



## Implementation of a Kalman Filter to Improve RSSI-Based Trilateration Accuracy Using the LoRa RFM95W Module

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| Article Info                                                                                                                                                                                                                                                                                           | Abstract                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            |
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| <p><b>Article History:</b><br/> Submitted 07 Jul 2026<br/> First Revised 29 Aug 2026<br/> Accepted 21 Sep 2026<br/> First Available Online 30 Sep 2026<br/> Publication Date 30 Sep 2026</p> <hr/> <p><b>Keyword:</b><br/> Location Base Service;<br/> Trilaterasi;<br/> RSSI;<br/> Kalman Filter.</p> | <p>Internet of Things (IoT)-based positioning has become increasingly important for monitoring and navigation applications. This study proposes a LoRa-based positioning system using Received Signal Strength Indicator (RSSI) measurements filtered by a Kalman Filter. The filtered RSSI values are converted into distance using the Log-Distance Path Loss model, while the target position is estimated through trilateration. Positioning accuracy is evaluated by comparing the estimated coordinates with GPS coordinates obtained from a u-blox NEO-6M module using the Haversine distance. Experimental results show that the Kalman Filter improves RSSI stability and reduces distance fluctuations, leading to more consistent position estimates. However, the positioning accuracy remains lower than GPS, particularly in dynamic environments. Despite this limitation, the proposed system demonstrates the potential of LoRa as a low-power, long-range positioning solution. Future work will focus on adaptive filtering methods to further improve positioning accuracy.</p> |

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### 1. Introduction

Accurate positioning has become an essential requirement in various Internet of Things (IoT)-based applications, particularly in navigation systems, asset monitoring, and moving object tracking. The Global Positioning System (GPS) has long been the primary technology for obtaining geographic information; however, GPS has several limitations, such as dependence on environmental conditions, potential accuracy degradation in

certain areas, and relatively high power consumption [1]. These limitations encourage the development of alternative technologies capable of providing location determination in a more efficient, stable, and energy-saving manner.

LoRa (Long Range) is a low-power wireless communication technology with wide coverage that is increasingly used in IoT applications. With characteristics such as low power consumption, long-distance transmission capability, and high sensitivity to signal strength (Received Signal Strength Indicator or RSSI), LoRa has significant potential as a supporting technology for positioning systems [2]. Unlike GPS, which relies on satellites, LoRa-based location estimation methods can utilize variations in radio signals to estimate the distance between devices.

One method that can be used in LoRa-based positioning systems is trilateration. This technique calculates the position of an object using relative distances from several reference points with known coordinates [3], [4], [5], [6], [7], [8]. These distances are obtained from RSSI values processed using the log-distance path loss model. However, because RSSI measurements are inherently fluctuating, the accuracy obtained through trilateration is generally limited, and positioning errors tend to propagate through each iteration of the estimation process [6], [8], [9], [10]. This approach allows the system to estimate position without fully depending on satellite technology. After the coordinate estimation is obtained, its accuracy can be evaluated by comparing it with GPS position data using the Haversine method.

Conventional satellite positioning systems like GPS often suffer from high power consumption and signal degradation in obstructed environments [1], [11]. To address these challenges, low-power wide-area networks (LPWAN) such as LoRa have emerged as viable alternatives for terrestrial geolocation [2], [4]. Location estimation in LoRa systems primarily relies on the Received Signal Strength Indicator (RSSI) mapped through the Log-Distance Path Loss model and resolved via trilateration [3], [5], [12]. However, RSSI signals in real-world deployments are highly prone to temporal fluctuations, geometric errors, and environmental noise [13], [14], [15]. Under severe non-line-of-sight (NLOS) or multipath-fading conditions, the geometric intersection point required to resolve trilateration may fail to exist altogether, further compounding the inherent limitations of range-based localization [16].

To stabilize position tracking, various linear and non-linear filtering methods, such as the Kalman Filter, have been integrated into localization pipelines [6], [10]. Real-world RSSI deployments remain vulnerable to noise sources such as electronic interference and signal blocking, which can substantially degrade trilateration accuracy even when the underlying noise is modeled as Gaussian [9], [10]. Notably, even under clean line-of-sight open-field conditions, RSSI-based trilateration retains a non-negligible baseline error in the range of several meters to tens of meters, indicating that environmental obstruction is not the sole source of localization uncertainty [17]. Evaluating distance errors across varying operational conditions including indoor and outdoor deployments remains critical for defining the precision limits of LPWAN tracking [18]. Beyond conventional filtering, alternative approaches such as LoRa-based localization for GPS-less emergency scenarios [19], GPS-free geolocation frameworks [11], extended-range LoRa link characterization at 2.4 GHz [20], and machine learning-based signal feature fusion for

improved distance mapping [7] have also been explored to enhance positioning robustness. Beyond RSSI-based LoRa systems, similar trilateration challenges have been documented in other RSSI-based wireless technologies; for instance, WiFi-based indoor trilateration incorporating reference-point correction has been shown to roughly halve positioning error compared to unassisted trilateration under obstructed indoor conditions [12]. To clearly define the technical contribution of this study, Table 1 provides a comparative summary against recent RSSI-based localization literature.

**Table 1.** State-of-the-Art Comparison of Wireless Localization Approaches

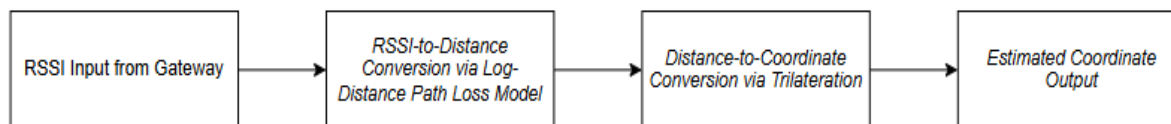
| Reference                        | Target Environment                        | Algorithm / Filtering Technique                         | Parameter Measured                 | Positioning Performance / Key Finding                                                                                                    |
|----------------------------------|-------------------------------------------|---------------------------------------------------------|------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|
| Suroso et al. (2020) [2]         | Indoor                                    | Log-Distance Path Loss Model                            | RSSI, Distance                     | Baseline indoor RSSI signal degradation analysis                                                                                         |
| Kavetha et al. (2022) [4]        | Outdoor Open Field                        | LoRa Trilateration Algorithm                            | RSSI, Coordinates                  | Evaluated range boundary under LOS & NLOS conditions                                                                                     |
| Anugrah et al. (2020) [6]        | Outdoor / NLOS                            | RSSI + Trilateration + Kalman Filter                    | RSSI, Coordinates                  | Kalman-filtered RSSI estimates converged closer to actual position than raw (unfiltered) RSSI estimates                                  |
| Rusli et al. (2016) [12]         | Indoor                                    | RSSI + Trilateration                                    | RSSI, Distance                     | Improved indoor positioning accuracy over conventional RSSI-trilateration baseline                                                       |
| Vazquez-Rodas et al. (2020) [17] | Outdoor                                   | Low-cost LoRa RSSI ranging                              | RSSI, Distance                     | Average error 8.55–12.11 m (5.7–6.7%) persists even under clean LOS conditions, indicating baseline RSSI noise as an inherent limitation |
| Islam et al. (2023) [7]          | Outdoor                                   | ML-based multi-feature distance mapping + Trilateration | RSSI, SNR, SF, Distance            | MAE of 43.97 m; ~26.6% accuracy improvement over RSSI-only trilateration                                                                 |
| <b>Proposed Work</b>             | Terrestrial Open-Space (Building Rooftop) | Log-Distance + Trilateration + 2D Kalman Filter         | RSSI, Coordinates, Haversine Error | MAE 25.99 m; mitigates Gaussian noise but constrained by spatial multipath outlier (114.58 m)                                            |

## 2. Methods

### 2.1 System Overview

This study designs and implements a Location-Based Service (LBS) system using LoRa technology by utilizing the Received Signal Strength Indicator (RSSI) to estimate position and subsequently comparing the results with GPS data to assess localization accuracy. The entire system is integrated through a carefully mapped wiring structure to

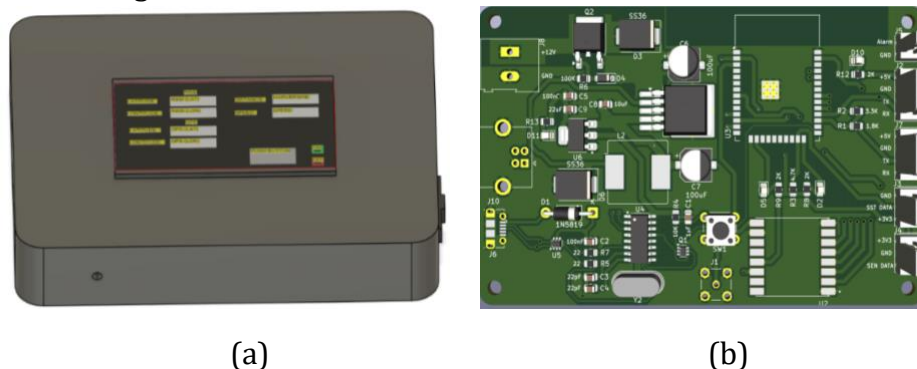
ensure seamless inter-module communication. Specifically, the LoRa module captures the incoming signal and extracts the RSSI value, the ESP32 processes the algorithm to compute distances and coordinates, the GPS module provides benchmark data for real-time validation, the Nextion display visualizes the execution outcomes locally, and the server logs all telemetry data simultaneously. The structural overview of the coordinate conversion process is illustrated in the block diagram in Figure 1.



**Fig. 1.** Block diagram for converting RSSI values into coordinate points.

## 2.2 Hardware and Software Implementation

The system was empirically evaluated in an open-field environment to minimize multipath interference. On the software side, an embedded firmware was developed for the ESP32 to process localized algorithms, while the Nextion HMI interface was designed to visualize coordinates, distance estimations, and real-time localization errors. All modules are interconnected through a optimized wiring structure to ensure stable inter-module data exchange.



**Fig. 2.** Proposed hardware design: (a) Enclosure with HMI display, (b) 3D PCB layout render.

## 3. Results and Discussion

This section presents the experimental results of the sensor and hardware performance. The LoRa RFM95W module was rigorously evaluated to determine its Received Signal Strength Indicator (RSSI) characteristics. By applying the Log-Distance Path Loss model, the resulting positioning and distance errors were systematically analyzed.

The field data collection was conducted through direct empirical testing in the northern region of Surabaya. The distance between the reference towers was configured within a range of 20 to 30 meters. This specific setup was implemented because the initial calibration trials encountered substantial errors at shorter distances of 10 to 20 meters, necessitating an increased operational range of 20 meters and above to ensure signal stability.

These validation tests were executed on land to acquire the baseline structural data. A total of 8 distinct testing points were established, with four sequential measurements recorded at each position. To validate the system's accuracy, the coordinates generated by the trilateration algorithm were compared against the benchmark data from a hardware GPS receiver, and the final absolute distance errors were calculated using the Haversine formula. The comprehensive experimental outcomes are detailed in the following section.

### 3.1 Formatting Equations

To mathematically resolve and validate the positioning accuracy, three sequential formulations are implemented in the system.

#### 3.1.1 RSSI-to-Distance Conversion

To mathematically resolve and validate the positioning accuracy, three sequential formulations are implemented. First, RSSI values are converted into relative distances ( $d$ )[2] using the Log-Distance Path Loss model:

$$PL(d) = PL(d_0) + 10n \log_{10} \left( \frac{d}{d_0} \right) \quad (1)$$

$d$  = Distance between the node and the gateway.

$d_0$  = Reference distance (normally set to 1 meter).

$PL(d)$  = Path loss received at the node at distance  $d$ .

$PL(d_0)$  = Path loss at the reference distance

$n$  = Path Loss Exponent

#### 3.1.2 Trilateration Algorithm

Second, the estimated distances to three distinct reference stations ( $S_1, S_2, S_3$ ) are used to compute the physical coordinates ( $x, y$ ) of the target node, representing its latitude and longitude [3], [4], [5]. The geometric mathematical models for the three overlapping circles are expressed as follows:

$$\text{Circle S1 } d_1^2 = (x - x_1)^2 + (y - y_1)^2 \quad (2)$$

$$\text{Circle S2 } d_2^2 = (x - x_2)^2 + (y - y_2)^2 \quad (3)$$

$$\text{Circle S3 } d_3^2 = (x - x_3)^2 + (y - y_3)^2 \quad (4)$$

$d$  = Distance between the node and the gateway.

$x$  = X-coordinate (latitude) of the node.

$x_1$  = X-coordinate (latitude) of Gateway 1.

$x_2$  = X-coordinate (latitude) of Gateway 2.

$x_3$  = x-coordinate (latitude) of Gateway 3.

$y$  = Y-coordinate (longitude) of the node.

$y_1$  = Y-coordinate (longitude) of Gateway 1.

$y_2$  = Y-coordinate (longitude) of Gateway 2.

$y_3$  = Y-coordinate (longitude) of Gateway 3.

Where  $(x, y)$  is the estimated coordinate of the node,  $(x_1, y_1), (x_2, y_2), (x_3, y_3)$  are the fixed coordinates of the respective gateways, and  $d_1, d_2, d_3$  denote the calculated distances. Expanding these non-linear simultaneous equations yields:

$$d_1^2 = x^2 - 2x \cdot x_1 + x_1^2 + y^2 - 2y \cdot y_1 + y_1^2 \quad (5)$$

$$d_2^2 = x^2 - 2x \cdot x_2 + x_2^2 + y^2 - 2y \cdot y_2 + y_2^2 \quad (6)$$

$$d_3^2 = x^2 - 2x \cdot x_3 + x_3^2 + y^2 - 2y \cdot y_3 + y_3^2 \quad (7)$$

These independent non-linear equations cannot be solved directly. To linearize them, the equations are subtracted to eliminate the quadratic terms ( $x^2$  and  $y^2$ ). Subtracting the expanded equation of  $S_3$  from  $S_2$  yields the first linear equation, denoted as  $V_a$ :

$$x(x_3 - x_2) + y(y_3 - y_2) = \frac{(d_2^2 - d_3^2) - (x_2^2 - x_3^2) - (y_2^2 - y_3^2)}{2} = V_a \quad (8)$$

Similarly, subtracting the expanded equation of  $S_2$  from  $S_1$  establishes the second linear equation, denoted as  $V_b$ :

$$x(x_1 - x_2) + y(y_1 - y_2) = \frac{(d_2^2 - d_1^2) - (x_2^2 - x_1^2) - (y_2^2 - y_1^2)}{2} = V_b \quad (9)$$

By solving the previous linear equations of  $V_a$  and  $V_b$  simultaneously, the values of  $x$  and  $y$  that represent the intersection point of both equations can be successfully obtained. Through algebraic elimination and substitution, the definitive expressions for calculating each coordinate value are derived as follows:

$$y = \frac{V_b(x_3 - x_2) - V_a(x_1 - x_2)}{(y_1 - y_2)(x_3 - x_2) - (y_3 - y_2)(x_1 - x_2)} \quad (10)$$

$$x = \frac{V_a - y(y_3 - y_2)}{(x_3 - x_2)} \quad (11)$$

Once the relative Cartesian coordinates  $x$  and  $y$  are calculated through the trilateration process, they must be transformed back into geographic coordinates consisting of latitude and longitude in decimal degrees. This projection adjustment maps the local planar coordinates back onto the Earth's spherical surface by utilizing a designated origin point, where  $\phi_0$  represents the reference latitude and  $\lambda_0$  represents the reference longitude in radians. The mathematical formulations for converting these values into decimal degrees for latitude and longitude are defined as follows:

$$lat_{deg} = \left( \phi_0 + \frac{y}{R} \right) \cdot \frac{180}{\pi} \quad (12)$$

$$lon_{deg} = \left( \lambda_0 + \frac{x}{R \cdot \cos(\lambda_0)} \right) \cdot \frac{180}{\pi} \quad (13)$$

### 3.1.3 Haversine Formula for Error Validation

To evaluate the localization accuracy, the Haversine formula is employed to calculate the great-circle distance between the estimated coordinates and the actual GPS benchmark points [1], [11]. By utilizing the arcsine function, the shortest distance on the Earth's spherical surface is determined as follows:

$$d = 2r \times \arcsin\left(\sqrt{\sin^2\frac{\Delta\phi}{2} + \cos(\phi_1) \times \cos(\phi_2) \times \sin^2\frac{\Delta\lambda}{2}}\right) \quad (14)$$

- $d$  = distance between the node and the gateway.  
 $r$  = radius of the Earth (6371 km or 6371000 m).  
 $\phi$  = geographic latitude.  
 $\lambda$  = geographic longitude.  
 $\Delta\phi$  = difference in latitude between the two coordinate points.  
 $\Delta\lambda$  = difference in longitude between the two coordinate points.

### 3.2 Baseline Trilateration Performance (Pre-Filtering)

Based on the empirical field testing parameters described above, the raw localization performance of the system prior to the application of the Kalman Filter is structured sequentially across three tables:

**Tab. 2.** RSSI from Tower Reference

| Point No. | Tower 1 RSSI (dBm) | Tower 2 RSSI (dBm) | Tower 3 RSSI (dBm) |
|-----------|--------------------|--------------------|--------------------|
| 1         | -72                | -91                | -72                |
| 2         | -76                | -74                | -88                |
| 3         | -77                | -75                | -72                |
| 4         | -85                | -82                | -54                |
| 5         | -86                | -74                | -81                |
| 6         | -75                | -82                | -66                |
| 7         | -81                | -79                | -79                |

**Tab. 3.** The distance resulting from the log-distance path loss method

| Point No. | Tower 1 Distance (m) | Tower 2 Distance (m) | Tower 3 Distance (m) |
|-----------|----------------------|----------------------|----------------------|
| 1         | 13.12 m              | 82.28 m              | 13.22 m              |
| 2         | 25.95 m              | 22.60 m              | 29.23 m              |
| 3         | 19.98 m              | 19.41 m              | 17.91 m              |
| 4         | 36.81 m              | 31.70 m              | 3.57 m               |
| 5         | 39.58 m              | 17.92 m              | 17.58 m              |
| 6         | 21.58 m              | 30.30 m              | 11.20 m              |
| 7         | 22.64 m              | 22.86 m              | 20.91 m              |

**Tab. 4.** Error Distance Between Estimate and Actual

| Point No. | Estimated Latitude | Estimated Longitude | Actual Latitude | Actual Longitude | Distance Error (m) |
|-----------|--------------------|---------------------|-----------------|------------------|--------------------|
| 1         | -7.205084          | 112.741974          | -7.205669       | 112.741119       | 114.58             |
| 2         | -7.205679          | 112.74099           | -7.205669       | 112.74097        | 2.47               |
| 3         | -7.205645          | 112.741013          | -7.205584       | 112.740799       | 24.56              |
| 4         | -7.205528          | 112.740936          | -7.205473       | 112.740944       | 6.18               |
| 5         | -7.205609          | 112.740799          | -7.205674       | 112.740864       | 10.18              |

|         |           |            |           |            |       |
|---------|-----------|------------|-----------|------------|-------|
| 6       | -7.205568 | 112.741066 | -7.205623 | 112.74098  | 11.29 |
| 7       | -7.205636 | 112.741013 | -7.205672 | 112.741126 | 13.09 |
| Average |           |            |           |            | 26.05 |

As summarized in Table 4 and visually mapped in Figure 3, the raw trilateration system exhibits varying degrees of localization accuracy across the seven distinct testing locations. The system achieves its highest precision at Point 2, yielding a remarkably low distance error of 2.48 m.

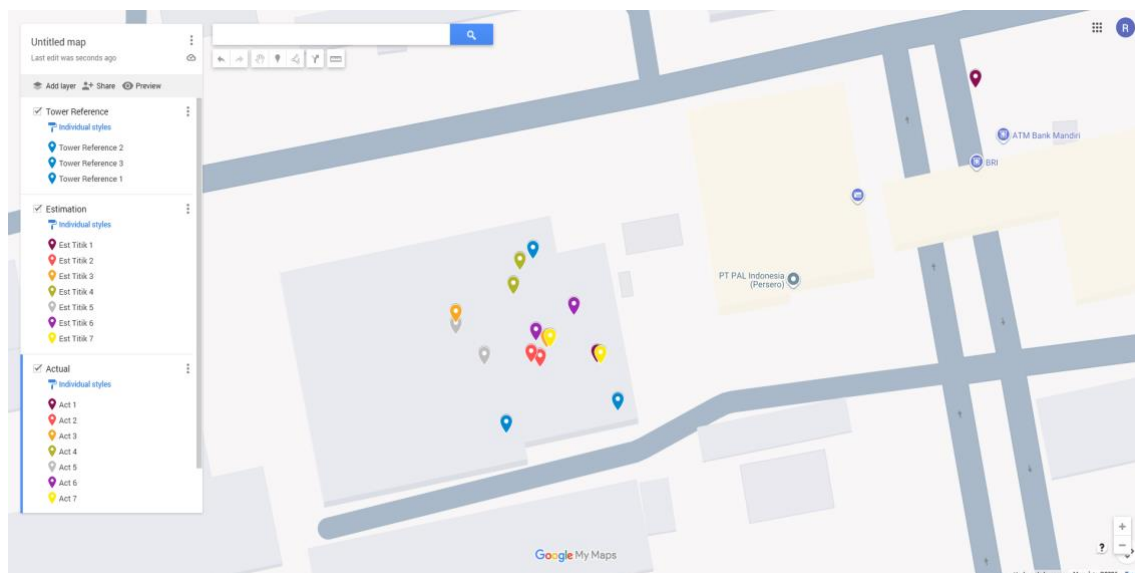


Fig. 3. Estimated and actual results on the map markers

Conversely, a severe positioning anomaly is observed at Point 1, where the calculated coordinates deviate by 114.58 m from the ground truth. This spatial outlier is primarily driven by localized signal multipath reflections from adjacent building structures and temporary Line-of-Sight (LOS) fluctuations on the rooftop during empirical data collection. Consequently, these RSSI distortions skew the overall baseline performance, resulting in a cumulative average localization error (MAE) of 26.05 m prior to filtering.

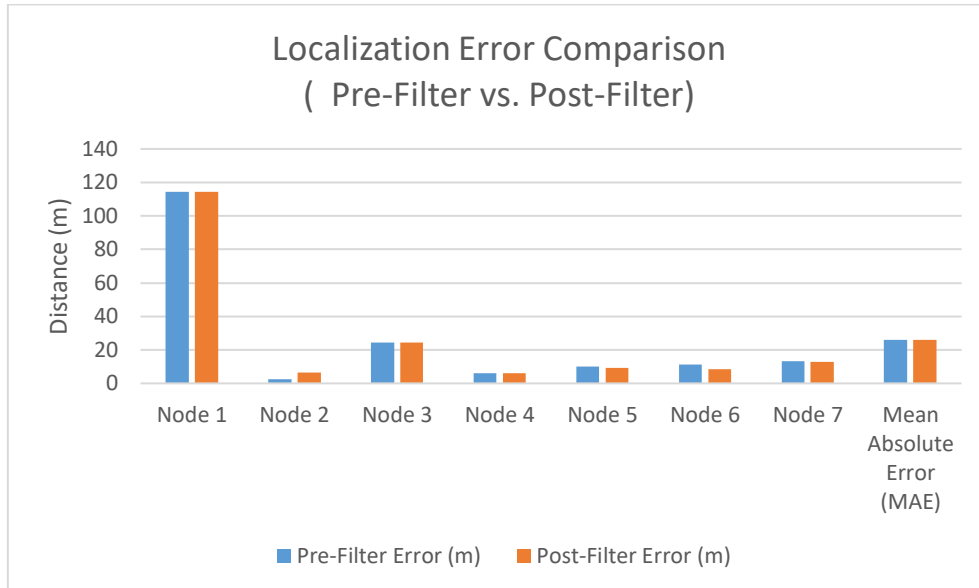
### 3.3 Kalman Filter Optimization and Accuracy Improvement (Post-Filtering)

To mitigate the positioning errors and signal fluctuations detailed in the previous subsection, the Kalman Filter algorithm was applied to the localization pipeline. This subsection evaluates the optimized positioning performance and quantifies the accuracy improvement achieved by the filter [6].

Tab. 5. Error Distance Between Kalman Filter Estimate and Actual

| Point No. | Kalman Latitude | Actual Latitude | Kalman Longitude | Actual Longitude | Distance Error (m) |
|-----------|-----------------|-----------------|------------------|------------------|--------------------|
| 1         | -7.205084       | -7.205669       | 112.741974       | 112.741119       | 114.58             |
| 2         | -7.205611       | -7.205669       | 112.740968       | 112.74097        | 6.45               |
| 3         | -7.205645       | -7.205584       | 112.741013       | 112.740799       | 24.56              |

|         |           |           |            |            |       |
|---------|-----------|-----------|------------|------------|-------|
| 4       | -7.205524 | -7.205473 | 112.740929 | 112.740944 | 5.91  |
| 5       | -7.205594 | -7.205674 | 112.740848 | 112.740864 | 9.07  |
| 6       | -7.205558 | -7.205623 | 112.741044 | 112.74098  | 8.53  |
| 7       | -7.205645 | -7.205672 | 112.741013 | 112.741126 | 12.81 |
| Average |           |           |            |            | 25.99 |



**Fig. 4.** Comparison error graph between post filtering and pre-filtering

Based on the empirical positioning data illustrated in Figure 4, a comparative analysis between the raw trilateration algorithm (pre-filtering) and the integrated Kalman Filter linear model (post-filtering) demonstrates a quantifiable transformation in system reliability. The localization discrepancies are mathematically summarized across seven testing nodes to evaluate spatial variance within the high-interference environment.

Prior to filtering, the raw trilateration algorithm yielded a Mean Absolute Error (MAE) of 26.05 m. A primary vulnerability is highlighted at Node 1, where severe signal degradation caused a maximum spatial error of 114.58 m. This positioning error is mainly attributed to structural multipath fading from surrounding rooftop walls and minor elevation variation during signal transmission, consistent with prior reports of severe RSSI degradation in noisy outdoor deployments [9], [10]. Under such conditions, the geometric intersection point required by the trilateration algorithm itself may become unreliable or fail to form altogether [16]. Conversely, the system achieved its highest raw accuracy at Node 2, with a minimal localized error of 2.47 m.

The implementation of the 2D Kalman Filter successfully stabilizes the dynamic tracking performance, compressing the cumulative MAE down to 25.99 m, a trend consistent with prior work showing that Kalman-filtered RSSI estimates converge closer to the actual position than raw, unfiltered estimates [6]. While Node 1 remains a persistent environmental anomaly due to the severity of the initial RSSI distortion (retaining an error of 114.58 m), a notable optimization is systematically achieved across the remaining testing nodes. For instance, at Node 2, the localized deviation is bound to 6.45 m, providing a predictable convergence boundary. Significant noise reduction is further observed at Node 4, Node 5, and Node 6, where tracking errors decreased from 6.18 m, 10.18 m, and 11.29 m down to 5.91 m, 9.07 m, and 8.53 m, respectively.

#### 4. Conclusion

The experimental results indicate that the application of the Kalman Filter provides a stabilized tracking performance within the high-interference environment. Although the cumulative average positioning error (MAE) demonstrated a modest reduction from 26.050 m to 25.988 m, the filter successfully suppressed localized RSSI fluctuations across the majority of the test nodes. A persistent limitation was observed at the first measurement point, where severe initial outliers remained unchanged and heavily skewed the overall average. This empirical evidence suggests that while the 2D Kalman Filter is highly effective in mitigating random Gaussian measurement noise, its convergence is constrained when the primary input contains large systematic errors or non-Gaussian multipath fading [16]. Consequently, while the proposed framework significantly enhances the kinematic stability and spatial consistency of the tracking trajectory, integrating supplementary outlier rejection algorithms such as confidence-based intersection determination for cases where the trilateration geometry becomes unreliable [16] or adaptive covariance tuning is recommended for future work to optimize absolute positioning accuracy.

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#### 6. Author's Note

The authors hereby declare that there is no conflict of interest related to the publication of this article. Furthermore, the authors confirm that the manuscript is original and free from any form of plagiarism.

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