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Short Paper

Improving WLAN Fingerprinting for Indoor Positioning: The Role of Signal Receiving Factors

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Abstract

Purpose – This study intends to analyze the critical factors affecting the accuracy of WLAN fingerprinting in Indoor Positioning Systems (IPSs) from the perspective of radio signal reception. Utilizing an Ishikawa diagram, the research aims to provide insights into the various environmental and technical factors that can degrade the performance of WLAN fingerprinting, which leverages the Received Signal Strength Indicator (RSSI) from Wi-Fi signals to estimate user location.

Method – The study employs an experimental approach, examining the effects of sample size, receiver models, and operator elevation on positioning accuracy. The approach involves controlled experiments to isolate the impact of each factor, followed by statistical analysis to identify trends and correlations.

Results – The study reveals that sample size directly correlates with accuracy, with larger samples improving precision. Receiver model variability introduces significant disparities in signal interpretation, impacting location estimation reliability. Operator elevation further complicates signal propagation, emphasizing the importance of standardizing deployment practices for consistent performance.

Conclusion – The study concludes that addressing these critical factors can substantially enhance the effectiveness of WLAN fingerprinting-based indoor positioning systems

Recommendations – To enhance WLAN fingerprinting accuracy and reliability in Indoor Positioning Systems, it is momentous to optimize sample sizes during calibration, standardize receiver equipment, and consider elevation effects in system design. These strategies can significantly improve location-based services across various applications and environments.

Research Implications – This study extends to both academic and practical domains. For researchers, it offers a structured framework to explore environmental impacts on indoor positioning system performance. Practitioners can leverage these insights to develop more robust and accurate indoor positioning systems, fostering wider adoption in applications such as navigation, asset tracking, and emergency response.

Keywords – sample size, indoor positioning system, receiver model, operator height, fingerprinting

INTRODUCTION

The pervasiveness of mobile devices and the growing demand for location-based services have propelled indoor positioning systems (IPSs) into the forefront of technological advancements (Fan & Sun, 2024; Li et al., 2018; Ozaki et al., 2023). WLAN fingerprinting has emerged as a promising approach among the various IPS techniques due to its reliance on the ubiquitous Wi-Fi infrastructure (Nguyen & Thuy Le, 2021; Pinto et al., 2021). This technique utilizes the Received Signal Strength Indicator (RSSI) of Wi-Fi signals to estimate the user's location by matching the RSSI measurements against a pre-generated fingerprint database (Nicholaus et al., 2024; Wei et al., 2024).

Despite its promising potential, the accuracy of WLAN fingerprinting is often hampered by a multitude of factors, including the signal-receiving environment (Aydin et al., 2020; Wei et al., 2024; Zuo et al., 2021). The signal-receiving environment encompasses the physical characteristics of the indoor space, such as the operators, reference points density (RPs density), reference points distribution (RPs distribution) and reference points height (RPs height), receiver models, sampling rate, and the number of samples. These factors can significantly affect the RSSI values, leading to erroneous location estimations (Boros, 2020; Liu et al., 2017; Zafari et al., 2019; Zhang et al., 2020). This study delves into this critical aspect by thoroughly analyzing the various signal-receiving factors that influence the accuracy performance of WLAN indoor positioning fingerprinting.

LITERATURE REVIEW

In Yeh et al. (2018), the focal point was the prominent RADAR fingerprint localization technique. This method utilized location fingerprinting for user positioning alongside signal propagation modelling using triangulation. The RADAR system boasts an average resolution of two to three meters, surpassing the precision of signal transmission models.

Numerous methodologies have emerged for Wi-Fi location fingerprinting after RADAR. The system in Yang et al. (2021) employed an advanced transfer learning approach incorporating customized hotspot detection and map space exploration, resulting in an average localization accuracy of 2.5 meters based on empirical evidence. Within an experimental setup, the Wi-Fi location service named "Calibration-Free Fingerprint Positioning Techniques," developed by Yeh et al. (2018), implemented k-nearest neighbour (k-NN) for positioning. The research demonstrated an average accuracy of 3.59 meters in locating a mobile phone. The service achieved an accuracy of 71.3% during its testing phase. To evaluate the effectiveness of diverse localization fingerprinting techniques, Boros (2020) devised a system merging magnetic field detection with a sensor fusion algorithm, offering potential solutions for localization challenges.

During a field experiment, it was observed that applying probabilistic linear discriminant analysis (PLDA) with Bayes rule for computing posterior probability in indoor positioning systems yielded an accuracy of 1.38 meters at the meter level (Yu & Li, 2021). The study by Caso et al. (2020) utilized Wi-Fi Received Signal Strength Indicator (RSSI) observations for indoor localization by averaging selected maximum RSSI observations to delve deeper into this technology. These observations were then employed in particle filter, Kalman filter, and location fingerprinting methodologies. By comparing different indoor positioning techniques based on factors such as energy efficiency, cost, and tracking accuracy, the study proposed alternative approaches to the conventional Kalman and particle filter algorithms, which were proven reasonably precise. Their validation through real-world scenarios indicated that their method could offer enhanced indoor positioning and location detection accuracy compared to previous techniques.

In addition to developing various systems, numerous researchers have investigated innovative algorithms. A Virtual Fingerprinting (ViFi) indoor positioning system was introduced by Xue et al. (2017), which generates virtual fingerprints through RSS prediction based on a Multi-Wall and Multi-Floor propagation model, thereby reducing the required number of measurements while maintaining accuracy. It enables a flexible mapping between the mobile terminal's location and the raw signal measurements. With ViFi, the number of measurements necessary to achieve the same level of accuracy as traditional fingerprinting methods can be reduced by a factor of seven. Furthermore, Zhang et al. (2020) presented Weighted K-nearest neighbour and Weighted Signal Intensity (WKNNS), a fingerprint-based indoor localization technique that leverages weighted K-nearest neighbour and weighted signal strength to enhance accuracy. The study results demonstrated that the WKNNS algorithm outperforms others.

Moreover Zuo et al. (2021), a proposal is made for an acoustic fingerprint technique aimed at precise indoor localization of intelligent mobile devices in dense Non-Line-of-Sight (NLOS) environments with limited anchor deployment. The ToA-DTB method, utilizing decision trees with bagging, demonstrates superiority over ToA-WKNN and ToA-ANN in complex indoor scenarios. When operating with only 2 Anchors in a dense NLOS setting, the likelihood of positioning error being less than 54 cm is 90%, less than 38 cm is 80%, and less than 30 cm is 64%.

To enhance location-based services, Aydin et al. (2020) a recommendation is put forth to utilize feature selection strategies to reduce computation duration for Wi-Fi fingerprinting. The time taken for positioning computation can be reduced by 75% through feature selection. Feature selection involves applying K-nearest neighbours (KNN) classification and regression techniques. The research advocates for adopting feature selection methods and illustrates their capability to decrease positioning computation times by 75%. Wu et al. (2018) proposed an innovative approach named DorFin, which integrates techniques such as robust regression, discrimination factor measurement, and reassembly of various standard fingerprints. DorFin outperforms existing methodologies significantly, achieving a mean error of 2.5 m and a 95th percentile error under 6.2 m while ensuring exceptional accuracy without additional expenses.

In the study by Alshami et al. (2015a), a novel adaptive indoor positioning system model was proposed for dynamic and multi-floor scenarios, incorporating a dynamic radio map generator, RSS confidence approach, and human presence effects integration (DIPS). The term "dynamic" in this context pertains to the impacts of device and user diversity. DIPS can attain 1.2 m for point positioning inaccuracy and 98% and 92% for floor and room positioning accuracy, respectively. RSS assurance enhances positioning accuracy for floor and room by 11% and 9% for various mobile devices. Considering the effect of human presence decreases inaccuracy by 0.2 m. DIPS achieves superior placement without needing extra access points compared to alternative methodologies.

Research areas such as establishing fingerprint databases have recently gained attention. To alleviate the workload, shorten training periods, and enhance the adaptability and simplicity of fingerprinting techniques, Pinto et al. (2021), a new strategy to enhance IPS accuracy by optimizing the distribution of APs in the environment and applying an advanced probability-based algorithm. By assuming that a log-distance path loss model can adequately represent the RSS distribution across the environment, a simulation framework is developed to explore the impact of key positioning algorithm components on accuracy. The effectiveness of the proposed technique is confirmed using a real-world testbed dataset. The accuracy results demonstrate a strong correlation between trends validated through simulation and those verified through dataset processing when utilizing an ideal AP design. These findings suggest that the strategy can identify the appropriate factor combination through initial simulations to design a more effective IPS employing a probability-based placement algorithm.

The investigation presented by Nguyen & Thuy Le (2021) proposed an innovative technique for indoor localization relying solely on RSSI vectors without prior knowledge of the pose. The proposed solution integrates machine learning (ML) with a modified kNN algorithm. Gaussian Process Regression (GPR) is the ML approach employed in the suggested methodology. By utilizing the RSSI vector, GPR anticipates the location of the pose during the system's online phase. This prediction assists the kNN algorithm in reducing the search area, thereby decreasing the computational burden. The proposed technique also entails a distributional analysis of the k nearest points to evaluate the precision of the estimated pose and derive a roster of dependable locations. The suggested approach's precision and timing were evaluated on a challenging BBIL dataset containing noisy RSSI signals due to rapid object movement. The experimental results illustrate that the proposed system significantly outperforms conventional kNN or WkNN algorithms. Compared to other methods with known initial positions, the root mean square error (RMSE) of the optimal trajectory in the 10 m by 25 m room is 1.78 m, showcasing its competitiveness.

This manuscript delves into impact factors rather than focusing on similar works that centre on developing distinct systems, employing various methodologies, and establishing fingerprint databases. Some impact factors have been scrutinized previously. The study by Alshami et al. (2015b) introduced mathematical concepts and parameters to compare WLAN RSSI fingerprinting locations. Nevertheless, certain impact factors have already been explored (Abusara et al., 2017; Pirzada et al., 2017).

The author in Liu et al. (2017) identified various impact factors utilizing the Ishikawa diagram, assuming that certain identified factors are consistent, irrelevant, and beyond control. The study only considered five criteria: access point (AP) density, AP distribution, signal interference, attenuation factor, and RP density. The authors' primary focus was on the influence of manageable factors on positioning accuracy, depicted by a rectangular enclosure in Figure 2B. This paper incorporated all non-algorithmic factors outlined in the study by Liu et al. (2017) but did not investigate their impact, illustrated by a rectangular enclosure in Figure 2A. These factors are recognized as signal-receiving elements. As far as my knowledge goes, there has not been a systematic examination providing a synopsis of the impact factors using Ishikawa diagrams and a detailed analysis of signal-receiving-related factors, which constitute the central theme of this paper.

METHODOLOGY

Analysis and Summary of Potential Impact Factors Using the Ishikawa Diagram

This section first introduces the primary quality control tool, the Ishikawa diagram, by presenting an example and the diagram in Figure 1. The Ishikawa diagram is among the top seven essential factor identification tools. The other six tools for factor identification are a check sheet, control chart, scatter diagram, Pareto chart, histogram, and stratification.

These six techniques highlight factor identification. However, the Ishikawa diagram is the first-factor identification step. It could help to organize some of the data generated during pre-analysis and data collection planning. Additionally, this methodology can be applied to various issues and customized by users to suit their needs (Antony et al., 2021).

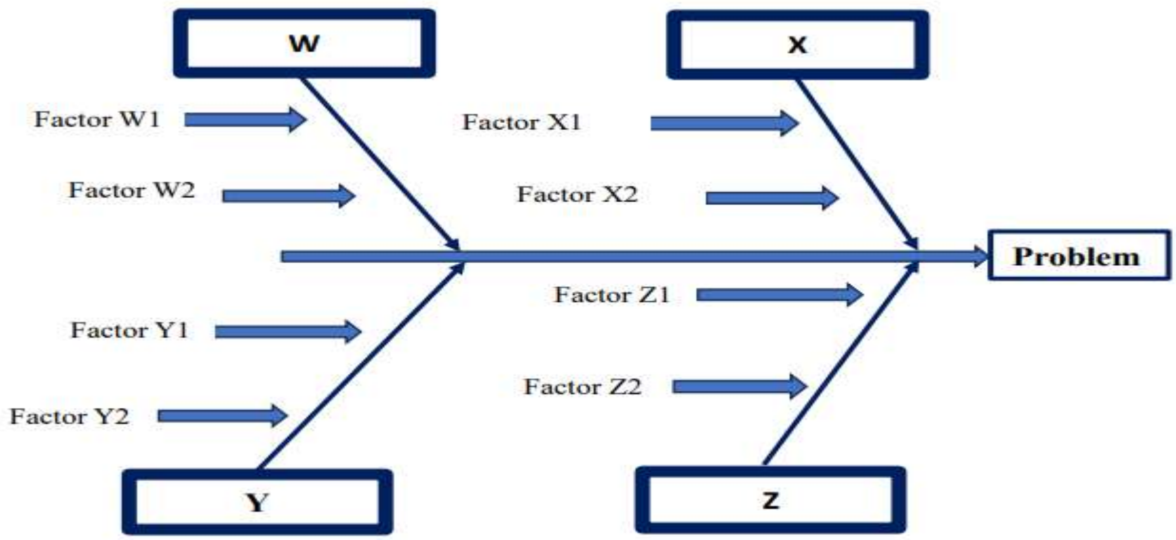

Figure 1. Ishikawa diagram for input-output interaction factors

After identifying factors efficiently, the subsequent step is to understand the actual cause of factors and their implication on indoor positioning performance. In addition, this procedure promotes cluster participation and the use of cluster knowledge in indoor positioning performance. The Ishikawa illustration structure also aids a researcher in envisaging good systematic order and tracking a structured approach (Liu et al., 2017).

The Ishikawa Diagram Structure for WLAN Fingerprinting

The process of creating an Ishikawa diagram starts with identifying a problem of concern. The impact factors on the positioning performance of a WLAN RSSI fingerprinting system are the issues in this paper. The following step is to decide how to classify the factors. In this paper, the process progression method is chosen for a WLAN RSS fingerprinting system. The factors considered in this paper are the receiving factors in the position of the fingerprinting system in either the online or offline phase.

In the WLAN fingerprinting positioning system, a radio signal is initially transmitted from APs (offline/online), and the receiving signals start from transmitters to receivers (offline/online) in the environment. Performance may be affected by this step. Hence, the critical factors should be analysed step-by-step in detail.

The transmitters send out the radio signal, which receivers pick up. Indoor physical environment and radio waves from other sources can impact the RSSI. For instance, operator height, reference point density (RPs density), reference point distribution (RPs distribution), and reference point height (RPs height) can all affect indoor positioning accuracy. Other parameters, such as receiver models, sampling rate, and number of samples, might affect the radio signal receiving.

According to the research, several factors affect indoor signal receiving, so it is essential to take care of them while choosing locations for data collection. Figure 2 uses an Ishikawa diagram to connect the possible effect elements that could affect the WLAN RSS location fingerprinting performance. In Figure 2, the WLAN RSS location fingerprinting position performance is represented by the "fish head," and the "fish bones" are the primary and auxiliary components. The next section explains the considerations and assumptions made regarding these issues throughout this study.

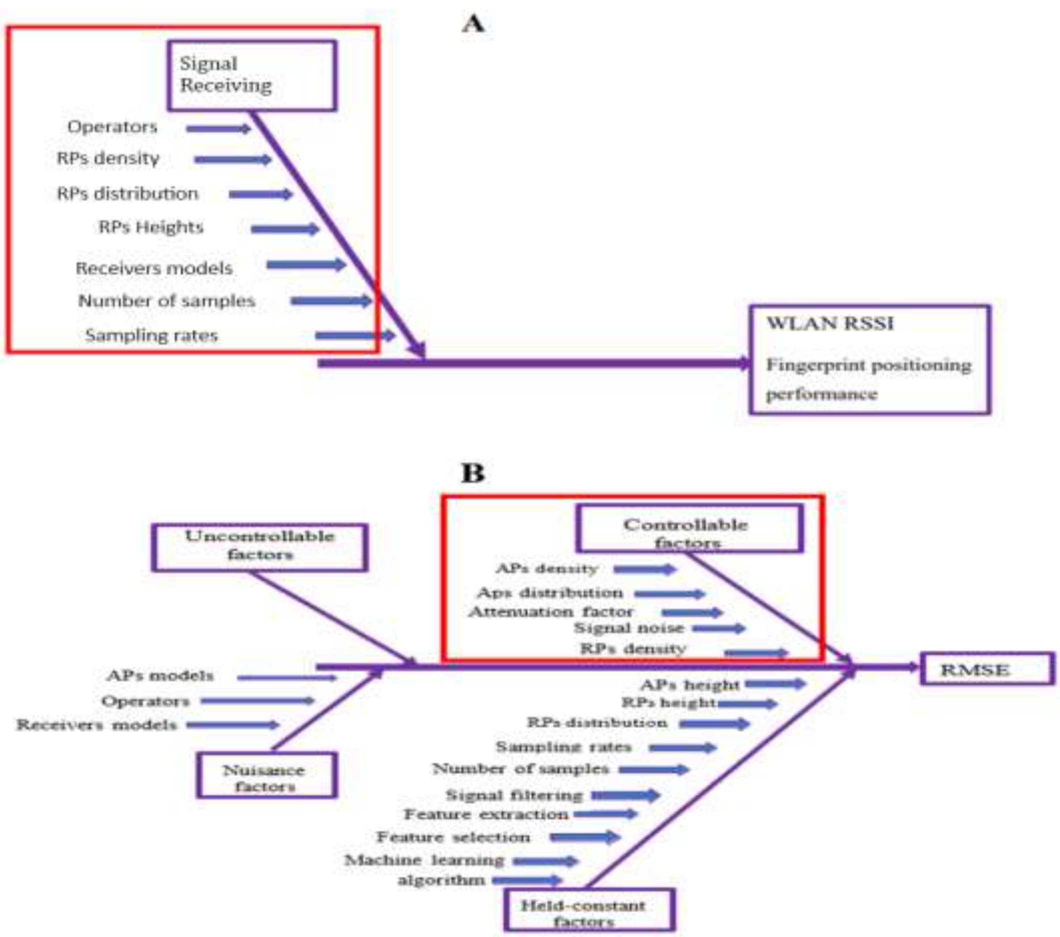

Figure 2. Ishikawa diagram for signal-receiving factors

Experiment Setup

The environment is meticulously configured in the WLAN indoor positioning fingerprinting experiment to ensure reliable and consistent data collection. The sampling rate is set at 1 Hz, providing a steady stream of signal strength measurements. Reference

Points (RPs) are maintained at a constant height on the ground floor, distributed evenly at intervals ranging from 1 to 1.5 meters, creating a dense grid with 74 RPs. To evaluate the impact of sample size on fingerprinting accuracy, the experiment collects different numbers of samples per RP: 20, 30, and 40. Five Access Points (APs) are strategically positioned, ensuring medium signal power levels (≤-30 dBm) throughout the area, providing comprehensive coverage for the fingerprinting process.

Two receiver models, the Dell Inspiron N5050 and the Huawei Y330-U11, are used to gather RSS data, representing typical consumer-grade devices. The operator holds the devices at three distinct heights: 2 meters, 1.6 meters, and 1.3 meters to simulate different user scenarios, such as holding the device above the head, at chest level, and near the waist, respectively. This variability in operator height helps understand the effect of device position on the received signal strength. By carefully controlling these factors, the experiment aims to create a robust and detailed fingerprint database, facilitating accurate and reliable indoor positioning. The summary of WLAN indoor positioning fingerprinting for the study is shown in Table 1.

Table 1. Summary of WLAN indoor positioning fingerprinting experiment setting

Factors	Options
Sampling rate	1 Hz
RPs heights	Constant (at ground floor level)
RPs distribution	1-1.5m
Number samples	20, 30, 40
RPs density	74
APs density	5
Receiver model	Inspiron N5050, Y330-U11, iNote beyond
Operator height (position)	2m, 1.6m,1.3m,
APs power	MEDIUM(≤-30*dBm*)

RESULTS AND DISCUSSION

Effect of the person (operator) who collects fingerprints on WLAN indoor positioning

The operator height or the position at which a device is held is a critical factor in WLAN fingerprinting, as it influences the received signal strength (RSS). This impact arises from the human body's interaction with signal propagation, potentially causing reflection, diffraction, and absorption of the Wi-Fi signals. To understand this effect, three operator heights were analysed: 2 meters, 1.6 meters, and 1.3 meters, which correspond to typical device usage scenarios like holding the device above the head, at chest level, and near the waist, respectively.

2 Meters (Above the Head)

Holding the device at 2 meters typically places it above most obstructions, including the operator's body. This height allows for a relatively clear line of sight to the access points (APs), often resulting in higher and more consistent RSS values. As depicted in Figure 3, the RSS values at 2 meters exhibit less fluctuation compared to lower heights, maintaining a more stable signal across different fingerprint locations. This stability is due to minimal signal obstruction and reduced multipath effects, where the signal reaches the receiver via multiple paths due to reflections.

1.6 Meters (Chest Level)

Holding the device at 1.6 meters, the device is at chest level, a common position for device usage. However, this height introduces potential obstructions from the operator's body, particularly the chest and arms, which can attenuate the signal. Figure 3 indicates moderate fluctuation in the RSS values at this height. The signal strength is generally lower than 2 meters, with noticeable dips due to body obstruction. The variation suggests that while the device receives direct signals, the impact of the human body introduces more variability compared to the higher position.

1.3 Meters (Waist Level)

Holding the device at 1.3 meters, near the waist, positions it behind the most substantial part of the body, especially when walking or standing upright. This height maximizes the obstructive effect of the human body on the signal. As shown in Figure 3, the RSS values at 1.3 meters demonstrate significant fluctuation, with frequent and pronounced drops in signal strength. The human body at this position acts as a major barrier, absorbing and reflecting the signal, resulting in the lowest and most inconsistent RSS values among the three heights.

In conclusion, operator height significantly affects the received signal strength in WLAN fingerprinting, primarily due to the human body's interference with signal propagation. The data reveals a clear trend: higher device positions yield more stable and stronger RSS values, while lower positions lead to greater signal attenuation and variability. The finding is consistent with the study by Liu et al. (2017) on the impact of user orientation on the WLAN fingerprinting indoor positioning service. The study highlighted how a user is oriented, such as their body position or direction, which can influence how accurately a system can determine their location using a mobile device. However, the study mainly focused on this orientation factor. It did not consider another variable: the height at which the mobile device is held or positioned during the localization process.

This oversight is significant because, as this study indicates, the device's height can also affect localization accuracy. In other words, not only does the user's orientation matter, but the height at which the device is carried or held can also play a crucial role in how precisely the system can pinpoint the user's location. The difference in signal strength can range from 19% to 21% at the same location. For applications requiring high accuracy and consistency in indoor positioning, holding the device at or above chest level (1.6 meters or higher) is preferable.

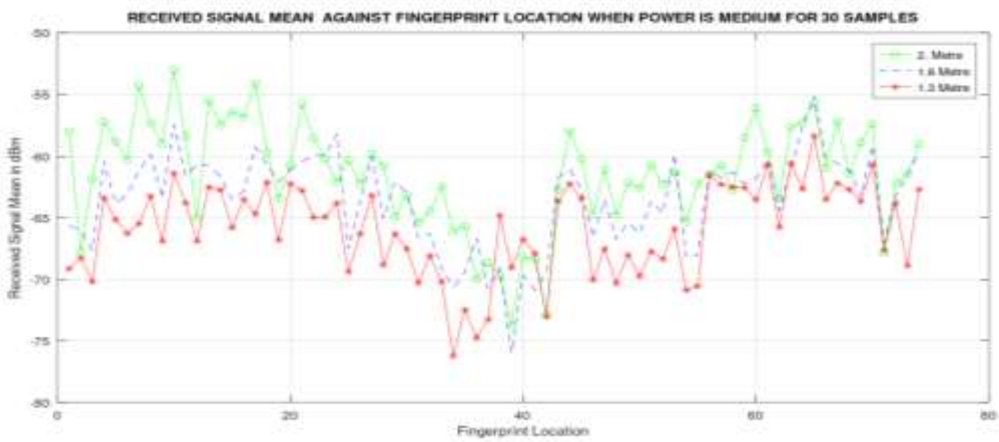

Figure 3. Analysis of the effect of an operator in WLAN indoor fingerprinting

Effect of the Receiver Models on WLAN Indoor Positioning

The receiver model, or the device used for collecting WLAN signal data, can impact the received signal strength (RSS) due to hardware and antenna design differences. The study examines the effect of three different receiver models from different manufacturers, namely Dell Inc., Huawei, and Itel, on WLAN indoor fingerprinting.

Dell Inc. (Inspiron N5050)

The Dell Inspiron N5050 is a laptop with a standard Wi-Fi card and built-in antennas, typical of consumer-grade laptops. The hardware and antenna design of the Dell Inspiron N5050 provides moderate sensitivity and consistency in capturing RSS values. The larger form factor and placement of antennas in a laptop can lead to relatively stable signal measurements. The RSS data collected with the Dell Inspiron N5050 shows moderate variability, as indicated in Table 2, which may influence the device's position and orientation. This model suits scenarios where portability is not a primary concern and stable signal measurements are needed.

Huawei (Y330-U11)

The Huawei Y330-U11 is a smartphone with a compact design and built-in Wi-Fi capabilities typical of mobile devices. The smaller form factor and integrated antennas of the Huawei Y330-U11 can lead to higher variability in RSS measurements due to hand placement and device orientation. However, its mobility makes it useful for flexible data collection. The RSS data collected with the Huawei Y330-U11 exhibits higher variability than the Dell Inspiron N5050, as shown in Table 2. This variability can be attributed to the mobile nature of the device, making it less consistent for fingerprinting unless the device orientation and handling are carefully controlled.

Itel

Itel smartphones are budget-friendly devices with standard Wi-Fi capabilities. Similar to the Huawei model, Itel smartphones have a compact design, and their RSS measurements can be affected by hand placement and device orientation. The RSS data collected with an Itel smartphone shows similar variability to the Huawei Y330-U11, as demonstrated in Table 2, indicating that lower-end smartphones may introduce higher fluctuations in RSS values. These devices require careful handling to ensure consistent data collection.

In summary, the receiver model plays a significant role in the accuracy and consistency of WLAN fingerprinting. Different devices from various manufacturers can produce varying RSS values due to differences in hardware, antenna design, and form factor. Dell Inc. (Inspiron N5050) provides more stable and consistent RSS measurements, making it suitable for scenarios requiring reliable signal data. Huawei (Y330-U11) and Itel models exhibit higher variability in RSS values due to their compact design and sensitivity to handling. They are more suitable for flexible and mobile data collection but require careful device orientation and handling control to minimize variability.

The findings are consistent with the study by (Q. Yang et al., 2019) on analysing WLAN's RSSI for indoor positioning. The study highlighted choosing a network card with a large measurement range for data collection because using network cards at their maximum measurement range for positioning can influence how accurately a system can determine their location using a mobile device. However, the study mainly focused on the Access Point (AP) received signal strength factor and did not consider another variable: the receiver model used for data collection.

This oversight is significant because, as this study indicates, the receiver model can also affect localization accuracy. In other words, not only does the AP matter, but the type of receiver model used for data collection can also play a crucial role in how precisely the system can pinpoint the user's location. The difference in signal strength can range from 14% to 20% at the same location.

Table 2. RSSI variation effect due to receiver model

Manufacturer	Device model	Min (dBm)	Max (dBm)	Range (dBm)
Dell inc	Inspiron N5050	-69	-24	-45
Huawei	Y330-U11	-70	-28	-42
Itel	iNote beyond	-89	-30	-44

Effect of the Number of Samples on WLAN Indoor Positioning

The number of samples collected at each reference point (RP) is crucial for the reliability and accuracy of WLAN fingerprinting. This discussion examines the impact of collecting different sample sizes (20, 30, and 40 samples per RP) on the stability and precision of received signal strength (RSS) data. The graph provided in Figure 4 illustrates the RSS values against fingerprint location for these sample sizes, with the power set to medium.

20 Samples per RP

Collecting 20 samples at each RP provides a basic level of data collection. However, this sample size might not be sufficient to average out transient signal fluctuations and noise, resulting in less stable RSS values. The green line represents the RSS values for 20 samples per RP. This line fluctuates more than the higher sample sizes, indicating higher variability and less reliable signal data. This can lead to less accurate fingerprinting and increased positioning errors.

30 Samples per RP

Increasing the sample size to 30 per RP provides a better balance between data collection effort and signal reliability. This number of samples helps average short-term variations and noise, providing a more stable RSS profile. The blue line corresponds to the RSS values for 30 samples per RP. The fluctuations are less pronounced than with 20 samples, indicating improved stability. This sample size offers a more reliable signal profile, which can enhance fingerprinting accuracy and reduce positioning errors.

40 Samples per RP

Collecting 40 samples at each RP further enhances the robustness of the signal data. This larger sample size ensures that transient anomalies are effectively averaged out, providing the most precise representation of the signal environment. The red line represents the RSS values for 40 samples per RP. It exhibits the least fluctuation and the most stable RSS values among the three sample sizes. This extensive data collection minimizes variability and maximizes the accuracy of the fingerprint database, leading to higher positioning accuracy.

In summary, the number of samples per RP is a crucial determinant of the reliability and accuracy of WLAN fingerprinting. The analysis reveals a clear trend: increasing the sample size enhances the stability and accuracy of the RSS data, thereby improving the overall fingerprinting performance. A sample size of 30 or more per RP is recommended to achieve high accuracy in indoor positioning systems. This sample size balances the effort involved in data collection with the need for reliable signal profiles. The study shows that the difference in signal strength can change up to 21% for different samples. This finding is consistent with the study conducted by Sa'ahiry et al. (2021) on the effect of sample sizes in the fingerprinting database for the WLAN system. However, the reported findings by Sa'ahiry et al. (2021) raise the contradiction between the conclusion that samples are adequate based on the stability of the mean and the implication that samples are superior based on the lower standard deviation and less dispersion in the data. This raises questions about which metric (mean stability or standard deviation) should be prioritized when determining the optimal sample size. Therefore, the choice of sample size should be guided by the balance between required accuracy and practical considerations such as data collection effort and computational resources.

Figure 4. Illustration of the RSS values against fingerprint location for different sample sizes

CONCLUSIONS AND RECOMMENDATIONS

WLAN location fingerprinting is a cost-effective method; however, it still faces challenges in real-world applications due to considerations related to radio signal reception. The applicability and effectiveness of location fingerprinting can be enhanced by thoroughly examining potential radio signal reception parameters and investigating their impact patterns. Despite the complexity of the problem, it has not been extensively explored.

This paper uses the Ishikawa diagram to provide a foundation for further research to investigate the impact of radio signal reception factors on the accuracy of positioning performance in RSSI location fingerprinting. In the future, additional factors will be identified and analyzed to verify their impact further and develop strategies for mitigating issues, ultimately improving the quality of WLAN location fingerprinting platforms.

PRACTICAL IMPLICATIONS

The study conducted a comprehensive examination of the influence of signal-receiving factors on the accuracy of WLAN indoor positioning fingerprinting. Through their analysis, the researchers identified seven key factors that significantly impact accuracy: sampling rate, reference point (RP) height, RP distribution, number of samples, access point (AP) distribution, receiver model, and operator height. These factors were determined to be the most critical in affecting the performance of WLAN fingerprinting indoor positioning systems (IPSs). The research not only elucidated these crucial elements but also investigated the implications of their findings for the design and implementation of WLAN fingerprinting IPSs. By providing insights into these influential factors, the study contributes valuable knowledge to enhance the accuracy and efficacy of indoor positioning systems utilizing WLAN fingerprinting techniques.

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DECLARATIONS

Conflict of Interest

The researcher declares no conflict of interest in this study.

Informed Consent

No personal or private information was directly utilized in the conduct of this study.

Ethics Approval

As no personal information was used, ethics approval was unnecessary.

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