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Design and Deployment of a Hybrid Neural Network for Real-Time GPS Correction in Slow Moving, Low SWaP, UAV Flight Systems

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Abstract

The global surge in demand for unmanned aerial vehicles (UAVs), projected to reach \$91 billion by 2033, spans diverse applications in urban environments. However, achieving accurate horizontal geo-localization in urban settings remains challenging due to poor GPS performance, creating a significant barrier to effective drone operations, even in static or slow-moving deployments. Recreational-grade GPS systems, commonly used in low Size, Weight and Power (SWaP) UAVs, suffer from residual errors exceeding 100 meters in urban environments, severely limiting real-time navigation accuracy and drone autonomy. Although capable of good accuracy in conventional aerospace deployments, existing traditional aerospace-ready GPS receivers are expensive, power-intensive, and heavy, making them unsuitable for low SWaP drone deployment. Existing performance-enhancing post-processing techniques for recreational GPS are limited by the real-time requirements and the noise, power, and computational constraints inherent to drone operations. This underscores the critical need for accurate, robust, lightweight, and power-efficient urban localization solutions for UAVs. In this work, we present a hybrid Integrated Recurrent Neural Network–Deep Neural Network (IRNN-DNN) architecture, capable of running on embedded microcontrollers with recreational-grade L1C GPS receivers. Leveraging Long Short-Term Memory (LSTM) networks, the IRNN-DNN model captures temporal dependencies and spatial error patterns across multiple concurrent GPS receivers, allowing real-time error correction. Field tests with MTK3339 GPS receiver on UAVs in static test conditions showed, with a 2D residual error of 1.71 meters at 10 Hz, a 30% improvement over existing models—validate the IRNN-DNN approach as a promising embedded solution for enhancing urban localization performance in constrained UAV applications.

Keywords: Machine learning; Neural networks; Multipath mitigation; Real-time GPS correction; Urban drone operations

Introduction

Floreano and Wood (2015) identified the transformative potential of drones in logistics and urban air mobility (UAM), positioning them as a technological milestone capable of revolutionizing sectors such as transportation and disaster mitigation. They highlighted the significant impact of autonomous drones in civilian applications, particularly for navigating complex environments and providing more efficient transportation solutions. Even earlier, MacSween-George (2003) envisioned a "drone Uber" concept, proposing using drones for human transportation. Collectively, these works reflect early optimism about the role of drones in reshaping logistics and mobility. While these works focused on large-scale, high capacity systems, practical deployment has remained limited due to range, power, payload and regulatory compliance (Raivi et al. 2023).

Consequently, the research community is increasingly turning toward small, ultra-low SWaP (Size, Weight and Power) as a more viable near-term alternative.

While many broad definitions exists for low SWaP drones (U.S. Army. 2010; Elmeseiry et al. 2021; Mohsan et al. 2022; Federal Aviation Administration 2023), this study specifically focus on mini and micro Class 1 drones (Ariante and Del Core 2025), operationally defined here as drones weighing under 5 kg and costing less than \$3000. These small platforms are widely adopted for specialized tasks that require precise static or near-static positioning near obstacles, particularly in dense urban environment. Examples include property inspections, static surveillance and threat monitoring, terrestrial mapping, close-range photography and videography, urban traffic monitoring at intersections and parking lots, and IoT sensor deployment and monitoring (Kim et al. 2013; Sorbelli 2018; Al-Turjman et al. 2020; Barmounakis and Geroliminis 2020; Thoa Mac et al. 2020; Togola et al. 2020; Kabbabe Poleo et al. 2021; Kalaitzakis et al. 2021; Elsayed et al. 2022; Al-Dharrab 2023; Kim et al. 2024; Dhawde et al. 2025). These applications share a critical operational characteristic central to this paper: the drone is primarily deployed in static or near-static configurations

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at specific heights, often in close proximity to reflective structures and obstacles in dense urban environments.

Although not fully autonomous, these drones typically feature operator-assistive capabilities such as hovering, landing, and stable positioning at fixed locations. These features are particularly sensitive to Global Positioning System (GPS) localization errors (Lima and Pereira 2021; Sun et al. 2023), especially when operating with low-cost, recreational-grade single-frequency GPS receivers commonly integrated with microcontroller-based flight computers architectures (Shetty and Gao 2015; Septian et al. 2022). Ensuring robust and reliable GPS localization under these static and highly constrained operational conditions remains a critical research and operational challenge (Gao et al. 2013; Su et al. 2022; Reid and Neish 2023; Zou et al. 2023) of interest to the research community.

Operational standards for drone applications specify that horizontal positioning errors must remain below 3 meters with at least 90% probability, and vertical errors within approximately 12.5 feet (3.81 meters) under similar reliability constraints (Bauranov and Rakas 2021; Fontaine 2023). Despite these clear guidelines, reliably achieving this accuracy in urban environments remains challenging due to frequent satellite dropouts, severe multipath reflections, and signal degradation (Gowda et al. 2017; Zhang et al. 2023).

Under optimal, open-sky, conditions, GPS-based localization can achieve lateral accuracies within 1 meter. Yet, in dense urban areas with obstructions, accuracy drops significantly (Hamza et al. 2024), often resulting in horizontal errors of hundreds of meters due to multipath (see Fig. 1) (Michalski and Czajewski 2004). Multiple studies also illustrate that vertical positioning errors are further compounded by this issue, typically exceeding horizontal inaccuracies by at least 50%, and sometimes surpassing 100 meters (Zogg 2002; Alkeryd 2006; Chan et al. 2006; Wing and Frank 2011). Traditional guidance, navigation, and control (GNC) approaches for drones and UAVs often rely on complex sensor suites—such as radar, depth sensors, and stereo cameras—combined with computationally intensive algorithms requiring high floating point operations per second (FLOPS) capability (see Table 1). However, the size, weight, and power demands of these systems make them impractical for lightweight, low-SWaP drone platforms (Kumar et al. 2023).

To address these limitations, this paper proposes a machine learning (ML) model that combines conventional signal processing with lightweight neural architectures to enhance the positioning static accuracy of low-cost, recreational-grade GPS receivers (Nathan 2024) operating urban environments near obstacles. The study focuses specifically on improving horizontal (2D) localization performance in

static or slow-moving conditions; altitude behavior was monitored but not systematically evaluated. Our Integrated Recurrent Neural Network-Deep Neural Network (IRNN-DNN) model reduces 2D positional GPS error to under 2 meters (50% Circular Error Probability (CEP)) in real-time on embedded microcontroller platforms during simulated urban UAV operations, all at operational speeds exceeding 10 Hz. The remainder of the paper is organized as follows: Section 2 discusses related work on GPS error correction and ML approaches. Section 3 details the proposed IRNN-DNN model, including its architecture, deployment, and experimental methodology. Section 4 presents and discusses the experimental results and Section 5 concludes with a summary of the findings and future directions.

Literature review: current GPS error mitigation methods

Traditional GPS error correction methods have relied heavily on techniques like Differential GPS (DGPS) and Real-Time Kinematic (RTK) systems. RTK, which sends correction carrier-phase measurements from a base station to a mobile platform and achieves centimeter-level precision in real-time, is, however, an expensive solution that demands additional hardware. While strict line-of-sight (LOS) between the base station and rover is not a technical requirement, recent experimental studies (Fan et al. 2019b; Medina et al. 2021; Tavaszi et al. 2024a) have demonstrated that non-line-of-sight (NLOS) conditions between the base and rover can lead to performance degradation. DGPS is unsuitable for fast-moving drones as it introduces latency and communication delays, and increases reliance on additional infrastructure, raising costs (Gross et al. 2016; Tavaszi et al. 2024b). In contrast, Precise Point Positioning (PPP) methods don't operate in real-time; instead, they rely on post-processing to enhance accuracy (Magsi et al. 2024). Although hybrid PPP-RTK combinations exist, they still require substantial infrastructure and entail significant operational complexities (Kim 2021). These methods are also generally unsuitable for targeted UAM applications, where dynamics and urban environments exacerbate these issues (Li et al. 2023).

Limitations of traditional approaches have led to the adoption of ML techniques to enhance GPS localization accuracy in urban settings (Du et al. 2020; Kanhere et al. 2022; Meng et al. 2022; Zou et al. 2023; Qi et al. 2024; Zhao et al. 2024; Zheng et al. 2024; Yu et al. 2024b). ML algorithms have demonstrated an ability to learn complex patterns and predict multipath errors, offering solutions that are faster, more precise, and adaptable to varying urban conditions. ML methods have also seen considerable success in correcting other forms of GPS error (Jia et al. 2024; Tete et al. 2024; Tohidi and Mosavi 2024; Hu et al. 2024; Yu et al.

2024a). The paper by Kanhere et al. (2022) presented a DNN model that reduced Global Navigation Satellite System (GNSS) positioning errors down to 5.9 (± 5) m. Mohanty and Gao (2023a) then explored a coupled approach using Graph Neural Networks (GNN) with Kalman filters for positioning. In their second paper, Mohanty and Gao (2023b) examined how Convolutional Neural Networks (CNN) learn and correct GNSS positioning errors in

smartphones. By integrating neural networks to correct and augment GNSS data, the authors show an improvement in lateral positioning performance with errors reduced to 2.6 meters while moving in a vehicle on the interstate. This approach is extended by Huang et al. (2025) to low-quality smartphone GPS data, resulting in Root Mean Square Error (RMSE) concentrated under 10 meters, with 3.86 meters in the best-case scenario, while a car is in motion.

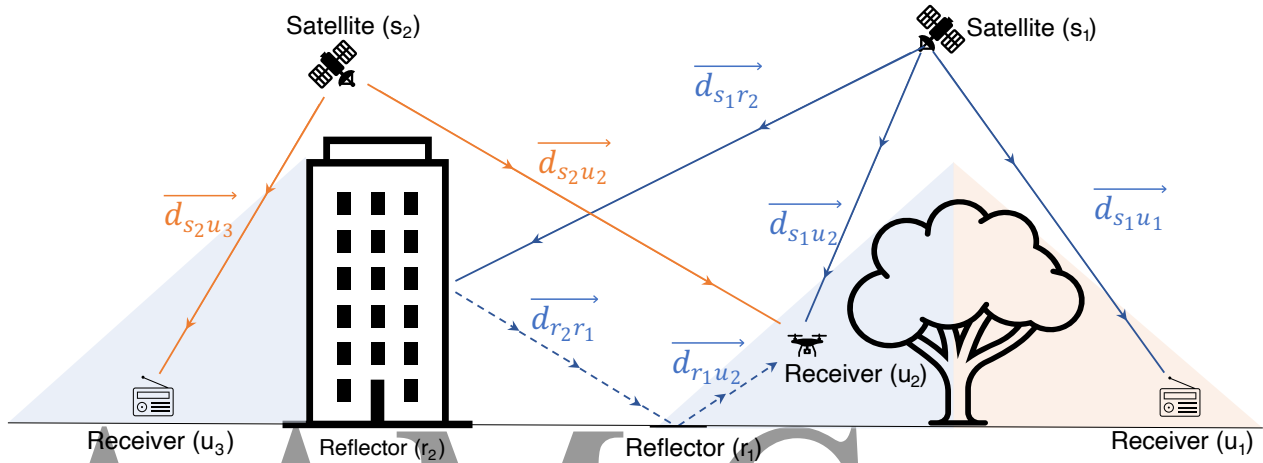


Fig. 1. Illustration of GPS signal propagation paths demonstrating multipath and non-line of sight (NLOS) effects leading to potential reception delays and accuracy degradation in GPS receivers. Multipath interference occurs when GPS signals reflect off surfaces, creating multiple signal paths to the receiver. The reflected path, $\overrightarrow{d_{s_1r_2}}: \overrightarrow{d_{r_2r_1}}: \overrightarrow{d_{r_1u_2}}$, is longer, i.e. takes more time to reach the receiver, than the direct path $\overrightarrow{d_{s_1u_2}}$. These delayed signals cause positional errors of up to hundreds of meters, particularly in urban environments with numerous reflective surfaces.

Table 1. Comparison of Static GPS Localization Methods for Low-SWaP UAV Systems in Urban Environments: Accuracy, Power, Computational Cost, and Deployment Trade-offs.

Method / Equipment	Accuracy (50% CEP, meters)	Power Consumption (Watts)	Computational Load (FLOPS)	Cost (USD)	Size/Weight	Primary Use Case	Key Limitations
L1C GPS, (MTK3339) (MediaTek 2016; Abedi et al. 2020)	3-5	Very Low 0.15 W	$10^4 - 10^5$	~\$ 30	16 x 16 mm <5 g	Basic localization for low-SWaP UAVs	• Highly susceptible to multipath • Degraded urban performance
Multi-Frequency GNSS (NEO-M9N) (u-blox 2023; Miletiev et al. 2024)	1-2	Low - Moderate 0.3 - 1 W	$10^5 - 10^6$	~\$ 70	12 x 16 mm 5-7 g	Suitable for standard UAV applications.	• Degraded urban performance.
Dual Freq RTK (ZED-F9P) (Janos and Kuras 2021; Robustelli et al. 2023; Miletiev et al. 2024; Tavasci et al. 2024c; u-blox 2024).	0.01-0.2	Moderate (~100-200mW)	$10^6 - 10^7$	~\$150-\$250	22 x 17 mm ~10 g	Precision agriculture, surveying, autonomous UAVs	• Requires base station or correction service • Degraded urban performance
Dual Freq PPP (Romero-Andrade et al. 2021a; Hohen-sinn et al. 2022; Ogutcu et al. 2025)	0.01-0.5	High (~500mW)	$10^7 - 10^8$	>\$500	35 x 25 mm >10 g	Global UAV operations where base stations are unavailable	• Long convergence time • Performance affected by ionospheric conditions.
IRNN-DNN (This work) STM32H747 (STMicroelectronics 2023) with training on PC	1.71	Additional 0.1-0.3 W for running ML model on STM32H747	$\sim 10^5$	No cost to implement software method	< 5 g	Enhanced reliability of existing single frequency GPS receivers 33 Kbits per sub-model	• Requires extra compute and memory overhead • 20-30% more CPU utilization

(note) This table contrasts existing approaches across cost, performance, and deployment feasibility. It highlights trade-offs between localization accuracy, system power budget, and operational limitations (Stempfhuber 2013; Wang et al. 2020; Romero-Andrade et al. 2021b; Xin et al. 2024; Halaj and Kačmařík 2024; Chen et al. 2025; Xiao et al. 2025). The IRNN-DNN approach (this work) offers a lightweight embedded solution capable of near mid-grade accuracy at minimal cost and power, without requiring external infrastructure.

While these ML techniques have demonstrated improved accuracy in 2D localization for ground-based applications, they face greater challenges when applied to the 3D localization domains, as required for drone operations (Mishra and Palanisamy 2023). The degrees of freedom in UAV are higher, with six variables (x, y, z axes, and roll, pitch, yaw) compared to the three in ground-based movement (x, y, z axes, and orientation). This makes drone navigation a complex multi-objective optimization problem, with far more demanding real-time precision, safety, and reliability requirements. Airborne GPS correction implementations are also significantly more complex than ground implementations due to the need for rapid control over multiple physical forces (thrust, drag, lift, weight), SWaP constraints, and greater safety regulations (Mulgaonkar et al. 2014; Fan et al. 2019a). Drones must also contend with diverse form factors, environmental disturbances, and 3D mapping

challenges not faced by ground vehicles (Doukhi and Lee 2021). The lack of explainability in ML algorithms from the previous paragraph is a key issue in transitioning them to aerospace, where explainability, certification, and trust in safety-critical applications are vital (Brunton et al. 2021). The DNN model in Kanhere et al. remains a "black box" and lacks interpretability. The model's decisions are not easily or physically interpretable by humans, making it challenging to certify such systems for aerospace applications. CNN, GNN, and other ML models (Mohanty and Gao 2023b; Mohanty and Gao 2023a; Huang et al. 2025) also lack physical interpretability. While automotive applications may not require the same level of transparency, aerospace demands the ability to verify and validate algorithms rigorously, making the black-box nature of these models a significant limitation. Consequently, the existing ground-based autonomous solutions fail to address these complexities,

necessitating advanced, real-time ML algorithms tailored for precise, 3D aerial navigation.

Current traditional GPS solutions designed for planes and helicopters are not effective for drone operations in urban environments due to significant differences in operational needs and conditions. Aircraft operate at high altitudes, where GPS signals encounter minimal multipath interference, unlike drones. Additionally, planes and helicopters follow stable, linear paths with lower demands for rapid, precise localization, whereas drones need highly responsive GPS for real-time maneuvering and obstacle avoidance in complex urban terrains (Xia et al. 2018; Ryll et al. 2020; Angelina Fernandez et al. 2022). SWaP constraints on drones also make it impractical to integrate the bulky, high-power aerospace GPS hardware typically used in traditional aircraft (Wendel et al. 2006; Zhou et al. 2017). These challenges underscore the need for specialized GPS solutions tailored to the unique conditions and demands of urban drone operations.

Despite advancements in research, a critical gap persists in developing real-time, accurate, efficient, and explainable localization systems specifically designed for autonomous drone operations in urban environments. This paper addresses this gap by leveraging recent advancements in ML and localization technologies from related fields. Our scientific contribution is the development of a robust, geometry-aware GPS error correction model that enhances localization accuracy for drones operating in obstructed urban areas, providing both efficiency and interpretability in real-time applications. We leveraged recent developments and emerging ideas in ML and localization technologies in adjacent fields.

- First, position-based error correction using only GPS signals and satellite positions has become feasible with advanced ML techniques. Lan et al. (2020) and Ramavath & Perumalla (2024) illustrate how neural networks can effectively model and predict positioning errors using satellite positional data, offering comparable accuracy over traditional methods.
- Second, hierarchical learning structures have shown promise in improving localization accuracy in complex environments. Tursunboev et al. (2022) demonstrated a hierarchical federated learning approach where small, specialized models are aggregated by a larger model to achieve better performance.
- Third, recent work by Chowdhary et al. (2023), Sharma et al. (2022) and Nayfeh et al. (2023) provides a promising development in deployment pathways for ML models on low-power embedded hardware.

In the subsequent section, we detail how our proposed method, IRNN-DNN, leverages these principles to achieve

high-accuracy positioning through a combination of neural networks and data fusion strategies designed specifically for drone operations.

Methodology

GPS pseudorange equations for single point precision (SPP) technique are well studied and defined in the literature (Borre et al. 2006). For a satellite, s , and receiver, r , the geometrical range between the satellite and receiver is given by r_r^s . Then the pseudorange equation P_r^s is given by:

$$P_r^s = r_r^s + \epsilon_r^s + \delta_r^s \quad (1)$$

$$r_r^s = \sqrt{(x_s - x_r)^2 + (y_s - y_r)^2 + (z_s - z_r)^2} \quad (2)$$

where ϵ_r^s includes the time offset, ionospheric, tropospheric induced, and other error terms. (x_s, y_s, z_s) and (x_r, y_r, z_r) are the positions of the satellite and the receiver respectively. δ_r^s represents the multipath error component and is of most interest to this study.

Then for all the visible satellites, h , and receivers, i , it is possible to create a system of equations $\mathbf{P}$, representing all the pseudorange and multipath errors:

$$\mathbf{P} = \begin{bmatrix} r_1^1 + \epsilon_1^1 + \delta_1^1 \\ \vdots \\ r_1^h + \epsilon_1^h + \delta_1^h \\ r_2^1 + \epsilon_2^1 + \delta_2^1 \\ \vdots \\ r_i^h + \epsilon_i^h + \delta_i^h \end{bmatrix} = \begin{bmatrix} x \\ y \\ z \end{bmatrix} \quad (3)$$

$$p = \begin{bmatrix} (x_1 - x_2) & (y_1 - y_2) & (z_1 - z_2) \\ (x_1 - x_i) & (y_1 - y_i) & (z_1 - z_i) \\ (x_2 - x_3) & (y_2 - y_3) & (z_2 - z_3) \\ \vdots & \vdots & \vdots \end{bmatrix} \quad (4)$$

$$= \begin{bmatrix} \alpha_2^1 \\ \alpha_i^1 \\ \alpha_3^2 \\ \vdots \end{bmatrix}$$

where p represents the positional constraints α_i^j between the multiple sensors mounted on the drone platform, and $[x, y, z]^T$ is the position of the drone. Raytracing, is a commonly proposed method to solve this system of equations, (Yuan et al. 2020). Raytracing is however computationally expensive, dependent on accurate 3D environment models, susceptible to transformation errors, and has limited real-time feasibility (Lv et al. 2021a; Baasch et al. 2022; Ryzhov 2023). Extending the work done by Farej and Ismail (2023), the 5 GPS receivers used in the study (GPS 1A, 1B, 1C, 2A & 2B) have unique satellite-obstacle-receiver geometry. The small deviations (on the order of millimeters) in multipath errors are a consequence of the spatial arrangement of the receiving antennas on a drone. We propose that

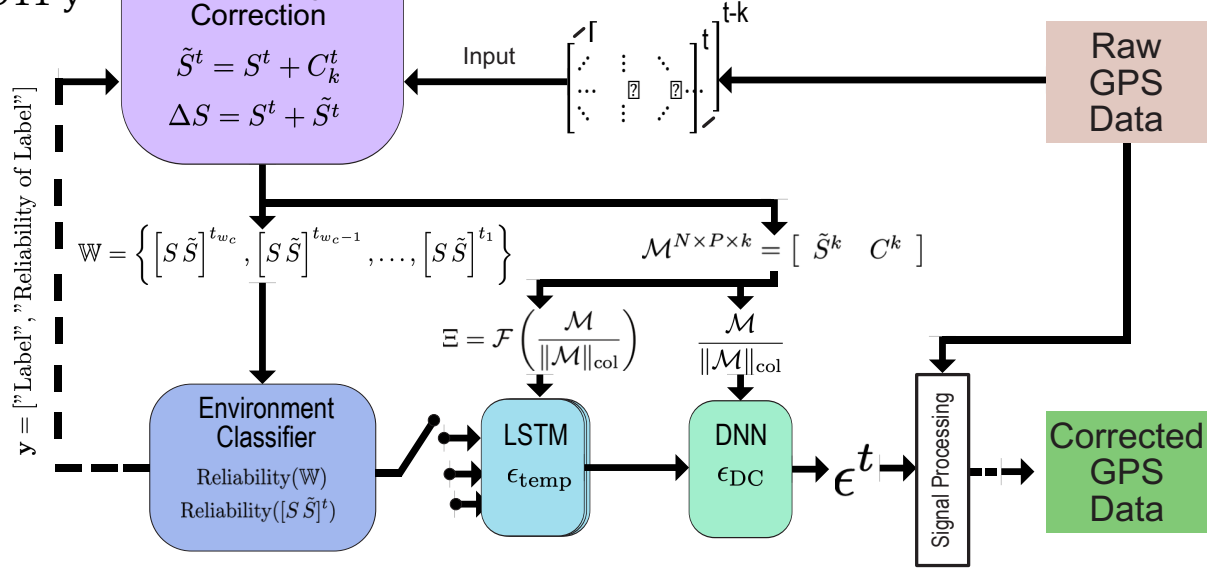


Fig. 2. Detailed architecture of the IRNN-DNN Algorithm for Enhanced GPS Data Correction. The LSTM network handles temporal dependencies in the data, while DNN processes the data for identifying DC error components.

multipath discrepancies in signals lead to predictable, measurable changes in performance, between the GPS receivers used, can be exploited to reduce the multipath errors using ML. IRNN-DNN offers a promising alternative, that leverages a data-driven model to learn error patterns, predict and offer multipath corrections.

The rest of this section is organized as follows: the first sub-section introduces the candidate ML model; the second sub-section introduces the experimental setup and the data set; the third subsection introduces the environment(s) in which the study is conducted, and the final sub-section introduces the metrics used to measure the performance of the algorithm.

Proposed ML model for Drone GPS Localization

Based on prior literature (Liu et al. 2019; Du et al. 2020; Kanhere et al. 2022; Meng et al. 2022), we propose the IRNN-DNN model to integrate a Long Short-Term Memory (LSTM) network with a fully connected Deep Neural Network (DNN) to capture and correct multipath GPS errors efficiently. The LSTM handles temporal dependencies in time-series GPS data. The DNN complements the LSTM by addressing non-sequential errors, including constant sensor offsets and other pseudorandom noise. The proposed IRNN-

DNN algorithm identifies recurring geometric configuration-induced discrepancies and utilizes specialized error correction ML models to improve GPS performance.

The design, deployment, and implications of the algorithm's three foundational components (see Fig. 2) are discussed subsequently.

Windowed Inverse Variance Weighted Correction Filter

The windowed inverse variance weighted correction filter (IVF) enhances the accuracy and robustness of GPS sensor data by dynamically weighing each GPS measurement based on its variance. This transparent, statistical approach reduces the influence of noisy data, allowing the model to focus on more reliable inputs. IVF method employs a dynamically sized window of values denoted as $\mathbf{W}$ characterized by a size m . The normalized sensor measurement at time, t , is represented as a matrix $\mathbf{S}^t$:

$$\mathbf{S}^t = \{s_1^t, s_2^t, s_3^t, s_4^t, s_5^t, \dots\} \quad (5)$$

$$s_n^t = \{s_{n1}^t, s_{n2}^t, s_{n3}^t, \dots, s_{nk}^t\}^T \quad (6)$$

where measurements of an individual sensor n at time t , across k number of parameters, are denoted in the column vector as, s_n^t . The sensor measurements are normalized with an initial validated measurement at $t = 0$.

When all the sensors are initialized, validated and normalized, the IRNN-DNN algorithm itself is initialized. For each parameter j within the sensor i , calculate the variance σ_{ij}^2 over the window $\mathbf{W}$ as in (7):

$$\sigma_{ij}^2 = \frac{1}{m-1} \sum_{k=t-m}^{t-1} (s_{ij}^k - \mu_{ij})^2 \quad (7)$$

$$\mu_{ij} = \frac{1}{m} \sum_{k=t-m}^{t-1} s_{ij}^k \quad (8)$$

where μ_{ij} is the mean value of the parameter j in sensor i over the window $\mathbf{W}$ with size m .

The deviation, ΔS_{ij}^t , of the current measurement from its running previous window's mean, μ_{ij} , is given by

$$\Delta S_{ij}^t = S_{ij}^t - \mu_{ij} \quad (9)$$

$$C_{ij} = w_{ij} \times \Delta S_{ij}^t \quad (10)$$

where C_{ij} is a correction element in C_k^t , the correction matrix applied to the latest sensor data, S^t . C_{ij} applies the correction to the i^{th} sensor's j^{th} parameter.

The weight w_{ij} for each parameter in each sensor is inversely proportional to the variance

$$w_{ij} = \frac{\kappa_j}{\sigma_{ij}^2 + \epsilon} \quad (11)$$

where κ_j is some parameter specific tunable gain parameter, initially set to 1, σ_{ij}^2 is the variance and ϵ is a small constant added to prevent division by zero. Then:

$$\tilde{S}^t = S^t + C_k^t \quad (12)$$

where $\tilde{S}^t$, the matrix with corrected sensor values, is obtained by adding the correction matrix C_k^t to S^t .

The IVF algorithm is scalable and adaptable to varying sensor counts and parameters. It detects and corrects outliers early, improving data quality for ML. Unlike traditional filtering techniques, such as low-pass filters (LPFs) or Kalman filters (KFs), which require system-specific tuning and external data, the IVF operates without the need for pre-configuration, making it more adaptable. By applying a transparent signal processing technique, IVF ensures verifiable inputs, enhancing system reliability and aiding compliance with aerospace certification standards. Its traceable data treatment boosts transparency, critical for regulatory adherence before ML predictions.

Environment Classifier

The full composite IRNN-DNN model with one common LSTM and DNN is very large in size, with a large memory footprint, and is extremely difficult to run in real-time on low-power, lightweight embedded systems. To enable real-time execution on low SWaP, embedded systems, the authors developed environment and error-specific sub-models that run real-time on embedded microcontrollers. An ML environment classifier (EC) categorizes the operating environment type as open field, semi-urban, or urban. It selects the appropriate environment-specific RNN-DNN sub-model for optimal GPS corrections. This classifier also serves as a system parameter controller for subsequent IVF and EC operations. This approach reduces memory and computation demands, making real-time deployment feasible on low SWaP systems.

The environment classifier, $\mathcal{C}(\cdot)$, analyzes a sliding window of sensor data, called the data window, $\mathcal{W}$, to ascertain sensor-measurement reliability and environment. In this

study, a DNN was used as the classifier. Each instance of measurement is structured as a data frame $[S^t \tilde{S}^t]$ (refer to eq.(5) and (12)). Multiple data frames are combined to form $\mathcal{W}$, whose length is controlled by a pre-set, environment-specific numerical parameter, w_c . Then, $\mathcal{W}$ is a 3D matrix where data frames are stacked from the newest to the oldest:

$$\mathcal{W} = \{[S \tilde{S}]^{t_{w_c}}, [S \tilde{S}]^{t_{w_c-1}}, \dots, [S \tilde{S}]^{t_1}\}, \quad (13)$$

$$\mathcal{W} \in \mathbb{R}^{w_c \times 2n \times k}$$

where t_{w_c} is the latest data frame and t_1 is oldest data frame, and w_c is the length of the window. From each data frame, a difference matrix, ΔS , is constructed and evaluated against a predetermined threshold:

$$\Delta S^t = S^t - \tilde{S}^t \quad (14)$$

$$\tau = \begin{bmatrix} \vdots & \vdots & \vdots \\ \tau_1 & \tau_2 & \dots & \tau_n \\ \vdots & \vdots & \vdots \end{bmatrix} \quad (15)$$

where τ is the threshold matrix, where each column, τ_n , derived from historical observations and is parameter and sensor specific. Each GPS sensor's data is evaluated individually and assigned a reliability label. The GPS sensor data is discussed in the following sub-section of the paper. In this study, τ_n is set to $[\mu_1, \mu_2, \dots, \mu_k]^T$ (see (8)). A data frame is considered reliable if most of its columns are below the threshold.

$$Reliability([S \tilde{S}]^t) = \begin{cases} 1, & \text{if } \sum_{i=1}^k \mathbf{1}(|\Delta S_i| \leq \tau_i) \geq \frac{k}{2} \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

where $\mathbf{1}(\cdot)$ is an indicator function that returns 1 if the condition is true and 0 otherwise for k sensors. Then for each window $\mathcal{W}$:

$$\Delta \mathcal{W} = \{\Delta S^{t_{w_c}}, \Delta S^{t_{w_c-1}}, \dots, \Delta S^{t_1}\} \quad (17)$$

$$Reliability(\mathcal{W}) = \begin{cases} 1, & \sum_i^{w_c} Reliability(\forall \Delta S^t \in \Delta \mathcal{W}) \geq \tau_c \\ 0, & \text{otherwise} \end{cases} \quad (18)$$

where $\Delta \mathcal{W}$, the data window difference matrix, is constructed and evaluated against τ_c , a tunable threshold parameter. In this study, this threshold is set at $0.5w_c$. A data window is deemed reliable if most of its frames are reliable. Otherwise, then the latest data frame is discarded, and the next window is evaluated. If w_c consecutive data windows are unreliable, the algorithm is halted. If the data window is reliable, it is passed as input to $\mathcal{C}(\cdot)$; then:

$$\mathbf{y} = [Label, Reliability of Label] = \mathcal{C}(\mathcal{W}) \quad (19)$$

where $\mathbf{y}$, is the output of the neural network. By integrating data from all sensors, a single poorly performing sensor is

prevented from misleading the algorithm. This is important for ensuring the redundancy, and reliability needed for aerospace applications. Preliminary validation suggests that the classification accuracy is near 100%, with a few occasional misclassifications, though concerns around overfitting and optimization exist (see Fig. 3a).

RNN+DNN

The RNN+DNN model processes inputs within a structured three-dimensional matrix, $\mathcal{M}$, which encapsulates multi-sensor time-series data:

$$\mathcal{M}^{N \times 2k \times W} = [\tilde{\mathcal{S}}^k \quad \mathcal{C}^k], \mathcal{M} \in \mathbb{R}^{N \times k \times W} \quad (20)$$

where N represents the number of GPS sensors on the drone (with $N = 5$ in the current study), k signifies the number of monitored parameters per GPS (with $k = 11$ as the designated key parameters in this study), and W is the dynamically tunable window size corresponding to the number of sequential data points considered for each parameter. This allows the LSTM (a type of RNN model) to capture both immediate and delayed error effects while reducing memory footprint. The selection of the starting value of $W = 25$ is predicated on empirical observations of data indicating that a 2.5-second window typically includes sufficient data to generate counteracting error signals in an urban environment.

The input, normalized based on individual predictor characteristics, is flattened to a 2D matrix, Ξ , by $F(\cdot)$, and fed into an LSTM, $H_{RNN}(\Xi, \theta)$, which predicts multipath error contributions:

$$\Xi = F\left(\frac{\mathcal{M}}{\|\mathcal{M}\|_{col}}\right); \Xi \in \mathbb{R}^{(N \cdot W) \times P} \quad (21)$$

$$\epsilon_{temp} = H_{RNN}(\Xi, \theta) \quad (22)$$

where ϵ_{temp} is identified temporal GPS error at the instant of measurement. Subsequently, these predictions are processed through a DNN model, $H_{DNN}(x, \theta)$, that works on identifying the instantaneous aperiodic and DC errors in GPS, ϵ_{DC} , as shown in the equation below.

$$\epsilon_{DC} = H_{DNN}\left(\left[\left(\frac{\mathcal{M}}{\|\mathcal{M}\|_{col}}, \epsilon_{temp}\right)\right], \theta\right) \quad (23)$$

where θ are a set of parameters that include the associated weights for the input, connected, and output layers of the model, along with any associated bias values as learned by the model during the training stage.

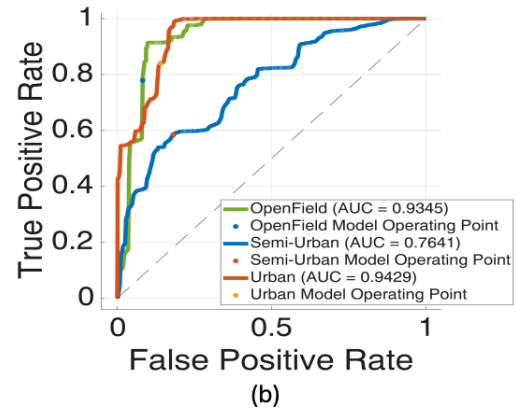
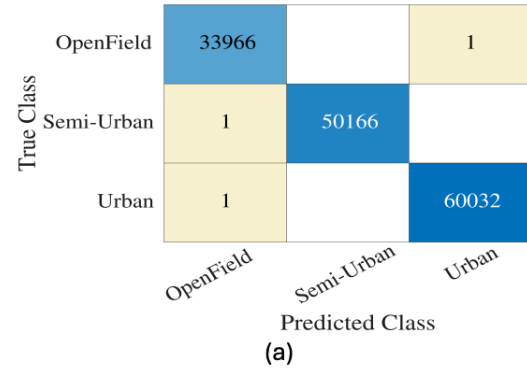


Fig. 3. Environment Classifier performance. (a) Confusion matrix showing classification accuracy across OpenField, Semi-Urban, and Urban environments. (b) ROC curves with AUC values indicating strong performance in OpenField (0.9345) and Urban (0.9429), but lower in Semi-Urban (0.7641).

The final RNN-DNN neural network models as trained and evaluated are small enough to be deployed on embedded computers like STM32H747 (Arduino 2021) for real-time processing. Early testing has revealed that each RNN-DNN takes ~33 Kbits of memory and three sub-models can be run concurrently on an embedded microcontroller (Fig. 4) at 10 Hz. Further optimization and additional testing of the algorithm on device are ongoing. The computational load of the proposed IRNN-DNN model was estimated based on the number of parameters and the inference frequency. Each sub-model contains approximately 1,000 parameters, corresponding to a memory footprint of roughly 33 kilobits (~4 kilobytes) assuming 32-bit floating-point representation. Three sub-models operate concurrently, resulting in a total parameter count of approximately 3,000. Each inference involves one multiplication and one addition per parameter, yielding an estimated 6,000 floating-point operations per inference cycle across all sub-models. At an operational frequency of 10 Hz, this results in a total computational demand of approximately 60,000 floating-point operations per second (FLOPS). This computational load is compatible with typical mid-range microcontrollers such as

the STM32H747, enabling real-time deployment without dedicated acceleration hardware.

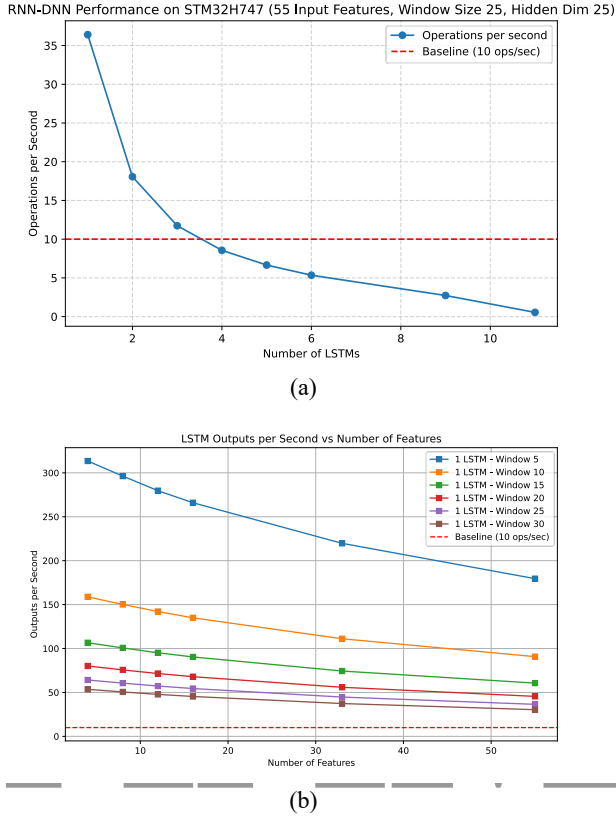


Fig. 4. RNN-DNN performance on STM32 embedded microcontroller. (a) Processing time vs. number of LSTMs, showing that the system can achieve 10Hz operation with three RNN-DNN sub-models running at once. (b) RMSE vs. number of features, indicating headroom for feature optimization and future applications.

Error Correction Module

An error correction module employs the inverse haversine equation to generate corrected coordinates, based on predicted error, labeled 'Corrected GPS Data'. This data is compared with ground truth GPS data to validate accuracy. The output of the error comparison function, $\mathbf{Y}_\epsilon$, is 3 element vector:

$$\mathbf{Y}_\epsilon = \langle n_\epsilon \quad e_\epsilon \quad h_\epsilon \rangle^T \quad (24)$$

where n_ϵ is the north error (primarily influenced by the error in the latitude component), e_ϵ is the east error (primarily influenced by the error in the longitude component) and h_ϵ is the altitude error.

In summary, the IRNN-DNN algorithm enhances GPS accuracy by leveraging multiple spatially separated antennas on a drone to detect and correct multipath errors. Each GPS receiver has its receiving antenna placed at a different

location on the drone. Consequently, the satellite-obstacle-receiver geometry is slightly different for each sensor. The IRNN-DNN algorithm uses these minimal differences to identify if an obstacle is present and its spatial relation to the drone. The LSTM and DNN know the relative position of the sensors to each other, and they study how each GPS receiver's performance changes over time to identify and solve a system of temporal-spatial equations to identify the characteristics of expected multipath error components based on historical matching. The LSTM network uses rapid and successive GPS measurements to track and encode changes in each sensor's performance. The DNN uses statistically significant temporal and spatial variations in the reported positions between GPS sensors to mitigate errors. The IVF ensures that the sensors feed reliable data to the model, and changes in the sensor's reliability are known to the other components of the algorithm.

Experimental Setup and Dataset

Based on well-established performance characteristics (Ford 2023; Alexović et al. 2023; De Angelis and Giulietti 2023), the Holybro X500 V2 drone (Holybro 2023) was chosen for this study. The study isolates the satellite-obstacle-receiver geometry and multipath effects, rather than drone movements by following well-established static receiver methodologies (Jumaah et al. 2018; Suzuki et al. 2020b; Suzuki et al. 2020a). Introducing dynamic motion would add other confounding variables (e.g. inertial drift, aerodynamics, flight controller noise...)

To simulate realistic hovering conditions, the drone is mounted to a tripod with a ball joint. The ball joint permits minor multi-axis movement (on the order of a few centimeters) and rotates up to 90° in the x and y-axis (parallel to the ground plane), and full 360° rotation on the z-axis (perpendicular to the ground), while remaining power and position stabilized at 29-35% throttle. This simulates the drone hovering exactly 5 feet above the ground over a fixed location, like a drone would when delivering a package. The drone corrects for small gusts of wind on its own and is rotated until the front of the drone faces east. This setup ensures the safe operation of the drone in flight-restricted locations and serves as a valuable step to get certification for full flight tests in the future. Fig. 5 depicts the setup used to conduct the study. It should be noted that during all tests, UAV altitude remained constant, and no deliberate vertical maneuvers were performed. Thus, data primarily captured horizontal spatial errors.

Five MTK3339 (MediaTek 2016) GPS receivers (1A, 1B, 1C, 2A & 2B) each with its own dedicated 28dB active gain antenna, called sensors henceforth, are used for

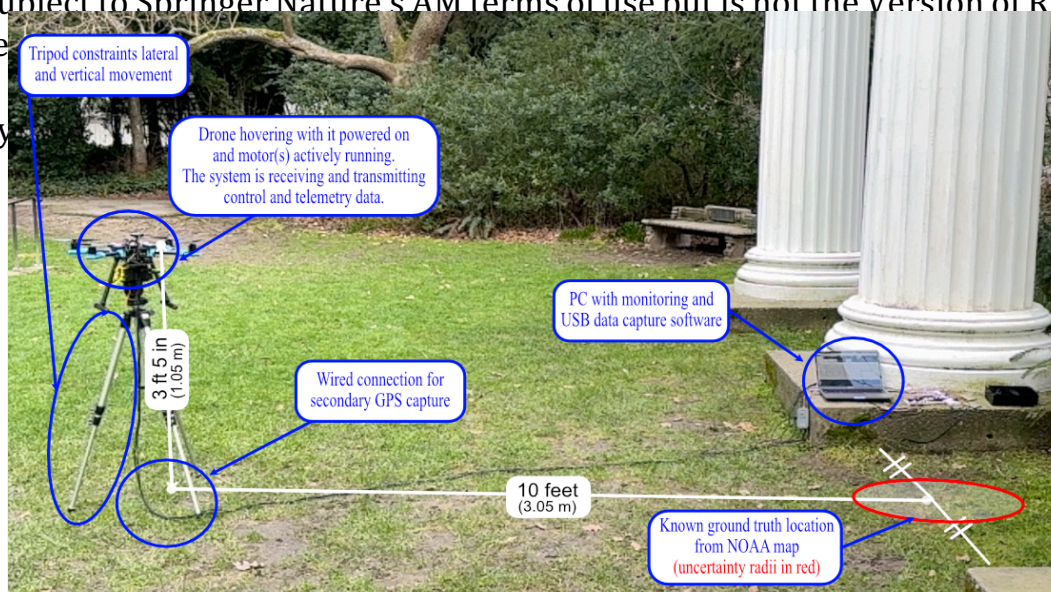


Fig. 5. Picture of test setup in situ. The drone is mounted on a tripod at a fixed height of 5 feet, with its propellers spinning at full power. A data tether ensures reliable transmission of data to a laptop computer running a data capture program. The entire setup is positioned 10 feet from the central column, which has precisely known coordinates.

data acquisition. A breakout board is used to connect the sensors to a PRJC Teensy 4.1 microcontroller (2021) which parses and structures the output messages from the receivers. The GPS sensors are arranged in a square-pentagonal pattern. Sensors 1A, 1B, 2A, and 2B anchor the corners of a square with 140 mm sides, and sensor 1C is located at the front of the drone 75 mm from the geometric center of the drone, equidistant between 1A and 1B (Fig. 6.) The sensors

capture, processes and translates L1 satellite radio signals using a manufacturer specific, black box implementation of the SPP algorithm. Other satellite constellations are not used for this study as the governing body, the Federal Aviation Administration (FAA), only authorizes GPS system for airborne navigation in US airspace (FAA 2014).

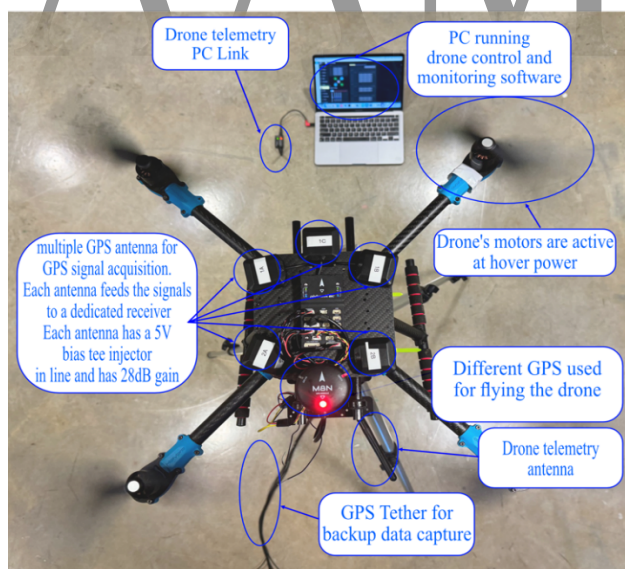


Fig. 6. UAV Ground Station Integration Test with experimental GPS DAQ Setup on UAV. This image captures a UAV secured to a tripod, with propellers engaged to emulate in-flight dynamics and signal environment. A wireless transmitter-receiver, visible next to the computer, relays telemetry data in real-time, facilitating direct command transmission and live data monitoring to replicate true flight conditions for rigorous system validation. The antennas of the test system, marked with white labels, are positioned on the drone's extremities to ensure wide sky visibility and accurate signal reception

In contrast to studies that focus on manipulating raw PSR data (Andert et al. 2013; Kanhere et al. 2022; Bai et al. 2022; Grenier et al. 2023), IRNN-DNN highlights the utilization of National Marine Electronics Association (NMEA) (2002) data as a standardized, economical, and more accessible alternative. This approach builds upon previous work and ensures compatibility and interoperability across various GPS devices (Bao et al. 2022; Jagiwal and Shah 2022; Ladino and Sama 2024; Ramavath and Perumalla 2024). Processed NMEA messages ('Raw GPS' data), were collected and reported in real-time at 10 Hz, with sensors configured to calculate from scratch and report a new GPS location fix once every 0.1 secs, ensuring real-time satellite data processing for SPP with no repetition of unresolved GPS fixes. Table 2 describes the NMEA 0183 messages gathered and how they were used for this study. The microcontroller parses 55 parameters, across the 5 sensors, including reported position,

Dilution of Precision (DOP) values, speed, altitude, satellite count(s), fix type(s), magnetic variance, and antenna properties, and is then used to train the IRNN-DNN model. Fix type in the NMEA messages refers to the quality and accuracy of the GPS position fix. In this study, only valid SPP based GPS fixes (type 1 or 2) were considered. Wide Area Augmentation Services (WAAS) augmented data were included where available. All post post-processed or simulated (3-8) were excluded or not collected. Additionally, the data sets include the reported dilution of precision (DoP) value(s); the type of antenna used for the fix (0-ceramic patch, 1-external, 2-active); the number and IDs of visible satellites and their ranges, calculated receiver speed, altitude and magnetic variance reported was part of collected parameters. While satellite ID and reported pseudorange were collected but were excluded from IRNN-DNN training, instead were used for post-training validation and monitoring.

Table 2. National Marine Electronics Association (NMEA) message types, descriptions, and relevance to study

NMEA message	Description	Relevance to study
GGA	Global Positioning System Fix Data: Provides latitude, longitude, altitude, and fix quality.	HIGH. Essential for gathering GPS parameters. Used in ML training
GSA	GPS DOP and Active Satellites: Provides Dilution of Precision (DOP) and the satellites used for navigation.	HIGH. Essential for assessing GPS quality. Used in ML training
GSV	Satellites in View: Describes satellites in view, including IDs, elevation angles, azimuths, and signal strengths.	HIGH. Used to understand satellite geometry. Only satellite count was used in ML training
RMC	Recommended Minimum Navigation Information: Includes time, date, speed/course over ground.	HIGH. Used for navigation data integration. Used in ML training
GRS	GPS Range Residuals: Provides information about the residuals in the range measurements	MEDIUM. Used for GPS monitoring. Not used for ML training.
GST	GPS Pseudorange Noise Statistics: Provides statistics about the pseudorange noise	LOW Not used for ML training. Secondary monitoring

Fig. 8 illustrates the hardware and data architecture of the proposed enhanced GPS localization system. The 'Raw GPS' data is processed in the flight computer. MATLAB (Mathworks 2023) is used on a desktop PC to train and test the models with live flight data. The PC is used as a stand-in for the flight computer for rapid iteration testing.

Environment and Test Location

For the study, 5 locations near the University of Washington: three urban, one semi-urban, and one open-field site (control) were selected. The test locations were classified using the open sky metric (Deng et al. 2022), shown in Fig. 7, and the characteristics described in Table 3. These locations were selected to reflect the real-world restrictions placed on UAVs, including near no-fly zones near air/seaports, and dense urban areas, where GPS uncertainty poses a risk to traffic and other infrastructure. Testing unrestricted locations would not have provided a meaningful evaluation of the algorithm for UAM due to a fundamental constraint: UAVs cannot operate safely without reliable GPS, yet GPS accuracy can't be validated without flight testing. Our controlled setup at these restricted locations ensures confidence in the proposed algorithm's reliability, supporting the case for obtaining a testing license for full flight studies.

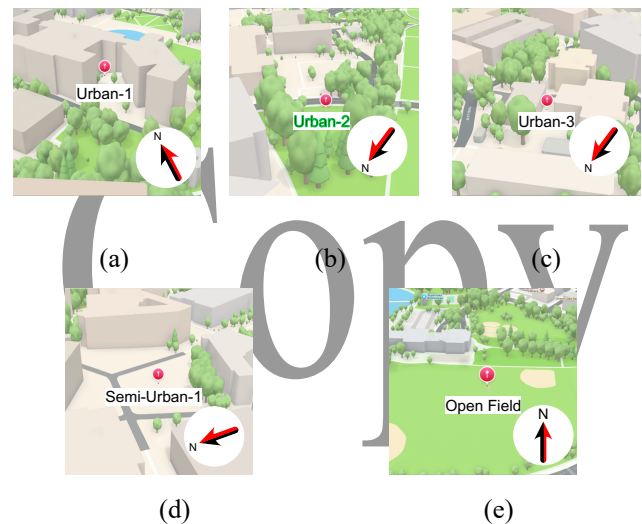


Fig. 7. UAV testing sites near the University of Washington: (a) Urban-1, (b) Urban-2, (c) Urban-3, (d) Semi-Urban-1, and (e) Open Field.

To minimize the impact of other changing environmental confounding variables like orbital deviations, ionospheric effects, wind, and drift, the ground truth values were calculated not using GPS data but using survey maps. 2D trilateration with National Geodetic Survey (NGS) map, National Oceanic and Atmospheric Administration (NOAA) geolocation markers, and monuments/structures with defined positions accurate to within 15 centimeters, were used to determine ground truth (U.S. Geological Survey 2018). The test drone's actual position is then mathematically calculated based on measured offsets from the known reference position as shown in Fig. 5.

Table 3. Key attributes of locations tested

Location	Key Error Type and Contributing Factors
Urban-1	Omni-directional obstructions with no soft reflectors
Urban-2	Significant obstruction on one side with multipath errors
Urban-3	Parallel, aligned obstructions with significant multipath error
Semi-Urban-1	Distant omni-directional hard reflectors with varying soft reflectors contributing to multipath error
Open Field	Control environment with minimal multipath errors

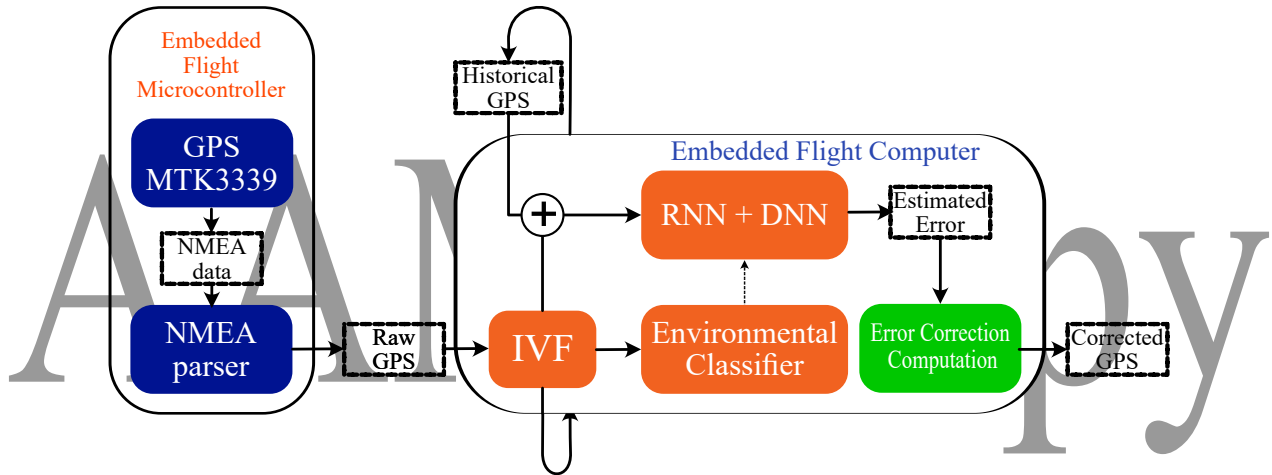


Fig. 8. Block diagram illustrating the architecture of an Embedded Flight Microcontroller integrated with a Flight Computer for enhanced GPS data processing. Data flows from the GPS receiver through the NMEA parser to the flight computer, where it undergoes environment classification, inverse variance filter, hybrid neural network processing, and error correction to produce accurate and reliable GPS data.

Evaluation Metrics

To comprehensively evaluate the performance of GPS localization for UAVs, this study employs five key metrics: residual magnitude error (ϵ_d), angular error (θ), altitude error (e_{alt}), ellipsoidal uncertainty (EU) error ($\|Y_e\|_2$), and dynamic accuracy index (DAI). These metrics different aspects of accuracy and reliability in GPS (Table 4.)

Residual magnitude error represents the 2D horizontal distance between the GPS-reported position and the actual ground truth position, while angular error measures the bearing difference between the estimated and actual positions (Fig. 9 (a)). Together they define the 2D residual error vector. Angular error is used to detect systemic deviations in reported positional offsets, which may indicate the presence of specific obstacles affecting signal propagation in

specific directions. This directional component of the error helps in understanding whether multipath interference or signal obstructions are influencing GPS accuracy from specific directions. For example, if obstacles are found in the East-West directions (Urban-3 location in Fig. 7(c)), angular errors will be higher in that direction compared to the North-South direction. These values are calculated using the inverse haversine formula. The Residual Altitude error, e_{alt} , quantifies the difference in altitude between the GPS reading and the ground truth (Fig. 9 (b)). The EU error represents the Euclidean norm $\|Y_e\|_2$ of the horizontal and vertical error and provides a 3D positional uncertainty measure.

Table 4. Performance Metrics and Evaluation Criteria for GPS Error Correction.

Metric	Impact on UAV Operations	Evaluation Criteria
Residual Magnitude Error (ϵ_d)	High residual magnitude errors directly affect a UAV's ability to navigate accurately	Should be within 3-meter radii without any specific directional bias
Angular Error (θ)	A low angular error improves path-following and route planning	
Altitude Error (e_{alt})	Accurate altitude information is critical for UAVs flying at varying heights, especially when operating near obstacles or in airspace corridors. Altitude residuals were monitored for completeness; however, since UAV altitude was held static during tests, dynamic vertical behavior was not a primary evaluation criterion.	Should be within ± 3.81 meters
Ellipsoidal Uncertainty Error ($\ Y_e\ _2$)	A low EU error ensures that combined positional errors do not compromise safety or result in collisions	Should be under 10 meters
Dynamic Accuracy Index	A lower DAI signifies that the system maintains high localization accuracy while processing data at high speeds	Lower value indicates better performance

All error metrics are reported using two measures: Mean error (μ) and RMSE. Reporting both metrics provides a more comprehensive assessment of the algorithm. The equations used are as follows:

$$\mu = \frac{1}{N} \sum_{i=1}^N (\epsilon_i - \hat{\epsilon}_i) \quad (25)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\epsilon_i - \hat{\epsilon}_i)^2} \quad (26)$$

where ϵ is the error metric's ground truth value, $\hat{\epsilon}$ the estimated error and N is the total number of error points predicted by the algorithm. μ quantifies if there is a systemic bias in GPS corrections, while RMSE captures the overall accuracy.

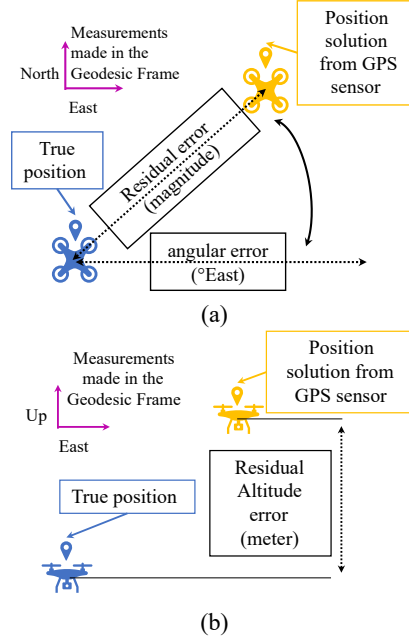


Fig. 9. GPS error metrics defined. (a) Residual error, presented as non-negative, pairs with angular error in radians east to define the error vector direction. (b) Altitude error, in meters, with positive values indicating a reported position above the true ground level.

The Dynamic Accuracy Index (DAI) is a new metric introduced in this paper to provide a more comprehensive measure of GPS localization performance. DAI is a critical metric because it addresses the dual challenge of achieving high positional accuracy and frequent updates—both essential for UAV operations. A lower DAI value indicates superior performance. DAI is defined as the ratio of mean accuracy (in meters) to the frequency of position reporting (in Hz):

$$DAI = \frac{\text{Mean Accuracy}}{\text{Frequency of Position Reports}} \left[\frac{m}{Hz} \right] \quad (27)$$

Results and Discussion

This section evaluates the IRNN-DNN model's performance in two parts. The first part reviews unaided GPS performance, identifying error patterns that can be used to improve localization. The second part examines the IRNN-DNN algorithm's ability to reduce GPS errors.

Baseline Performance

To establish a performance baseline, GPS data was collected in open-field, semi-urban, and urban environments without correction algorithms.

A spatial analysis using polar plots (Fig. 10) reveals that errors in the open-field environment are tightly clustered around the true position, indicating minimal directional bias. The GPS fix in these conditions include WAAS

augmentation signal, though these were sparsely reported by the receiver. Majority of the fixes (95%+) used only SPP technique and other tested locations had no WAAS fixes. This contrasts with semi-urban settings, where the error distribution becomes more elliptical with no WAAS augmented fixes, suggesting directional biases, lower accuracy and greater variability.

In semi-urban environments (Fig. 10(b)), the data spread becomes more elliptical, indicating a directional bias where errors increase in certain azimuth directions due to building reflections. This increased spread in error is confirmed by the altitude time series in Fig. 11 (b), where altitude fluctuations are larger compared to the open-field scenario. Sensor 2B initially reports errors exceeding 100 meters before stabilizing, while sensor 2A shows an initial deviation of around -46 meters followed by an overshoot to +46 meters before converging.

Urban environments present the most significant challenges to GPS accuracy, as illustrated by the wide residual spread in Fig. 10(c). Directional biases are prominent due to obstructions causing severe multipath reflections. The altitude error plot in Fig. 11 (c) further emphasizes this, with pronounced fluctuations indicating complex signal behavior. A multifaceted low-frequency noise component is observed, with signals exhibiting similar patterns across different sensors but not in other environments, including a periodic sinusoidal oscillation approximately every 90 seconds. This periodic pattern suggests that some errors are not random but influenced by recurring environmental factors, which opens the potential for predictive modeling. Within urban environments, obstructions significantly increase error variability. Examining Fig. 15 (a), Urban-1, with omnidirectional obstructions, showed the highest error, with some outliers exceeding 300 meters. Urban-2, characterized by obstruction on only one side, demonstrated improved performance but retained notable residual errors. Urban-3, with urban canyon obstruction geometry, exhibits poor performance, with error patterns closely linked to obstruction geometry. These observations establish that obstructions strongly affect GPS accuracy, with error variability closely linked to environmental geometry.

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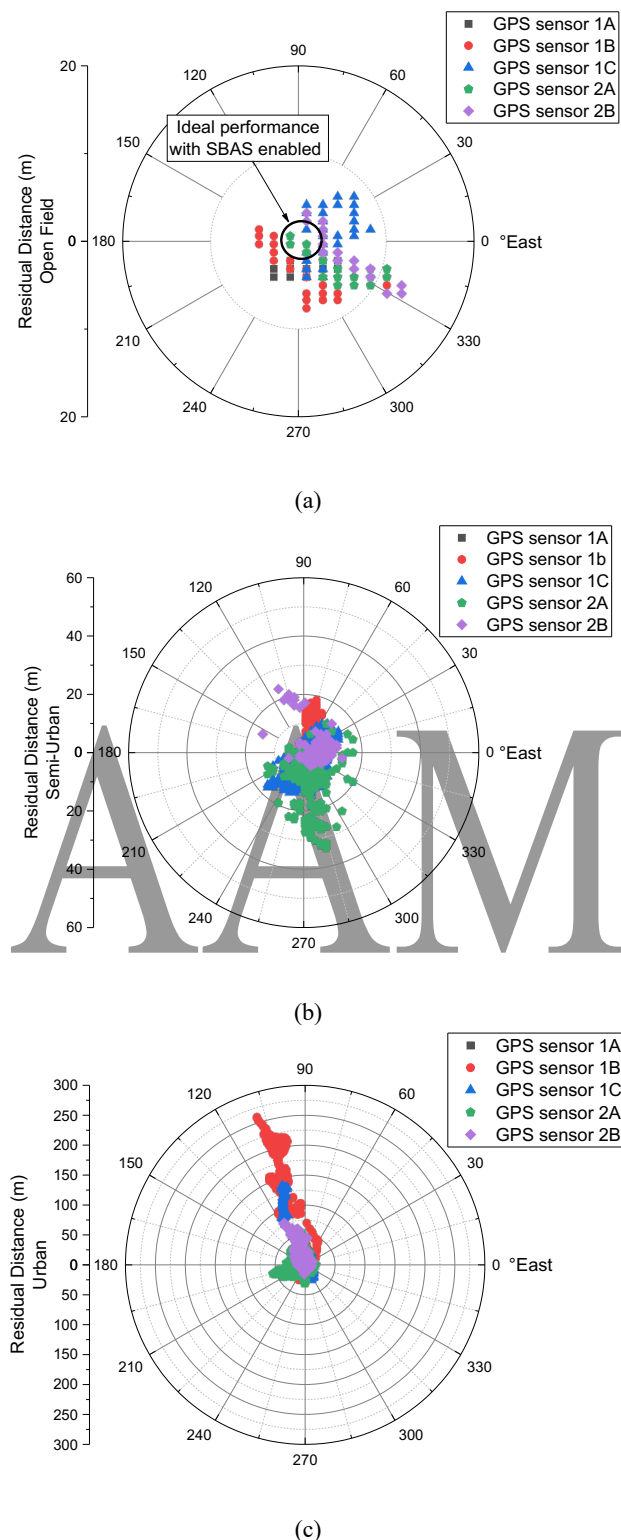
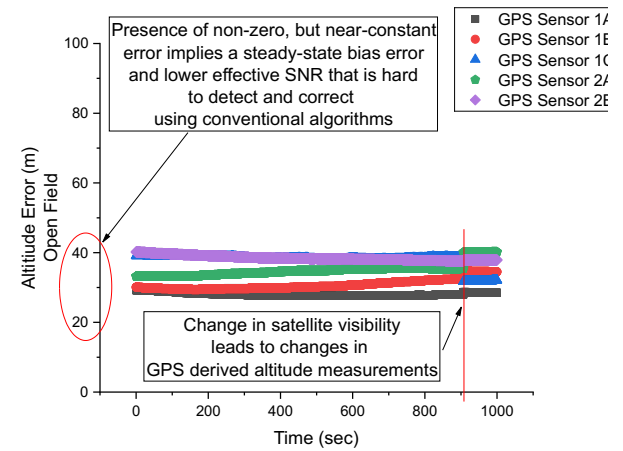
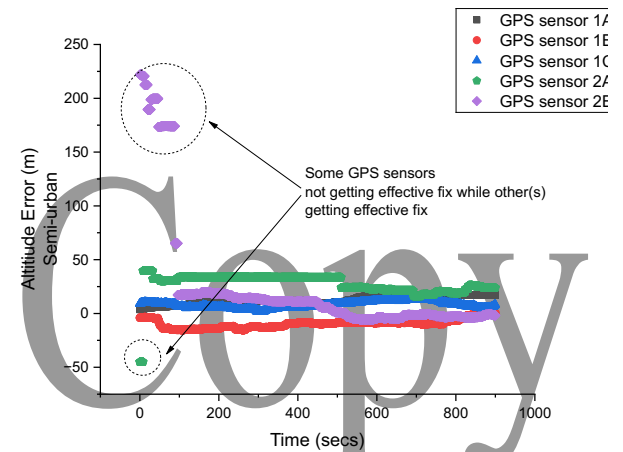


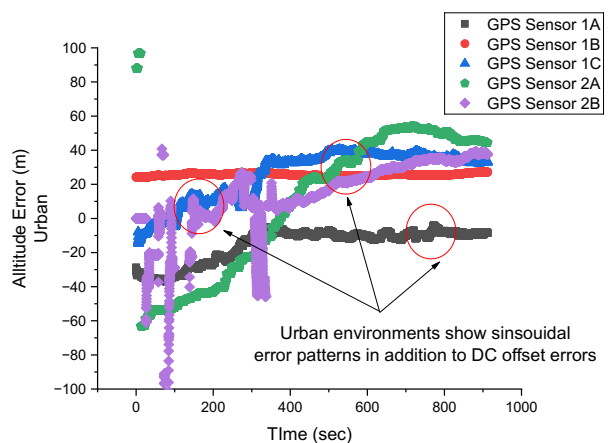
Fig. 10. Baseline residual offset errors recorded by five GPS receivers (GPS 1A, GPS 1B, GPS 1C, GPS 2A, and GPS 2B) in different environmental conditions: (a) Open Field, (b) Semi-Urban, and (c) Urban environments. The top row of each panel displays polar plots that represent the residual error in meters as a function of azimuth angles, illustrating how GPS accuracy varies with satellite geometry across different environments.



(a)



(b)



(c)

Fig. 11. Baseline altitude offset errors recorded by five GPS receivers (GPS 1A, GPS 1B, GPS 1C, GPS 2A, and GPS 2B) in different environmental conditions: (a) Open Field, (b) Semi-Urban, and (c) Urban environments.

Patterns of interest in GPS Error Signals.

To analyze signal behavior in urban environments, Fig. 13 examines angular, magnitude, and altitude errors from three GPS sensors over 20 hours, sampled at 10 Hz. Only 3 GPS sensors (1A, 1B, & 1C) are used instead of all 5. The extended sampling duration (20 hours) at high resolution generated vast amounts of data points, and including all 5 GPS sensors introduces excessive redundancy without any additional meaningful insights. Additionally, reducing the sensor count helped optimize the computational efficiency.

Table 5. Key attributes of sensor configurations tested

Parameter Reported	RMSE 3-Sensor Configuration	RMSE 5-Sensor Configuration	P-value
Localization Parameter(s)	0.257	0.268	3.2E-23
DOP Values (s)	0.309	0.260	4.8E-13
Satellite Visibility	0.322	0.339	4.5E-21
Reported Navigation Data(s)	0.057	0.057	4.5E-32
Fix Time	0.136	0.140	2.5E-28

Table 5 shows that the RMSE values of the parameters used by the IRNN-DNN model are relatively similar. The positional parameters (L2-norm of latitude, longitude, and altitude) 's RMSE values between three sensors (1A, 1B, & 1C) and 5-sensor (1A, 1B, 1C, 2A, & 2B) are 0.257 m³ and 0.268 m³ respectively with a p-value (paired T-test) of 3.2E-23. This indicates that the difference is not statistically significant ($p \geq 0.05$). Confirming that the integrity of the error pattern analysis is not compromised by using fewer sensors. Similar patterns hold for other parameters (see Table 5 & Fig. 12.) The selection of these three specific sensors was based on their relative positions, and signal stability. For short-term events, all 5 GPS sensors were used to maximize available data, maximize resolution, and detect finer-scale discrepancies.

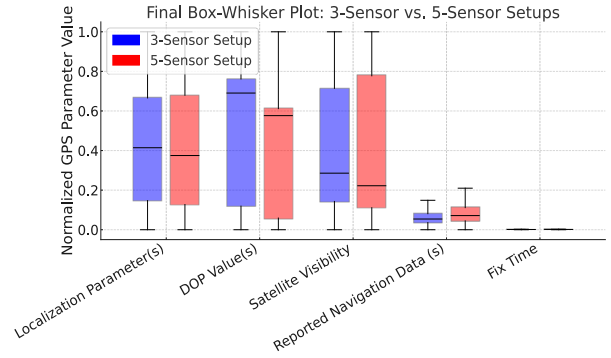


Fig. 12. Box-whisker plot of GPS parameter in 3-sensor and 5-sensor setups. The Localization Parameter represents the L2 norm of latitude, longitude, and altitude, while the DOP Value is the L2 norm of HDOP, VDOP, and PDOP. The comparison demonstrates that reducing the number of sensors does not introduce significant variations in these key positioning metrics, validating the use of a 3-sensor configuration.

The angular errors in Fig. 13 (a) display notable fluctuations, with periodic spikes attributed to shifts in satellite geometry and urban obstructions. These spikes indicate the sensors' sensitivity to abrupt changes in the signal path, with variations between sensors suggesting differences in their signal processing algorithms. Averaging sensor errors doesn't necessarily reduce the error, suggesting that increasing sensor count alone may not improve localization accuracy.

Magnitude errors, as seen in Fig. 13 (b), occur in bursts, likely due to transient environmental factors like moving obstacles or changes in satellite-obstacle geometry. Despite the spatial proximity of the sensors, their errors are not phase-correlated at higher frequencies, implying that high-frequency noise (1-0.1 Hz) and low-frequency noise (0.1-0.001 Hz) require separate correction approaches. These bursts can reach deviations exceeding 50 meters, reflecting the challenges of maintaining consistent GPS accuracy in urban settings.

Fig. 13 (c) shows altitude errors exhibiting periodic oscillations, suggesting that low-frequency patterns are present and potentially predictable. While systematic errors indicate that less frequent sampling could be effective for modeling these trends, large datasets are necessary to capture long-term signal behavior accurately.

The spatio-temporal patterns in GPS errors highlight the need for an adaptive correction model handling spatial and temporal dynamics. The correlation between satellite-obstacle geometry, periodic signal fluctuations, and low-frequency noise components suggests the IRNN-DNN model is suitable.

Performance of Proposed Algorithm

1000 seconds of test data were used to evaluate the performance of the algorithm. The IRNN-DNN model showed strong performance in meeting drone system requirements in environments with degraded GPS signals. The mean error was reduced to below 3 meters in all test locations (Table 6). The reduced mean highlights the model's ability to improve GPS localization. Before applying the algorithm, ϵ_d ranged from 10.26 to 29.96 m. The algorithm reduced the mean error from 1.71- o 2.43 meters. Similarly, the ϵ_{alt} and the EU error shows significant reductions in mean error. The consistent reduction in RMSE values for all errors suggests that the IRNN-DNN model effectively minimizes the error in GPS.

Table 6 also highlights another important trend. The RMSE values and mean values are very close to one another in almost all metrics (Semi-Urban 1's ϵ_{alt} is only exception) after the application of the model. For example, Urban-1's ϵ_d has a mean of 14.73 m and a RMSE of 19.56 m, but after correction, both mean and RMSE converged to 2.43 m indicating that the algorithm not only reduces average error but also the variance in performance. ϵ_{alt} and EU error follows a similar trend, demonstrating a stabilizing effect.

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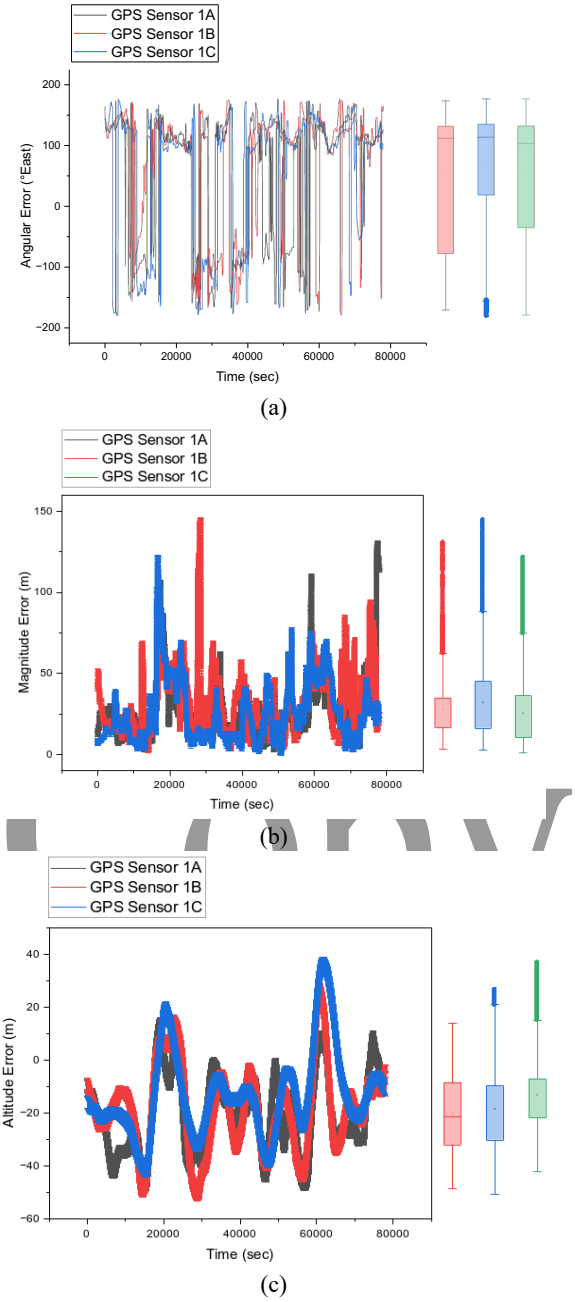


Fig. 13. Angular, magnitude, and altitude errors of three GPS sensors in an urban environment over 20 hours at 10 Hz. a) Angular error shows frequent fluctuations and periodic spikes caused by satellite geometry and urban obstructions, with notable sensor variability; (b) Magnitude error displays sporadic drift and sudden deviations, reflecting environmental impacts and higher variance; and (c) Altitude error reveals a periodic pattern with sinusoidal oscillations, suggesting cyclical satellite configurations. These findings highlight exploitable frequency and spatio-temporal patterns for GPS error correction.

This closeness between the mean and RMSE suggests that outliers and large error fluctuations have been effectively suppressed. The following subsections analyze the model's performance across the evaluation metrics in detail.

Residual Distance and Angular Error

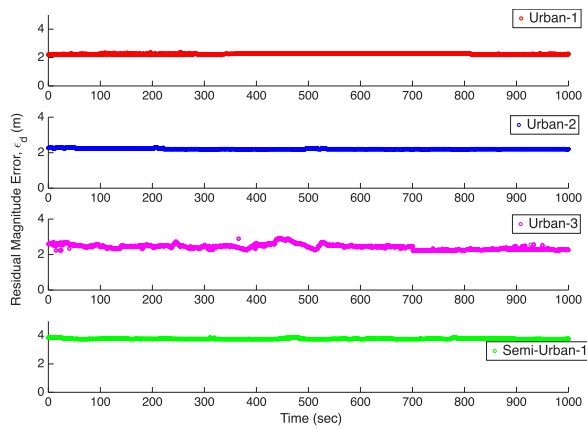


Fig. 14. Residual magnitude error post-correction for four different urban and semi-urban scenarios for the first 900 seconds of algorithm running. Each plot illustrates how the magnitude error varies over time for the corresponding scenario, highlighting the capability of the algorithm to correct magnitude errors.

IRNN-DNN improves performance, is generally stable, and minimizes fluctuations (Fig. 14). It adapts well to environmental changes, showing resilience during shifts in satellite visibility in the 1000 seconds of data, with limited performance deterioration. This suggests effective filtering of inaccuracies caused by reflected satellite signals. Conventional methods like ray tracing achieve similar accuracy, but not in real-time (Lv et al. 2021b).

After applying the IRNN-DNN algorithm (Fig. 15 (b)), residual positional errors are concentrated around the center, indicating a marked reduction in both angular and magnitude errors. This correction suggests that the model effectively mitigates noise and multipath effects, enhancing localization accuracy. The more focused distribution and the formation of structured arcs imply that the model dynamically adapts to satellite-obstruction-receiver geometry factors, thereby reducing systematic errors. Additionally, the presence of fewer extreme outliers demonstrates the robustness of the model.

Examining different environments establishes that obstructions strongly affect GPS accuracy, with error variability closely linked to environmental geometry. In Urban

Location 1, which is surrounded by three close reflectors and has limited sky visibility along one axis, pre-correction errors are significant in multiple directions due to signal reflections. After IRNN-DNN correction, errors along the East-West (E-W) axis, previously the worst-performing, significantly decrease. This location also demonstrates the lowest variance, indicating high correction accuracy. Similarly, in Urban Location 3, which is enclosed by reflectors on parallel sides with severely constrained satellite visibility on the E-W axis, the model achieves high post-correction precision, especially along the E-W axis. In contrast, Urban Location 2, with only a single reflector on the South-West (S-W) axis and generally good visibility along the North-South (N-S) axis, performs less optimally along the N-S axis but shows improved results on the E-W and S-W axes, underscoring the model's ability to correct errors in geometrically complex environments with obstructions.

In Semi-Urban Location 1, although the IRNN-DNN model continues to reduce errors, it exhibits greater variance in performance compared to urban environments. This supports the idea that the model's correction is influenced by the geometric configuration of obstacles. If the correction were purely statistical, similar accuracy would be observed across all settings. Instead, the increased variability in errors in semi-urban areas, despite fewer obstructions, suggests that the model learns and adapts based on geometry-specific factors affecting signal propagation, rather than merely fitting data trends. The relatively poorer performance at Urban Location 2, which has fewer obstructions, further supports this hypothesis, as it contains only one reflective surface.

A comparison between Urban-3 and Semi-Urban-1 further clarifies these dynamics. Urban-3, with its consistent reflection patterns and restricted sky visibility, provides stable signal conditions that allow the model to achieve high correction accuracy. Conversely, Semi-Urban-1's variability—affected by factors like changing weather and human activity—indicates that the model is not simply performing statistical fitting but is actively learning from the obstruction geometry and real-time multipath effects. This is important as it provides a foundation for physically explaining the model's performance using ray tracing.

Table 6. Statistical measures of GPS accuracy before and after the application of the IRNN-DNN algorithm on test data. ϵ_d is the Residual Magnitude Error, ϵ_{alt} is the Altitude Error and $\|Y_\epsilon\|_2$ is Ellipsoidal Uncertainty Error.

Location	Statistical measure(s) before						Statistical measure(s) after					
	ϵ_d (m)		ϵ_{alt} (m)		$\ Y_\epsilon\ _2$ (m)		ϵ_d (m)		ϵ_{alt} (m)		$\ Y_\epsilon\ _2$ (m)	
	μ	RMSE	μ	RMSE	μ	RMSE	μ	RMSE	μ	RMSE	μ	RMSE
Urban-1	14.73	19.56	50.48	50.49	52.59	54.05	2.43	2.43	3.35	3.87	4.14	4.58
Urban-2	17.66	21.05	51.59	51.71	54.53	55.86	2.79	2.92	5.89	6.29	6.51	6.93
Urban-3	10.26	14.19	48.00	48.00	49.08	50.06	2.33	2.33	2.30	2.75	3.27	3.59
Semi-Urban-1	29.96	34.72	60.00	60.00	67.07	69.33	1.71	1.81	0.21	1.46	1.73	2.32

Altitude Error

Fig. 16 shows the residual altitude error after applying the IRNN-DNN correction. Notably, the altitude error range is significantly reduced from -50 to 100 meters pre-correction to -3 to 10 meters post-correction. However, some variability remains, with errors fluctuating even during stationary UAV hover, indicating that the model's altitude predictions are not entirely stable. This residual instability, even during stationary UAV hover, reflects the model's limitations in vertical error prediction, consistent with the fact that the experimental setup maintained a constant drone height. Thus, altitude corrections observed in this study are incidental rather than the result of systematic model optimization.

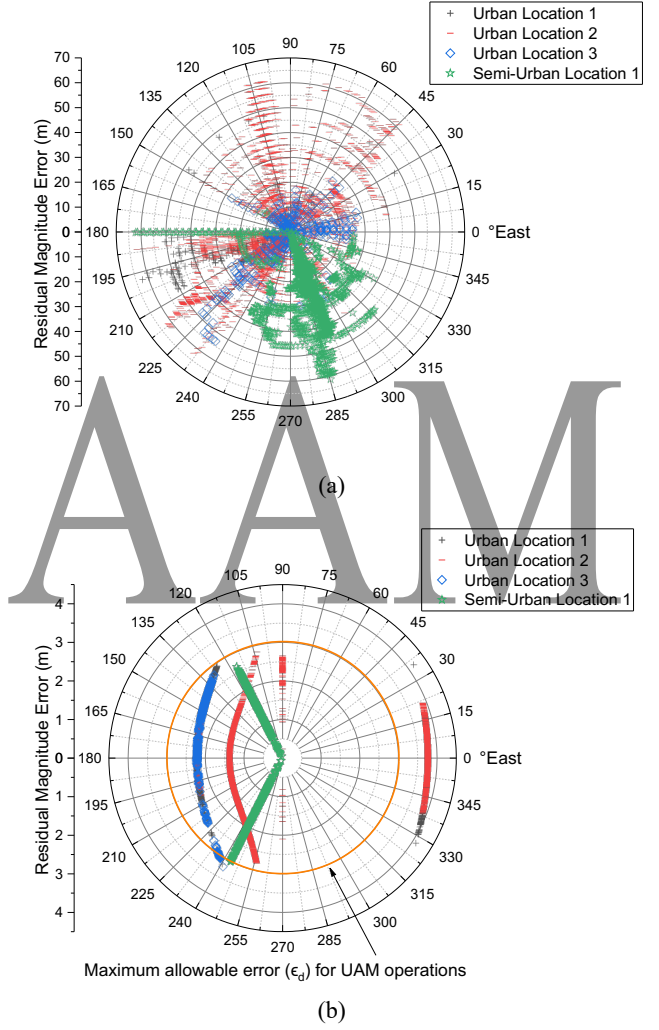


Fig. 15. GPS localization performance: (a) before and (b) after applying the proposed IRNN-DNN model. The radial axis represents the magnitude of the residual error, while the angular positions correspond to the error direction in degrees east.

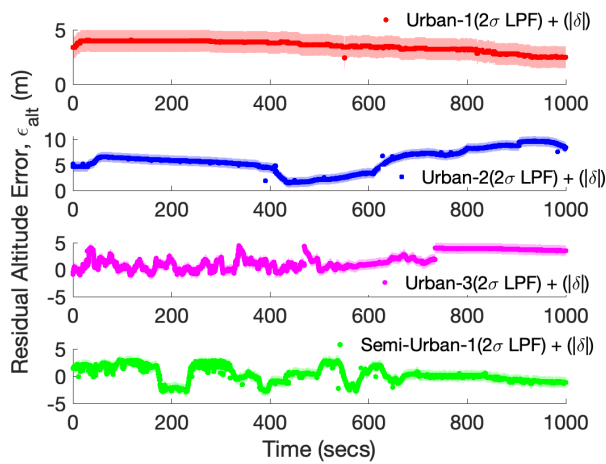


Fig. 16. Residual altitude error post-correction for four different urban and semi-urban scenarios. Each plot illustrates how the altitude error varies over time for the corresponding scenario, highlighting the capability of the algorithm to correct altitude errors.

A consistent over-correction of 10 meters across various scenarios was observed, indicating model bias and inadequate training parameters. To enhance performance isolation, this offset is adjusted, acknowledging that additional training and more data may alleviate overfitting. The model was retrained with the same parameters employed for magnitude correction. Although the model achieves altitude errors below the critical 3.81-meter threshold in some cases, demonstrating acceptable accuracy, significant future studies are needed to validate this hypothesis.

Despite these limitations, the patterns in residual errors offer valuable insights into the underlying signal behavior. Whenever a new satellite enters or exits the sensor's view, the LSTM detects a brief spike in error. The DNN then uses this predicted error, along with historical sensor data and position-obstruction geometry, to forecast the overall error in the current measurement, which is subsequently corrected. Evidence supporting this behavior is visible through a comprehensive examination of Fig. 13, Fig. 15, and Fig. 16.

From examining Fig. 16, one observes that the more varied the signal characteristics, the less stable the model's performance. In environments with heavy obstruction, such as 'Urban-1,' the residual errors are relatively stable, indicating that the model is performing well in correcting errors. This suggests that when the satellite signal is consistently obstructed or reflected, the model can make more reliable corrections.

In contrast, environments with dynamic satellite-obstacle-receiver geometry, such as 'Urban-2,' show greater variance in performance. As the satellite transitions from bad (reflected path) to good (direct path) visibility, the model's performance fluctuates. When the reflected and direct paths

are well-separated, the model performs well. However, when the paths are not distinct, the model struggles, leading to more error variability.

In 'Urban-3,' the satellite signal rapidly oscillates between reflected and direct paths in a relatively periodic manner. To evaluate and explain the performance of our model, we analyze the 'Urban-3' location and use raytracing to trace how the signal from a specific satellite impacts GPS performance. As the satellite moves across the sky, its path is perpendicular to obstructions. At low azimuth angles, the direct path to the satellite is blocked, and only reflected signals are detectable. This results in reduced confidence in the GPS predictions, causing significant oscillations in the raw GPS stream as the sensor attempts to localize accurately.

As the satellite approaches an azimuth angle of 90 degrees (directly overhead), the direct path becomes visible, leading to lower variance between consecutive GPS measurements and a more consistent error pattern. The LSTM network identifies this behavior and predicts "where" the error is in relation to the satellite's position. It uses this insight to anticipate the error pattern, resulting in lower magnitude residual errors. However, the constant oscillation introduces significant uncertainty into the raw GPS stream, leading to larger variability and the characteristic oscillatory behavior in the residual errors.

The key factor here is the ratio of direct to reflected path signals. When this ratio is more constant, the model's performance becomes more stable but less effective in magnitude correction. On the other hand, when there is more oscillation in this ratio (i.e., frequent switching between reflected and direct paths), the system can handle the predictions better, leading to lower magnitude residual errors but more variability.

In summary, when the ratio of direct to reflected signals remains constant, the model performs consistently but with higher residual errors. Conversely, frequent oscillations in this ratio allow the model to reduce errors but introduce more variability. This tradeoff, shown in Fig. 16, demonstrates the model's ability to learn the satellite-obstacle-receiver geometry. This physical explanation is an equivalent to utilizing ray tracing to correct GPS errors. This physical explanation is crucial for understanding how the model works, which is essential for aerospace certification. While the algorithm does not explicitly determine the exact location or nature of an obstacle, but it can infer its presence and directional influence based on the observed multipath effects. By analyzing the discrepancies in GPS signals received by multiple antennas, the model can identify whether obstacles are present on one side, on multiple sides, or all around the drone and how far away they are. This is evident in the preferential corrections applied by the algorithm where the nature of the correction provides insight into the

surrounding environment. The residual angular error clearly indicates this preferential axis of corrections as seen in Fig. 15 (b) and this correlates with number and direction of obstacles as described in Fig. 7 and Table 3. If the multipath interference is stronger in one direction, the corrections reflect this asymmetry. This capability can be used to enhance the robustness of the GPS correction process by dynamically adapting to spatial distortions in signals without requiring an explicit obstacle mapping.

The consistency of preferential corrections along certain spatial axes supports a key physical interpretation: the model's success is closely tied to meaningful spatial separation of input signals in the horizontal plane. The hardware configuration emphasized horizontal (2D) spatial separation, with antenna placement primarily designed to capture lateral positional deviations rather than vertical variations. This design choice is further validated by the behavior of the e_{alt} metric. Since vertical spatial separation was minimal in the experimental setup, the model lacked sufficient vertical signal diversity to learn meaningful corrections along the altitude axis. Consequently, while strong and stable error corrections were achieved in the horizontal plane, residual vertical errors remained relatively unstable. In this context, e_{alt} effectively serves as a null hypothesis test, reinforcing that without significant spatial structure along a given axis, the IRNN-DNN model cannot reliably predict or correct errors. The observed stability of horizontal corrections, contrasted with the variability of vertical corrections, underscores the model's reliance on spatial diversity and supports the conclusion that performance is fundamentally linked to environmental geometry.

Ellipsoidal Uncertainty (EU) Error

The IRNN-DNN model significantly improves Ellipsoidal Uncertainty (EU) errors, mirroring the enhancements observed in residual and altitude errors. It achieves consistent positioning within a 10-meter tolerance across all environments, which is critical for safe airspace management.

The introduction of the IRNN-DNN model significantly reduces EU error across all environments. In Urban-1, mean horizontal precision error decreases dramatically from 52.586 m to 4.137 m, with a corresponding drop in standard deviation from 12.91 m to 0.63 m. Similar improvements are noted in other urban scenarios, with errors reduced to under the 10 m requirement, underscoring the model's reliability in complex settings. The consistent reduction in mean and standard deviation of EU error highlights the model's robustness in addressing challenges like signal obstructions and multipath reflections inherent to urban environments.

Comparative Trade-off Analysis of Correction Methods

Beyond accuracy improvements, practical deployment in urban UAV operations requires careful consideration of trade-offs in power consumption, computational load, and system cost. To better contextualize the benefits of the proposed IRNN-DNN model, a Pareto analysis was conducted, comparing its characteristics against those of conventional GNSS correction approaches as summarized in Table 1.

High-accuracy techniques such as multi-frequency GNSS, dual-frequency PPP, and dual-frequency RTK achieve meter level or even centimeter level precision under ideal conditions (Montenbruck and Steigenberger 2025; Tang et al. 2025). However, their performance degrades significantly in dynamic urban environments due to signal obstructions and multipath reflections. Moreover, these methods impose substantial cost, power, and computational burdens, often requiring 10^6 to 10^8 FLOPS, making them less suitable for small, low-cost UAV platforms. Cloud-based RTK and offboard machine learning solutions reduce onboard computational demands but introduce dependencies on uninterrupted network connectivity and subscription services, which can be vulnerable to urban communication outages and accumulate significant operational costs over time.

In contrast, the IRNN-DNN model achieves a favorable balance among these competing factors. It delivers mid-grade localization accuracy (~ 1.7 meters CEP) at modest computational cost ($\sim 10^5$ FLOPS) and a minimal increase in power consumption (0.1–0.3 W), without requiring additional hardware investment. Importantly, its embedded design enables real-time operation even in dense, dynamic urban conditions without reliance on external correction services or persistent network access. This represents a practical Pareto trade-off: further improvements in accuracy would require disproportionate increases in cost, power, or complexity. These characteristics position the IRNN-DNN approach as a lightweight, practical solution for enhancing low-drift GPS accuracy in slow-moving UAV operations, especially for resource-constrained platforms.

Dynamic Accuracy Index (DAI) and Comparisons with existing ML-based GPS Correction Models

Several prior studies from the literature review section have studied the use of ML based GPS/GNSS correction methods, primarily using LSTM, CNNs or deep learning models. While a direct comparison of ML correction algorithms for 3D localization correction with drone GPS data is not feasible due to myriads of reasons discussed previously, the IRNN-DNN model demonstrated impressive performance compared to existing methods proposed in literature, see Table 7.

Table 7. Strengths of IRNN-DNN compared to existing methods in literature.

Method	Strength	Weakness
LSTM-only Models	Captures temporal dependencies	Fails with a-periodic noise
CNN Based Models	Good for structured spatial corrections	Struggles with dynamic conditions
Kalman Filter Techniques	Computational efficiency	Requires manual tuning of models
IRNN-DNN Model	Combines LSTM for temporal errors + DNN for non-sequential errors	Requires more training data

Unlike LSTM only approaches which struggle to capture non-sequential, aperiodic errors such as sensor biases, sudden multipath reflections common in UAV environments (see Table 7) (Alos and Dahrouj 2022), IRNN-DNN's DNN and IVF correct for these non-temporal errors. While CNN is used for GPS corrections, excels in recognizing static, structured patterns, the rapidly changing environmental conditions cause CNNs to struggle (Zou et al. 2020). IRNN-DNN's optimized sub-models tackle each error type in each specific type of environment separately, with LSTMs providing temporal memory. This makes IRNN-DNN highly suitable for UAM operations. Other non-ML based models like Kalman Filters provide state-estimation with low computation costs, they require highly accurate error models, challenging requirements to meet with UAV operations (Da Silva and Da Cruz 2016; Borup et al. 2020). IRNN-DNN uses data-based techniques to learn these error models, eliminating the need for direct tuning, and allowing for continued self-learning. Some recent hybrid approaches (CNN-LSTM) provide promising results. However, these structures are computationally intensive, need additional sensors, making them challenging to deploy in low SWaP UAV environments. IRNN-DNN with its ability to run on embedded microcontrollers and its sub models, is ideally positioned for use in UAM operations.

Traditional filter only methods from literature exhibited a DAI of 5.11 meters/Hz, with an accuracy of 5.11 meters at around 1 Hz for GPS localization in surface applications. A combined filter and neural network approach improved this to a DAI of 2.17 meters/Hz, achieving an accuracy of 2.6 meters at approximately 1.2 Hz for GPS data, fused with additional sensor data like IMUs sampled at higher frequency rates. In contrast, the IRNN-DNN model achieved a DAI of 0.17 meters/Hz, corresponding to an accuracy of 1.71 meters at 10 Hz, representing a significant reduction in error and enhancement in processing speed.

The metrics support the conclusion that the IRNN-DNN

Table 8. Performance of IRNN-DNN compared to existing methods in literature.

Method	Accuracy (m)	Frequency (Hz)	DAI (m/Hz)
Traditional Filter Only (Mohanty and Gao 2023b)*	5.11	~1	~5.11
Filter + Neural Network (Mohanty and Gao 2023a)*	2.6	~1.2	~2.17
GA-BPNN(Huang et al. 2025)*	3.86	-	-
Vision Based Localization(Sohn et al. 2008)	8.58	30	0.286
IRNN-DNN Model	1.71	10	0.17

*The papers do not specify the exact frequency of data collection. They are best estimates based on examining published data model excels in urban conditions with more complex reflector configurations, potentially surpassing traditional expectations for GPS accuracy in such contexts. This outcome implies that the model is capturing essential characteristics of the multipath interference, which are then used to fine-tune the algorithm's correction parameters.

Conclusions

GPS localization with ML is a highly saturated field. However, existing models lack optimization for real-time UAV applications due to constraints of cost, SWaP and available computation. The IRNN-DNN model addresses this critical gap by providing a real-time, accurate, and efficient localization system for autonomous UAM operations. Unlike conventional methods, IRNN-DNN dynamically corrects GPS error and achieves meter-level positional accuracy by detecting, and matching obstacle geometries to multipath effects. This study has four key findings.

First, this study demonstrates that hybrid DNN-LSTM models can effectively mitigate multipath effects in GPS. By leveraging hierarchical ML model, that can be deployable on embedded microcontrollers, IRNN-DNN offers an

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alternative to ray tracing for solving multipath error correction in SPP equations.

Secondly, the modular architecture is computationally efficient and offers an alternative method for low SWaP environments. IRNN-DNN has been successfully ported and deployed on an STM32 microcontroller, and achieves high-speed, real-time operation at 10 Hz with headroom to spare. The modular architecture also allows integration with other sensors and/or models to further improve and optimize for different applications and different environments. This positions IRNN-DNN to be used as a sensor fusion method as well.

Third, this paper introduces a new metric, DAI, to address a critical gap in drone localization performance characterization. Unlike existing metrics, DAI combines the temporal and spatial aspects of drone localization requirements into a singular metric. This metric is important for characterizing the performance of a low-power embedded system. IRNN-DNN sets the benchmark value at 0.17.

Finally, this study establishes a firm foundation for dynamic flight testing with drones. The strong performance of this algorithm shows convincing evidence to deploy a drone with this algorithm to conduct future controlled flight tests in a dense urban environment.

Study limitations and Future Directions

While the model's performance has been validated in controlled environments, comprehensive in-flight testing of the drone GPS was not feasible due to regulatory constraints in place. However, this study serves as a critical proof-of-concept, providing a foundation for securing the necessary permissions for extensive flight testing from regulatory authorities. While this setup is effective in isolating multipath effects, it does not fully replicate a UAV's motion, dynamics, and interferences. Future studies will address these challenges through dynamic flight tests and detailed comparisons with other existing GPS correction methods in more diverse and broader range of environments to ensure exhaustive validation.

Another significant limitation is that the algorithm was tested in a priori locations. While the algorithm is expected to perform identically in other locations, as the inputs are normalized and the algorithm matches data to previously seen obstacle geometries, more experimental studies are needed to test this claim in detail. Future research will focus on expanding available GPS data sets over various urban locations and geometry to enhance applicability and test generalizability.

While the IRNN-DNN model achieves significant improvements in horizontal GPS localization accuracy, its ability to correct vertical (altitude) errors remains limited.

This behavior arises because the model relies on spatial separation between concurrently operating sensors to learn and predict systematic multipath distortions. In the current experimental setup, vertical spatial diversity is minimal, resulting in insufficient information for reliable altitude correction. Future work will expand the dataset to include 3D obstacle environments, vertical separation of sensors, and dynamic altitude changes, enabling a more comprehensive evaluation and improvement of full 3D localization capabilities.

Future research efforts will focus on building on the findings of this study, by exploring hybrid physics-informed ML models, such as Hamiltonian or Lagrangian frameworks, to further improve the model's ability to capture signal propagation dynamics and mitigate other error sources.

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