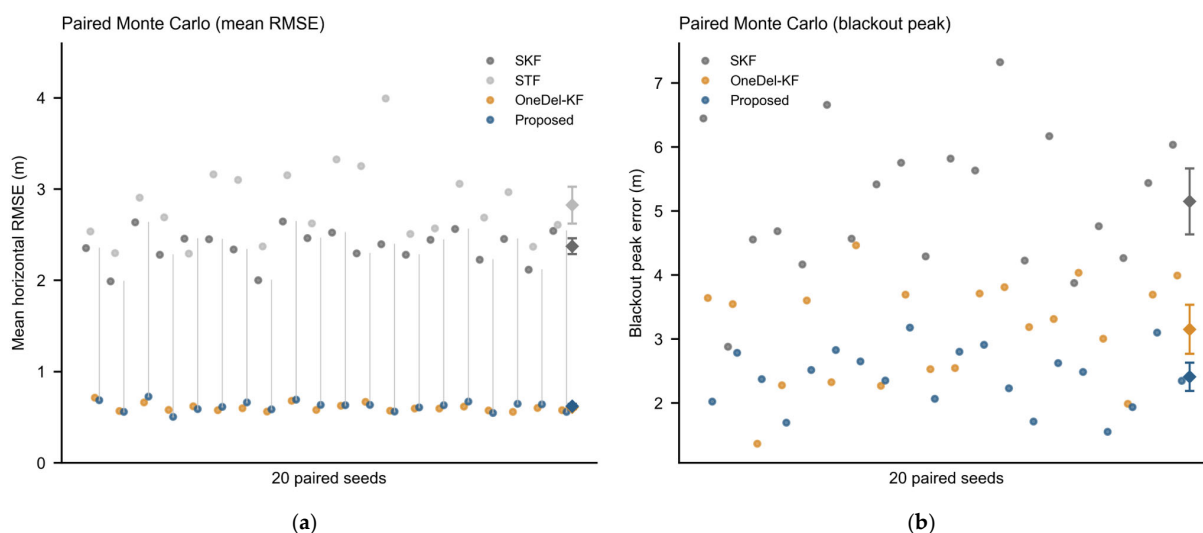


Figure 11. Paired Monte Carlo evaluation under hybrid anomaly channels: (a) per-seed mean horizontal RMSE with group means and 95% CIs; (b) blackout-window peak errors for the same seeds. Diamonds with vertical whiskers at the right of each panel denote the cross-seed group mean and its 95% CI.

4.5. Computational Cost

All computations were performed on a single desktop CPU (AMD Ryzen 5 7500F). One complete 243 s simulation takes 6.0 ± 0.1 s, i.e., about 5 ms per 0.2 s output step—an order of magnitude inside the real-time budget. The offline GRU training (60 epochs) takes 63.2 s, and the GWO hyperparameter search (with 15 candidate trainings) takes about 16 min; a single 50-step inference window costs 1.45 ms. All compared filtering methods (the standard KF, the gated STF, OneDel-KF, the fixed-hyperparameter GRU-KF, the multi-step delay filter, and the proposed method) were implemented in the same MATLAB environment (R2021b) on the same desktop CPU (AMD Ryzen 5 7500F) and evaluated under identical simulation settings, with shared random seeds, and under identical termination conditions (a fixed 243 s simulation horizon), so the wall-clock figures in Table 6 are directly comparable. The offline costs—GRU training (63.2 s) and GWO hyperparameter optimization (about 16 min)—are one-time pre-deployment costs and are reported separately from the online inference cost (1.45 ms per window) and the per-epoch filtering cost (about 5 ms), which together determine the real-time applicability of the proposed method.

5. Conclusions

To address the coexistence of random measurement delays and intermittent data loss in weak-communication environments, this paper proposes an adaptive multi-UAV cooperative localization method integrating timestamp-based anomaly diagnosis, GWO-GRU virtual measurement reconstruction, and multi-step augmented filtering. In the deterministic hybrid-anomaly simulation, the proposed method reduces the mean east and north RMSE by 69.1% and 75.2%, respectively, and decreases the mean RMSE over the six horizontal channels from 2.200 m to 0.608 m. The mean up RMSE is also reduced from 1.469 m to 0.785 m, indicating improved localization accuracy during persistent delays and the programmed communication blackout.

Component-wise ablation showed that the timestamp diagnosis and the multi-step delayed update contribute most of the mean-error reduction ($2.200 \text{ m} \rightarrow 0.611 \text{ m}$), while the GWO-optimized GRU reconstruction acts inside and immediately after the outage (blackout peak 1.508 m and recovery 18.4 s, versus 2.414 m and 114.4 s for the delay filter alone), and an unadapted fixed-hyperparameter GRU degrades rather than helps the filter. In 20 paired Monte Carlo runs, the improvement over the standard KF was observed to be highly significant (paired-t $p = 3.7 \times 10^{-21}$, $d_z = -10.6$); compared with the strongest delay-aware baseline, no statistically significant difference was detected between the full-trajectory means ($p = 0.18$), and it was observed that the advantage concentrates in the blackout-window peak ($p = 5.6 \times 10^{-4}$; the blackout-window mean difference, $p = 0.13$, is not significant). The method stayed between 0.456 m and 1.183 m in mean horizontal RMSE across fifteen channel conditions, the synchronization-bias sensitivity matches the designed tolerance budget, and the per-epoch cost (about 5 ms plus 1.45 ms for one GRU window) is an order of magnitude inside the 0.2 s real-time budget. The simulation scenarios were constructed from flight data collected with the DJI Matrice 350 RTK platform, the communication anomalies were included in the simulation, and all evaluations were performed offline; hardware-in-the-loop validation, onboard real-time flight validation, clock drift beyond the hybrid tolerance, and non-line-of-sight UWB effects remain the focus of future work. Accordingly, the GWO-GRU module is a blackout-oriented component: it reconstructs missing measurements and suppresses peak errors during prolonged communication loss, whereas the full-trajectory mean-error reduction is dominated by the timestamp diagnosis and the multi-step delayed update. The DJI Matrice 350 RTK platform was used to collect the flight data that drive the simulation scenarios.

No hardware-in-the-loop or onboard real-time flight validation of the proposed algorithm has been conducted in this work; such validations are left for future studies.

Author Contributions: F.Y., P.W. and W.M. conceived the study. F.Y., P.W. and S.P. designed the methodology. F.Y., W.M. and S.P. performed the software work. F.Y., P.W. and W.M. completed the validation. P.W., F.Y. and S.P. carried out the formal analysis. F.Y., W.M. and P.W. conducted the investigations. P.W., S.P. and W.M. provided the resources. F.Y., W.M. and S.P. managed the data. F.Y. and P.W. drafted the manuscript. P.W., S.P. and W.M. revised and polished the paper. F.Y. and W.M. completed the figure visualization. P.W. and S.P. supervised the research. P.W. and S.P. managed the project. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CKF	Cubature Kalman Filtering
CRC	Cyclic Redundancy Check
GDOP	Geometric Dilution of Precision
GNSS	Global Navigation Satellite System
GRU	Gated Recurrent Unit
GWO	Gray Wolf Optimizer
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
OOSM	Out-of-Sequence Measurements
RMSE	Root Mean Square Error
SNR	Signal-to-Noise Ratio
STF	Strong Tracking Filters
UAV	Unmanned Aerial Vehicle
UWB	Ultra Wide Band
VB	Variational Bayesian

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