Multi-Floor IPS, a simplified indoor positioning system study*

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***Abstract*—Indoor positioning systems are a relatively new positioning tool that aims to supplement or replace the usage of Global Positioning Tools for indoor positioning. However; there are little to no studies on Indoor positioning systems in a multi-floor model. This paper aims to provide further knowledge on multi-floor indoor positioning models through demonstrating and analyzing the process of creating a multi-floor indoor positioning model, analysis of machine learning models and how well they perform in a multi-floor indoor positioning model. This paper also aims to introduce two new metrics, Average Grid from Target and Average Distance from Target to better quantify IPS performance as well as the effects of feature filtering, grid size, and data point density on positioning accuracy. The paper also demonstrates the effects of varying grid size on the machine learning model, through Average Grid from Target (AGT). The experiment was conducted on the 6th and 7th floor hallways of KMITL Lifelong Learning Center at King Mongkut's Institute of Technology Ladkrabang. With each part of the hallway being segmented into 1x1 metre grids. Two Android devices running a modified open-source IPS data collection application were used to gather RSSI data across approximately 600 grids per floor. A dataset of 12,640 points was collected across two floors using a filtered set of 378 BSSIDs containing "cmkl" or "kmitl." Experiments with different grid sizes showed that different parameter settings are better for optimizing solely for accuracy or for Average Grid from Target (AGT). The study concludes that a 7×7m grid size offers the best balance between accuracy and precision for IPS applications. A simple WiFi access points filter was implemented. It lowered training time, computational load as well as slightly improved model stability.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

Indoor Positioning Systems (IPS) aim to help users navigate effectively inside of buildings or enclosed areas. This type of navigation proves difficult to create when using common methods for navigation. The most widely used system for navigation is the Global Navigation Satellite System (GNSS) which uses a combination of satellites and ground control stations that aim to calculate ground positions by trilateration. The most well-known GNSS is called the Global Positioning System (GPS). The usage of GPS comes with many caveats as the accuracy of the GPS diminishes when it is used indoors due to the fact that most buildings are built from dense materials like concrete and various metals, which the low power signal from the satellite can not penetrate. The usage of GPS often results in scattering, shadowing, blind spots and signal attenuation, which noticeably affects the accuracy [1]. That is why there have been various methods created for IPS to address the shortcomings of GNSS as well as provide accurate navigation in areas that may not be able to use GNSS

There have been many methods developed for the usage of IPS. One of the most well-known and commonly used methods is trilateration. Trilateration works by measuring signal strength in relation to the distance from the transmitter via Received Signal Strength Indicator (RSSI) fingerprinting [5]. The fingerprinting technique consists of two phases. An initial offline phase, and the following online phase. In the offline phase, radio maps are created by collecting RSSI data. The data is then passed onto the online phase where end devices calculate their position based on the coordinates assigned to each RSSI-emitting device, such as Bluetooth Low Energy (BLE) devices. These BLE devices are often used for RSSI fingerprinting due to its low power consumption and ease of deployment. A mobile device can then be used to track a user's location by triangulating the user's device using the distance between the mobile device and the different BLEs. This is a good method as most RSSI signatures are distinct; however, there are shortcomings with this method. An example of a shortcoming is that RSSI is affected by environmental noise, which can cause errors in location estimation [2]. Another shortcoming is that some buildings may be unsuitable for BLEs and BLEs require precision placement to be effective.

The usage of Machine Learning in conjunction with IPS has been shown to be effective to improve the performance of IPS. For example, a work by H.T. Gidey et al. [3] uses online heterogeneous transfer learning to improve the accuracy by combining data from different domains. By using Machine Learning algorithms such as Support vector Machines (SVM), Decision Trees, k-Nearest Neighbor (kNN), Random Forests, and Neural Networks (NN) it may be possible to remedy the

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shortcomings of IPS systems by treating it as a classification problem. This makes the positioning precision be within a range, so while it may not be able to provide a user's exact location, it can give a relatively reliable estimate on the user's area.

In our previous work, we implemented an IPS using a large grid size (16.75×15m) to reduce the number of classification labels, making the problem more manageable within time constraints. While this approach provided a functional implementation, it left several questions unanswered. Specifically, we sought to determine how the number of data points influences IPS performance, whether a reliable IPS can be implemented with a limited number of BSSID to control feature space complexity, and how small a grid size can be while still maintaining reasonable positioning accuracy. Building on this prior work, this paper further explores the use of classification-based IPS by refining our approach to ground truth reliability in experimental settings. We evaluate the effects of feature filtering on model complexity, discuss the trade-offs between grid size and precision, and analyze the advantages and limitations of our implementation. To better quantify accuracy, we introduce two new evaluation metrics: Average Grid from Target (AGT) and Average Distance from Target (ADT). Through this study, we provide deeper insights into the design considerations for IPS, offering practical takeaways for improving indoor positioning accuracy.

II. Literature Review

IPS have been extensively studied, with a range of techniques developed to address the challenge of accurate localization within indoor environment. Traditional methods of IPS like Wi-Fi RSSI fingerprinting have been enhanced through the use of various ML algorithms, for example, k-Nearest Neighbor (kNN) [6], [7], [11], Random Forest (RF) [6], [11], [10], Support Vector Machine (SVM) [6], [7], [11] and Multi-Layer Perceptron (MLP) [6], [7]. Because positioning can be treated as a classification problem, ML algorithms based on statistics and regression are well-suited for this task. With this in mind, the improvement of data collection is essential, as the quality of RSSI data points significantly impact on IPS accuracy. This could be done by training datasets with readings from different devices and collected at different times of the day, as noted in [8]. Several studies have proposed methods to refine dataset quality to better train fingerprinting algorithms used in positioning systems, such as combining Human Activity Recognition (HAR) using sensors with fingerprint collection [9] and the development of coordination-based Android applications [12]. These efforts have contributed modest improvements to IPS performance and created chances to develop IPS even more with additional data points.

Deep learning approaches, such as Graph Neural Networks (GNNs) [7] and Convolutional Neural Networks (CNNs) [9], have demonstrated superior performance over traditional ML algorithms when a sufficient number of data points are available. Despite existing work, key environmental variables, such as the resolution of fingerprint grids and the spatial distribution of reference points, have not been comprehensively investigated. In this paper, we emphasize the critical role of these factors in IPS and aim to systematically analyze and identify the most effective configurations for multi-floor environments. Our objective is to enhance the accuracy, reliability, and overall performance of IPS by considering various influencing parameters and optimizing system design accordingly

III. Methodology

For the purpose of developing a Multi-Floor IPS model. This experiment was conducted on the 6th floor and 7th floor hallways of the CMKL building. This location was chosen as it provided us with two near identical hallways on two different floors. This allowed for an easier grid distribution as the grid mapping on the 6th and 7th floor were near identical due to how similar the hallways are. The area also had regular traffic by students and teachers, allowing us to have a realistic testing environment where we could see the effects of regular foot traffic on the testing environment. To match the physical environment to the virtual environment, 1 metre by 1 metre grids were measured, taped and labelled on the floor. The criteria for usable grids were grids that were in the hallway and grids that did not have a permanent obstruction in place like a vending machine or a printer. The total amount of grids per floor was around 600+ grids. After the grids were created, data was collected through the use of two android phones. The mobile application used on the android devices was taken from an open source project of the paper called "ML-BASED MULTI-FLOOR IPS: A COMPARISON" [4]. This mobile application allows us to upload a map of the area and then segment it into identically sized grids.

During the taping of the 6th floor, we encountered some challenges related to the varying types and orientations of the tiling panels in certain areas. This created a slight deviation from the uniformity of the floor tiles, which we were relying on to accurately measure the straightness of the 1-meter grid. To measure this, we typically used the distance from the edge grooves of the tiles to the edge of the 1-meter grid, checking for consistency. However, we were able to overcome these challenges in two key areas: the cafeteria and the study area.

In the cafeteria, the solution was straightforward. We simply measured the difference in distance between the grooves of the standard tiles and those used in the cafeteria. By adjusting the measurements accordingly, we were able to maintain an accurate grid despite the variation in tile type.

The lounge area presented a more complex challenge due to the tiles being in different sizes and orientation, as shown by the image above (4.) . To address this, we created a single straight line across the lounge using a tape measure from a fixed point which we proceeded to use as the reference line as shown above. We then took 1-meter measurements using a measuring tape (2.). A second reference line was used to make sure that the measuring tape was straight so that the 1 metre grid would not be slanted. Additionally, we had to account for the wear and tear on the area used for our experiment. Human traffic and cleaning activity had the potential to slightly shift or damage the tape, which could impact the grid's accuracy. However, by monitoring and adjusting for any movement in the tape, we were able to maintain the integrity of our measurements throughout the process.

The data collected resulted in xxx amount of points collected for floor 7 and xxx amount of points collected for floor 6

IV. Result

Collected Data Points		# BSSID
Filtering Features	Non-Filtered	1799
	Filtered	378

TABLE I: Total Bssid Before and After Filtering

Grid Count	Grid Size Variations							
	1x1	3x3	5x5	7x7	9x9	11x11	13x13	15x15
Total Grid	483	96	47	29	28	16	18	9

TABLE II: Total unique Grid present and Used for each grid size experiment training

The dataset used in this study consisted of 12,640 data points collected across 1x1m^2 grids distributed among the floors of our experimental setup. By filtering the available BSSID to utilize only SSID with 'kmitl' or 'cmkl' we end up with 378 unique BSSID, spanning across the 2 floors of the experiment. A rationale behind filtering WiFi signals in this experiment is to determine whether only easily known BSSID can be utilized in implementing IPS. 9019 data points were collected on 6th floor and 3621 data points were collected on 7th floor.

To explore how different parameter settings impact model training, we systematically iterate through various configurations, training the model multiple times under each setting. The table below highlights the best results observed. Notably, the highest accuracy and the best AGT (Average Grid from Target) do not come from the same parameter setting.

This suggests that these metrics prioritize different aspects of performance—optimizing for accuracy does not necessarily yield the best AGT and vice versa. This insight provides a key perspective as we analyze the results in more detail. Another thing of note is, according to Figure 2, from 7x7m grid size onwards, our best AGT measured across different model starts to plateau which could indicate diminishing returns from increasing experiment grid size.

V. Discussion

By conducting our experiment across multiple grid sizes, we can visualize the tradeoff between grid size and precision. To quantify this, we calculate the average grid deviation from the target and multiply it by each grid size's diagonal length, as shown in Figure 2. This figure illustrates the expected deviation in predictions when a model is trained on a specific grid size, should an error occur.

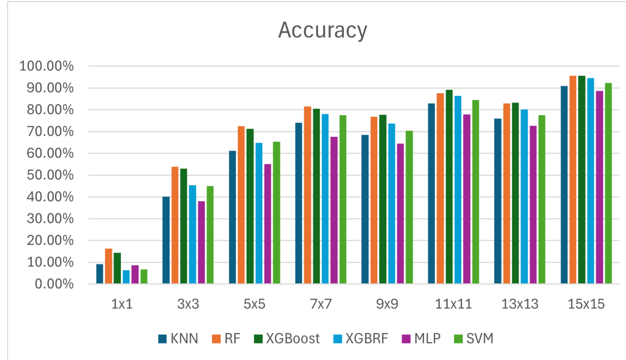

Fig. 1: Model Accuracy on Different grid size

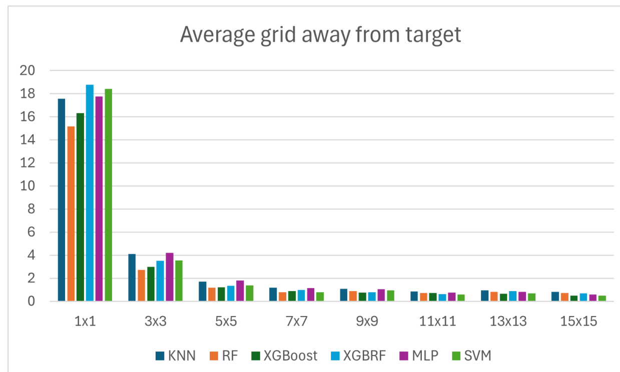

Fig. 2: Model Average grid away from Target on Different grid size

While a 15×15m grid size performs well on the graph, it inherently limits accuracy to that resolution. In cases where predictions are correct, the location remains constrained within a 15×15m area, which may not be suitable for applications requiring higher precision—such as those needing to pinpoint areas smaller than this grid size.

Through this experiment, we find that a 7×7m grid size offers the best balance between accuracy and precision. Below demonstrates our Average Distance away from Target metric (ADT) which is a byproduct between AGT and diagonal length of used grid size. Utilizing 7x7m grid size minimizes error while remaining small enough for use in precision-dependent applications. However, it is important to note that these findings may not generalize to all IPS implementations in different environments. The results suggest that increasing grid size does not necessarily improve accuracy or even precision; in some cases, performance actually declines, as shown in the chart. This highlights the need for careful consideration when selecting a grid size based on the specific requirements of an IPS deployment.

Training an IPS model involves significant computational challenges, particularly when dealing with high-dimensional feature spaces. In our experiment, we implemented a simple Wi-Fi access point filtering approach, selecting only access points containing cmkl and kmitl in their names. This dras-

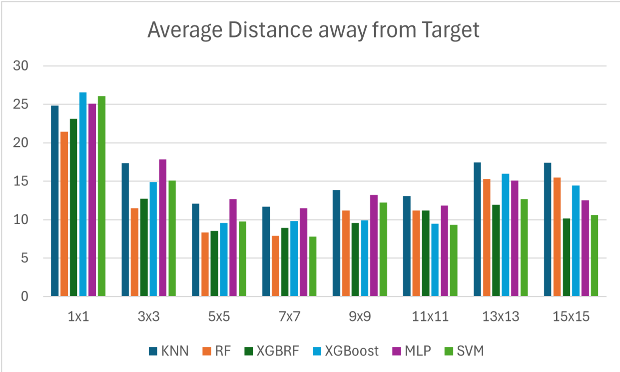

Fig. 3: Average Distance Error Across Different Grid Resolutions

tically reduced the number of access points used as features, making the training process more efficient.

While the filtering method we applied was relatively simple, it had a surprisingly large impact on computational feasibility. By reducing the number of BSSID features from 1799 to 378, we were able to train models across a wide range of grid sizes (1×1 to 15×15) without overwhelming our hardware. In contrast, attempting to train on the full, unfiltered set quickly became impractical—our RTX 3080 Ti struggled even with the smallest grid size. Although we didn't record exact runtimes, the difference in resource demands was stark. This raises questions about the actual utility of the full feature set and suggests that a more systematic study of feature selection or dimensionality reduction could be worthwhile in future works.

Interestingly, our results indicate that filtering access points did not negatively impact the model's learning process. A comparison of training trajectories for the 1×1 grid experiment shows that the filtered model performed comparably to the unfiltered one, if not slightly better in terms of convergence. This suggests that reducing feature dimensionality not only accelerates training but may also make learning more stable.

VI. Conclusion

In conclusion, this paper extends our previous work by refining the implementation of an IPS using a classification-based approach. Through our experiments across multiple grid sizes, we visualized the trade-offs between grid size and precision, showing that increasing grid size does not necessarily improve accuracy and may, in some cases, lead to worse performance. Our findings suggest that a 7×7m grid size offers the best balance between accuracy and precision, making it suitable for applications that require finer localization. However, we acknowledge that these results may not generalize to all environments due to variations in WiFi signal behavior and building structures.

Additionally, we implemented a simple filtering method to limit the number of WiFi BSSID features, preventing excessive model complexity while maintaining comparable performance to an unfiltered approach. This method significantly reduced training time and computational requirements, allowing us to complete model training across multiple grid sizes efficiently. Our results indicate that reducing feature dimensionality not only accelerates training but may also contribute to more stable learning. To better assess IPS performance, we introduced two new evaluation metrics—Average Grid from Target (AGT) and Average Distance from Target (ADT)—which provide a clearer understanding of prediction deviation. Ultimately, our study highlights key considerations in IPS design, particularly in grid size selection and feature filtering, and offers insights for improving indoor positioning accuracy in practical implementations.

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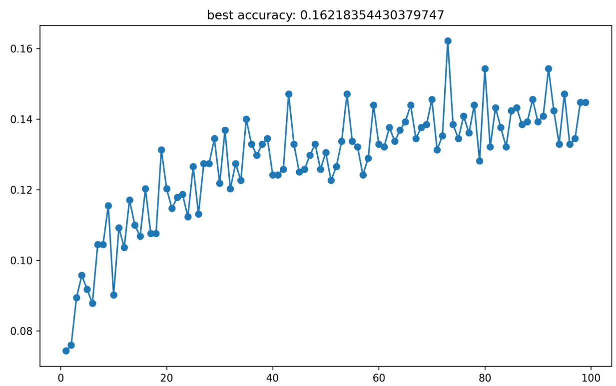

Fig. 4: RF Model accuracy with BSSID filtering (1x1)

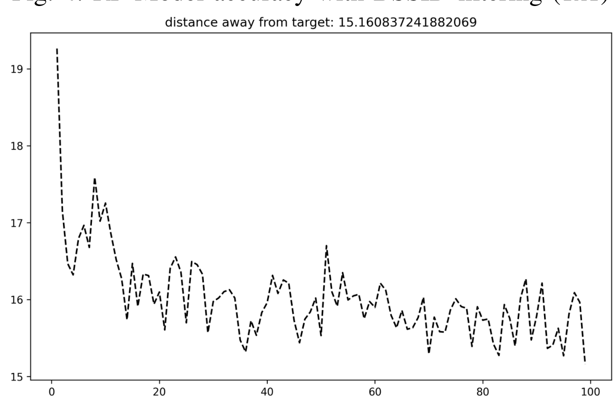

Fig. 5: RF Model AGT with BSSID filtering(1x1)

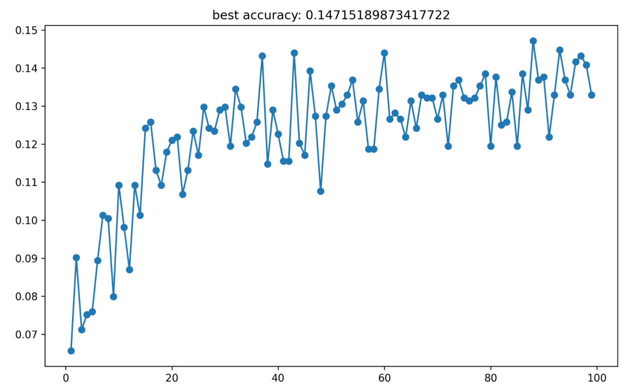

Fig. 6: RF Model accuracy without BSSID filtering(1x1)

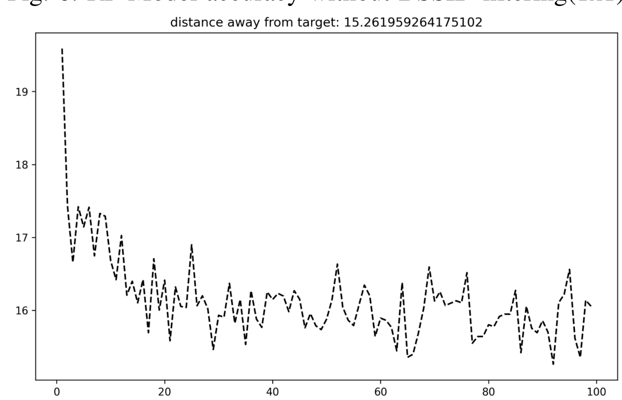

Fig. 7: RF Model AGT without BSSID filtering(1x1)