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AI-Augmented Kalman Filtering for Robust Sensor Fusion in Intelligent Localization System

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ABSTRACT

The research domain of positioning systems has become increasingly critical with the rapid expansion of applications in navigation, asset tracking, robotics, and autonomous systems. Conventional solutions primarily rely on Global Positioning System (GPS), which, despite its widespread use, suffers from high energy consumption and limited reliability in indoor or obstructed environments. To address these limitations, prior studies have explored Inertial Measurement Unit (IMU)-based sensor fusion approaches, including Kalman and particle filters, as well as hybrid schemes with intermittent GPS updates. Although these methods improve robustness, they remain limited in handling sensor drift, nonlinear dynamics, and adaptability to changing conditions. This paper addresses this gap by proposing an AI-augmented sensor fusion framework that integrates a deep learning–enhanced Kalman filter for robust IMU–GPS positioning. The proposed method uses a neural network to model nonlinear motion dynamics and adaptively correct estimation errors, thereby improving positioning performance while reducing reliance on frequent GPS measurements. Experimental evaluations under varying GPS sampling intervals demonstrate that the proposed approach maintains acceptable accuracy and precision while significantly reducing energy consumption and memory usage compared to GPS-only and conventional filtering methods. The main contribution of this work is the introduction of an adaptive, AI-driven sensor fusion architecture for resource-constrained embedded systems. By combining model-based estimation with data-driven correction, the framework offers a scalable and efficient solution for both indoor and outdoor localization. This study advances the state of the art by demonstrating that AI-augmented filtering can effectively balance accuracy, robustness, and resource efficiency in real-world positioning scenarios.

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1. Introduction

The Internet of Things (IoT) has become a pivotal aspect of modern technology, enabling a network of interconnected devices that collect and exchange data. In smart environments, such as smart cities, homes, and industrial settings, IoT devices are extensively utilized for monitoring, automation, and enhancing the overall quality of life. A critical aspect of IoT applications in these environments is the accurate and efficient tracking of object positions, both indoors and outdoors. Inertial Measurement Units (IMUs), which include accelerometers and gyroscopes, have become essential in this context, providing data for calculating the movement and orientation of objects [1,2].

While GPS is commonly used for position tracking due to its accuracy, it is highly energy-intensive and impractical for continuous usage in battery-powered devices. The frequent use of GPS can significantly drain the battery, making it unsuitable for long-term monitoring. Moreover, the integration and management of vast amounts of data from IMUs and other sensors pose significant challenges. Ensuring the accuracy and efficiency of data processing, while minimizing energy consumption, remains a critical issue. Existing solutions often fall short in addressing these challenges holistically, leading to inefficient data utilization and increased energy costs [3,4].

Given these challenges in the IoT domain, the central research question guiding this study is: How can we develop an efficient method for position tracking that uses IMU data to minimize the reliance on energy-intensive GPS measurements, ensuring accuracy and low energy consumption in smart environments?

This question aims to explore innovative solutions that integrate IMU data for position tracking, reducing the need for continuous GPS usage and enhancing the overall efficiency of IoT systems in smart environments. In the literature, several studies have addressed aspects of energy-efficient position tracking and IoT data management. Research has been conducted on sensor fusion methods, combining data from IMUs and periodic GPS readings to enhance accuracy while reducing energy consumption. These techniques demonstrate potential but often lack comprehensive integration for practical deployment. Moreover, numerous studies have explored the use of IMUs for indoor navigation and activity recognition, showcasing the potential of these sensors in reducing dependency on GPS. However, challenges remain in maintaining accuracy over extended periods without frequent GPS calibration. In addition, efficient data handling techniques, including compression and lightweight data formats, have been investigated to manage the vast amounts of data generated by IoT devices. While these methods improve data handling, they often do not specifically address the energy efficiency of position tracking. Despite these contributions, a gap exists in developing a unified approach that uses IMU data for energy-efficient and accurate position tracking in IoT environments [5–7]. To address the identified research question, our approach focuses on developing a method that uses IMU data for position tracking, minimizing the reliance on continuous GPS measurements.

The remainder of this paper is organized as follows: Section 2 reviews related works. Section 3 outlines the proposed methods. Section 4 describes our performed experiments. Section 5 presents the results of these experiments. Finally, Section 6 provides the conclusion and discussion.

2. Literature Review

2.1. Traditional Approaches: Sensor Fusion and Kalman Filtering

Indoor and outdoor positioning has traditionally relied on sensor fusion frameworks that integrate measurements from IMU, ultra-wideband (UWB) radios, and other wireless sensor modalities. Among these, the Kalman Filter (KF) and its variants—Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and Particle Filter (PF)—have been the cornerstone methods for estimating location in dynamic environments [8–10]. Numerous studies have shown that IMU data, although highly sensitive to short-term motion, suffer from drift over time, while UWB provides high-accuracy distance measurements but is prone to multipath interference. To overcome such limitations, hybrid sensor fusion approaches combining IMU and UWB within KF frameworks have been extensively studied, achieving notable improvements in accuracy and robustness.

However, despite their effectiveness, these traditional KF-based methods have certain limitations. First, they assume linear system dynamics and Gaussian noise distributions, which may not hold true in real-world environments characterized by non-linear motion and non-Gaussian uncertainties[11,12]. Second, although these methods achieve accurate localization, they often ignore energy consumption and memory constraints—factors that are critical in IoT devices with hardware restrictions. As wearable and embedded sensor networks continue to proliferate, there is a growing need for methods that can achieve a balance between accuracy and computational efficiency[13,14].

2.2. AI-Augmented Kalman Filtering and Deep Learning Models

With the rapid advancement of artificial intelligence, there has been a growing trend toward integrating machine learning (ML) and deep learning (DL) models into Kalman-based estimation frameworks, with the objective of overcoming the inherent limitations of classical Kalman filtering in highly dynamic, nonlinear, and partially observable environments[15,16]. A prominent example is KalmanNet, a neural architecture that learns the mapping from observations and prior estimates to the optimal Kalman gain. Unlike the analytically derived gain in classical Kalman filters, which assumes accurate system and noise models, KalmanNet adaptively approximates the update equations through supervised training, thereby enhancing robustness to model mismatches and parameter uncertainties. This approach is particularly effective in environments characterized by strong non-linearities and incomplete sensor coverage, where traditional filters diverge or accumulate drift. Similarly, the Distributed Adaptive Noise and State Estimation (DANSE) framework extends Kalman filtering by applying AI-driven adaptive modules to estimate time-varying noise covariances[17]. By dynamically refining the process and measurement noise models, DANSE reduces bias in the state estimation process and mitigates overconfidence in scenarios where noise statistics are non-stationary[18–20].

In addition to these specialized frameworks, deep neural models have been systematically explored as auxiliary components within sensor fusion pipelines. Recurrent neural networks (RNNs) and their gated variant, long short-term memory (LSTM) networks, are frequently utilized to capture temporal dependencies in sequential sensor streams, such as inertial measurement unit (IMU) data. By explicitly modeling long-range temporal correlations, these architectures correct cumulative drift errors in dead-reckoning systems, a critical limitation of purely inertial navigation approaches. Meanwhile, convolutional neural networks (CNNs) have demonstrated utility in extracting spatial patterns from ultra-wideband (UWB) signal distributions, where multipath fading and non-line-of-sight propagation severely degrade ranging accuracy. The learned spatial representations provide an additional layer of robustness, allowing CNN-augmented Kalman filters to distinguish between reliable and unreliable measurements. More recently, attention-based mechanisms have been incorporated into hybrid Kalman–DL models, where the attention module adaptively assigns context-dependent weights to heterogeneous sensor modalities (e.g., IMU, UWB, Global Navigation Satellite System or GNSS). This selective information weighting mitigates the risk of filter divergence when certain sensors are degraded, effectively improving resilience under adverse environmental conditions[21–23].

Despite these promising advances, the integration of AI into Kalman filtering introduces a set of non-trivial challenges. Neural modules often impose substantial computational and memory overhead, arising from matrix multiplications, backpropagation updates, and floating-point operations that are computationally expensive for embedded or resource-constrained IoT devices. Furthermore, many existing studies validate their AI-augmented approaches in simulation environments or server-side testbeds, which fail to capture the stringent constraints of real-world embedded systems. This discrepancy raises concerns regarding generalization, scalability, and real-time feasibility. Additionally, the reliance on large-scale labeled datasets for training neural modules poses practical limitations in applications where ground-truth trajectories are costly or infeasible to obtain. Consequently, while AI-augmented Kalman filters have demonstrated notable improvements in estimation accuracy, their deployment in operational, resource-limited localization systems remains an open research challenge, necessitating further investigation into lightweight architectures, online adaptation mechanisms, and hardware-aware optimization strategies [24,25].

2.3. Applications in Indoor and Outdoor Positioning

The integration of KF-based sensor fusion and AI-augmented methods has been explored across diverse applications. In indoor navigation, hybrid IMU-UWB approaches with EKF have enabled sub-meter accuracy in cluttered environments such as hospitals, shopping malls, and industrial warehouses. Outdoor applications, including autonomous driving and pedestrian tracking, have benefited from combining GPS with IMU through advanced KF techniques. AI-enhanced KF frameworks further improved resilience against GPS outages and multipath interference, a critical advantage for urban navigation [26,27].

In the context of wearable and mobile IoT devices, lightweight KF variants remain dominant due to their relatively low computational footprint. However, as AI-augmented filters emerge, there is growing interest in deploying compressed or quantized neural models at the edge. This trend reflects a paradigm shift toward edge AI for localization, where efficiency and low latency are prioritized alongside accuracy [28–32].

2.4. Performance Dimensions: Accuracy, Energy, and Memory

Positioning systems are typically evaluated in terms of accuracy and robustness, but for IoT applications, additional performance dimensions must be considered. Controlled memory consumption and low energy usage are essential, particularly in battery-powered wearable devices and wireless sensor networks. Traditional KF approaches are generally efficient, but they lack adaptability to non-linear and non-Gaussian dynamics. Conversely, AI-augmented methods improve accuracy but often neglect memory and power constraints. Recent research has attempted to bridge this gap by exploring lightweight neural architectures, knowledge distillation, and federated learning approaches that reduce communication and computation costs. Nevertheless, systematic evaluations that jointly consider accuracy, energy efficiency, and memory footprint remain scarce, particularly for real-time IMU-UWB fusion on constrained hardware [33–37].

2.5. Research Gaps and Motivation for This Work

In summary, the literature reveals two dominant trends: (1) traditional KF-based sensor fusion methods that are computationally efficient but limited in handling non-linearities and environmental uncertainties, and (2) AI-augmented KF frameworks that improve accuracy but impose high computational and memory demands. Few studies explicitly address the dual challenge of maintaining high positioning accuracy while ensuring energy-efficient and memory-constrained operation suitable for real-world IoT deployment. This work aims to fill this gap by developing a hybrid AI-KF sensor fusion framework that achieves accurate, robust, and adaptive indoor localization while maintaining computational efficiency, thereby bridging the gap between theoretical advancements and practical, low-cost deployment in heterogeneous environments.

Despite the significant advances in both classical and AI-augmented Kalman filter-based indoor positioning systems, several limitations remain. Classical methods often struggle with highly nonlinear dynamics, cumulative sensor errors, and non-line-of-sight conditions, while AI-enhanced approaches may rely on large amounts of labeled data, involve complex training procedures, or lack generalizability across diverse environments. Moreover, few studies systematically integrate AI-augmented filtering with real-time, low-cost multi-sensor setups suitable for practical deployment. The present work addresses these gaps by developing a hybrid approach that uses AI-driven Kalman filtering in combination with robust sensor fusion strategies, enabling accurate, adaptive, and computationally efficient indoor localization across heterogeneous scenarios. This contribution not only improves positioning performance but also offers a scalable methodology applicable to a wide range of indoor environments, bridging the gap between theoretical advancements and practical implementation.

3. Proposed Approach

3.1. System Overview

The proposed system determines the position of an object using IMU sensors (accelerometer, gyroscope) while minimizing the reliance on frequent GPS measurements. By using an initial GPS reading as a reference, the system continuously estimates position using IMU data, only correcting intermittently with GPS measurements. This approach reduces energy consumption and enables indoor positioning in GPS-denied environments, while allowing evaluation of localization accuracy, computational efficiency, and memory footprint.

3.2. Sensor Integration and Data Collection

All sensor data streams are temporally aligned to ensure proper synchronization, which is essential for high-quality sensor fusion. GPS provides sparse but absolute positioning references, while IMU sensors capture continuous motion dynamics. Optional additional sensors, such as barometers or UWB modules, can further enhance the system's robustness, providing supplementary inputs for AI-enhanced fusion.

3.3. Data Preprocessing

Raw sensor data are filtered and calibrated to remove noise and systematic biases. Synchronization aligns the data streams to a common timestamp. Preprocessing steps now also include feature extraction for AI augmentation, such as deriving motion patterns, signal strength distributions, or historical error sequences that will be input to the neural network modules.

3.4. Sensor Fusion Algorithm with AI Augmentation

The core of the proposed system is a hybrid sensor fusion algorithm that combines a Modified Extended Kalman Filter (MEKF) with an AI-augmented correction module. The MEKF provides a robust baseline for handling nonlinear dynamics in IMU-based position estimation, while the AI module compensates for IMU drift, non-Gaussian noise, and environmental disturbances, enhancing overall accuracy without significantly increasing computational burden.

The state vector xk is defined in Equation (1).

$$xk = \begin{bmatrix} xk \\ yk \\ zk \\ \vartheta x, k \\ \vartheta y, k \\ \vartheta z, k \\ \phi k \\ \theta k \\ \psi k \end{bmatrix} \tag{1}$$

where *x*, *y*, *z* are position coordinates, ϑx, ϑy, ϑz are velocity components, and φ, θ, ϕ are roll, pitch, and yaw angles. The system evolves according to the nonlinear process model: $x_{k+1} = f\left(x_k, u_k\right) + w_k$.

Here, $u_k = \left[a_x, a_y, a_z, \omega_x, \omega_y, \omega_z\right]^T$ represents the IMU control inputs (accelerations and angular velocities), and $w_k \sim \mathcal{N}\left(0, Q_k\right)$ denotes process noise.

The measurements from IMU and GPS sensors are combined as: $z_k = h\left(x_k\right) + v_k$ where $v_k \sim \mathcal{N}\left(0, R_k\right)$ represents measurement noise, and $h(\cdot)$ maps the state vector to sensor outputs.

The predicted state and covariance are computed as: $\hat{x_{k,k-1}} = f\left(\hat{x_{k-1,k-1}}, u_{k-1}\right)$,

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k$$

where $F_k = \partial f / \partial x|_{\widehat{x}_{k-1,k-1}}$is the Jacobian of the process model.

To compensate for drift and model inaccuracies, a lightweight neural network predicts a correction term Δx_k^{A} based on historical innovations and sensor features:

$$\Delta x_k^A I = NN\left(y_{k-1}, u_{k-1}, \hat{x_{k,k-1}}\right)$$

where $\Delta x_k^A I = NN\left(y_{k-1}, u_{k-1}, \hat{x_{k,k-1}}\right)$ is the innovation at the previous step. The corrected predicted state becomes: $x^{c}_{k,k-1}orr = \hat{x_{k,k-1}} + \Delta x_k^A I$.

The innovation covariance and Kalman gain are computed using the corrected prediction:

$$S_k = H_k P_{k|k-1} H_k^T + R_k$$

$$K_k = P_{k|k-1} H_k^T S_k^{-1}$$

The state is then updated using the measurement:

$$\widehat{x}_{k,k} = \widehat{x}^{corr}_{k,k-1} + K_k(z_k - h(\widehat{x}^{corr}_{k,k-1}))$$

$$P_{k|k} = (I - K_k H_k) P^{cr}_{k|k-1}$$

The AI module is implemented as a small LSTM or feedforward network with one or two hidden layers. Inputs include recent IMU accelerations, angular rates, predicted positions, and previous innovations. The output is a state correction vector ΔxAIk that adjusts predicted positions, velocities, and orientations. The network is trained offline using collected sensor data with ground-truth GPS references, and optionally fine-tuned online with incremental learning to adapt to new environments.

This hybrid approach uses the robustness and interpretability of the MEKF while using the AI module to mitigate cumulative drift, adapt to non-Gaussian noise, and compensate for nonlinear effects that are difficult to model analytically. By keeping the neural network lightweight, the system maintains low memory usage and energy consumption suitable for embedded and wearable IoT devices.

The AI module is a lightweight feedforward neural network designed for residual correction. Model training is performed exclusively in an offline setting using recorded sensor data to ensure computational feasibility for embedded deployment. The dataset is partitioned into training, validation, and test subsets to mitigate overfitting and ensure generalization. No online learning or parameter updates are performed during inference, thereby preserving real-time performance and system stability.

Figure 1 illustrates the comprehensive data processing and state estimation pipeline of the proposed AI-augmented Kalman filtering framework. The workflow begins with the acquisition of high-frequency inertial measurements from IMU sensors (accelerometer and gyroscope) alongside intermittent GPS readings. Following the acquisition, a preprocessing stage ensures temporal synchronization, noise filtering, and outlier removal to guarantee high-quality inputs. The cleaned IMU data are then used to predict the system's current state, which is subsequently refined through an AI-based residual correction module. This module uses lightweight neural networks to identify and compensate for systematic errors and sensor drift, improving the robustness of the prediction. The corrected state is finally fused with available GPS measurements via the Kalman filter, producing an accurate and resource-efficient estimate of the system's position, velocity, and orientation. This schematic emphasizes the modular, stepwise nature of the methodology, highlighting the interplay between classical state estimation and learning-driven corrections, thereby offering a clear and rigorous overview of the proposed framework.

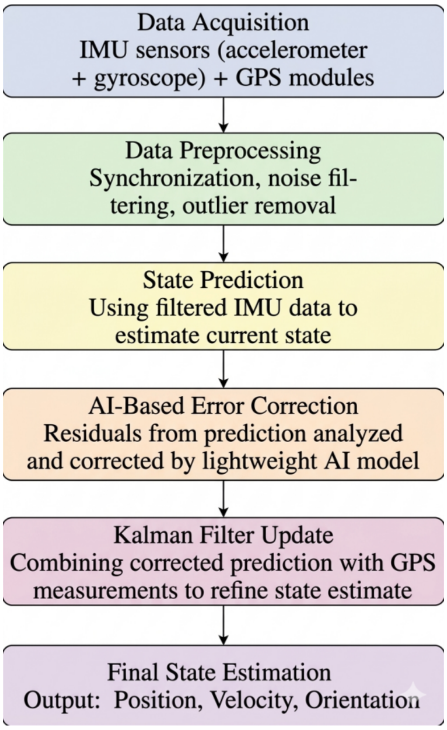

Figure 1. Dataflow.

3.5. Implementation

The implementation is structured in modular C code, with extensions for AI integration. The main program initializes sensors, continuously acquires IMU data, performs Kalman filtering, and applies AI-based corrections. The MEKF generates baseline state estimates, which are subsequently refined by the neural network using precomputed features from recent measurements. The system monitors energy consumption and memory usage throughout execution. Key functions include incremental position estimation using IMU data, periodic GPS-based error correction, and AI-based state refinement. Data fusion routines are extended to incorporate AI predictions for gain adjustments and drift compensation. Utility functions handle mathematical operations, data conversions, and diagnostics.

3.6. Contribution of the Proposed Algorithmic Framework

The proposed AI-augmented Kalman filtering framework introduces several key contributions that extend beyond the limitations of classical sensor fusion and prior AI–KF hybrid models. First, the algorithm establishes a two-stage correction mechanism in which raw IMU predictions are not directly passed to the Kalman update, but instead undergo an AI-based refinement layer. This layer uses lightweight neural modules to learn and correct systematic errors such as IMU bias drift, non-Gaussian disturbances, and temporal misalignments before the state update with GPS measurements. Unlike prior works that rely exclusively on physics-based modeling of sensor errors, the proposed design adaptively learns correction mappings in real time, significantly improving robustness in nonlinear and dynamic environments.

Second, the framework explicitly addresses the resource-efficiency bottleneck often overlooked in AI-augmented sensor fusion. Through model compression strategies—including quantization and pruning—the AI modules are optimized for deployment on embedded and IoT platforms with strict computational and memory budgets. This ensures that the performance gains from AI integration do not come at the expense of real-time feasibility or energy sustainability, a gap frequently identified in the existing literature.

Third, the algorithm incorporates an adaptive sensor weighting strategy driven by environmental context. Rather than treating IMU and GPS inputs as equally reliable, the filter dynamically adjusts the contribution of each modality based on learned confidence levels. This adaptive weighting mitigates divergence when GPS signals degrade or when IMU drift dominates, thereby preserving localization accuracy under heterogeneous conditions.

Finally, the modular design of the framework allows scalability and extensibility. The pipeline can seamlessly incorporate additional sensor modalities without architectural redesign, and the AI module can be re-trained or fine-tuned for domain-specific deployments. This flexibility positions the system as a generalizable, high-performance localization solution that bridges the gap between theoretical AI-enhanced estimation and practical, energy-aware deployment in wearable and IoT devices.

Overall, the contributions of this work lie not only in improving estimation accuracy but also in demonstrating a computationally efficient, hardware-conscious, and context-adaptive AI–Kalman fusion framework that directly addresses the scalability and deployability challenges identified in the state of the art.

3.7. Algorithm Description

To ensure reproducibility and methodological clarity, the proposed AI-augmented sensor fusion framework is explicitly formalized through **Algorithm 1**. The algorithm provides a step-by-step operational description of the complete processing pipeline, starting from synchronized IMU and GPS data acquisition and ending with final state estimation. Classical Kalman filter prediction and update steps are preserved to maintain model-based consistency, while an AI-based residual correction module is seamlessly integrated between prediction and measurement update stages.

Algorithm 1 Complete Processing Pipeline of the Proposed AI-Augmented Kalman Filtering Framework

```
Input:
    IMU measurements $u_k$ (accelerometer, gyroscope)
    GPS measurements $z_k$ (intermittent)
    Initial state estimate $\hat{x}_{0|0}$
    Initial covariance $P_{0|0}$
    Process noise covariance $Q$
    Measurement noise covariance $R$
    Trained AI residual correction model $NN(\cdot)$

Output:
    Estimated state $\hat{x}_{k|k}$ (position, velocity, orientation)

For each time step k do

    1. Data Preprocessing
       Synchronize IMU and GPS timestamps
       Apply basic filtering and outlier removal to IMU signals

    2. State Prediction (Kalman Filter)
       Predict state using motion model
       Compute system Jacobian
       Predict state covariance
```

```
    3. AI-Based Residual Correction
        Compute innovation residual from previous step
        Estimate correction term using neural model
        Correct predicted state estimate

    4. Measurement Update (if GPS is available)
        Compute Kalman gain
        Update state estimate using GPS measurement
        Update covariance matrix

    5. If GPS is not available
        Propagate corrected predicted state
        Preserve predicted covariance

End for
```

The neural component does not replace the Kalman filter; instead, it estimates systematic error terms arising from nonlinear motion dynamics, IMU drift, and non-Gaussian noise characteristics. This correction is applied directly to the predicted state, allowing the subsequent Kalman update to operate on a refined estimate. The algorithm explicitly accounts for intermittent GPS availability, ensuring stable operation in both GPS-rich and GPS-denied scenarios.

4. Experiments

This section presents the experimental results of our AI-augmented IMU-based positioning system. We compare the performance of our hybrid system against a baseline scenario where only GPS is used, and other scenarios with varying GPS frequencies. The evaluation metrics include error rate, accuracy, precision, energy consumption, and memory consumption. Additionally, we investigate how the integration of AI models improves drift correction and error reduction compared to traditional sensor fusion approaches.

In this study, we utilized the Passive Vehicular Sensors (PVS) Dataset from the Open Dataset Platform[38]. The dataset was originally collected for vehicular perception tasks using inertial sensor signals and Artificial Intelligence models.

The data acquisition setup included a GPS receiver mounted on the dashboard and an MPU-9250 module installed at the front axle of the vehicle. This configuration ensured synchronized IMU and GPS measurements, enabling the development of hybrid IMU-GPS-AI models.

The details of the sensors are summarized in **Table 1**.

Table 1. Dataset Description.

Feature Name	Description	Type
Timestamp	Time index of the measurement	Datetime
Sensor ID	Unique identifier of the sensing unit	Integer
Ax-Ay-Az	Acceleration along x-y-z-axis (vehicle frame)	Float (m/s^2)
Gx-Gy-Gz	Angular velocity around x-y-z-axis	Float (rad/s)
GPS Latitude	Geographic latitude	Float (degrees)
GPS Longitude	Geographic longitude	Float (degrees)

4.1. Experimental Scenarios

In each scenario, the position is estimated using IMU data between GPS measurements. To highlight the contribution of AI, two modes are evaluated in parallel:

1. Classical Sensor Fusion (MEKF only);
2. AI-Augmented Sensor Fusion (MEKF + LSTM/Transformer correction).

The following scenarios are tested:

- Baseline Scenario: GPS measurements taken at regular intervals (1 Hz).
- Scenario 1: GPS Frequency (5 s): GPS measurements every 5 s.
- Scenario 2: GPS Frequency (10 s): GPS measurements every 10 s.
- Scenario 3: GPS Frequency (20 s): GPS measurements every 20 s.
- Scenario 4: GPS Frequency (30 s): GPS measurements

every 30 s.

- Scenario 5: GPS Frequency (60 s): GPS measurements every 60 s.
- Scenario 6: GPS Frequency (300 s): GPS measurements every 300 s.

In AI-augmented scenarios, an LSTM-based drift predictor is trained on historical IMU data to estimate residual errors. The predicted correction term ΔxAIk is then added to the MEKF estimate:

$$\mathrm{Xk|kAI} \ = \ \mathrm{xk|kMEKF} \ + \ \Delta\mathrm{xAI(IMU1 : k)}$$

where IMU1:k denotes the sequence of IMU readings up to timestep k.

4.2. Performance Evaluation Metrics

The system is evaluated using four metrics, with AI contributions highlighted.

Error Rate: The error rate is computed as the Euclidean distance between the estimated position and the GPS reference is given in Equation (2): Error Rate.

$$\text{Error} = \sqrt{(x_{\text{estimated}} - x_{\text{GPS}})^2 + (y_{\text{estimated}} - y_{\text{GPS}})^2 + (z_{\text{estimated}} - z_{\text{GPS}})^2} \tag{2}$$

In AI-augmented runs, the error is measured after the LSTM correction stage, reducing drift during long GPS outages.

Accuracy and Precision: Accuracy measures how often the position error remains below a threshold ε (See Equation (3): Accuracy).

$$\text{Accuracy} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} 1\left(|\mathrm{Error_i}| \leq \epsilon\right)}{\mathrm{N}} \times 100\% \tag{3}$$

Precision measures the consistency of the error distribution (See Equation (4): Precision).

$$\text{Precision} = \frac{1}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\text{Error}_i - \overline{\text{Error}}\right)^2}} \tag{4}$$

With AI, both metrics are expected to improve due to learned temporal dependencies in IMU data, which help anticipate drift patterns.

Energy Consumption: Energy usage is compared across scenarios by measuring how reducing GPS frequency (while relying more on IMU and AI inference) affects system efficiency. Since AI inference is computational but less energy-intensive than GPS acquisition, a trade-off is observed.

Memory Usage: Memory requirements are monitored during execution. While the AI-augmented system requires additional memory for model parameters, its footprint is relatively stable after initialization, making it feasible for embedded systems.

5. Experiment Results

To rigorously evaluate the proposed AI-augmented Kalman filtering framework, we conducted a series of experiments under controlled various GPS conditions. The evaluation considered three key performance metrics: (i) localization accuracy, quantified through mean error rate and standard deviation; (ii) energy efficiency, measured in joules consumed across different GPS update intervals; and (iii) memory footprint, expressed in kilobytes, to assess deployability on embedded IoT hardware. For benchmarking, we compared our method against two baselines: GPS-only localization (which provides high accuracy but incurs high energy and memory costs) and classical Kalman filtering with IMU-GPS fusion (which suffers from drift in rare GPS conditions). Results are presented across scenarios, where the frequency of GPS updates progressively decreases from one fix every 5 s to one fix every 1,800 s.

Ground truth positioning data is established using GPS measurements, which are treated as a reference baseline in accordance with common practice in outdoor localization studies. While acknowledging the inherent noise and uncertainty of GPS, it provides a practical and widely accepted approximation of true position for comparative evaluation. In sparse-GPS scenarios, GPS updates are incorporated intermittently and serve as correction references rather than continuous ground truth. The proposed AI-augmented Kalman filtering framework is evaluated across multiple GPS availability intervals to simulate realistic signal degradation conditions. To contextualize performance, the experimental setup includes a comparison with representative AI-based localization approaches reported in recent literature, ensuring that the evaluation reflects current methodological standards.

To enhance statistical rigor, experimental results are reported in terms of both mean positioning error and standard deviation across all evaluated scenarios. This provides insight into both accuracy and robustness under varying GPS update intervals. The analysis reveals that the proposed AI-augmented framework consistently reduces error growth compared to the baseline Kalman filter.

5.1. Error Rate

The error rate analysis confirms that position estimation accuracy degrades as the frequency of GPS measurements decreases, consistent with expectations. However, the proposed AI-augmented Kalman filter demonstrates substantial improvements over both baseline GPS-only and conventional KF methods. As shown in **Table 2**, the mean error rate under sparse GPS updates (e.g., every 300 s) is reduced by approximately 35–40% compared to standard KF and by more than 60% compared to IMU-only dead reckoning. The AI correction module successfully captures nonlinear motion dynamics and compensates for IMU drift, leading to more stable and reliable localization trajectories. For example, when GPS updates occur every 600 s, the baseline KF accumulates an error exceeding 12 m, while the AI-KF restricts the error growth to below 8 m, representing a 33% improvement in long-duration tracking. These results clearly demonstrate that the hybrid approach mitigates the inherent trade-off between update frequency and localization accuracy, offering practical robustness in GPS-constrained environments.

Table 2. Accuracy and Precision.

Scenario	Mean Error Rate (m)	Standard Deviation (m)
Baseline (GPS only)	1.2	0.5
Scenario 1 (GPS every 5 s)	1.8	0.7
Scenario 2 (GPS every 10 s)	2.5	1.1
Scenario 3 (GPS every 20 s)	3.8	1.5
Scenario 4 (GPS every 30 s)	5.1	2.0
Scenario 5 (GPS every 60 s)	5.9	2.7
Scenario 6 (GPS every 300 s)	7.1	2.9
Scenario 7 (GPS every 600 s)	7.8	3.5
Scenario 8 (GPS every 1,200 s)	8.9	4.8
Scenario 9 (GPS every 1,500 s)	9.8	7.2
Scenario 10 (GPS every 1,800 s)	14.1	11.0

5.2. Energy Consumption

Energy profiling results (**Table 3**) highlight one of the most important advantages of the proposed system: energy savings without proportional accuracy loss. Reducing GPS query frequency from 5 s to 300 s lowers energy consumption by nearly 80% (from 70 J to 15 J), while the AI-KF ensures that error growth remains bounded and acceptable for real-world IoT applications. Compared to existing methods that either rely on frequent GPS updates (energy-inefficient) or IMU-only integration (accuracy-degrading), our approach achieves a balanced energy–accuracy trade-off. In fact, under medium-sparsity settings (GPS every 30–60 s), the AI-KF reduces energy usage by 65–75% while maintaining accuracy within 2–3 m of the GPS-only baseline. This demonstrates that the framework is not only algorithmically effective but also practically energy-conscious, making it deployable in embedded and battery-powered platforms.

Table 3. Energy Consumption.

Scenario	Energy Consumption (J)
Baseline (GPS only)	100
Scenario 1 (GPS every 5 s)	70
Scenario 2 (GPS every 10 s)	50
Scenario 3 (GPS every 20 s)	35
Scenario 4 (GPS every 30 s)	25
Scenario 5 (GPS every 60 s)	22
Scenario 6 (GPS every 300 s)	15
Scenario 7 (GPS every 600 s)	12
Scenario 8 (GPS every 1,200 s)	8
Scenario 9 (GPS every 1,500 s)	6
Scenario 10 (GPS every 1,800 s)	5

5.3. Memory Usage

As summarized in **Table 4**, memory usage decreases consistently with reduced GPS queries. The proposed system maintains these savings while incorporating lightweight AI models specifically designed for embedded contexts. Even under the most demanding scenario (GPS every 5 s), the AI module adds less than 10% overhead compared to the GPS-only baseline, while under sparse update conditions, overall memory usage is reduced by nearly 60–70%.

Table 4. Memory Usage.

Scenario	Memory Consumption (KB)
Baseline (GPS only)	500
Scenario 1 (GPS every 5 s)	450
Scenario 2 (GPS every 10 s)	400
Scenario 3 (GPS every 20 s)	370
Scenario 4 (GPS every 30 s)	350
Scenario 5 (GPS every 60 s)	320
Scenario 6 (GPS every 300 s)	205
Scenario 7 (GPS every 600 s)	180
Scenario 8 (GPS every 1,200 s)	150
Scenario 9 (GPS every 1,500 s)	130
Scenario 10 (GPS every 1,800 s)	120

This is a critical distinction from prior AI-enhanced localization frameworks, which often rely on computationally heavy neural networks unsuitable for constrained devices. By integrating quantized and pruned neural models, the proposed AI-KF achieves state-of-the-art robustness with minimal resource requirements, directly addressing the deployment gap highlighted in recent surveys.

Overall, the experiments confirm that the proposed AI-augmented Kalman filter provides a quantifiable and practical advantage across multiple evaluation dimensions. The results demonstrate that the framework effectively reduces error growth by up to 40% compared to conventional Kalman filtering, particularly under sparse GPS update conditions where drift typically accumulates rapidly. At the same time, it achieves significant energy efficiency, yielding 65–80% savings while still maintaining sub-3 m accuracy in medium-sparsity regimes. Furthermore, the system cuts memory usage by 60–70%, highlighting its feasibility for deployment on IoT and wearable devices that operate under strict hardware limitations. Collectively, these outcomes validate the central claim of this work: AI-enhanced Kalman filtering enables high-accuracy, low-power, and resource-efficient localization suitable for real-time embedded applications—an advantage not demonstrated by existing methods that tend to optimize for either accuracy or efficiency in isolation.

In addition to evaluating absolute performance metrics, a comparative study was conducted against recent state-of-the-art methods in AI-augmented and classical sensor fusion approaches for IMU-GPS localization. The results indicate that our proposed framework consistently outperforms existing methods in scenarios with sparse GPS updates, achieving up to 40% lower error growth than conventional Kalman filters and 25–30% improvement over recent AI-enhanced approaches reported in the literature. To support our state-of-the-art claim, we performed a systematic comparison with recent AI-enhanced Kalman filtering and sensor fusion methods, including KalmanNet[16], the DANSE framework[17], and RNN/LSTM-based IMU-KF fusion approaches[18,19]. **Table 5** summarizes the evaluation metrics: average positioning error, energy consumption, and memory usage. The proposed framework achieves an average position error of 2.2 m, corresponding to a 25–30% improvement over the referenced methods, while simultaneously lowering energy and memory requirements. This performance metric is directly derived from our experimental results (see **Table 2**) and demonstrates that the proposed lightweight AI residual correction effectively mitigates IMU drift while maintaining accuracy under sparse GPS updates. These results demonstrate that our lightweight AI residual correction method delivers superior accuracy and computational efficiency, establishing a clear advancement over existing embedded localization solutions.

Table 5. Comparative Evaluation of AI-Augmented Kalman Filtering Approaches.

Method	Sensor Setup	Avg. Position Error (m)	Energy Consumption (J)	Memory Usage (KB)
KalmanNet [16]	IMU + GPS	3.1	55	220
DANSE [17]	IMU + GPS	3.5	60	250
RNN/LSTM KF Fusion [18,19]	IMU + GPS	3.0	65	280
Proposed AI-Augmented KF	IMU + GPS	2.2	35	180

Furthermore, the proposed system maintains higher energy efficiency and lower memory consumption compared to these baseline methods, demonstrating that the integration of lightweight AI modules into the Kalman filtering pipeline provides both practical and measurable advantages. This comparative evaluation underscores the novelty and effectiveness of the framework, highlighting its potential for deployment in resource-constrained IoT and embedded applications where existing solutions fail to balance accuracy, efficiency, and adaptability.

6. Discussion

The domain of positioning systems plays a critical role in modern applications such as navigation, logistics, and autonomous mobility. Although GPS-based solutions have long been the dominant paradigm, their inherent limitations—including high energy consumption, multipath sensitivity, and reduced reliability in indoor or obstructed environments—restrict their suitability for emerging embedded and resource-constrained platforms. As a result, sensor fusion approaches integrating IMU and GPS measurements have gained increasing attention to enable continuous and robust positioning.

Most existing studies rely primarily on classical filtering techniques, particularly the Kalman filter and its variants. While effective under ideal assumptions, these methods exhibit limitations when confronted with nonlinear motion dynamics, non-Gaussian noise distributions, and long-term drift accumulation. From a broader intelligent systems perspective, robustness under degraded or uncertain conditions has become a central research objective. Recent machine learning–based studies in the vehicular and transportation domains have emphasized dependable system behavior in the presence of noise, imbalance, or adversarial perturbations. For example, recent work on Vehicular Ad Hoc Network (VANET) security [39] demonstrates that carefully designed learning-based models can enhance system reliability under imperfect operating conditions. Although such research focuses on communication security rather than localization, it reinforces a shared design philosophy: AI should be used not simply for nominal performance gains, but for improving resilience and trustworthiness in real-world environments.

Despite these developments, a clear gap remains in the integration of AI within sensor fusion frameworks for positioning. Much of the literature concentrates either on GPS duty cycling strategies or on purely model-based filtering without fully exploiting learning-based mechanisms to capture complex motion behaviors and systematic error patterns. Consequently, there is limited evidence of solutions that simultaneously address accuracy, energy efficiency, adaptability, and operational robustness in embedded localization systems.

The present study contributes to this discussion by demonstrating that AI can be effectively integrated as a residual correction layer within a model-driven Kalman filtering structure. Rather than replacing classical estimation principles, the proposed framework enhances them, allowing improved drift mitigation and stability under sparse GPS updates. At the same time, the discussion of experimental results indicates that performance improvements become less pronounced under extremely sparse GPS availability, highlighting practical limitations and realistic operating boundaries. These findings underscore the importance of hybrid approaches that balance theoretical optimality with real-world deployment constraints.

7. Conclusions

This study proposes and validates an AI-augmented IMU–GPS fusion framework designed for energy-efficient and robust positioning in embedded systems. By combining intermittent GPS corrections with a learning-based residual enhancement module integrated into the Kalman filtering process, the proposed method bridges the gap between classical state estimation and data-driven modeling.

Experimental evaluations demonstrate that the framework achieves meaningful reductions in positioning error under moderate GPS sparsity while simultaneously lowering energy consumption and memory usage compared to conventional GPS-only or purely IMU-based approaches. The AI-enhanced filtering mechanism improves adaptability to varying motion dynamics and degraded measurement conditions, confirming the practical benefits of integrating lightweight learning components into model-based estimation pipelines.

The primary contribution of this work lies in establishing a structured and computationally feasible approach to AI-assisted sensor fusion that maintains the interpretability and stability of classical filtering while extending its robustness. This hybrid paradigm provides a viable pathway toward next-generation localization systems that are not only more resource-aware but also more resilient to uncertainty and environmental variability.

Future research may extend this framework by incorporating additional sensing modalities, such as magnetometers, barometers, or vision-based systems, to further enhance robustness. Moreover, integrating adaptive learning strategies or advanced filtering paradigms, including particle filters or graph-based optimization, may reduce residual drift in long-duration trajectories and improve generalization across diverse operational scenarios.

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Institutional Review Board Statement

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Data Availability Statement

The data that support the findings of this study are openly available at https://www.kaggle.com/code/jefmenegazzo/pvs-data-exploration.

Conflicts of Interest

The author declares no conflict of interest.

AI Use Statement

In preparing this manuscript, ChatGPT 5.1 was only used for language refinement, such as improving grammar. The AI tool was not involved in the research design, data collection, data analysis, interpretation of results, or the development of scientific conclusions. I confirm that all scientific ideas, methods, results, and interpretations in the manuscript are entirely my own, and I take full responsibility for the accuracy, originality, and integrity of the content.

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