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Indoor Localization: BLE, Machine Learning, and Kalman Filtering for Resource-Constrained Devices

Arjun Samavedam[1] and Vickie Hallisey[#]

[1]Montgomery Blair High School, USA
[#]Advisor

ABSTRACT

The growing complexity of indoor environments and limitations of the Global Positioning System (GPS) require accessible yet efficient indoor localization solutions in areas such as navigation and asset management across various sectors such as airports, and warehouses. Existing solutions often come with a trade-off between accuracy, efficiency, and setup burden, hindering their deployment on resource-constrained edge devices. This project addresses the challenge by introducing a novel indoor localization system that leverages Bluetooth Low Energy (BLE) beacons and lightweight machine learning models such as the Random Forest and KNN to develop a system capable of accurate and computationally efficient location prediction. By combining Received Signal Strength Indicator (RSSI) fingerprinting approaches with preprocessing techniques, resulting data can be cleaner and mitigate major issues caused by sensor noise and multipath fading effects. This preprocessing step allows for faster model training and facilitates deployment on low-power edge devices like mobile phones, robots, and microcontrollers without the need for more complex solutions. This project offers a comprehensive evaluation of varying combinations of preprocessing algorithms and machine learning models. The results demonstrate that the Kalman filter can significantly reduce multipath and sensor noise, enabling faster model training and higher accuracy. The Kalman filter allowed the Random Forest model to achieve an accuracy of 95% given just 52 training samples, resulting in prediction times under 5 microseconds. This eliminates the need for complex, resource-intensive solutions, empowering the system to achieve high performance with efficient machine learning.

Introduction

Indoor localization, also known as indoor positioning, is utilized to determine the location of individuals or objects within enclosed spaces. The increasing complexity of indoor environments, combined with GPS limitations, underscores the critical need for accurate and efficient indoor localization systems [6]. These systems are indispensable for ensuring safety, security, navigation, and asset management across diverse settings, including hospitals, airports, warehouses, and factories [12]. Unlike the Global Positioning System (GPS), which provides reliable location and timing information globally under optimal sky visibility conditions, indoor positioning systems utilizing signal-based estimation require alternative approaches to approximate an object's location.

One method of estimation is trilateration, in which location is estimated based on the measured distances between the user's device and at least three fixed reference points. Estimation is performed by interpreting the received signal strength and signal time. However, indoors, this method faces challenges due to signals reflecting off of other surfaces and disappearing before reaching the target (multipath fading) [2][7].

Another prevalent method of estimation is fingerprinting, in which estimates are reliant on pre-built database of signal signatures (fingerprints) at known locations within the area of interest [5] [8]. It is composed of two primary phases:

1. Offline Phase: Data is stored in a fingerprint database from a site survey conducted where signal strengths (Wi-Fi, Bluetooth, etc.) are measured at various reference points throughout the environment.
2. Online Phase: A device measures the signal strengths from available beacons in its current location, and this real-time signal signature is compared to the fingerprints in the database using pattern matching algorithms, and a prediction of the location of the device is provided.

While Wi-Fi offers extensive coverage, its accuracy is hampered by signal variability. Research investigates methods like Angle of Arrival (AoA) and Time of Arrival (ToA) to improve Wi-Fi precision, alongside Wi-Fi-specific fingerprinting techniques. Additionally, despite its broader coverage, Wi-Fi consumes more power compared to BLE. Bluetooth Low Energy (BLE) emerges as a powerful contender due to its low power consumption, scalability, availability, and accuracy. The advantages due to BLE signals experiencing less multipath fading compared to Wi-Fi, make it a promising technology for the future of indoor localization [11].

Literature Review

Fingerprinting, leveraging Received Signal Strength Indicator (RSSI) data, is a cornerstone technique for indoor localization. Traditionally, researchers have relied on K-Nearest Neighbors (KNN) algorithms and their variations [13][4] (weighted KNN, iterative weighted KNN) along with Support Vector Machines (SVMs) to achieve accuracy levels around 90%.

Recent research introduced deep learning models like Convolutional Neural Networks (CNNs) [9][14] and Long Short-Term Memory (LSTM) networks [1] to the scene. These models boast the potential to achieve even higher accuracy (above 90%) by automatically extracting meaningful features from raw RSSI data. However, this improvement comes with the trade-off of requiring larger training datasets and significant processing power.

Many existing approaches incorporate traditional filtering techniques like Interquartile Range (IQR) [10] and moving average [2] filters to clean the RSSI data by removing outliers. This pre-processing step enhances the overall quality of the fingerprint data used to train localization models, leading to improved performance. While these models offer enticing accuracy gains, they come with a trade-off: increased training time, computational complexity, and power consumption. These can be significant hurdles for real-world deployments, especially when considering the time needed for fingerprinting and the limitations of battery-powered edge devices like mobile phones and robots.

Indoor localization technologies continue to evolve, with Bluetooth maintaining its dominance due to affordability and widespread availability. Current fingerprinting strategies based on RSSI patterns are prevalent, and current research focuses on refining algorithms and models to improve accuracy and mitigate challenges such as multipath fading effects when estimating position. Multipath fading occurs when radio signals traverse multiple paths to reach the receiver, caused by reflections from various objects in the area (Figure 1). This results in signals being weakened or out of sync, causing unwanted inconsistencies and fluctuations in data [5].

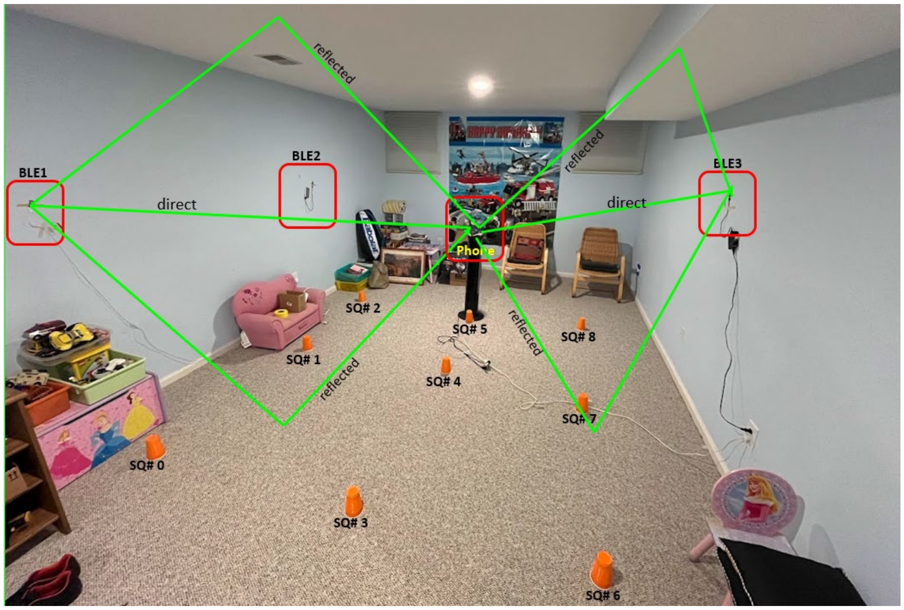

Figure 1. Multipath Fading shown using the green lines representing the reflected signal paths.

Data Processing and Models

Pre-Processing Methods

Capturing RSSI signals presents several challenges due to environmental noise (multipath fading) and sensor limitations, which cause RSSI measurements to fluctuate and make it difficult to train models for accurate indoor localization. To address these issues, three main pre-processing methods were evaluated.

From current research, the Interquartile Range (IQR) method focuses on identifying and removing outliers by calculating the range that covers the middle 50% of the data, effectively eliminating values that might distort the overall pattern. Another method, Moving Average, smooths out the data by averaging a window of recent RSSI readings, reducing the influence of outliers while preserving the general pattern of the data, leading to a smoother signal.

The proposed method, the Kalman Filter, is a robust algorithm that adapts to fluctuating and error-prone signals [3]. When interpreting Bluetooth signals, it incorporates the previous signal estimation, the current RSSI measurement, and predefined variables of sensor error and environmental errors (multipath fading) to provide an estimate of the true signal strength.

Machine Learning Models

Various machine learning classification models have been explored to tackle the inherent complexities of RSSI data, especially in indoor settings. To achieve efficient performance from a lightweight model that can run on resource-constrained devices such as a smartphone, I experimented with several approaches.

1. The K-Nearest Neighbor (KNN) model classifies data points based on their similarity to existing labeled data points. When predicting on data points from fingerprinting, unseen RSSI values can be placed and compared to the known RSSI data points, finding the square that is the majority among the "nearby" data points.
2. The Random Forest model utilizes multiple decision trees with random subsets of the data to create splits and predict unseen RSSI values by voting on the aggregation of the decision tree results. This model is more

resilient to noise and outliers than other models, a desired ability given a data set where multipath fading can introduce errors and fluctuation in RSSI data.

3. The 1D Convolutional Neural Network (1D CNN) learns informative features from sequential data like the RSSI values from multiple beacons in this project. These features can capture the spatial relationships between signals, which is important for differentiating between fingerprint locations. While powerful, 1D CNN can be more complex to train and require more data compared to the other models.
4. Support Vector Machines (SVM) create multiple binary problems by finding a line of separation that maximizes the margin between the data points belonging to two different squares, repeating to include all squares. When classifying new data, the SVM can see which side of the line a new data point falls into and predict a square based on the sub-classification that returns the highest prediction score.

Experiment Setup for Data Collection

Area And Experimentation for Fingerprinting

A room divided into a 3x3 grid was dedicated to fingerprinting, with Bluetooth beacons forming a triangle around the perimeter. Orange cups represent the center a square (50” x 50”), each of which was given an index. Phone was 4 feet above the ground, and the beacons were 5 feet above the ground (Figure 2).

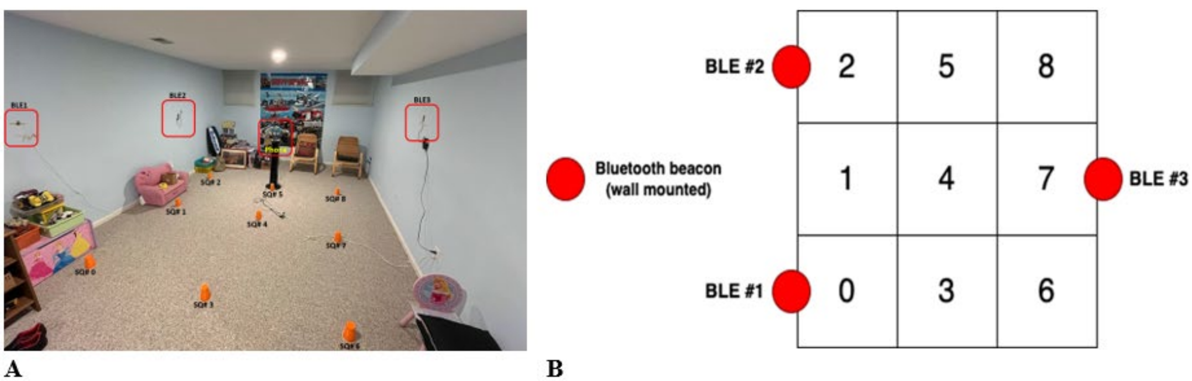

Figure 2. Fingerprinting Experimentation. As seen in Figure 2A, the floor diagram and experimentation setup for Fingerprinting is captured. As seen in Figure 2B, the diagrammatic representation for Setup for Fingerprinting is shown.

Area And Experimentation for Understanding the Effects of Multipath Fading on the RSSI

To understand effects of multipath fading, a Bluetooth beacon was set up both inside and outside the house, with a tape measuring showing increments of 3 feet. Phone was 4 feet above the ground, and a beacon was 5 feet above the ground (Figure 3).

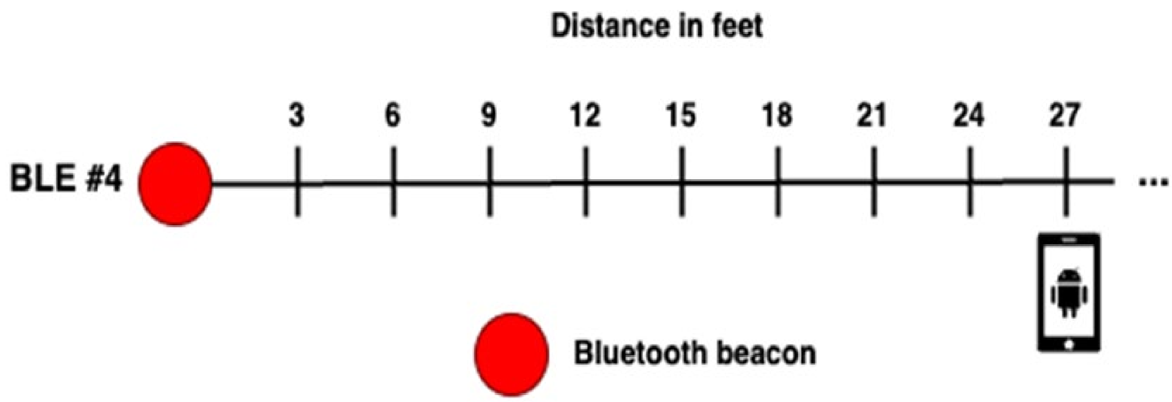

Figure 3. Multipath Fading Experimentation.

Engineering Methodology

The overall methodology follows fingerprinting approach and is broken down into an offline and online phase (Figure 4). During offline phase, data is collected, split for training/testing and validation, pre-processed, and machine learning models are trained based on this data. The offline phase is also called as training phase. During online phase, the "unseen" data after data collection and data split step is used instead of live RSSI values, which are then pre-processed and fed into the pre-trained machine learning models, predicting and outputting the location of the user. The online phase is also called as execution or prediction phase.

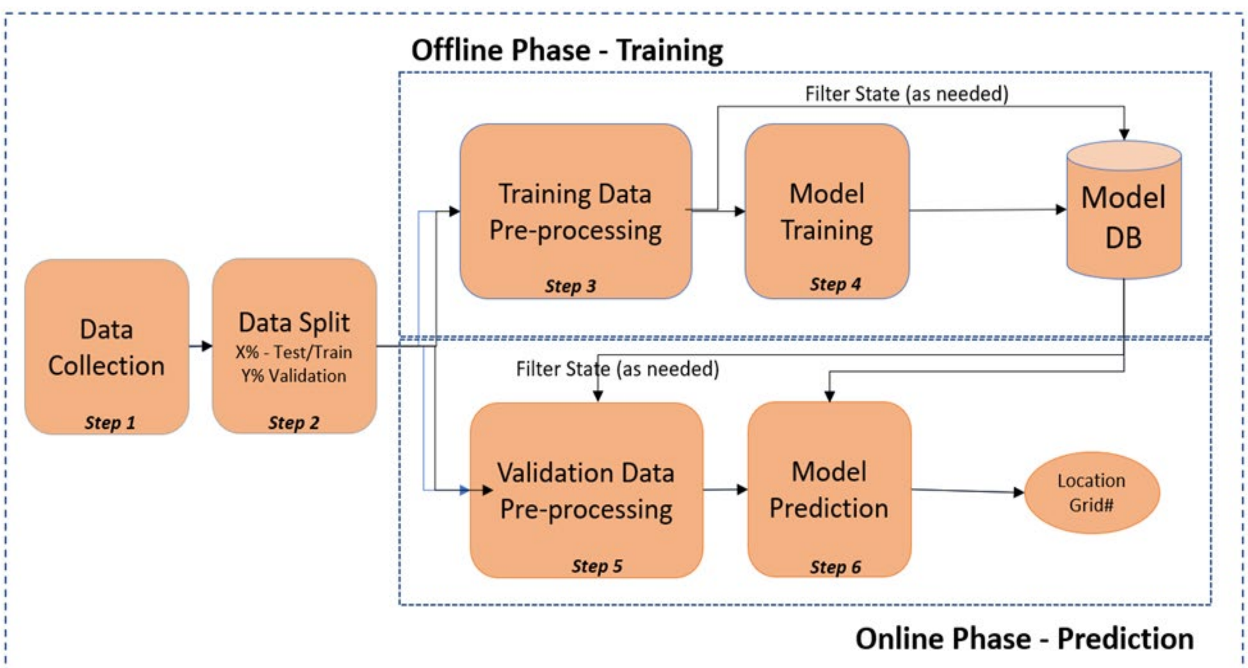

Figure 4. Overall Fingerprinting Methodology.

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Data Collection & Data Split

All data was collected with an Android phone. The data collection app was developed using Java in Android Studio and allowed a user to specify the current square index and the amount of data to be collected. After collection was complete, the app would create a POST request of the data in JSON format to a local server, which would save the data as a CSV file in a local directory (Figure 5).

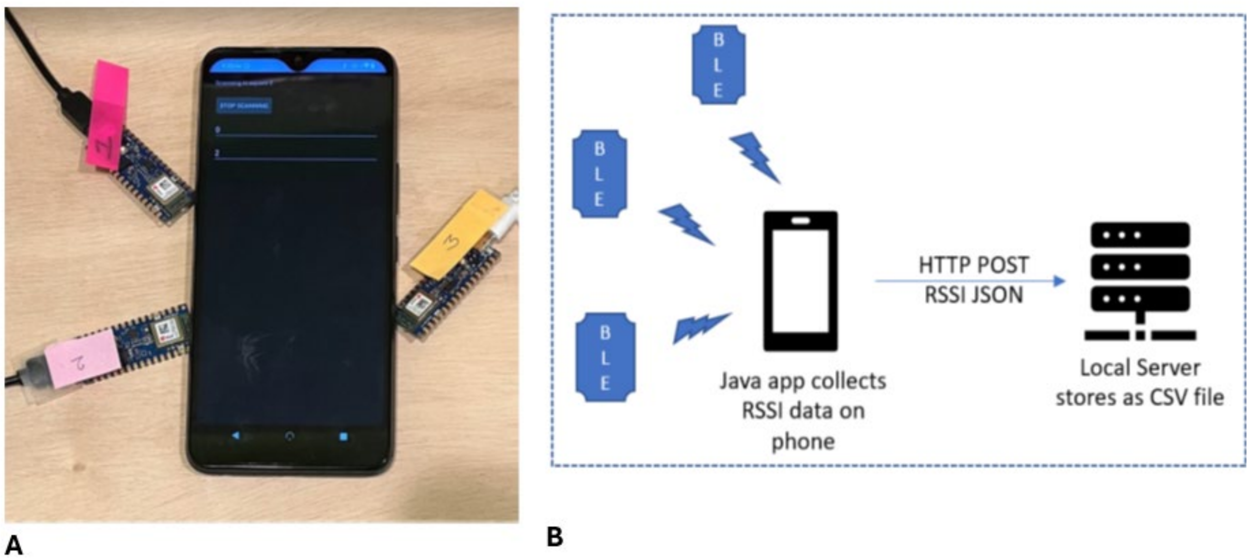

Figure 5: Data Collection Methodology. As seen in Figure 5A, an Android phone with app & Arduino BLE is shown. As seen in Figure 5B, Data Collection Methodology is diagrammatically displayed.

Data Collection Understanding the Effects of Multipath Fading on the RSSI

Data for viewing sensor and environment error on the signal were collected in samples of 32 values at each increment of 3 feet both indoor and outdoor. Indoor data ended at 48 feet, and outdoor data ended at 60 feet (Figure 3). During the data split step, the data collected was split into 40% and 60% such that a portion was used for the training phase, and the rest "unseen" data was used during validation phase.

Data Collection for Fingerprinting

To train machine learning models, large amounts of data are required to both train and test. The fingerprinting data consisted of 5760 samples per beacon per square and took 1.5-2 hours per cycle (each sample takes ~1 second to collect). Data collection for all 9 squares was conducted over the course of a week (Figure 2A and Table 1).

Table 1. Sample RSSI values.

Square #	BLE1 (dBm)	BLE2 (dBm)	BLE3 (dBm)
0	-73	-78	-80
0	-65	-79	-85
0	-64	-90	-75
……	……	……	……
8	-80	-92	-67

8	-73	-93	-71
8	-76	-93	-63
8	-74	-92	-67

Training Data Pre-Processing: Kalman Filter

The collected data consisted of 51,840 data points. Each of these pre-processing methods (IQR, Moving Average, Kalman Filter) were applied to the data, and saved as separate CSV files to be used for the model training, testing, and accuracy (Figure 6).

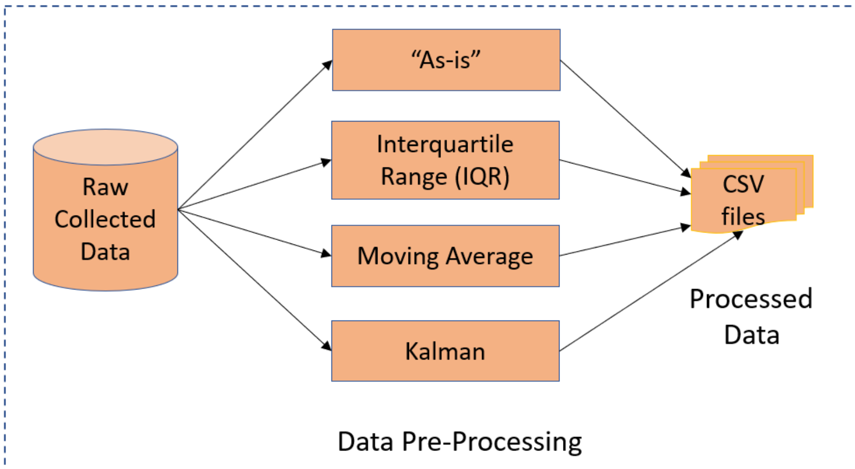

Figure 6. Pre-processing Methodology.

RSSI inaccuracies and large fluctuations can be attributed to 2 primary types of error in the setup. Beacon transmits power can vary and the phone's RSSI measurement can have errors, creating measurement error. The Bluetooth signal bounced off walls and other things in the room while traveling from beacon to phone, creating process error. These two errors contribute to the RSSI signal variations and make the RSSI signal harder for localization algorithms. These initial error coefficients can be estimated using data from setup 2, allowing the Kalman filter to be applied (Figure 7).

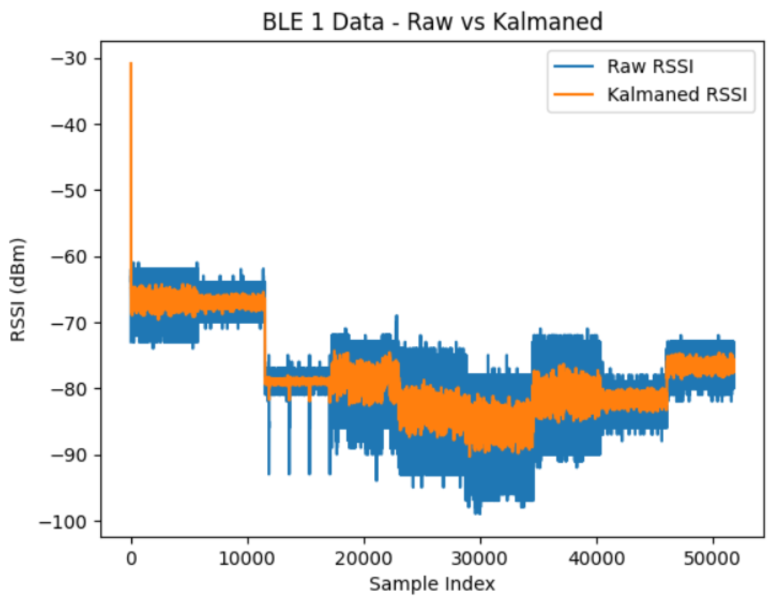

Figure 7. Shows improvements upon a BLE's RSSI values using Kalman Filter.

Measurement Variance was estimated using data collected outdoors, where multipath fading is minimal. This provides a baseline for "clean" RSSI measurements.

Process Variance was estimated by computing the difference between the variances of outdoor (low multipath) and indoor (high multipath) RSSI data. This captures the additional variability introduced by the indoor environment.

The Kalman filter transforms uncertain RSSI signals into accurate estimations of the true RSSI value. Uncertainty is adjusted using the measurement and process variances. The estimation error is iteratively updated from iteration to iteration, initially being the process variance, and adjusting to accommodate the changing nature of the RSSI signal. The true RSSI value is estimated by adjusting previous estimate based on how uncertain the current estimate is (Kalman gain). The estimation error is then calculated for the next iteration, where the cycle repeats. Equations 1-3 illustrate the Kalman Filter calculations below:

Equation 1:

$$KG = \frac{E_{est}}{E_{est} + E_{mea}}$$

KG Kalman Gain
E_{est} Estimation Error
E_{mea} Measurement Error

Equation 2:

$$EST_t = EST_{t-1} + KG \cdot (MEA_t - EST_{t-1})$$

EST_t Current Estimate
EST_{t-1} Previous Estimate
MEA_t Current Measurement
KG Kalman Gain

Equation 3:

$$E_{est_t} = (1 - KG) \cdot E_{est_{t-1}}$$

E_{est_t} Error in Current Estimate
$E_{est_{t-1}}$ Error in Previous Estimate
KG Kalman Gain

Machine Learning Model Training & Validation

Fingerprinting for indoor localization is a classification problem, where the RSSI readings collected constitute a distinctive "fingerprint" for each location on the 3x3 grid. To determine the location of RSSI data, I utilized supervised machine learning models typically employed for classification tasks such as K-Nearest Neighbor (KNN), Random Forest, 1D Convolutional Neural Network (1D CNN), and Support Vector Machines (SVM) (Figure 8).

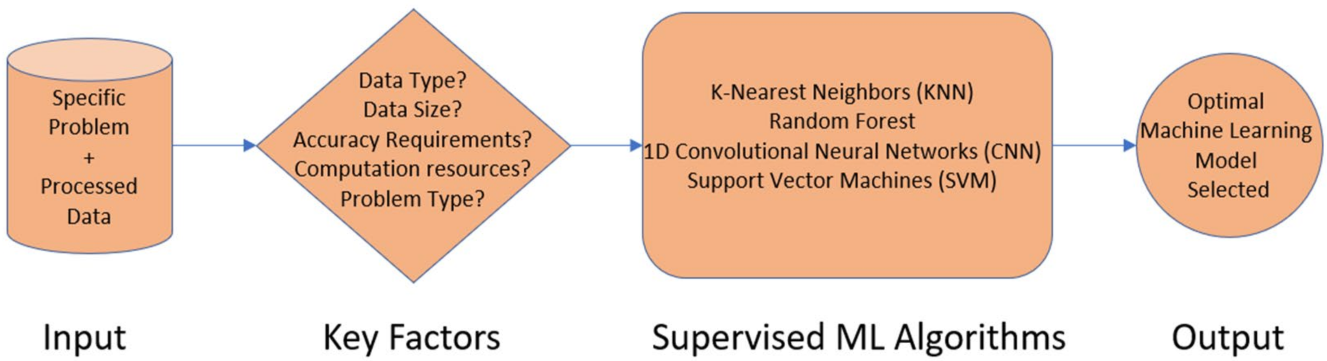

Figure 8. Machine Learning Model Training.

Here are specific details of these model implementations:

1. K-Nearest Neighbor (KNN) was implemented with number of neighbors as 3 which means for any new data point, so the model considered the 3 most similar data points from the training data to make a prediction. Number of neighbors tested ranged from 2-10 neighbors, with 3 yielding the best accuracy and all of them taking approximately the same amount of time.
2. Random Forest was tuned to consist of 50 trees, a maximum depth set to maximize growth, and a minimum sample specification, I utilized the scikit-learn GridSearchCV library to pinpoint the best parameter combination.
3. 1D Convolutional Neural Network (1D CNN) was constructed with 64 filters per layer, with the final layer facilitates classification into 9 predefined categories or locations. The model was given inputs such that one training sample contained a block of 4 data points. This was chosen because no significant improvements were noticed when the block size was increased.
4. Support Vector Machines (SVM) was implemented with RBF kernel which is most popular kernel as per my research.

To establish a baseline performance reference, the 4 machine learning models were implemented, trained and tested using a range of training samples. To find an optimal number of training samples required while achieving an accuracy threshold (95%), each of these models trained with samples ranging from 4 to 1000 and stored as models to be used in the Validation Stage.

Code was implemented and tested within a Python environment using Jupyter Notebooks. The Scikit-learn (Sklearn) library was used for data manipulation, preprocessing, and the implementation of various machine learning models (KNN, Random Forest, SVM). The TensorFlow library was used for the implementation of the 1D Convolutional Neural Network (1D CNN). Lastly, Ctime was utilized for performance analysis during the prediction phase for measuring prediction time per sample.

Finally, the trained models were evaluated on the unseen validation data (~60% of the total data). By testing on completely new data, the model would provide a more reliable estimate it would perform on real-world data. All of the models that were created in the training stage were used in this state to compute the accuracy and prediction time for each run. All the results were stored in CSV files for further analysis.

Results

Measurement and Process Variance Calculation

The plots (Figure 9) clearly illustrate the phenomenon of multipath fading in the indoor environment compared to the outdoors. The plots show a more significant fluctuation in the indoor signal compared to the smoother outdoor signal, reflecting the presence of multipath fading indoors. Utilizing the collected data, key signal characteristics are quantified.

Measurement Variance = 30; Process Variance = 90

Based on the calculated measurement and process variances, a Kalman Filter is used to process the data. The orange line captures the smoother RSSI by Kalman filtering.

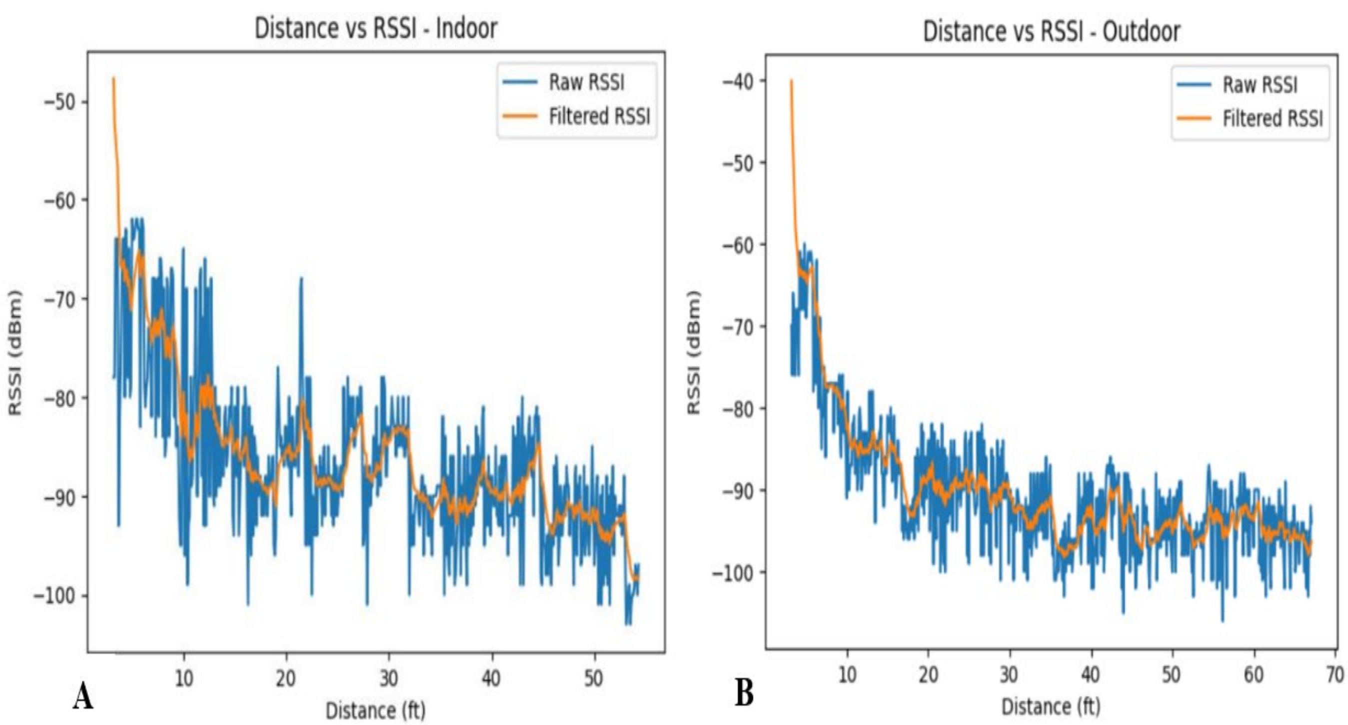

Figure 9. RSSI Indoor and Outdoor. As seen in Figure 7A, Distance vs RSSI is plotted when experiment was conducted indoors. As seen in Figure 7B, Distance vs RSSI is plotted when experiment was conducted outdoors.

Model Accuracy Plots

For the models KNN, Random Forest, and SVM, I trained them on datasets with increasing sample sizes, from 4 to 500, in steps of 4. There wasn't a significant improvement in performance after 500 samples, so the graphs (Figure 10) only show results up to that point.

For the 1D CNN model, I used a step size of 32 because smaller steps didn't significantly improve performance. The model was trained with significantly more samples as the model required a larger amount of data to reach 90%.

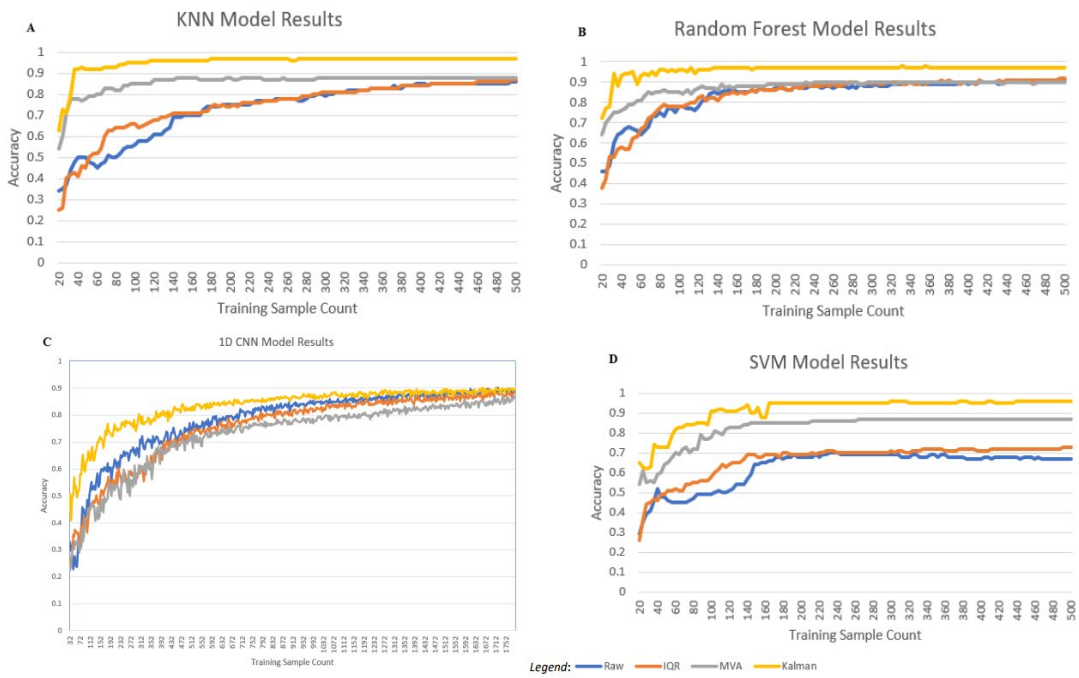

Figure 10. Machine Learning Model Results. As seen in Figure 10A, the KNN model results are plotted and shown. Figure 10B shows Random Forest model results, figure 10C shows 1D CNN model results, and figure 10D shows SVM model results respectively.

Data Analysis and Discussion

Key findings regarding pre-processing techniques, model selection, and distance error analysis highlight the strengths of the Random Forest model while acknowledging the potential of the 1D CNN for specific applications (Table 2).

Pre-Processing Impact

All pre-processing methods improved model performance over raw data. Interquartile Range (IQR) filtering effectively removed outliers, leading to a slight increase in the rate of accuracy improvement for all models. Moving average filtering yielded the most significant improvement, enabling models to maintain higher accuracy even with limited training data compared to IQR. The Kalman filter provided the greatest overall improvement, achieving both higher final accuracy and faster accuracy increase. It smoothed data, removed outliers, and accounted for environmental/sensor errors, resulting in a strong estimate of the true RSSI value

Table 2. Data showing model comparison.

Model	Accuracy (%)	Number of Training Samples	Prediction Time (μs)	Distance Error (in)
Random Forest	95	52	4.18	84.08

Support Vector Machines	95	52	4.18	104.94
k-Nearest Neighbors	95	92	65.26	102.37
1D-CNN	90	7000	6.43	68.225

Model Performance

Within 1,000 samples using the Kalman filter, both the Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) models reached an accuracy of 97%. Meanwhile, the Random Forest model achieved an even higher accuracy of 98%. Considering a 95% accuracy threshold, the Random Forest model required only 52 training samples to reach this level of accuracy. The K-Nearest Neighbors (KNN) model achieved 95% accuracy with 92 samples, while the Support Vector Machine (SVM) needed 164 samples. On the other hand, the 1D Convolutional Neural Network (CNN) required 7,000 samples to achieve a 90% accuracy. Additionally, the Random Forest model exhibited the fastest prediction time, averaging 4.18 microseconds per sample.

Distance Error Analysis

While less accurate overall, the 1D Convolutional Neural Network (CNN) demonstrated the lowest distance error, averaging 58 inches for incorrect predictions. This is attributed to CNN's ability to extract spatial relationships and informative features from RSSI values, allowing it to estimate locations with an average error of only one square (50" x 50").

Model Selection

Random Forest emerged as the strongest model due to its superior accuracy, faster training speed, and lower prediction time compared to other models.

Conclusion

In this project, I designed a novel indoor localization system using Bluetooth Low Energy (BLE) beacons. This system prioritizes both accuracy and efficiency, making it ideal for various applications.

Computationally Efficient Solution

The computationally efficient solution achieved high accuracy, reaching 98% using a Random Forest machine learning model. It also demonstrated rapid prediction times of just 4 microseconds per user sample and reduced the training data collection amount to 52 samples for 95% accuracy. The system achieves impressive results and meets the engineering goals set forth. The combination of the Random Forest model and Kalman filter delivers high accuracy while reducing the training data required, resulting in faster training times and a more efficient system overall.

The Kalman Filter

The Kalman filter plays a critical role in the system's success. By compensating for environmental and sensor errors, it greatly improves model accuracy and drastically reduces the number of training samples needed to reach adequate accuracy. This allows the system to achieve high accuracy with a smaller training dataset, saving time and resources.

Efficient System Deployment

The system excels in both accuracy and deployment speed. Offline setup takes only 1 minute per fingerprinting location, while online user location using RSSI signal retrieval takes just seconds. This rapid deployment process achieves 95% accuracy, making it ideal for dynamic environments. Users can retrieve their current location with high accuracy within seconds.

Project Outcomes

This project demonstrates significant advancements in indoor localization using Bluetooth and machine learning. The system offers high accuracy, fast prediction times, and efficient deployment using a fingerprinting setup. This paves the way for faster and more precise indoor navigation using machine learning with Bluetooth signals. Overall, the project successfully developed an accurate and efficient indoor localization system. By combining a Kalman filter with a Random Forest model, it achieved high results while minimizing training time and deployment effort. This project presents a significant step forward in Bluetooth-based indoor localization, opening doors for various applications requiring precise and rapid location tracking.

Limitations and Future Directions

Some avenues that can be considered to address limitations and to expand this work include:

1. Expand Testing Area: Scale the testing area to evaluate the system's performance in larger and more complex environments.
2. Sensor Selection: Investigate the effects of using multiple sensors and explore efficient methods for selecting the three closest sensors based on trilateration.
3. Active Beacon Participation: Implement a mechanism for active beacon participation in RSSI signal measurement to increase the number of available sensors and improve localization accuracy.
4. Microcontroller-Based Implementation: Optimize the system for deployment on microcontroller-based devices to enable more widespread and cost-effective applications.
5. Hybrid Model Exploration: Explore the potential benefits of combining Random Forest and CNN models to leverage their respective strengths and potentially achieve even higher accuracy.

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