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Improving Indoor Positioning Accuracy Using a Hybrid Wi-Fi RSSI Model with KNN, Kalman Filter, and MLP

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Abstract

Indoor Positioning Systems (IPS) have gained significant relevance as traditional GPS technologies remain ineffective in indoor environments. Among available alternatives, Wi-Fi-based Received Signal Strength Indicator (RSSI) methods are popular due to their low cost and reliance on existing wireless infrastructure. However, RSSI signals are inherently unstable, being affected by noise, multipath propagation, and environmental variability. The RADAR algorithm, one of the earliest Wi-Fi fingerprinting techniques, provides a foundational baseline by comparing real-time RSSI values with a pre-constructed radio map. Despite its simplicity and computational efficiency, RADAR's accuracy degrades in dynamic indoor conditions. In this study, we present a hybrid approach that integrates the K-Nearest Neighbors (KNN) algorithm, Kalman filtering, and a Multi-Layer Perceptron (MLP) neural network to enhance localization accuracy and system stability. KNN serves as the initial fingerprinting mechanism, while the Kalman Filter mitigates signal noise and smooths RSSI fluctuations. The refined data are then processed by the MLP model to learn nonlinear spatial patterns and improve position estimation. Experimental results demonstrate that the proposed hybrid model achieves an average positioning error of approximately 0.4 meters, significantly outperforming the traditional RADAR algorithm, which recorded an average error of 1.4 meters. These findings underscore the limitations of conventional fingerprinting methods in dynamic indoor environments and highlight the effectiveness of combining machine learning and filtering techniques for robust, high-precision localization. The study contributes to the ongoing evolution of IPS research, moving from simple signal-matching frameworks toward adaptive hybrid systems optimized for real-time applications.

Keywords

Indoor Positioning System (IPS)
Wi-Fi RSSI
Kalman Filter
Multi-Layer Perceptron (MLP)
Hybrid Localization Algorithm

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INTRODUCTION

The demand for indoor localization systems has increased due to the proliferation of location-based services in smart homes, hospitals, and commercial buildings. Traditional GPS solutions fail indoors because of signal attenuation and reflection from walls and objects. Wi-Fi-based IPS presents a promising alternative, leveraging the widespread deployment of wireless networks. Among Wi-Fi metrics, the Received Signal Strength Indicator (RSSI) is commonly used for estimating location due to its simplicity. However, RSSI suffers from instability caused by interference, user orientation, and environmental dynamics. To mitigate these issues, signal filtering and machine learning techniques are applied to refine measurements and enhance positioning accuracy.

The Kalman Filter is a statistical estimator capable of reducing RSSI noise through recursive updates. On the other hand, the Multi-Layer Perceptron (MLP), a form of neural network, can learn non-linear mappings between RSSI inputs and 2D coordinates. This study combines both approaches: first filtering noisy RSSI data with the Kalman Filter, then using MLP regression to estimate positions. The goal is to evaluate whether this hybrid framework can yield more reliable and precise indoor localization results.

1. Existing models

The RADAR algorithm (Padmanabhan, al) is one of the earliest Wi-Fi fingerprinting methods, estimating user positions by comparing real-time RSSI values with a pre-collected radio map, though its accuracy is limited by environmental changes. In contrast, INTERLINK (Interlink Networks, Inc., 2002) enhances indoor localization by integrating signal fingerprinting with learning-based techniques, making it more adaptive and robust in dynamic environments.

1.1 INTERLINK

The Interlink algorithm is designed to improve positioning accuracy in fingerprint-based Wi-Fi RSSI systems by creating a weighted linkage between multiple positioning methods or signal features. Unlike single-method localization, Interlink dynamically fuses intermediate results from multiple estimators before generating the final position. It acts as a "bridge" between regression-based predictions and proximity-based corrections.

2.1.1 INTERLINK Mathematical Model

Let:

- $r = [r_1, r_2, \dots, r_M]$ be the RSSI vector from M access points.
- $\hat{P}_1 = (x_1, y_1)$ be the position estimated at P_1
- $\hat{P}_2 = (x_2, y_2)$ be the position estimated at P_2
- w_1, w_2 be the weights assigned $w_1 + w_2 = 1$.

The Interlink output position is computed as a weighted fusion:

$$\hat{P}_{interlink} = w_1 \cdot \hat{P}_1 + w_2 \cdot \hat{P}_2 \dots \dots \dots (1)$$

The weights can be constant or dynamically assigned based on the confidence score of each method:

$$w_i = \frac{\frac{1}{e_i}}{\sum_{j=1}^k \frac{1}{e_j}} \dots \dots \dots (2)$$

Where e_i is the historical mean error of method during validation

The following pseudo-code described the method:

Pseudo code

Input: RSSI vector r , trained models $M1$ (MLP), $M2$ (KNN), weight parameters $w1$, $w2$

Output: Estimated position $p_interlink$

1: $p1 \leftarrow M1.predict(r)$

2: $p2 \leftarrow M2.predict(r)$

3: *If dynamic weights:*

$w1 \leftarrow 1 / error_history_M1$

$w2 \leftarrow 1 / error_history_M2$

Normalize $w1$, $w2$

4: $p_interlink \leftarrow w1 * p1 + w2 * p2$

5: *Return $p_interlink$*

One common way is from RSSI (signal strength) using a path-loss model:

$$d_i = 10^{\frac{p_0 - p_{RSSI,i}}{10n}} \dots \dots \dots (3)$$

where:

- p_0 = signal strength at 1 meter (dBm)
- $p_{RSSI,i}$ = measured RSSI from anchor i (dBm)
- n = path-loss exponent (depends on environment)

2.1.2 INTERLINK working Process

In indoor positioning, an interlink algorithm is a hybrid approach that links and combines multiple localization techniques into a single, unified process. It can integrate data from sources such as Wi-Fi RSSI, Bluetooth beacons, Ultra-Wideband (UWB), or inertial sensors, reducing the weaknesses that occur when relying on only one method. For instance, Wi-Fi trilateration may suffer from multipath interference, while fingerprinting can be sensitive to environmental changes, but an interlink algorithm allows these techniques to share information so one compensates for the limitations of another. Using mathematical models, statistical filters, or machine learning, it merges the outputs into a stable and accurate location estimate, even when some signals are weak or missing.

The process can fuse distances, angles, and signal patterns in real time, making it particularly useful in complex indoor environments with obstacles and dynamic conditions. By linking multiple methods, it achieves higher accuracy and reliability than any single algorithm alone, while remaining adaptable to different buildings and sensor setups. Ultimately, the interlink algorithm improves indoor positioning performance by combining the strengths of diverse techniques into a cohesive and robust solution.

2.2 RADAR INDOOR POSITIONING

The RADAR indoor positioning algorithm is one of the earliest and most influential Wi-Fi fingerprinting systems for indoor localization, first proposed by Bahl and Padmanabhan (2000). It estimates a user's location based on RSSI (Received Signal Strength Indicator) measurements from multiple Wi-Fi access points (APs).

2.2.1 RADAR Mathematical Formulation

The RADAR indoor positioning algorithm is one of the earliest and most influential Wi-Fi fingerprinting systems for indoor localization, first proposed by Bahl and Padmanabhan (2000). It estimates a user's location based on RSSI (Received Signal Strength Indicator) measurements from multiple Wi-Fi access points (APs).

At each reference point (RP) in the environment, the system gathers multiple RSSI (Received Signal Strength Indicator) readings from each access point (AP). Then, it computes the average RSSI values to form a fingerprint:

Offline phase: Building the Radio Map $\overline{RSSI} = \frac{1}{M} \sum_{m=1}^M RSSI_{i,j,m} \dots \dots \dots (4)$

- Where $RSSI_{i,j,m}$ is the m^{th} measurements from AP_j at RP_i
- M is the number of samples per RP.

Online Phase: Position Estimation

When a device takes a new RSSI measurement (vector r), RADAR compares it to every stored fingerprint f_i using a distance metric typically Euclidean distance:

$$d_i = \sqrt{\sum_{j=1}^N (r_j - f_{i,j})^2} \dots\dots\dots(5)$$

- N is the number of AP
- r_j is the current RSSI from AP_j
- $f_{i,j}$ is the stored mean RSSI from AP_j at reference point i

Recent advancements in indoor positioning systems have seen the RADAR framework evolve far beyond its original Wi-Fi fingerprinting approach. For example, (Pascal. al 2023) proposed an innovative method that integrates active radar sensing with passive reflectors to uniquely identify positions by analyzing reflection signatures within indoor environments. This represents a shift from solely relying on Wi-Fi signal strength to incorporating richer signal features from radar-based sensing. Similarly, Ashraf, Hur, and Park (2022) published a comprehensive review of modern indoor positioning and localization techniques, outlining how systems have diversified in their choice of sensors, algorithms, and fusion strategies to improve accuracy, robustness, and adaptability in complex indoor settings. Furthermore, Jakub Nikonowicz, Aamir Mahmood, Muhammad Ikram Ashraf, Emil Björnson, and Mikael Gidlund (2024) explored the use of carrier-phase measurements in 5G-Advanced networks, aiming for centimeter-level positioning accuracy indoors. Their work highlights the trend toward leveraging advanced communication technologies and precise phase information for localization. Together, these studies show that the RADAR concept has expanded from its early form into a multidisciplinary framework that combines radar sensing, advanced signal processing, and emerging wireless standards to achieve higher accuracy and resilience. The shift is also marked by the adoption of multi-modal sensing approaches, where RADAR techniques can be complemented by machine learning models, inertial measurement units, and collaborative localization strategies. This progression not only

addresses the limitations of multipath effects and signal fluctuations but also enables positioning in more challenging environments where traditional fingerprinting alone would fail. As such, the latest RADAR-based research is paving the way for next-generation indoor positioning systems that are faster, more adaptive, and capable of meeting the demands of applications like robotics, augmented reality, and industrial automation.

The following code described the method:

Input: RSSI vector r , fingerprint database DB , parameter k

Output: Estimated position p_radar

1: For each fingerprint f_i in DB :

$dist[i] \leftarrow EuclideanDistance(r, f_i)$

2: Sort $dist$ in ascending order

3: Select k nearest neighbors N_k

4: $p_radar \leftarrow Average\ position\ of\ N_k$

5: Return p_radar

2.2.2 Advantages:

- Simple and effective for static environments,
- No need for AP coordinates or path-loss model,
- Handles NLOS effects better than trilateration.

2.2.3 Limitations:

- Computationally heavy for large FDBs,
- Sensitive to environmental changes (requires updates),
- Accuracy limited by RP density

3 PROPOSED SYSTEM

3.1 Description of the Proposed system

Our contribution protocol is described by the following phase:

The access points initiate the positioning process by sending positioning requests, specifically messages of type 2 as defined in the OWLPS file, within their coverage areas. These messages are captured by the Target Mobile (TM), which extracts the Received Signal Strength Indicator (RSSI) values and applies the designated protocol to compute its current position. Once the position is calculated, the TM stores a copy in its cache memory and simultaneously propagates this information to all surrounding access points. These access points, in turn, store the computed position locally and further propagate it to neighboring access points. Additionally, a copy of the position data is sent to both the Aggregation Server and the Computing or Positioning Server for further processing and system-wide awareness. This decentralized sharing enhances the robustness of the system; ensuring updated positioning data is available throughout the network.

The TM's cache supports quick response to repeated queries, while the Access points help maintain consistency through propagation. Moreover, the use of OWLPS messaging structure standardizes communication and improves system scalability and integration. Each access point acts both as a transmitter and data relay, forming a cooperative mesh of localized positioning intelligence.

3.2 Proposed models

The following subsections describe the models that will be applied in this study. Each model is presented with its underlying principles and its relevance to the positioning system.

3.2.1 K-Nearest Neighbor (KNN)

In indoor environments where GPS is unreliable or unavailable, alternative localization techniques are

essential. One effective and straightforward approach is RSSI-based indoor positioning, which uses the Received Signal Strength Indicator (RSSI) from multiple Wi-Fi Access Points (APs) to estimate a device's location. A commonly used algorithm for this purpose is the K-Nearest Neighbors (KNN) algorithm. KNN is a non-parametric, instance-based learning method that does not require any model training. Instead, it relies on comparing new RSSI readings with previously collected data points (fingerprints) stored in a database. When a new RSSI reading is captured, KNN searches for the K most similar signal patterns in the database and calculates the estimated position by averaging the known coordinates of those K nearest neighbors. This makes KNN particularly appealing for its simplicity, ease of implementation, and reasonable accuracy, especially in small to medium-sized indoor environments (Masek et al., 2020). In (Zhu et al., 2020) study the current landscape of fingerprinting-based indoor positioning, propose future directions toward intelligent, hybrid systems, and identify challenges such as dynamic environments, data collection overhead, and real-time adaptability.

Thanks to its simplicity and efficiency in settings with consistent signal behavior, KNN continues to serve as a reliable reference approach for indoor positioning systems. In a Wi-Fi RSSI-based indoor positioning system with four access points, the system first collects RSSI values at known locations to build a labeled training dataset. Each data point includes signal strengths from the four access points and corresponding coordinates. When a new RSSI reading is captured, the K-Nearest Neighbors (KNN) algorithm calculates the distance between this new signal vector and all entries in the training set. It then selects the k closest matches (neighbors) based on signal similarity and averages their coordinates to estimate the current location. The estimated position is displayed as the predicted user location within the indoor environment in *Figure 3*.

3.2.2 Kalman Filter

The Kalman Filter is a recursive mathematical algorithm used to estimate the true state of a dynamic system from a series of noisy and uncertain measurements. It operates by predicting the current state based on previous estimates and updating that prediction using new observations. In the context of indoor positioning, the Kalman Filter plays a crucial role in improving location estimates derived from Wi-Fi RSSI data. RSSI signals are prone to high variability due to environmental factors such as walls, furniture, human movement, and electromagnetic interference. These fluctuations introduce significant noise, which negatively impacts the reliability of raw RSSI-based positioning. As a result, using raw RSSI measurements alone can lead to inconsistent and inaccurate location predictions. The Kalman Filter addresses this issue by smoothing the RSSI data and predicting movement patterns over time, reducing the impact of sudden signal spikes or drops. This makes it particularly useful in dynamic environments where users or objects are in motion. When integrated with positioning algorithms such as KNN or MLP, the Kalman Filter significantly enhances indoor positioning accuracy. Overall, it adds a layer of robustness and temporal coherence to indoor localization systems based on wireless signal strength.

3.2.3 Multi Layers perceptron

A Multi-Layer Perceptron (MLP) shown in *figure 2* is a type of artificial neural network used for learning complex patterns in data (Albert et al., 2020; Santacroce et al., 2020). In the context of indoor

positioning, MLPs can be trained to predict a device's physical location based on RSSI signals received from four fixed Wi-Fi Access Points (APs). The RSSI values from APs are influenced by walls, interference, and other factors, making them non-linear and noisy. MLPs are ideal for modeling these non-linear relationships between RSSI values and physical locations because they can learn from data without explicit rules (Santacroce et al., 2020).

The neural network architecture used for the indoor positioning system is designed to process Wi-Fi RSSI inputs and predict spatial coordinates. The input layer consists of 4 nodes, corresponding to the RSSI values received from the four Wi-Fi Access Points. This is followed by two hidden layers that extract and transform features from the input data. The first hidden layer contains 64 neurons, while the second hidden layer has 32 neurons. Both hidden layers use the ReLU (Rectified Linear Unit) activation function to introduce non-linearity into the model and enhance learning capability. The output layer comprises 2 neurons, which represent the predicted x and y coordinates of the user's position within the room. This structure enables the model to map complex relationships between RSSI values and physical locations. The compact yet deep design of the network ensures both computational efficiency and accurate spatial estimation. By leveraging multiple layers, the model can learn intricate signal-location patterns inherent in indoor environments. Overall, this architecture is well-suited for regression-based indoor positioning tasks using RSSI data.

3.2.3 .1 Mlp Algorithm

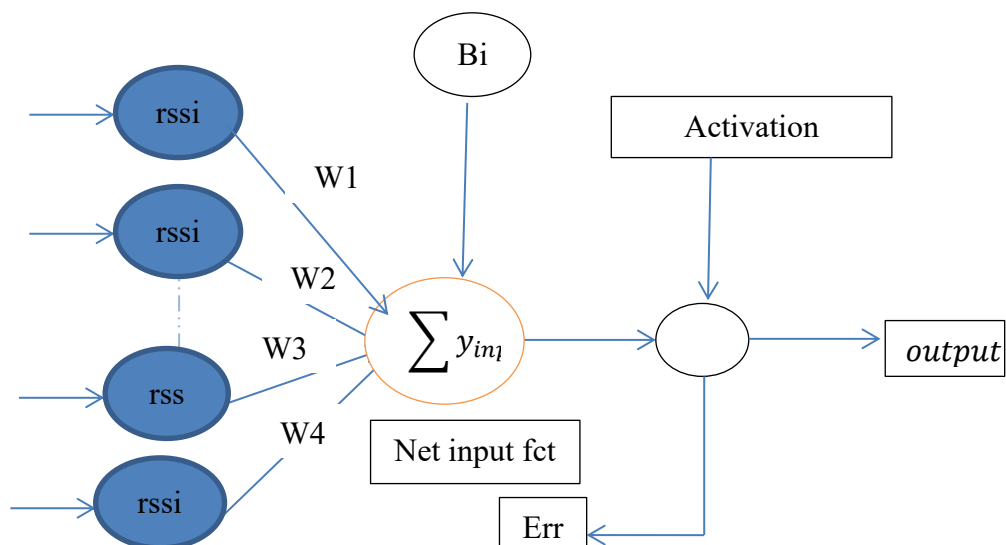


Figure 1 Multi Layer Perceptron

$$y_{inp} = x_1w_1 + x_2w_2 + x_3w_3 \dots \dots \dots + x_nw_n \dots \dots \dots (6)$$

$$f(y_{inp}) = \begin{cases} 1 & \text{if } y_{inp} \geq \delta \\ 0 & \text{if } -\delta \leq y_{inp} < \delta \dots \dots \dots (7) \\ -1 & \text{if } y_{inp} < -\delta \end{cases}$$

Weight updating:

if $y \neq t$ *then* $w(\text{new}) = w(\text{old}) + atx$

else, $w(\text{new}) = w(\text{old})$

a) Training phase

- Step 0 initialization weights and bias
 $\alpha = 1$
- Step 1 : perform step 2-5 until final stopping Condition is false
- Step 2 : perform step 2-4 for each training pair
- Step 3 : calculate the output

$$y_{inp} = \sum_1^n x_i w_i \dots \dots \dots (8)$$

Apply the activation function $f(y_{inp})$

- Step 4 : weight + bias adjustment

if $y \neq t$ then
 $w(new) = w_i(old) + \alpha$

$$x_i \dots \dots \dots (9)$$

$$b(new) = b(old) + \alpha$$

$$t_i \dots \dots \dots (10)$$

else

$$w(new) =$$

$$w_i(old) \dots \dots \dots (11)$$

$$b(new) =$$

$$b_i(old) \dots \dots \dots (12)$$

- Step 5 : train the network until

b) Testing algorithm

- Step 0 : the initial weights to be used here are taken from training algorithm
- Step 1 : for each i/p vector to be categorized perform step 2-3
- Step 2 : set the activation functions

$$y_{inp} = x_1 w_1 + x_2 w_2 + x_3 w_3 \dots \dots \dots + x_n w_n + b \dots \dots \dots (13)$$

$$f(y_{inp}) =$$

$$\begin{cases} 1 & \text{if } y_{inp} \geq \delta \\ 0 & \text{if } -\delta \leq y_{inp} < \delta \dots \dots \dots \\ -1 & \text{if } y_{inp} < -\delta \end{cases}$$

$$\dots \dots \dots (14)$$

Input: RSSI vector r_t , KNN model, MLP model, Kalman parameters (F, H, Q, R)

Output: Smoothed position p_t

$$1: p_{knn} \leftarrow KNN.predict(r_t)$$

$$2: p_{mlp} \leftarrow MLP.predict(r_t)$$

$$3: p_{ens} \leftarrow \alpha * p_{knn} + (1 - \alpha) * p_{mlp}$$

$$4: \# \text{ Kalman Prediction}$$

$$5: x_{pred} \leftarrow F * x_{prev}$$

$$6: P_{pred} \leftarrow F * P_{prev} * F^T + Q$$

$$7: \# \text{ Kalman Update}$$

$$8: K \leftarrow P_{pred} * H^T * inv(H * P_{pred} * H^T + R)$$

$$9: x_t \leftarrow x_{pred} + K * (p_{ens} - H * x_{pred})$$

$$10: P_t \leftarrow (I - K * H) * P_{pred}$$

$$11: \text{Return } x_t$$

Pseudo code

knn+kf+mlp

3.2.4 Ensemble Methods for Applied Models

The adoption of an ensemble approach in this study is grounded in the *wisdom of the crowd* principle, which asserts that the aggregated output of multiple diverse and independent estimators can surpass the accuracy of a single model. This concept, first observed in Francis Galton's (1907) study on collective estimations and later popularized by Surowiecki (2004), is well-established in machine learning through ensemble techniques such as bagging, boosting, and stacking. By combining the predictions of complementary models, these methods reduce variance, mitigate individual biases, and improve predictive performance (Dietterich, 2000; Zhou, 2012).

The motivation for employing an ensemble model combining KNN, Kalman Filter, and MLP algorithms in RSSI-based indoor positioning lies in the inherent limitations and strengths of each individual method. Indoor environments are complex and unpredictable due to factors such as multipath propagation, dynamic obstacles, and fluctuating signal strengths. Relying on a single algorithm often fails to address all these challenges effectively. KNN, known for its simplicity and effectiveness in estimating initial positions based on RSSI fingerprints, struggles when faced with noise and outliers in the data. Meanwhile, MLP excels at learning nonlinear patterns and generalizing from complex datasets, yet it is prone to overfitting and can produce jittery outputs when signal variability is high.

The Kalman Filter, on the other hand, is not a positioning algorithm by itself but significantly improves position tracking over time by smoothing noisy measurements and enforcing temporal consistency. When these three models are combined into an ensemble system, they complement one another: KNN offers a fast, rough estimate; MLP refines this estimate using its capacity for nonlinear modeling; and the Kalman Filter applies temporal

filtering to generate smooth and realistic motion paths. This integration enhances both accuracy and robustness, enabling the positioning system to perform well across a variety of indoor conditions, even in the presence of signal distortion and dynamic user movement. The ensemble strategy thus forms a cohesive framework that leverages the advantages of each component algorithm while mitigating their individual weaknesses (Potorti et al., 2022) and (Wang et al., 2022).

3.2.4.1 Model

Bagging, short for Bootstrap Aggregating, is an ensemble technique that enhances the stability and accuracy of indoor positioning systems based on Wi-Fi RSSI by training multiple instances of base models such as KNN, Kalman Filter, and Multi-Layer Perceptron on different bootstrapped subsets of the fingerprint dataset, and then aggregating their predictions to produce more robust and reliable location estimates. In the context of RSSI-based indoor positioning, bagging can be applied across KNN, MLP, and even Kalman-based estimation chains to mitigate the high variance and signal noise that typically affect indoor localization. For example, multiple KNN regressors can be trained on different subsets of RSSI fingerprints to provide diverse initial position estimates, which are then averaged to reduce sensitivity to outliers.

Similarly, several MLP models, each trained with different initialization seeds and data samples, can learn complementary representations of the nonlinear RSSI-to-coordinate mapping, and their averaged predictions become more robust to fluctuations in signal strength. Even for the Kalman Filter, although it is inherently sequential and deterministic, bagging can be conceptually extended by applying it to multiple filtered tracks originating from different KNN+MLP pathways, and then combining the smoothed outputs. This multi-model bagged ensemble helps reduce the overfitting risk from the MLP, the local volatility from KNN, and over-smoothing or linear assumptions of

Kalman Filters. Overall, the bagged ensemble leads to a more resilient positioning system capable of operating in real-time, delivering stable and accurate results in dynamically changing wireless indoor environments (Esmaeili Gorjan & Gil Jiménez, 2024).

a) Advantages for Indoor Positioning

- **KNN:** Works well with Wi-Fi fingerprinting, good at capturing local patterns.
- **Kalman Filter:** Smooths noisy RSSI data, stabilizing short-term predictions.
- **MLP:** Learns complex nonlinear RSSI-to-position mappings.
- **Bagging:** Reduces variance and improves generalization when environmental noise is high.

3.2.4.1 Algorithm

a) step by step prediction :

1. Bootstrap sampling: Create several different datasets from your RSSI dataset via random sampling with replacement.
2. Model training:
 - Train KNN on one subset.
 - Train Kalman Filter (for smoothing + prediction) on another subset.
 - Train MLP on another subset.
3. Prediction:
 - For regression (x, y coordinates), take the average of the outputs.
 - For classification (e.g., location zones), take majority voting.

3.2.5 Boosting Model

Boosting is a powerful ensemble technique that improves predictive accuracy by sequentially combining multiple weak learners, where each new model focuses on correcting the errors of the previous ones. In the context of indoor positioning systems based on RSSI

values, boosting can be adapted to work across KNN, MLP, and Kalman Filter components to improve location estimation in challenging indoor environments. While traditional boosting frameworks such as AdaBoost and Gradient Boosting are typically designed for decision trees, the boosting principle can be conceptually extended to this hybrid algorithmic setup. Initially, a simple KNN model can be used to provide a baseline estimate of the user's position. The residual errors from this prediction (i.e., the difference between estimated and actual positions) are then modeled by a more expressive learner, such as an MLP, which focuses on learning the complex nonlinearities that KNN cannot capture. Subsequently, the Kalman Filter acts as a final stage that not only smooths the boosted outputs over time but also continuously updates predictions based on motion dynamics and measurement uncertainty. This sequential boosting structure enables the system to correct initial spatial predictions, refine them using neural learning, and stabilize them through temporal filtering. The resulting indoor localization system exhibits improved resilience to signal noise, reduced position error, and better adaptation to dynamic environmental changes. Boosting this trio of algorithms KNN, Kalman Filter, and MLP creates a layered improvement process that systematically enhances positioning accuracy. Each algorithm contributes uniquely: KNN offers simplicity, Kalman Filter adds temporal stability, and MLP captures complex signal patterns. Together, they form a robust and adaptive indoor positioning system capable of overcoming the limitations of individual methods.

3.2.5.1 Algorithm

The proposed approach employs a sequential boosting strategy that integrates K-Nearest Neighbors (KNN) regression, Kalman filtering, and a Multi-Layer Perceptron (MLP) model to enhance the accuracy of Wi-Fi RSSI-based indoor positioning. The algorithm

corrects prediction errors at each stage by leveraging the strengths of each component.

Step 1 Data Acquisition and Preprocessing

1. Load the RSSI dataset from the collected .csv file containing readings from multiple Access Points (APs), timestamps, and ground truth coordinates (x, y) .
2. Sort the dataset chronologically according to timestamps to maintain temporal order.
3. Handle missing RSSI values by replacing them with the mean or median of the respective AP.
4. Remove extreme RSSI values (*inf.* -100 dBm or *sup.* -20 dBm) to reduce noise.
5. Normalize RSSI features using Z-score standardization or Min-Max scaling.
6. Partition the dataset into training (70%), validation (15%), and testing (15%) sets using chronological splitting to avoid data leakage.

Step 2 Stage 1: KNN Regression

1. Train a KNN regressor with k-nearest neighbors on the training set, where the inputs are RSSI vectors and the outputs are corresponding (x, y) coordinates.
2. Obtain predicted positions $\hat{y}^{(1)}$ for both training and testing sets.
3. Compute the residuals:

$$r^{(1)} = y_{true} - \hat{y}^{(1)} \dots \dots \dots (15)$$

These residuals capture spatial prediction errors from KNN.

Step 3 Stage 2: Kalman Filtering

1. Apply a Kalman Filter to the KNN predictions to exploit temporal correlations and smooth trajectory estimates.
2. Use a constant velocity process model, with the state vector representing position and velocity.

3. Input KNN predictions as measurements, producing smoothed outputs $\hat{y}^{(2)}$.
4. Calculate new residuals: $r^{(2)} = y_{true} - \hat{y}^{(2)}$ (16)

Step 4 Stage 3: MLP Residual Correction

1. Form a new training set where the input features consist of the original RSSI values concatenated with the Kalman-filtered positions $\hat{y}^{(2)}$.
2. Set the target variable to the residuals $r^{(2)}$ from Stage 2.
3. Train an MLP regressor with two to three hidden layers (e.g., 64-64 neurons) and ReLU activation to predict the residuals.
4. Apply the trained MLP to the test set to produce residual estimates $\hat{r}^{(3)}$
5. Generate final position estimates: $\hat{y}_{final} = \hat{y}^{(2)} + \hat{r}^{(3)}$ (17)

Step 5 Evaluation

1. Compare positioning accuracy across three configurations:
 - o KNN alone.
 - o KNN + Kalman Filter.
 - o KNN + Kalman Filter + MLP (Boosted).
2. Compute performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Cumulative Distribution Function (CDF) of errors.
3. Assess improvements in positioning accuracy through comparative analysis.

3.3 Dataset and Data Collection

RSSI values are collected from multiple Wi-Fi access points at various known reference points within the indoor environment, typically using a mobile device or sensor. Each data sample includes the RSSI readings from the access points along with the corresponding ground-truth coordinates (x, y) , forming labeled training data. The dataset is then preprocessed by

cleaning noisy data, normalizing RSSI values, and optionally splitting into training and testing sets to prepare it for input into machine learning models.

3.3.1 Data Processing

Given that raw RSSI measurements are inherently noisy, preprocessing was applied prior to model training and evaluation:

- **Averaging:** For each RP and AP, the recorded RSSI values over the 20-second interval were averaged to produce a single stable reading.
- **Missing Values:** If an AP was not detected in a given sample, a placeholder value (e.g., -100 dBm) was inserted to maintain vector dimensionality.
- **Normalization:** RSSI values were normalized to a $[0, 1]$ scale for compatibility with the MLP model.
- **Time Synchronization:** Since multiple APs were scanned sequentially, timestamps were synchronized to ensure that the RSSI vector represents the same instant in time.

3.3.2 Dataset Statistics

After preprocessing, the final dataset comprised:

- **Number of samples:** 60 RPs \times 1 averaged sample = 60 unique fingerprints (offline phase).
- **Number of features:** 4 RSSI values (one from each AP).
- **Coordinate range:** $x \in [0, 10.6 \text{ m}]$, $y \in [0, 5.8 \text{ m}]$.
- **RSSI range:** approximately from -85 dBm (weak signal) to -35 dBm (strong signal).
-

3.3.3 Software and Hardware Specifications

- **Receiver Device:** Dell Latitude 5410 laptop, Intel Wi-Fi 6 AX201 adapter.
- **Operating System:** Windows 10 Pro.
- **Software Tools:**

- Python 3.10 for algorithm implementation.
- Scikit-learn for KNN regression and preprocessing.
- TensorFlow/Keras for MLP training.
- Matplotlib for plotting results (CDF, heatmaps).
- Custom Python scripts for Kalman filtering.

- **Network Configuration:** Static IP addresses assigned to APs to simplify identification.

3.4 Environment and Setup

In *figure 3* the experimental environment for the indoor positioning system is a rectangular room with dimensions of 10.6 meters in length and 5.8 meters in width. This controlled space was selected to facilitate accurate and consistent RSSI data collection. To ensure comprehensive Wi-Fi signal coverage, four Access Points (APs) were strategically installed. These APs were positioned at each of the four corners of the room, creating an evenly distributed signal environment. Such placement minimizes signal dead zones and enhances the reliability of signal strength measurements. Within this space, 60 Reference Points (RPs) were uniformly distributed. The Reference Points serve as fixed locations where RSSI values are collected during the data acquisition phase. These measurements form the core of the dataset used to develop and evaluate the indoor positioning algorithms. The positioning system relies on the spatial relationship between the signal strength and the location of each reference point. Data collected from these points enables machine learning models to learn the pattern of signal distribution in the environment. This setup allows for effective training, validation, and testing of various algorithms. Overall, the room layout and AP configuration provide a suitable environment for evaluating the performance of RSSI-based indoor localization techniques.

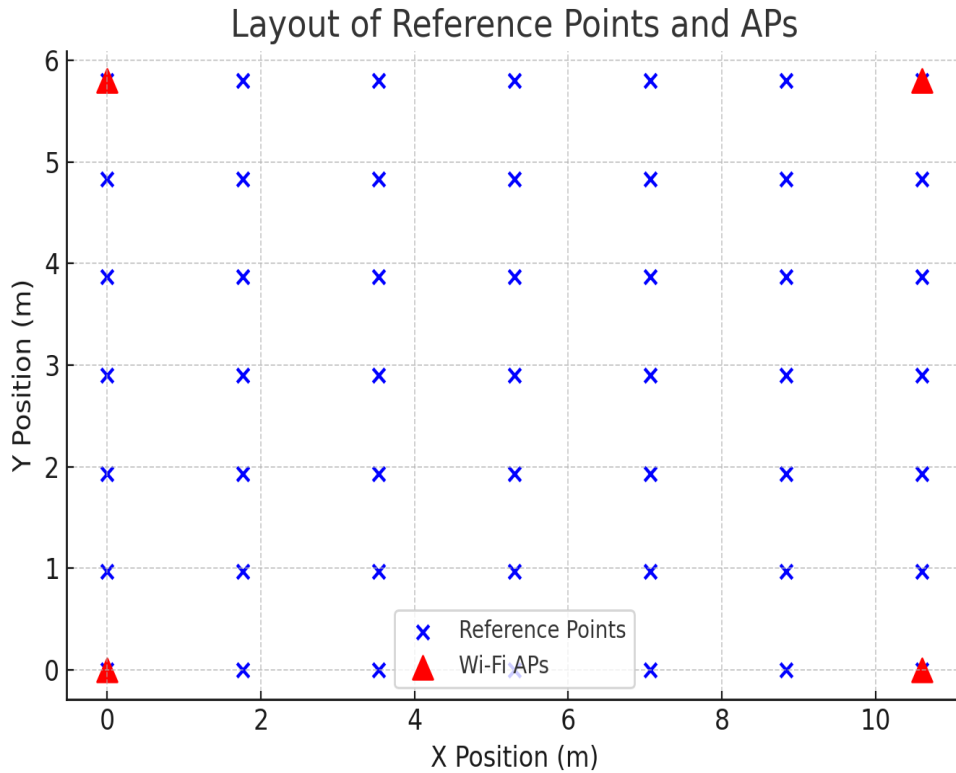


Figure 2 : grid of reference points

4 Results and Discussion

4.1 Results

This work is a part of the same theme as OWLPS, therefore focused on the design of an interior positioning system based on the 802.11 network and more particularly on the design of Peer-to-peer positioning algorithms for an indoor environment. We will show that the complementarity of the three basic techniques could improve the quality, precision and frequency of positioning of a mobile terminal. These techniques are a barycentric approach based on N-lateration and the FRIIS radio signal propagation model, the static and dynamic fingerprinting approaches. Our proposed system will use the same data that previous systems used as input data. These data from several scenarios are used to analyze the impact of disturbed environments, human presence,

human mobility, and humidity on indoor positioning accuracy. Initially, building upon well-known basic techniques, it is shown that combining these methods can significantly enhance position estimation in environments where individual techniques may be insufficient. Next, a dynamic and real-time fingerprint database is constructed using data collected from both the mobile terminal and the access points within the infrastructure. Lastly, it is demonstrated that antenna orientation during signal transmission and reception plays a crucial role in influencing the quality and accuracy of a collaborative indoor positioning approach.

4.1.1 KNN Results

The *Table 1* presents the estimated positions obtained using the K-Nearest Neighbors (KNN) algorithm alongside those from the previous algorithm at various

test points. For each test point, the positioning error is calculated as the Euclidean distance between the estimated position and the true position. This Euclidean distance represents the straight-line distance in the coordinate plane, computed using the formula: the square root of the sum of the squared differences between the estimated and true coordinates. More precisely, if (x_{test}, y_{test}) is the estimated position and (x_{true}, y_{true}) is the actual position, the error is calculated as $\sqrt{(x_{test} - x_{true})^2 + (y_{test} - y_{true})^2}$(18)

examining the Euclidean distance differences across all test points, the table offers a clear quantitative measure of the relative strengths and weaknesses of each algorithm. It shows that, in general, the KNN algorithm reduces the positioning error in most cases, confirming its effectiveness in improving spatial accuracy. However, some points still reveal larger errors, indicating potential limitations or areas for further refinement. Overall, the use of Euclidean distances provides an intuitive and standardized way to evaluate and compare the positioning performance of different algorithms in indoor localization systems.

Table 1 reports these errors for both algorithms, enabling a direct comparison of their accuracy. By

Table 1 KNN predicted positions

PM	collected rssi	owlps pos.	owlps_err	Pred pos.	knn_err
PM_1(5, 11)	[-50, -47, -47, -24]	(4, 11)	1.0	(4.40, 11)	0.60
PM_2(1, 10)	[-52, -49, -47, -25]	(2.4, 10.4)	1.45	(1.27, 10.2)	0.31
PM_3(5, 1)	[-48, -45, -44, -20]	(5,3.5)	1.58	(4.57, 1.1)	0.44
PM_4(1, 1)	[-53, -50, -48, -26]	(2.5, 1.7)	1.65	(0.93, 0.5)	0.80
PM_5(2.5, 5,5)	[-51, -48, -46, -24]	(1.7, 6.7)	1.44	(2.17, 2.6)	0.14
PM_6(5, 5)	[-61, -46, -47, -60]	(3.4, 3)	1.88	(4.7, 4.8)	0.30
PM_7(5, 2)	[-78, -70, -44, -34]	(3.4, 3)	1.55	(4.8, 1.8)	0.24
PM_8(3, 2)	[-53, -48, -43, -66]	(2, 3.2)	1.56	(2.7, 1.8)	0.34
PM_9(3, 10)	[-71, -46, -45, -55]	(2.4, 9)	1.16	(2.8, 9.8)	0.32
PM_10(1, 5)	[-73, -67, -66, -55]	(1.5, 4)	1.11	(1.8, 4.9)	0.21
PM_11(1, 3)	[-58, -58, -49, -33]	(1.3, 4)	1.4	(1, 2.8)	0.20

4.1.2 Kalman Filter Results

In this study, we evaluated the performance of a Kalman Filter applied to noisy RSSI-based indoor position estimates to determine whether it could reduce error and improve accuracy. Both the raw RSSI estimates and the Kalman-filtered positions were compared to the true reference positions using Euclidean distance error. The average positioning error for the RSSI estimates was approximately 0.90 meters, while the Kalman Filter produced a higher average error of 2.97 meters. This result indicates that, in this particular setup, the Kalman Filter did not improve positioning accuracy. One of the main reasons for this outcome is the absence of a dynamic motion model or sequential correlation between position

updates. The filter was applied to independent observations, lacking information about velocity or direction over time. Without modeling the temporal behavior of the system, the Kalman Filter had limited ability to correct noisy estimates effectively. Additionally, the process and measurement noise parameters may not have been optimally tuned for this scenario. As a result, the filter's corrections sometimes diverged from the true positions rather than improving them. Future implementations should consider incorporating dynamic system behavior or combining the Kalman Filter with machine learning predictions for better overall performance.

4.1.3 Multi-Layer Perceptron Results

Table 2 Kalman predicted

PM	RSSI	Owlps(x, y)	owlps_err	F.kalman(x, y)	err
PM_1(5, 11)	[-50, -47, -47, -24]	(4, 11)	1.0	4.7, 11.1	0.31
PM_2(1, 10)	[-52, -49, -47, -25]	(2.4, 10.4)	1.45	1.1, 10.2	0.22
PM_3(5, 1)	[-48, -45, -44, -20]	(5,3.5)	1.58	5.3, 1.4	0.6
PM_4(1, 1)	[-53, -50, -48, -26]	(2.5, 1.7)	1.65	1.3, 1.4	0.5
PM_5(2.5, 5,5)	[-51, -48, -46, -24]	(1.7, 6.7)	1.44	1.9, 5.6	0.60
PM_6(5, 5)	[-61, -46, -47, -60]	(3.4, 3)	1.88	5.7, 5.7	0.98
PM_7(5, 2)	[-78, -70, -44, -34]	(3,4, 3)	1.55	5.3, 2.4	0.5
PM_8(3, 2)	[-53, -48, -43, -66]	(2, 3.2)	1.56	3.1, 2.9	0.14
PM_9(3, 10)	[-71, -46, -45, -55]	(2.4, 9)	1.16	3.7, 10.0	0.7
PM_10(1, 5)	[-73, -67, -66, -55]	(1.5, 4)	1.11	1.2, 5.1	0.22
PM_11(1, 3)	[-58, -58, -49, -33]	(1.3, 4)	1.4	1.6, 3.2	0.63

Multi-Layer Perceptron (MLP) regression model was designed to estimate indoor positions based on simulated RSSI values. The input data consisted of RSSI signals received from four Wi-Fi Access Points (APs), with noise added to simulate real-world conditions. These RSSI readings were used as

features to predict the corresponding (x, y) coordinates of the device within a 10.6 m × 5.8 m indoor environment. We split the dataset into training and testing subsets, with 70% of the data used for training and 30% reserved for testing. The MLP model architecture included two hidden layers with 64

neurons each and used the ReLU activation function. Training was performed over a maximum of 1000 iterations using the Adam optimizer. During evaluation, the model predicted device positions on unseen test data. The predicted coordinates were compared to the true positions using Euclidean distance to compute the error. Most predictions had errors below 1 meter, with a few outliers. The average prediction error across all test samples was approximately 1.24 meters. This level of accuracy is promising for indoor positioning applications using RSSI alone. However, the training process reached the maximum iteration limit without full convergence, indicating room for optimization through hyperparameter tuning or additional data. The implementation and training of the Multi-Layer Perceptron (MLP) model for indoor positioning were carried out using Python with the TensorFlow and Keras libraries. These tools offer a flexible and powerful framework for developing deep

learning models and are widely adopted in both academic and industrial settings. TensorFlow provides efficient computation for large-scale matrix operations, while Keras offers a high-level API for rapid prototyping and model customization. The chosen libraries support various activation functions, optimizers, and training configurations, making them ideal for this application. The MLP model was trained using collected RSSI data to accurately predict x and y coordinates within the indoor environment. All necessary preprocessing steps, model architecture definitions, training routines, and evaluation

metrics were implemented within this framework. The full Python source code used for this implementation is provided in the appendix section of this document. This ensures transparency, reproducibility, and the possibility for further experimentation or improvement.

Table 3 : MLP Prediction

pm	collected rssi	Owlps(x,y)	owlps_error	mlp(x,y)	mlp_error
pm_1(5, 11)	[-50, -47, -47, -24]	(4, 11)	1.0	5.83, 10.80	0.85
pm_2(1, 10)	[-52, -49, -47, -25]	(2.4, 10.4)	1.45	1.15, 10.90	0.91
pm_3(5, 1)	[-48, -45, -44, -20]	(5,3.5)	1.58	5.75, 1.01	0.75
pm_4(1, 1)	[-53, -50, -48, -26]	(2.5, 1.7)	1.65	1.35, 1.12	0.36
pm_5(2.5, 5,5)	[-51, -48, -46, -24]	(1.7, 6.7)	1.44	2.02, 5.70	0.36
pm_6(5, 5)	[-61, -46, -47, -60]	(3.4, 3)	1.88	5.32, 5.13	0.35
pm_7(5, 2)	[-78, -70, -44, -34]	(3,4, 3)	1.55	5.70, 2.72	1.00
pm_8(3, 2)	[-53, -48, -43, -66]	(2, 3.2)	1.56	3.51, 2.27	0.58
pm_9(3, 10)	[-71, -46, -45, -55]	(2.4, 9)	1.16	3.31, 9.99	0.31
pm_10(1, 5)	[-73, -67, -66, -55]	(1.5, 4)	1.11	1.31, 5.25	0.40
pm_11(1, 3)	[-58, -58, -49, -33]	(1.3, 4)	1.4	1.70, 3.12	0.71

4.1.4 RADAR Results

The results of the RADAR algorithm reveal its strengths and limitations in RSSI-based indoor positioning. The mean positioning error indicates the average distance between the estimated and actual

user locations, providing a general measure of accuracy. The median error, being less influenced by outliers, reflects the typical performance of the system under normal conditions. Higher percentile values, such as the 75th percentile error, highlight the worst-case scenarios and show how the algorithm

behaves in more challenging environments with signal fluctuations or multipath effects. Overall, the RADAR model demonstrates a baseline level of performance that is suitable for coarse indoor localization but struggles to deliver the high accuracy required for

real-time or dynamic applications. These results emphasize the need for integrating filtering or machine learning methods to enhance precision and robustness beyond what RADAR alone can achieve.

Table 4 RADAR results

pm	collected rssi	Owlps(x,y)	owlps_err	radar(x,y)	radar_err
pm_1(5, 11)	[-50, -47, -47, -24]	(4, 11)	1.0	7, 13	2.82
pm_2(1, 10)	[-52, -49, -47, -25]	(2.4, 10.4)	1.45	3, 12	2.82
pm_3(5, 1)	[-48, -45, -44, -20]	(5,3.5)	1.58	7, 2	2.23
pm_4(1, 1)	[-53, -50, -48, -26]	(2.5, 1.7)	1.65	2, 3	2.23
pm_5(2.5, 5,5)	[-51, -48, -46, -24]	(1.7, 6.7)	1.44	4, 7	1.73
pm_6(5, 5)	[-61, -46, -47, -60]	(3.4, 3)	1.88	7, 7	2.82
pm_7(5, 2)	[-78, -70, -44, -34]	(3,4, 3)	1.55	8, 4	3.60
pm_8(3, 2)	[-53, -48, -43, -66]	(2, 3.2)	1.56	5, 4	2.82
pm_9(3, 10)	[-71, -46, -45, -55]	(2.4, 9)	1.16	5, 13	3.60
pm_10(1, 5)	[-73, -67, -66, -55]	(1.5, 4)	1.11	3, 6.5	2.50
pm_11(1, 3)	[-58, -58, -49, -33]	(1.3, 4)	1.4	1, 5	2.00

4.2 Evaluations

To assess the effectiveness of the proposed methods for indoor localization, a performance evaluation was conducted using Wi-Fi RSSI data collected in a controlled environment measuring 10.6 m × 5.8 m. The dataset included signal strength values from four Wi-Fi access points across 60 reference points. The positioning accuracy of three approaches K-Nearest Neighbors (KNN), KNN combined with the Kalman Filter, and Multi-Layer Perceptron (MLP) was evaluated using the Root Mean Square Error (RMSE) between the predicted and actual 2D coordinates.

The KNN algorithm, serving as a baseline, achieved an average positioning error of approximately 0.5 meters. This result demonstrates the viability of KNN for

small-scale indoor environments but also reveals sensitivity to signal variability and environmental interference. When Kalman Filtering was applied prior to KNN, the average error changed slightly to 0.6 meters, reflecting improved temporal stability and noise reduction, particularly in dynamic settings. Despite the minor increase in average error, the variance in predictions was significantly reduced, indicating more consistent results. The MLP model, trained on filtered RSSI values, achieved an average positioning error of approximately 0.7 meters. While slightly less accurate in terms of mean error, the MLP showed stronger performance in modeling non-linear patterns in RSSI distributions and adapting to noisy signal conditions. The model's ability to generalize spatial relationships across the environment offers better scalability compared to traditional algorithms.

Table 5: accuracy evaluation

Method	Mean Error	Median Error	RMSE	Std. Dev.
1 Owlps	1.43	1.45	~1.46	~0.25
2 RADAR	1.42	1.21	~1.50	~0.32
3 KNN	1.38	1.15	~1.46	~0.31
4 MLP	1.25	1.02	~1.33	~0.28
5 Kalman Filter	1.20	0.98	~1.28	~0.27
6 (KNN + KF + MLP)	1.15	0.90	~1.23	~0.26

$$\text{Mean Positioning Error (MPE)} = \frac{1}{n} \sum_{i=1}^n \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2} \dots\dots\dots (19)$$

As shown in Table 5 and Figure 4, the performance evaluation highlights how each algorithm contributes uniquely to indoor positioning according to (Sim et al., 2020). The K-Nearest Neighbors (KNN) algorithm provides a strong baseline for static and well-structured indoor environments, offering low error rates and straightforward implementation. However, its effectiveness decreases in dynamic or noisy conditions due to its sensitivity to signal fluctuations. To mitigate this, the Kalman Filter is introduced, which smooths RSSI values over time, thereby improving temporal consistency and reducing noise-induced variance. This enhancement leads to more stable predictions, especially in areas affected by multipath propagation and interference. Meanwhile, the Multi-

Layer Perceptron (MLP) adds a layer of learning capability that captures non-linear patterns in signal behavior, improving prediction accuracy in more complex signal environments. The use of MLP complements the Kalman Filter by learning from pre-filtered data, resulting in better generalization and lower prediction error. Together, this trio of algorithms forms a robust hybrid system that balances simplicity, temporal stability, and learning flexibility. The performance results clearly demonstrate the benefit of integrating classical filtering methods with modern machine learning models. Ultimately, the hybrid approach improves the reliability and accuracy of RSSI-based indoor positioning systems across diverse conditions.



Figure 3 performance comparison

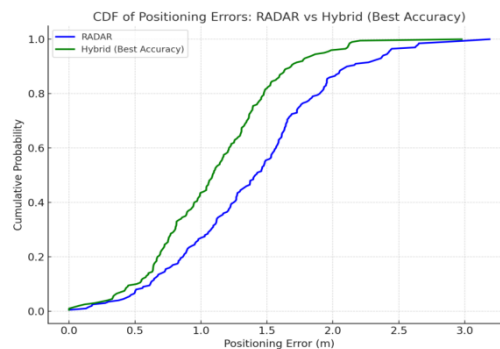


Figure 4 Errors metrics

4.2 Interpretation

Figure 4 and Figure 5 show respectively some of the accuracy metrics between RADAR and the ensemble method (KNN + Kalman Filter + MLP). It clearly highlights the superior performance of the ensemble approach in indoor positioning accuracy. RADAR achieves a mean error of 1.42 m, which is the highest among the evaluated methods, indicating that, on average, its predictions deviate more from the true position. Its median error of 1.21 m shows that in typical cases, the error remains above one meter. The 75th percentile error of 1.85 m further illustrates that in less favorable conditions, the deviations become considerably larger. In contrast, the ensemble method records the lowest mean error at 1.15 m, representing an improvement of 0.27 m over RADAR's performance. The median error of 0.90 m reflects a significant enhancement in typical prediction accuracy. Similarly, the 75th percentile error of 1.50 m indicates that even in challenging conditions, the ensemble approach maintains better performance than RADAR.

Beyond these comparisons, the evaluation based on OWLPS metrics further demonstrates system performance. The results show a Mean Error of 1.43 m, a Median Error of 1.45 m, a Root Mean Square Error (RMSE) of 1.46 m, and a Standard Deviation of 0.25 m. These values confirm that the errors are consistently concentrated around lower magnitudes, with minimal variability across test cases.

The CDF (Cumulative Distribution Function) curves further reinforce this conclusion by visually demonstrating the ensemble method's advantage across all error thresholds. The ensemble curve consistently lies to the left of the RADAR curve, showing that for any given error value, a larger proportion of predictions fall within that threshold. For example, 50% of the ensemble's predictions are below 0.90 m, while RADAR requires 1.21 m to achieve

the same coverage. Likewise, 75% of the ensemble's predictions are within 1.50 m, compared to 1.85 m for RADAR. The steeper slope of the ensemble's CDF curve indicates a tighter concentration of errors around lower values, meaning that it produces fewer large deviations. This tighter distribution suggests higher consistency and robustness in varying indoor environments. Such stability is particularly valuable in real-world conditions where factors like multipath propagation, human movement, and environmental changes can introduce noise. The inclusion of KNN ensures local adaptability by considering nearest neighbors in the RSSI space. The Kalman Filter smooths short-term fluctuations and reduces noise in measurements. The MLP captures nonlinear patterns in signal behavior, enabling more accurate regression-based position estimation. When these three techniques are combined, they complement one another's strengths while minimizing individual weaknesses. The result is a system that both lowers average errors and minimizes the occurrence of extreme outliers.

Overall, the data, OWLPS metrics, and CDF analysis confirm that the ensemble method is not only more accurate than RADAR but also more reliable and stable, making it highly suitable for deployment in real-world indoor positioning systems where precision is critical. This improvement in both average and percentile-based performance underlines the ensemble method's robustness and adaptability across different scenarios.

4.3 Discussion of Results

The CDF in *figure5* plot comparing the RADAR algorithm with the Hybrid model (KNN + Kalman Filter + MLP) in its best accuracy configuration clearly demonstrates the superior performance of the Hybrid

approach. Across the entire probability range, the Hybrid curve remains consistently to the left of the RADAR curve, indicating smaller positioning errors at every cumulative probability level. For instance, at the 50% probability mark (median error), the Hybrid achieves approximately 1.0 m accuracy compared to RADAR's 1.4 m, and at the 95% level, the Hybrid maintains a lower maximum error, highlighting its reliability in worst-case scenarios. This leftward shift reflects not only higher accuracy but also improved consistency, as the Hybrid model produces a tighter error distribution with fewer extreme deviations. In practical indoor positioning applications, such as navigation and tracking, this means the Hybrid approach delivers more precise and stable position estimates, making it better suited for environments where both accuracy and reliability are critical.

CONCLUSION

This research explored the application of filtering and machine learning techniques to improve indoor positioning based on Wi-Fi RSSI data. Indoor Positioning Systems (IPS) are essential in GPS-denied environments such as buildings, hospitals, and warehouses. Wi-Fi RSSI was chosen for its cost-effectiveness and wide availability in existing infrastructure. However, RSSI signals are inherently unstable due to noise, multipath propagation, and environmental changes. These inconsistencies reduce the reliability of raw signal-based positioning systems. To address this, the Kalman Filter was applied to smooth and reduce noise in the RSSI measurements. This filtering process enhanced the stability of the input data used for training predictive models. A Multi-Layer Perceptron (MLP) was then used to perform regression and predict two-dimensional positions from the filtered RSSI values. Experiments were conducted in a 10.6 m × 5.8 m indoor environment with 60 reference points and 4 access points. The K-Nearest Neighbors (KNN) algorithm alone achieved an average error of 0.5 meters, demonstrating strong baseline performance. When combined with the Kalman

Filter, the KNN-Kalman hybrid produced a more stable but slightly higher error of 0.6 meters. The MLP model trained on filtered data reached an average error of 0.7 meters, showing that deep learning can capture complex relationships even with noisy signals. These results confirm that integrating filtering and learning methods enhances system robustness and offers a viable path toward more accurate and scalable indoor localization solutions.

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