CONSISTENCY GATED COOPERATIVE LOCALIZATION FOR UAV SWARMS UNDER INTERMITTENT GPS

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ABSTRACT

Cooperative localization under intermittent Global Navigation Satellite System (GNSS) is challenging, as naive cooperation may degrade estimation when relative measurements are inconsistent. This paper proposes a two-stage localization framework for Unmanned Aerial Vehicle (UAV) swarms, where each agent maintains a local Extended Kalman Filter (EKF) estimate using Global Positioning System (GPS) and Inertial Measuring Unit (IMU) data, and applies a distributed refinement based on relative Ultra-Wideband (UWB) range and Angle of Arrival (AoA) direction constraints. Moreover, a lightweight consistency gate is proposed, which relies on residual and consensus indicators and determines whether cooperative refinement is accepted, preventing harmful updates without online ground truth. Simulation results demonstrate consistent improvements in formation-relevant relative accuracy and stable absolute positioning compared to GPS and GPS+EKF baselines under intermittent GPS availability.

***Index Terms*—** Cooperative localization, distributed optimization, ADMM, UWB, AoA

I. INTRODUCTION

Cooperative localization constitutes a fundamental capability for autonomous navigation in GNSS-denied environments, enabling agents to transcend individual sensor limitations through information exchange. Early architectures relied on centralized EKF, which, despite their theoretical optimality under linear-Gaussian assumptions, suffer from poor scalability and single points of failure [1]. Consequently, the field has shifted toward distributed paradigms, broadly categorized into sequential filtering and variational optimization.

Sequential methods, such as Distributed EKF (DEKF) and Covariance Intersection (CI), allow agents to fuse local states with neighbor estimates [2], [3]. However, these are mathematically sensitive to rumor propagation, where unmodeled cross-correlations recirculate within the network, leading to overconfident and inconsistent estimates [4]. While consistency-maintenance strategies have been proposed in the literature, they often necessitate conservative covariance inflation that unduly limits accuracy [5]. Conversely, optimization-based methods formulate localization as a distributed Maximum a Posteriori (MAP) problem. Techniques like the Alternating Direction Method of Multipliers (ADMM) are favored for their robustness and decomposability [6], with theoretical guarantees of convergence to centralized performance in connected sensor networks [7].

However, a fundamental vulnerability remains in existing distributed optimization frameworks: the assumption of *consistent observability*. Standard methods typically assume that relative constraints, while noisy, are statistically consistent with the underlying motion model [3], [8]. Recent UAV-swarm localization methods have also considered GNSS-denied operation using cooperative relative measurements and clustering-based communication structures [9]. This assumption breaks down under intermittent GNSS availability. When absolute anchors are sparse or momentarily unavailable, naive consensus mechanisms force agents to agree on a common global frame, often causing the entire formation to drift coherently. In such regimes, cooperative updates introduce negative transfer, degrading the performance of healthy agents below their non-cooperative baseline.

To address this structural limitation, this work proposes a consistency-gated cooperative localization framework. The main contributions of this work are the following:

- **A consistency-gated cooperative localization framework** that prevents harmful cooperative updates under intermittent GNSS. Unlike conventional cooperative filters that assume shared information is always beneficial, the proposed framework explicitly accounts for inconsistent or unreliable relative constraints and mitigates negative transfer effects in distributed estimation.
- **A two-stage estimation strategy** decoupling local observability recovery via EKF from cooperative refinement via distributed optimization. By separating absolute-state stabilization from relative consensus enforcement, the framework preserves local filter consistency while enabling scalable inter-agent correction.
- **A lightweight learning-based acceptance gate** using only runtime residual indicators, requiring no ground truth online. The gate operates as a data-driven re-

liability assessor, trained offline but deployed solely on measurable consistency features, ensuring practical applicability without additional sensing requirements.

The primary contribution of this work is not a new theoretical distributed optimization algorithm, but rather a practical consistency-aware cooperative localization architecture that combines local EKF estimation, distributed relative refinement, and a lightweight runtime acceptance mechanism suitable for intermittent GNSS conditions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a swarm of N UAVs operating in a shared 3D coordinate frame. Each UAV is equipped with a GPS system (as a GNSS receiver), an IMU and an UWB radar, and supported by at least two spatially separated base stations capable of providing high-resolution directional measurements via mmWave or massive MIMO (mMIMO) channel processing. Furthermore, each UAV $i \in \{1, \ldots, N\}$ estimates its state vector at time k, $\mathbf{x}_i[k] = [\mathbf{p}_i[k]^T, \mathbf{v}_i[k]^T, \mathbf{b}_{a,i}[k]^T]^T$, where $\mathbf{p}_i = [x_i, y_i, z_i]^T$, $\mathbf{v}_i = [u_{x,i}, u_{y,i}, u_{z,i}]^T$ and $\mathbf{b}_{a,i} = [b_{x,i}, b_{y,i}, b_{z,i}]^T$ represent position, velocity and accelerometer bias respectively.

The discrete-time motion model, drawn from [10], is:

$$\mathbf{x}_i[k] = \mathbf{F}\mathbf{x}_i[k-1] + \mathbf{B}(\mathbf{u}_i[k-1] - \mathbf{b}_{a,i}[k-1]) + \mathbf{w}_i[k] \quad (1)$$

where $\mathbf{u}_i$ represents the IMU-measured acceleration input, $\mathbf{b}_{a,i}$ models slowly varying accelerometer bias as a random walk process and $\mathbf{w}_i \sim \mathcal{N}(0, \mathbf{Q})$ denotes the process noise. The transition matrix $\mathbf{F}$ corresponds to the discrete-time constant-velocity state transition model, while input matrix $\mathbf{B}$ maps accelerometer inputs into velocity and position increments over the sampling interval, and $\mathbf{Q}$ is the process noise covariance.

The onboard sensors provide the following measurements:

- **GPS** provides absolute position $\mathbf{y}_k^{\text{GPS}} = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k^{\text{GPS}}$, where $\mathbf{H} = [\mathbf{I}_3 \ \mathbf{0}_6]$ and measurement noise $\mathbf{v}_k^{\text{GPS}} \sim \mathcal{N}(0, \mathbf{R}_{\text{GPS}})$.
- **IMU** provides accelerometer data $\mathbf{y}_k^{\text{IMU}} = \mathbf{u}_k + \mathbf{b}_{a,k} + \mathbf{v}_k^{IMU}$, with $\mathbf{v}_k^{\text{IMU}} \sim \mathcal{N}(0, \sigma_{\text{IMU}}^2)$, where the EKF compensates for the estimated accelerometer bias during propagation.
- **UWB** yields pairwise distances $y_{ij,k}^{\text{UWB}} = \|\mathbf{p}_{i,k} - \mathbf{p}_{j,k}\| + v_{ij,k}^{\text{UWB}}$, with noise $v_{ij,k}^{\text{UWB}} \sim \mathcal{N}(0, \sigma_{\text{UWB}}^2)$.

AoA-like direction information is assumed available indirectly via channel-state information–based angle estimation [11]. These directional estimates are modeled as relative AoA constraints in the proposed framework. This assumption only justifies the availability of directional constraints and is independent of the proposed estimation framework.

III. PROPOSED METHODOLOGY

Building upon the system model and measurement formulation of Section II, this section describes the cooperative estimation framework that integrates sequential filtering with distributed optimization. Each UAV executes local state estimation via an EKF, while cooperative refinement is performed through an ADMM consensus step. The cooperative refinement is formulated as MAP estimation, combining relative measurement likelihoods (UWB/AoA) with a Gaussian prior given by the EKF estimate. Moreover, a lightweight acceptance gate (classification tree) determines whether cooperative corrections are accepted at each update, ensuring robustness.

III-A. Local Sequential Estimation

Each UAV maintains a local EKF using IMU propagation and intermittent GPS updates, providing a locally consistent baseline estimate.

GPS updates are staggered across UAVs, as at each time step only a subset applies GPS correction, while others propagate inertially.

III-B. Cooperative Refinement

Cooperative refinement is formulated as a distributed MAP optimization problem, where each UAV minimizes a local objective combining relative measurement likelihoods and a Gaussian prior induced by the EKF estimate.

Based on the measurements mentioned in Section II, each UAV has a local cost function to minimize in the form of:

$$\begin{aligned} f_i(\mathbf{p}_i) = &\sum_{j \in \mathcal{N}_i^{\text{UWB}}} \frac{1}{2\sigma_{\text{UWB}}^2} (\|\mathbf{p}_i - \mathbf{p}_j\| - d_{ij})^2 \\ &+ \sum_{j \in \mathcal{N}_i^{\text{AoA}}} \frac{1}{2\sigma_{\text{AoA}}^2} \left\| \frac{\mathbf{p}_j - \mathbf{p}_i}{\|\mathbf{p}_j - \mathbf{p}_i\|} - \mathbf{a}_{ij} \right\|^2 \\ &+ \frac{1}{2} (\mathbf{p}_i - \mu_i)^T \mathbf{P}_{p,i}^{-1} (\mathbf{p}_i - \mu_i) \quad (2) \end{aligned}$$

where d_{ij} and $\mathbf{a}_{ij} \in \mathbb{R}^{3\times 1}$ are respectively the measured relative distance and the measured unit direction from UAVs i to j, $\mathcal{N}_i$ is the set of neighbors of UAV i and the two terms express the deviation between estimated and measured relative distances and angles respectively, μ_i is the EKF baseline position estimate and $\mathbf{P}_{p,i}$ is the EKF position covariance matrix. The AoA term penalizes disagreement between the estimated relative direction vector and the measured unit direction $\mathbf{a}_{ij}$ derived from channel-state information-based angle estimation.

In addition to these constraints, we include a quadratic prior centered at the local EKF position estimate μ_i, weighted by the EKF position covariance $\mathbf{P}_{p,i}$. This Gaussian prior stabilizes refinement under intermittent observability by penalizing excessive deviation from the EKF baseline.

Cooperative refinement is implemented using a standard distributed optimization scheme based on ADMM, enforcing agreement between local position estimates while incorporating relative UWB and AoA constraints. ADMM is used in this work as a representative distributed refinement mechanism.

III-C. Consistency Gated Acceptance

Under intermittent absolute observability, cooperative refinement is not inherently beneficial; the assimilation of inconsistent relative constraints can induce negative transfer and degrade the local estimate. To mitigate this risk, we introduce a lightweight acceptance gate that determines whether to apply the cooperative update based on runtime consistency indicators.

The gate is implemented as a binary classification tree. It operates solely on a feature vector comprising the ADMM convergence residuals and the normalized measurement residuals. Specifically, at the end of the cooperative refinement step k, the following consistency features are computed:

$$r_{\text{pri}} = \left(\sum_{i=1}^{N} \|\mathbf{p}_{i,k} - \mathbf{z}_{i,k}\|^2 \right)^{1/2} \tag{3}$$

$$r_{\text{dual}} = \rho \left(\sum_{i=1}^{N} \|\mathbf{z}_{i,k} - \mathbf{z}_{i,k-1}\|^2 \right)^{1/2} \tag{4}$$

$$\epsilon_{\text{UWB},i,j} = \frac{1}{\sigma^2_{\text{UWB}}} \left(\|\mathbf{p}_{i,k} - \mathbf{p}_{j,k}\| - d_{ij} \right)^2 \tag{5}$$

$$\epsilon_{\text{AoA},i,j} = \frac{1}{\sigma^2_{\text{AoA}}} \left\| \frac{\mathbf{p}_{j,k} - \mathbf{p}_{i,k}}{\|\mathbf{p}_{j,k} - \mathbf{p}_{i,k}\|} - \mathbf{a}_{ij} \right\|^2 \tag{6}$$

Equations (3) and (4) represent the ADMM global primal and dual residuals, serving as indicators of consensus disagreement and algorithmic stability [12]. Due to the nonconvex nature of range-based localization, ADMM convergence is not theoretically guaranteed, and monitoring these residuals helps detect poor convergence or divergence due to inconsistent constraints. Equations (5) and (6) represent the normalized squared residuals with respect to measurements d_{ij} and $\mathbf{a}_{ij}$, effectively capturing the local geometric tension between the prior and the relative constraints.

The classifier is trained offline using simulation data, where ground truth is available to generate labels based on whether the refinement stage reduces the Mean Relative Distance Error (MRDE). A 5-fold cross-validation procedure was employed, achieving a best classification accuracy of 86.1% across the evaluated scenarios. By mapping the convergence behavior (residuals) to estimation quality, the gate empirically identifies configurations likely to degrade estimation quality. The mechanism is decentralized and preserves consistency by reverting to the EKF prior when cooperative refinement is predicted to be detrimental.

Simulations consider a small UAV swarm under intermittent GPS, where only a subset of agents receives GPS updates at each timestep.

Algorithm 1 Gated Cooperative EKF-ADMM Positioning

Input: IMU, GPS, UWB and AoA measurements, ADMM penalty parameter ρ, number of ADMM inner iterations K, original states of UAVs $\mathbf{x}_i(0)$.
Output: Refined UAV position estimates $\mathbf{p}_i(t)$ for $i = 1, 2, \ldots, N$.
Initialize EKF states $\mathbf{x}_i(0)$, covariances $\mathbf{P}_i(0)$, consensus variables $\mathbf{Z}(0)$, and dual variables $\mathbf{U}(0)$.
for each timestep $t = 1, 2, \ldots, T$ **do**
    Perform EKF prediction using motion model and IMU input.
    if GPS is available, perform EKF correction.
    Initialize cooperative refinement with EKF position estimates.
    Perform $\mathbf{K}$ iterations of distributed cooperative refinement using UWB and AoA constraints.
    Compute consistency indicators and apply acceptance gate.
    Update estimate using cooperative refinement if accepted.
end for
Obtain final cooperative UAV trajectories $\mathbf{p}_i(t)_{i=1}^{N}$.

$$\text{MRDE} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} \frac{1}{T} \sum_{k=1}^{T} \left| \|\mathbf{p}_{i,k} - \mathbf{p}_{j,k}\| - \|\mathbf{p}^{\text{true}}_{i,k} - \mathbf{p}^{\text{true}}_{j,k}\| \right| \tag{7}$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \frac{1}{T} \sum_{k=1}^{T} \|\mathbf{p}_{i,k} - \mathbf{p}^{\text{true}}_{i,k}\|^2} \tag{8}$$

Relative measurements are available between neighboring UAVs. Performance is evaluated over all flight scenarios shown in Table I using Root Mean Squared Error (RMSE) and MRDE, as in (7) and (8), where $\mathbf{p}^{\text{true}}_{i,k}$ is the ground-truth position of UAV i at time k.

The two analyzed scenarios represent realistic multi-UAV flight conditions, where the UAVs rotate in a circular formation of increasing radius and altitude.

To simulate realistic conditions, GPS availability was staggered among UAVs with a fixed offset, so that at each iteration only one or two UAVs received direct GPS updates, which were communicated to their neighbors to preserve global anchoring. This configuration emulates bandwidth-limited or partially obstructed environments while allowing anchor information to be distributed via the cooperative consensus stage.

IV. SIMULATION SETUP

Simulations consider a densely connected swarm of $N = 5$ UAVs. Each UAV maintained bidirectional communication

Table I. Simulated Scenarios

No.	Init. Radius	Final Radius	Final Alt.
1	5 m	10 m	40 m
2	5 m	20 m	100 m

with neighbors, exchanging its latest position estimate $\mathbf{p}_i$, GPS measurement $\mathbf{y}^{GPS}$ and dual variable $\mathbf{u}_i$ after every update step. This ensured consistent propagation of positional constraints and preserved overall formation coherence.

The proposed method was compared against raw GPS, GPS+EKF and EKF+ADMM baselines, where EKF+ADMM serves as an ablation baseline isolating the contribution of the acceptance gate.

V. RESULTS AND DISCUSSION

V-A. Localization Accuracy

Fig. 1 illustrates the absolute RMSE evolution for all methods, whereas Table II summarizes the corresponding results over all scenarios and methods. The increased RMSE observed for EKF+ADMM reflects divergence under inconsistent relative constraints, highlighting the severity of negative transfer when refinement is applied indiscriminately. Raw GPS reduces absolute error but exhibits fluctuations. GPS+EKF further stabilizes estimates. The proposed method achieves the lowest RMSE, reducing error by approximately 50–60% relative to GPS+EKF.

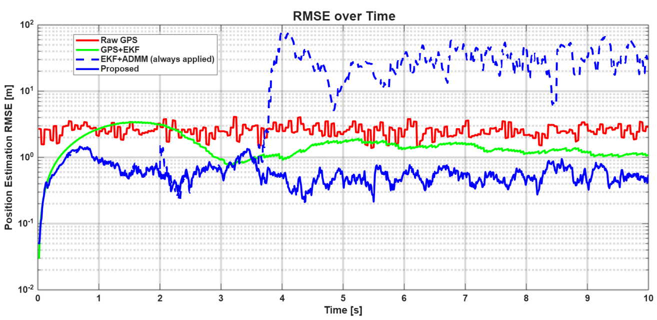

Fig. 1. RMSE, computed from (8), over time for the methods of Raw GPS, GPS+EKF, EKF+ADMM and proposed for the first scenario.

Fig. 2 complements the above observations by demonstrating the relative errors between the UAVs, whereas Table II summarizes the corresponding results over all scenarios and methods. It highlights the improvement in relative localization accuracy between UAV pairs. Although the absolute RMSE is reduced significantly, the proposed framework achieves approximately 60% reduction in MRDE compared to GPS+EKF. This behavior is particularly important in close-formation flight scenarios, where relative positioning accuracy is critical.

The proposed gated framework consistently achieves substantial reductions in both absolute and relative localization error, reaching 50–60% improvement compared to GPS+EKF. Importantly, gating prevents performance degradation observed when cooperative refinement is applied indiscriminately.

Table II. RMSE and MRDE Results

Scen.	Mean RMSE (m)				Improv. (%)
	Raw GPS	GPS+EKF	EKF+ADMM	Proposed	
1	2.510	1.581	19.741	0.597	+62.2%
2	2.572	1.802	25.412	0.861	+52.2%

Scen.	MRDE (m)			Improv. (%)
	GPS+EKF	EKF+ADMM	Proposed	
1	1.478	6.665	0.574	+61.2%
2	1.593	13.537	0.719	+54.9%

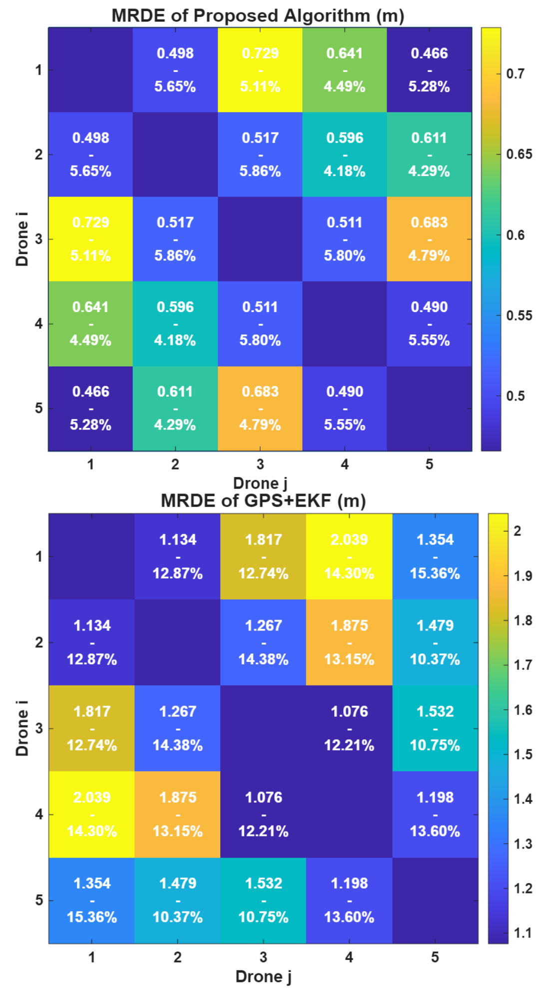

Fig. 2. MRDE and percentage relative error between UAV pairs for the first scenario, computed from (7), for the proposed algorithm and GPS+EKF.

V-B. Sensitivity Analysis

Sensitivity analysis with respect to GPS availability in Fig. 3 shows graceful degradation, while relative accuracy remains consistently superior.

Although absolute RMSE increases as GPS update rate decreases, the gated method maintains a consistent relative accuracy advantage, confirming robustness across sensing conditions. The absence of abrupt divergence across reduced GPS rates confirms that the gating mechanism preserves estimator stability under degraded observability.

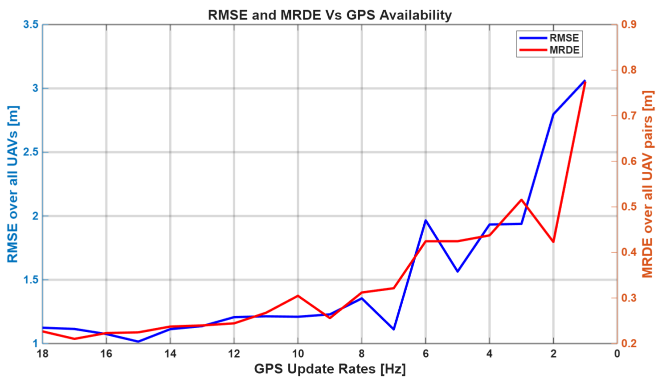

Fig. 3. Illustration of RMSE and MRDE when the GPS update rate of the simulations above is modified.

V-C. Computational Performance

Runtime performance is a critical factor for real-time deployment. To this end, average computation time per time step was measured across experiments, yielding the following:

- EKF-only updates complete in time of well below 1 ms per UAV, while ADMM adds overhead proportional to the number of iterations and UAVs. For $N = 5$ UAVs and $K = 10$ iterations, the average runtime per time step was on the order of a few milliseconds per timestep on a standard computer processor.
- Communication exchanges among UAVs were completed within the algorithm's update interval, and no communication-induced delays exceeded the discrete-time step used for estimation.
- Runtime scales approximately linearly with the number of UAVs, as each UAV solves a small optimization problem in each iteration. For larger swarms, distributed implementation strategies could be explored to maintain real-time feasibility.

VI. CONCLUSIONS AND FUTURE WORK

This paper presented a consistency-gated cooperative localization framework for UAV swarms under intermittent GPS.

The present simulations intentionally focus on controlled dense-connectivity conditions with Gaussian measurement noise to isolate estimator behavior and evaluate the effect of the proposed gating mechanism. Extensions toward sparse communication graphs, packet loss, asymmetric links, non-Gaussian sensing conditions, hardware validation and adaptive online gating constitute important future work.

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