Enhancing Multi-Floor Indoor Localization Accuracy Using Fingerprint-Based Dynamic *k*-NN Approach

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***Abstract*—Indoor positioning is an important area of focus for research due to its fundamental capabilities of tracking people and objects indoors in complex spaces. This study presents a novel approach to multi-floor indoor positioning using Wi-Fi received signal strength (RSS) fingerprinting, with our testing methods verified on two datasets, dense v. sparse data collection. The primary contributions we introduce are a voting scheme for floor differentiation and a dynamic "valid neighbor" selection technique for user localization, both implemented within a *k*-nearest neighbors (*k*-NN) framework. Our method incorporates floor-specific filtering and normalization to account for RSS distribution variations between floors. The approach was tested on a dense dataset of 609 Wi-Fi fingerprints collected across three floors of an engineering building, with varying room sizes and layouts. We amplified our voting scheme with additional components to make it robust and saw improvements in floor differentiation from 99.82% to complete accuracy in the dense dataset, and 94.93% to 97.46% accuracy in our sparse dataset. We also saw improvements in localization accuracy, achieving a mean distance error of 1.53 meters, with 42 out of 85 (52%) test samples falling under this average. This research contributes to the development of more reliable indoor positioning systems for complex multi-floor environments, addressing challenges such as access point (AP) placement, signal variability, and diverse spatial contexts.**

***Index Terms*—Indoor Positioning, Received Signal Strength, Fingerprinting, Multi-Floor Estimation, Normalization, User Localization**

I. Introduction

As IoT expands in indoor environments, the demand for reliable indoor location-based services (LBS) grows. While GPS is widely used for outdoor positioning, it often fails inside buildings due to weak signals. This limitation has led to the development of indoor positioning systems (IPS) for LBS use within facilities. IPS technologies, such as Wi-Fi, Bluetooth beacons, and radio frequency identification (RFID), are designed to provide accurate location data where GPS struggles. These systems integrate with IoT infrastructure to enable applications like indoor navigation, object tracking, and proximity-based services in indoor environments[1].

Wi-Fi-based fingerprinting stands out as a promising approach among the different indoor positioning techniques available, especially for multi-floor environments due to its simplicity, low cost, and ability to take advantage of existing infrastructure. This method leverages the received signal strength (RSS) from Wi-Fi access points (APs) to create unique spatial signatures, or "fingerprints," for different locations within a building. These methods typically involve a two-phase process: an "offline" training phase, where signal measurements are collected at known locations to create a fingerprint database, and an "online phase", where real-time signal measurements are compared against the database to estimate the user's location [2]–[4].

The field of indoor positioning has seen a significant shift towards machine learning (ML) techniques in recent years, aiming to enhance both the accuracy and reliability of localization models. Many ML algorithms have been applied to this domain, each offering unique advantages, with the likes of random forest (RF)[5], [6], support vector machines (SVM)[7], and gradient boosting (GB) techniques[8]–[10]. Research has also been conducted for multi-floor environments[11], using techniques like *k*-means region clustering-based fingerprint (RCF) model to handle multi-space indoor positioning by dividing service areas into optimal regions and implements a long short-term memory (LSTM)-based network for accurate location recognition with single RSS measurements. There has also been work on combining ensemble learning and LSTM networks that address temporal variation, spatial unevenness, and sample sparsity in fingerprint-based positioning[12]. However, the challenge of multi-floor indoor positioning lies in accurately distinguishing between floors while maintaining precise localization within each floor. To address such challenge, the *k*-nearest neighbors (*k*-NN) algorithm has been extensively studied for its simplicity and effectiveness[13]–[15].

The *k*-NN algorithm is a simple and effective method for its application in complex multi-floor environments, being a cornerstone in achieving high-precision indoor positioning. Its fundamental approach involves computing the similarity between a user's current signal readings and a database of pre-collected location fingerprints. The algorithm then identifies the *k* most similar fingerprints and estimates the user's position by aggregating their corresponding locations. Traditional distance metrics such as Euclidean distance or cosine similarity often struggle to capture the intricacies of signal propagation across different floors and through various architectural features[1]. To address the limitations of signal variability, diverse spatial contexts, and AP placement, recent research has explored dynamic k-NN approaches[12], [14]–[18], where the value of k or the weighting of neighbors adapts based on the physical characteristics and signal variability of each floor or location within a building.

Our research addresses multi-floor differentiation by introducing novel techniques within the k-NN framework[16]. We propose an amplified voting scheme for floor differentiation, which enhances the robustness of floor-level distinctions. Additionally, we incorporate a dynamic "valid neighbor" selection technique for user estimations, improving the accuracy of position estimation within each floor. A key innovation in our approach is the implementation of floor-specific filtering and normalization processes. This technique accounts for the unique RSS distribution patterns on each floor, allowing our algorithm to adapt to the specific signal propagation characteristics of different levels within a building.

The remainder of this paper is organized as follows. Section II reviews related work on ML approaches for multi-floor and indoor positioning. Section III details our methodology, including the fingerprinting process, the amplified voting scheme for floor differentiation, and the dynamic "valid neighbor" selection technique for localization. Section IV presents our dataset and analyzes and discusses the results. Section V concludes with insights on our findings and potential future directions.

II. Related Work

Existing indoor positioning methods found in literature strive to incorporate ML approaches capable of accurate localization results across all floors within widespread indoor environments. An et al.[19] extract a variety of additional attributes from mobile users alongside RSS values such as barometric pressure, accelerometer, and gyroscope measurements to improve floor differentiation. A slope formula, using collected air pressure as its variables, was created to visually map sudden fluctuations in the slope as changes in elevation. The trajectory of users was calculated using the latter collected measurements and the pedestrian dead reckoning (PDR) method. Narasimman and Alphones[6] tackled feature extraction before classification or regression by proposing the DumbLoc framework. This method utilizes RSS values from the strongest AP signals and normalized output labels, achieving high positioning accuracy without the need for optimization. DumbLoc achieved a mean 3-D positioning error of 8.45 meters and demonstrated superior performance compared to techniques like zero prediction and principal component analysis (PCA). Some studies have investigated the k-NN algorithm due to its simplicity and effectiveness in estimating a user's location based on the features of nearby fingerprints. Additionally, research has explored the integration of custom distance functions with the k-NN algorithm for indoor positioning. For example, Zhou et al.[13] proposed the Q weighted k-NN algorithm (Q-WKNN), which uses base Q to transform RSS into Q-based RSS, thereby enhancing positioning accuracy and real-time performance. Their study evaluated the Q-WKNN against other indoor positioning algorithms using data from Zenodo and underground parking databases. Wang et al.[14] developed a novel WKNN algorithm based on signal similarity and spatial positioning, examining the correlation between RSS similarity and position distance to boost the WKNN algorithm's accuracy. Another study by Wang et al.[15] introduced an improved Wi-Fi positioning method that incorporates fingerprint clustering and a signal-weighted Euclidean distance (SWED). Their experimental results, obtained from two test environments, showed that the position label-assisted (PL-assisted) clustering effectively represented the reference points' position distribution. Alfakih and Keche[20] propose an enhanced nearest neighbor algorithm, the nearest k^{th}-nearest neighbor (NK-NN), which uses all collected RSS samples instead of averages. Their method screens out noisy RSS testing samples and implements a differentiation process on the k^{th}-nearest training samples to improve positioning accuracy. Peng et al.[17] introduce a new Wi-Fi dynamic selection method for nearest neighbor localization. Their approach combines particle filtering and Kalman filtering to extract RSS characteristic values, addressing issues of particle degradation and noise filtering in Wi-Fi positioning. Abdulkarim and Sarhang[21] address RSS fluctuations in indoor environments by normalizing Wi-Fi AP RSS values. Their method integrates normalized RSS data with smartphone sensor measurements using a Kalman filter to improve positioning accuracy in complex indoor structures. Hu and Hu[18] introduce the static continuous statistical characteristics-soft range limited-self-adaptive WKNN (SCSC-SRL-SAWKNN) algorithm, which distinguishes between stationary and moving states in Wi-Fi positioning. Their method uses a moving window approach and cumulative mean of signals to enhance RSS stability, particularly in static scenarios. Our research is an extension of our previous efforts[16], utilizing a percentile and weighting scheme on fingerprint samples, with additional modules incorporated that cover floor differentiation and dynamic nearest neighbor selection. Although there exists notable literature on indoor positioning, achieving accurate estimations within indoor spaces remains a challenge.

III. Methodology

Our methodology for multi-floor user localization using k-NN consists of several key components: data collection and preparation conducted while the model is offline. The offline stage is followed by floor differentiation, data filtering, normalization, and user localization conducted during the model's online stage. Each of these components plays a crucial role in achieving accurate indoor positioning. The flowchart diagram in Figure 1 depicts the process steps across the offline and online stages[16].

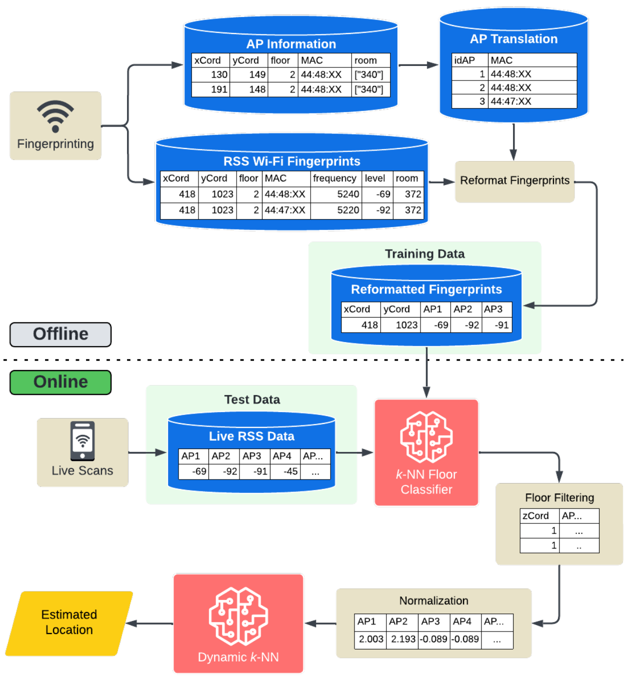

Fig. 1. Indoor localization multi-floor framework

A. Data Collection

The framework is contingent on populated RSS data to operate and perform estimations. Correspondingly, the motive of the offline stage is the collection of RSS values from a variety of different locations within the site of localization. The collection is done through the fingerprinting method. Fingerprints act as snapshots of RSS data from a marked position on a floor plan. The key attributes of a fingerprint are RSS value, Cartesian spatial (x, y) coordinates, and AP MAC address.

Two fingerprint sessions were orchestrated to gauge the model's performance under distinct conditions. The first session had fingerprints placed sparsely across the localization zone, and the other had a dense distribution of fingerprints across the same area. Fingerprints in the datasets were ordered following a grid formation. Each fingerprint in the dense set is placed 8 to 9 feet apart, while, in the sparse set, fingerprints were placed to seldomly accommodate every room, allowing for minimal sufficient neighbor selection. An arrangement of fingerprints in both sets can be seen in Figure 2. Taking into account the unpredictability of the RSS signal, 3 consecutive Wi-Fi scans were taken for each fingerprint. The strongest RSS value to each AP was stored for that fingerprint record. This includes both 2.4 GHz and 5 GHz frequency bands. A sample of raw fingerprint data is present in the "RSS Wi-Fi Fingerprints" table in Figure 1. The RSS values collected in this research exist in a range between -30 dBm and -100 dBm, where -30 indicates the AP is within arm's reach and -100 signals that the AP was not detected. The "AP information" table in Figure 1 is generated via the fingerprinting process to identify reliable APs that will be considered in data preprocessing.

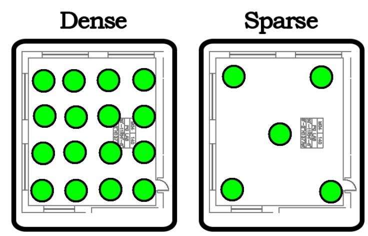

Fig. 2. Fingerprints in sparse v. dense training samples

B. Data Preparation

Before delivering fingerprint data to the model, fingerprint records are reformatted during the offline phase to reduce training time, enhance readability, and account for missing RSS values in fingerprint records. The "AP translation" table in Figure 1 is encoded using the previously identified trusted APs from the "AP information" table. APs are evaluated for reliability by how many usable RSS values each AP has accrued across all fingerprint records. Each identified AP is assigned an index in the AP translation table. Fingerprints are then reformatted into training data to only populate one record for each fingerprint. The RSS value to an AP from each fingerprint record is stored under the AP's respective column index. If no RSS value was received from that AP, an RSS of -100 will be stored in that cell indicating that the AP was not reached. Once fingerprints are restructured into the new format, they can be delivered to the model as training data.

C. Amplified Voting Scheme for Floor Differentiation

Floor differentiation is the first critical step in the online phase of our multi-floor indoor positioning system. Our approach for this task entails an amplified voting scheme that offers improved accuracy compared to simpler methods. To evaluate the similarity between test samples and the train reformatted fingerprints, we use the Euclidean distance metric. Euclidean distance is preferable here for its relative applicability to RSS data and minimum abstraction of requirements.

We chose to use 11 nearest neighbors based on empirical testing, which showed that this number provides a good balance between accuracy and computational efficiency. The increased number of training samples allows for a more reliable consensus, reducing the uncertainty in floor predictions. There was no cap limit, but 11 is a good size that takes advantage of the extensive fingerprint data we collected.

To address the inherent limitations of RSS in floor determination, amplified voting is a non-conventional approach to floor differentiation that acknowledges that RSS data, while valuable, may not be the optimal sensor data for accurate floor-level distinctions. The amplified scheme compensates for these limitations by introducing more rigorous criteria for floor determination. The amplified voting scheme process is followed throughout Figure 3.

A simple voting scheme identifies the floor with the highest count among the best neighbors. However, our research found that this approach is unsuitable for reliable floor determination.

In scenarios where floor differentiation relies solely on counts, especially in edge cases, this method can lead to significant differentiation errors. Such misclassification would result in completely misinterpreted and incorrect user localization, undermining the system's overall reliability.

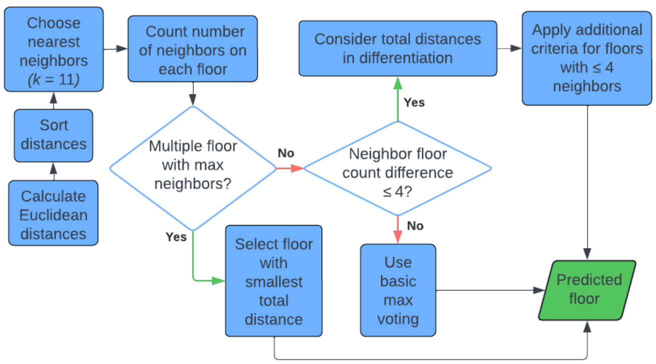

Fig. 3. Amplified voting scheme flowchart

The extended approach begins by computing and sorting Euclidean distances in ascending order between the test sample and all training samples. From these, the 11 nearest neighbors are selected and their corresponding floors are identified. The algorithm then polls how many neighbors came from each floor. Then, it calculates the total distance of neighbors for each floor by summing the distances of its representatives among the 11 neighbors. A layered voting scheme is applied to determine the final floor differentiation. This scheme includes several conditions to handle edge cases: when two floors have an equal number of votes, the floor with the smaller total distance is chosen. If the difference in floor counts does not exceed 4, the total distances are factored into the floor differentiation. In cases where a floor has at most 4 neighbors but could potentially be the correct floor, additional criteria are applied to prevent misclassification. If all these conditions fail to produce a clear result, the algorithm defaults to a basic maximum voting scheme.

D. Data Preprocessing

After floor differentiation, we apply filtering and normalization techniques to refine our data and improve location estimation accuracy.

1) Floor-Specific Filtering: Each floor estimation gets its floor-filtered training dataset. This step is crucial because RSS distributions can vary significantly between floors due to differences in layout and signal propagation.

2) Normalization: We use a standard scaler to normalize the RSS values by fitting the standard scaler on the filtered dataset for each floor and applying the scaling parameters to normalize the training and test samples. This can be expressed as the following:

$$\text{RSS}_{\text{normalized}} = \frac{\text{RSS} - \mu_{\text{floor}}}{\sigma_{\text{floor}}} \tag{1}$$

Standardization helps in dealing with heterogeneous floors by accounting for variations in physical layout and AP placement. Different floors can have distinct environmental factors influencing RSS values, such as obstructions or distance from APs. By standardizing RSS values relative to floor-specific statistics (μ_{floor} and σ_{floor}), the impact of these floor-specific differences is reduced, allowing for more consistent and comparable data across different floors. This approach enhances the reliability of localization and floor estimation algorithms by mitigating floor-specific signal variations.

This normalization process accounts for the physical differences in floor layouts and helps to improve the accuracy of our subsequent k-NN algorithm for user localization.

E. User Localization Using Dynamic Nearest Neighbors

The final step in our methodology is to estimate the user's precise location within the classified floor. The k-NN technique is employed for user localization; our implementation utilizes a 5-NN algorithm. This choice of k is based on assigned k values found in similar literature[18]. The RSS similarity metric[16] is applied as a distance function for determining nearest neighbors. The relevance of the similarity metric is:

- Compute RSS similarity between the test sample and training data.
- Weight these computations based on the percentile and weighting schemes.

As a component of this study, we introduce a novel "valid neighbor" selection technique to address the challenges of signal variability by considering distant and near reference points as potential neighbors. The dynamic valid neighbor selection algorithm sorts k neighbors by distance and evaluates them iteratively. It uses two thresholds: thr for individual distance differences and tot_thr for cumulative differences. For each neighbor, it calculates the distance difference from the previous neighbor. If this difference is below thr and the cumulative difference is below tot_thr, the neighbor is considered valid. The process continues until a threshold is exceeded or all k neighbors are evaluated. This method adapts to varying densities of reference points, efficiently excludes outliers, and can handle non-uniform distributions. The process is illustrated in Figure 4.

It should be noted that increasing fingerprint density would allow for more fine-grained estimations and more restrictive thresholds, with literature expressing that increasing the number of fingerprints enhances localization performance, observing improvements through iterative comparisons of metrics as the number of training fingerprints grew[22]. The thr and tot_thr can be adjusted to reinforce this behavior.

By combining these methodological components, our Wi-Fi RSS fingerprinting system aims to provide accurate and robust indoor positioning across multiple floors, leveraging the unique characteristics of RSS distributions and adapting to the specific layout of each floor.

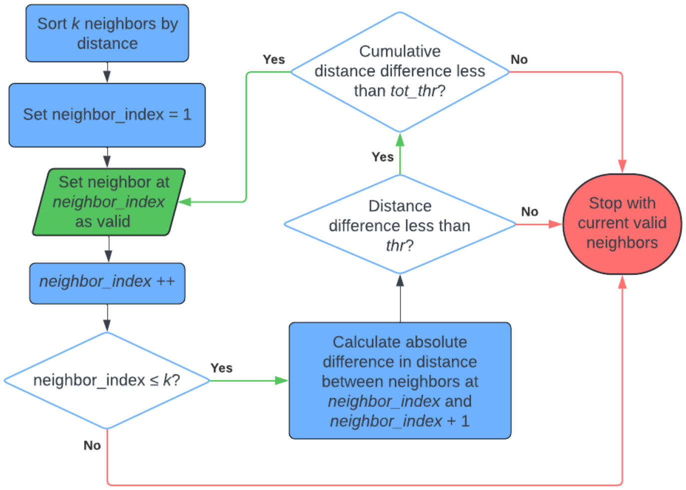

Fig. 4. Dynamic neighbor selection flowchart

IV. Results and Discussion

This section discusses our findings using the designed framework. In the context of user localization, the mean absolute error (MAE) measures the average absolute difference between the predicted location and the actual location of a user. Our analysis converts the MAE values from pixels to meters, making our results more practical to interpret. By expressing MAE in meters, we can better compare our findings to established standards and previous studies in the field.

A. Dataset

The collected dataset comprises RSS Wi-Fi scans (collected fingerprints) from the engineering building at the University of Detroit Mercy. To validate our findings, we collected fingerprint data across three respective floors within this building. Each floor exhibits varying room sizes and layouts, which allows us to capture a diverse range of environmental conditions that reflect the nuances of signal propagation in different spatial contexts. The distribution of fingerprints across the floors is shown in Table I.

TABLE I
Comparison of Fingerprints Collected Across Sparse v. Dense Dataset on Different Floors

Floor	Dense Fingerprints	Sparse Fingerprints
#1	207	61
#2	277	98
#3	125	64
Total	609	223

B. Analysis on Floor Differentiation

In this experiment, we compared the effectiveness of a simple voting scheme and an amplified voting scheme for floor determination on dense and sparse fingerprint data. As shown in Table II, for the sparse dataset, the integration of the amplified voting scheme led to an improvement in floor differentiation accuracy. The misclassified floor differentiations under the simple voting scheme were correctly predicted with the amplified approach, improving the accuracy from 94.93% to 97.46%. On the dense dataset, we also saw improvements from 99.82% to being completely accurate. This perfect classification rate underscores the effectiveness of the amplified voting scheme, particularly when combined with a comprehensive fingerprinting approach.

TABLE II
Comparison of Accuracy and Misclassifications Across Sparse v. Dense Dataset on All Floors

Fingerprint Type	Simple		Amplified	
	Accuracy	# Misclass.	Accuracy	# Misclass.
Dense	0.998	1	1	0
Sparse	0.949	4	0.975	2

C. Analysis on Localization Error

The analysis of estimation errors from the dense fingerprinting approach compared to the old sparse dataset reveals prominent improvements in indoor localization accuracy. The dense fingerprinting method, as shown in Figure 6, demonstrates a marked reduction in maximum error from approximately 8 meters to 3.8 meters, representing an improvement of over 50%. This approach also yields a tighter error distribution, with most errors falling between 0.5 and 2.5 meters, in contrast to the wider spread observed in the sparse dataset results depicted in Figure 5. The error progression in the dense fingerprinting method is notably tighter, indicating more consistent performance across various test points within the building. On the dense dataset, it achieved a mean distance error of 1.50 meters, with 42 out of 85 (52%) test samples falling under this average. The sparse dataset achieved an average distance error of 2.88 meters, with 44 out of 79 (55%) test samples falling under this average.

These improvements in accuracy and consistency have important implications for user localization. The enhanced precision, typically within 2.5 meters of the actual position for most cases, would allow for more reliable real-time tracking of user movement throughout the building. This level of accuracy is particularly beneficial for distinguishing between floors in multi-story buildings, assuming typical floor heights. The dense fingerprinting approach thus enables more precise and dependable user positioning at any given moment, making it suitable for a range of indoor positioning applications. While some variation in accuracy across different test points persists, the overall performance suggests that this method provides sufficiently precise location information for many practical indoor positioning scenarios, representing a substantial advancement over the sparse dataset.

D. Comparing Scenarios for Localization Visual Analysis

A visual representation of the results provides a clear and intuitive understanding of the performance difference between the dense fingerprinting approach and the sparse dataset.

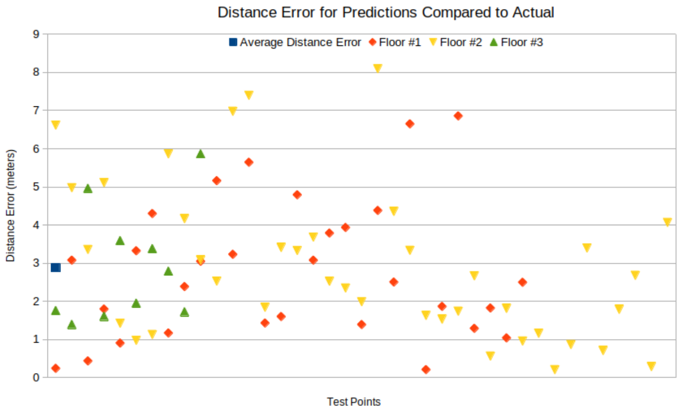

Fig. 5. Sparse dataset localization distance error (meters)

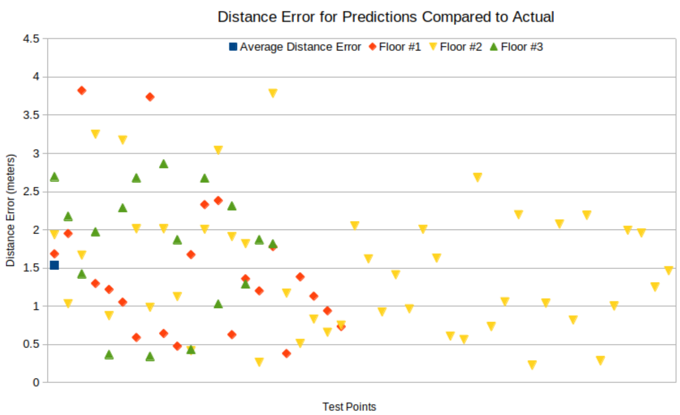

Fig. 6. Dense dataset localization distance error (meters)

Figures 7 and 8 show that the dense fingerprinting approach delivers more precise and consistent predictions across all test points, indicating its reliable accuracy in various locations and conditions within the indoor space. The closer, more controlled error progression visually translates to more precise and dependable user localization.

Looking at the fixed neighbor selection, across the two fingerprint types, our findings show that dense fingerprinting across all floors had an error under 1.90 meters, as shown in Table III. We also found that over 57% of the test samples from the first two floors had samples under their respective averages. Using the dynamic neighbor selection, our results indicated that dense fingerprinting across all floors had an error under 1.80 meters, as shown in Table IV. With this, we also noted that over 53% of the test samples from the first two floors were accounted for below their respective averages, with the last floor showing 35% of test samples falling under 1.77 meters.

Additionally, comparing Table IV and Table III, we see an overall decrease in average error in both sparse and dense

TABLE III
DISTANCE ERROR ON BOTH FINGERPRINT TYPES USING FIXED NEIGHBORS ON ALL FLOORS

Fixed *k*-NN	**Sparse**		**Dense**	
	Err. (m)	**% below avg.**	**Err. (m)**	**% below avg.**
Floor #1	3.24	0.60	1.74	0.59
Floor #2	2.80	0.56	1.52	0.58
Floor #3	3.42	0.70	1.86	0.47
All floors	3.04	0.55	1.65	0.52

TABLE IV
DISTANCE ERROR ON BOTH FINGERPRINT TYPES USING DYNAMIC NEIGHBORS ON ALL FLOORS

Dynamic *k*-NN	**Sparse**		**Dense**	
	Err. (m)	**% below avg.**	**Err. (m)**	**% below avg.**
Floor #1	2.79	0.53	1.47	0.64
Floor #2	2.93	0.56	1.47	0.54
Floor #3	2.90	0.60	1.77	0.35
All floors	2.87	0.55	1.53	0.52

fingerprinting. For sparse, the average error decreased from 3.04 to 2.87 meters using dynamic neighbor selection. For dense, the average error decreased from 1.65 to 1.53 meters using dynamic neighbor selection.

Overall, these findings signify the relevance of fingerprint types and dynamic neighbor selection.

Furthermore, the visual analysis highlights the potential of the dense fingerprinting approach in maintaining consistent performance across diverse indoor environments, with better adaptability to various architectural features and potential signal interference sources commonly found in complex indoor settings.

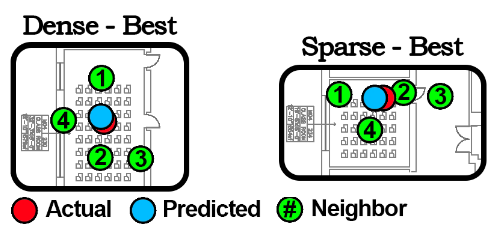

Fig. 7. The *k*-NN estimations comparing best case scenario for sparse v. dense dataset

E. Visual Analysis for User Localization Using Dynamic Nearest Neighbors

This section comparatively analyzes visually mapped localization results of dynamic and fixed neighbor selection methods using dense and sparse fingerprint datasets. This analysis aims to evaluate the impact of valid neighbor selection.

The visual representations of the sparse and dense datasets in Figures 9 and 10 reveal a notable benefit from implementing the dynamic number of neighbors selection approach. This improvement is visible in both conditions where there exists

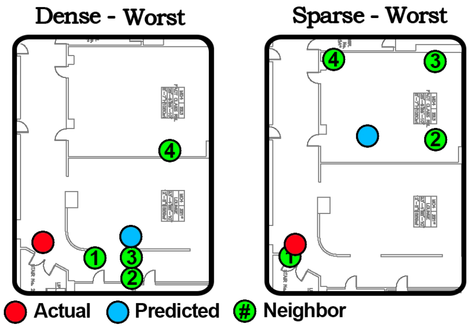

Fig. 8. The k-NN estimations comparing worst case scenario for sparse v. dense dataset

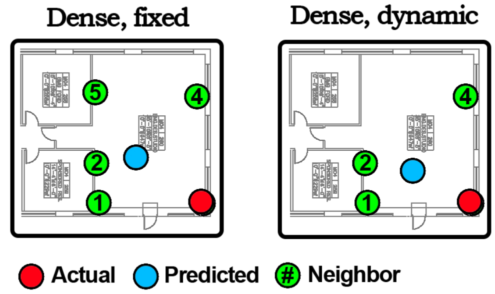

Fig. 10. Comparison of fixed v. dynamic neighbor selection in dense fingerprinting environment

a limited and extensive amount of fingerprints available in the dataset. In scenarios with fewer reference points, the inclusion of neighbors far from the test sample can introduce major inaccuracies in the user localization process. Meanwhile, in the context of dense fingerprinting data where we have an abundance of reference points, there is still a possibility that relatively distant points could be selected as neighbors due to the unpredictable nature of RSS, potentially introducing minor inaccuracies in the estimation process. The dynamic neighbor selection mitigates this issue by selectively choosing comparable sequential neighbors (thr) as well as restricting neighbors once the total distance (tot_thr) threshold is exceeded. This adaptive behavior ensures that even in a dense fingerprinting environment, where the impact of slightly mismatched neighbors might be less severe, we still maintain optimal accuracy by focusing on the most relevant data points.

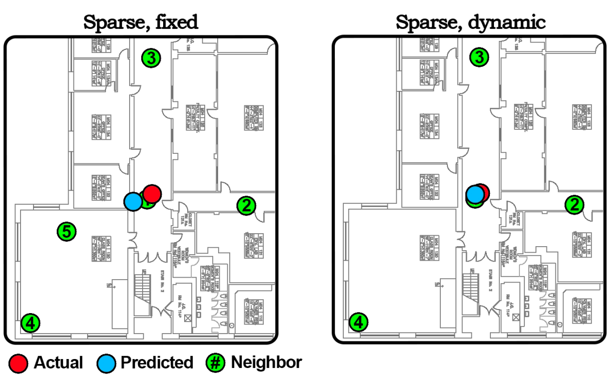

Fig. 9. Comparison of fixed v. dynamic neighbor selection in sparse fingerprinting environment

V. Conclusion

This research explores techniques for enhancing multi-floor indoor positioning accuracy using Wi-Fi RSS fingerprinting. Our primary contributions include an amplified voting scheme for floor differentiation and a dynamic "valid neighbor" selection approach for user estimations within the k-NN framework. These methodologies, coupled with floor-specific filtering and normalization processes, address the unique challenges posed by signal variability across different levels of a building.

To validate our approach, we assembled a comprehensive dataset comprising 609 Wi-Fi fingerprints, meticulously collected across three floors of an engineering facility. This diverse collection, encompassing varied room dimensions and layouts, provided a robust foundation for assessing our algorithms' efficacy in real-world, multi-story environments.

When using the amplified voting scheme approach, the proposed methodology achieved a 2.5% increase in floor differentiation on the sparse dataset and complete accuracy for the dense dataset, showcasing the effectiveness of our amplified voting scheme in comparison to the simple voting scheme. We also found an average distance error of 1.50 meters, with 53% of test samples falling under this average. The increase in training fingerprints and dynamic nearest neighbors proved its robustness by making real-time determinations about neighbor inclusion that a fixed number of neighbors and a limited count of fingerprints cannot provide.

For future work, incorporating additional data streams could enhance the system's capability to track user movement across floors. This multi-modal approach could extend the application of indoor localization to more dynamic and complex scenarios.

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