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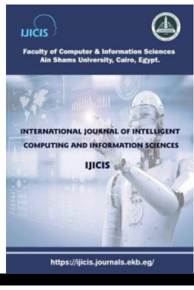

WLAN FINGERPRINTING INDOOR POSITIONING ACCURACY: ASSESSING THE EFFECTS OF ACCESS POINT POWER AND HIGH SIGNAL CORRELATION

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Abstract: *Recently, localization systems tailored for indoor environments have been introduced, leveraging the existing wireless local area network (WLAN) infrastructure. These systems utilize position fingerprinting methods rather than direction-based or time-of-arrival approaches to determine the spatial positions of mobile users. Nevertheless, experimental studies on these systems indicate that factors such as signal attenuation and scattering caused by the higher density of walls significantly impact the accuracy and performance of indoor positioning. Furthermore, the accuracy of indoor positioning systems (IPS) may be compromised by variations in environmental factors, including alterations in height, the introduction or removal of a WLAN Access Point (AP), or modifications to AP power settings. This paper analyses the impact of AP power through a probabilistic analytical model that exclusively utilizes high signal relations to mitigate the effects of low signal relations on WLAN fingerprinting-based IPS, thereby enhancing accuracy performance. A total of 33,300 RSS (Received Signal Strength) data points were collected from five access points and seventy-four reference points to develop the model. The dataset was gathered during the offline learning phase, with RSS readings systematically recorded to maintain consistency. During the online phase, 11,100 data points (33% of the total dataset) were introduced to test the model. Through comprehensive experimental evaluations, the proposed algorithm demonstrates an improvement in the accuracy of the IPS by an average of 15.794% as measured by the Root Mean Square Error (RMSE). The findings suggest that the integration of AP power and high signal relations can substantially enhance the accuracy performance of WLAN fingerprinting-based IPS.*

Keywords: *Wireless local area network, Indoor positioning system, Access point, Fingerprinting, Probabilistic.*

1. Introduction

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With the growing use of wireless technologies, location detection systems have become increasingly important. The implementation of localization services varies depending on the positioning techniques utilized. These systems enable context-aware applications by providing position-related information [1], [2]. They are also essential in supporting emergency response operations. In recent years, fingerprinting positioning methods using existing WLAN setups have been proposed for indoor settings where GPS is less effective [3], [4]. Such systems offer additional capabilities for modern WLAN networks [5]. Compared to techniques such as angle-of-arrival (AoA) and time-of-arrival (ToA), fingerprinting is relatively simpler to deploy [5], [6].

In alignment with this research trajectory, a multitude of extant scholarly works concentrate on optimizing accuracy performance through various methodologies. The most contemporary investigations concerning indoor positioning systems predominantly emphasize research to augment positioning precision and refine estimation algorithms. Conversely, a limited number of studies take into account the implications of transmitter power setting and the relationship between Received Signal Strength Indicator (RSSI) signals on accuracy performance. [7] demonstrated the feasibility and practicality of utilizing RSSI-based ranging technology for indoor three-dimensional spatial positioning systems through an in-depth analysis of RSSI characteristics. Building on this foundation, [8] investigated the relationship among path loss and the transmitting antenna altitude using a 2.4 GHz wireless signal. However, their study kept the WLAN Access Point (AP) power settings constant, leaving the effects of varying power levels on signal performance unexplored. In another study, Hu et al. examined the relationship amid signal propagation characteristics and variables such as AP elevation, communication distance, and propagation path for 5.8 GHz radio frequency transmission rather than focusing solely on 2.4 GHz frequencies. [9] extended the analysis to both indoor and outdoor environments, identifying significant differences in received signal strength due to variations in antenna height. [10] also investigated how user orientation and existence influenced RSSI measurements. [11], [12] highlighted that user orientation significantly impacts fluctuations in RSSI levels. They suggested incorporating RSSI data alongside user orientation awareness to enhance the accuracy of human-centric indoor positioning systems. However, their study did not explore the effects of signal relation or variations in Access Point (AP) power settings on positioning performance.

According to the reviewed studies, the factors influencing characteristics of indoor Received Signal Strength Indicator (RSSI), which directly hinder positioning accuracy, have not been systematically or quantitatively analysed within the context of RSSI-based indoor positioning methods. Additionally, existing research has yet to explicitly investigate the impact of AP power settings on the accuracy of Wireless Local Area Network (WLAN) fingerprinting-based Indoor Positioning Systems (IPS), particularly in scenarios with high signal correlations. Therefore, it is essential to evaluate how AP power settings affect the performance accuracy of WLAN fingerprinting-based IPS, focusing on high signal correlations.

This study analyses the transmitter's power setting variations and the role of high signal correlation, aiming to characterize 2.4 GHz RSSI behaviour in indoor environments quantitatively. By employing a probabilistic analytical model, the study examines the effects of these factors on IPS WLAN fingerprinting-based accuracy. The study key contributions are as follows:

– The study compiles RSSI datasets corresponding to various AP power settings utilizing a bespoke methodology tailored for IPS WLAN fingerprinting-based.

– This study presents a novel algorithm designed to identify substantial signal correlations and ascertain positions by conceptualizing position fingerprints and measuring Received Signal Strength Indicator (RSSI) values as distinct stochastic variables. The algorithm employs the probability density function (PDF) within the signal domain to augment the precision and dependability of the positioning methodology.

– The study evaluates the accuracy performance of the algorithm proposed in the context of IPS WLAN fingerprinting-based.

The structure of this paper is organized as follows. Initially, Section 2 elucidates the related work of the WLAN fingerprinting indoor positioning system. Subsequently, Section 3 elucidates the methodology and mathematical concepts of IPS WLAN fingerprinting-based and its operational mechanics designed to actualize our concept. Following this, Section 4 presents the performance outcomes alongside a discussion. Finally, Section 5 concludes the discourse and proposes avenues for future research.

2. Related work

Indoor positioning systems (IPS) based on Wireless Local Area Networks (WLAN) have gained significant attention due to their cost-effectiveness and wide availability. Various studies have explored the feasibility of using IEEE 802.11b access points (APs) for localization, leveraging Received Signal Strength Indicator (RSSI) values for positioning. These approaches commonly rely on fingerprinting, which maps RSSI values to predefined locations in an indoor environment to estimate a user's position [1], [12].

2.1 WLAN-Based Indoor Positioning Systems

Traditional IPS methods primarily utilize signal propagation models, location fingerprinting, or hybrid techniques to determine indoor locations. Fingerprinting-based approaches remain popular due to their robustness in complex environments, as they rely on RSSI measurements rather than requiring line-of-sight conditions like Time of Arrival (ToA) or Angle of Arrival (AoA) methods [13], [14]. However, RSSI-based positioning suffers from several limitations, including multipath effects, signal attenuation, and environmental interferences, which introduce inaccuracies in position estimation [15], [16].

Prior research has attempted to model these challenges by incorporating probabilistic techniques to improve location accuracy. Various studies have focused on RSSI-based location estimation and proposed probabilistic models to account for signal variability. These models often assume a straightforward relationship between signal strength and distance, but real-world environments introduce non-linear dependencies due to obstacles, dynamic changes, and interference [17], [18]. Traditional positioning models do not fully capture these variations, leading to significant errors in location estimation.

Despite advancements in WLAN-based indoor positioning, existing models struggle with adapting to environmental changes such as variations in access point power settings, furniture rearrangements, or human obstructions. These factors lead to inconsistencies in RSSI measurements, reducing positioning accuracy over time. Most conventional models do not incorporate mechanisms for dynamically adjusting parameters to mitigate these inconsistencies [19]. Additionally, existing fingerprinting approaches are often computationally expensive and require extensive data collection efforts for model training, limiting their scalability in real-world deployments.

To address these challenges, this study proposes an enhanced probabilistic model that refines RSSI-based positioning by integrating high-signal relations while mitigating the influence of low-signal variations. Unlike conventional approaches, the proposed model dynamically adjusts to environmental changes by incorporating adaptive filtering mechanisms and power variation compensation techniques. Through leveraging advanced signal behaviour prediction methods, the model aims to improve positioning accuracy in complex indoor environments. Furthermore, the proposed approach enhances scalability by reducing reliance on extensive pre-collected fingerprinting datasets, making deployment more efficient across diverse indoor settings. This research aims to bridge the gap between theoretical modelling and real-world applicability, ensuring that WLAN-based IPS remains robust, adaptable, and efficient for future localization applications.

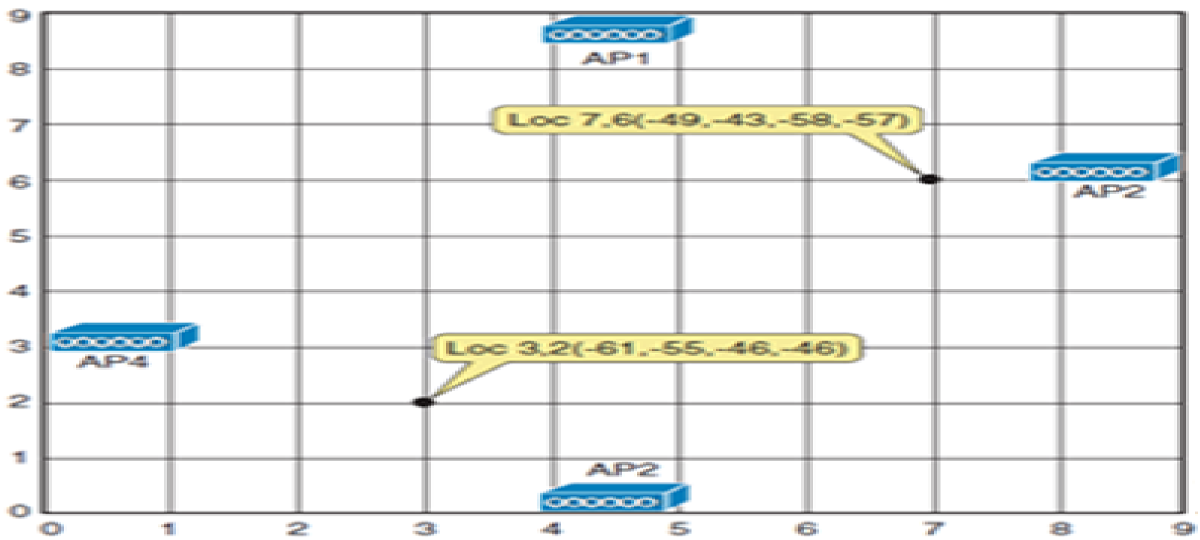

Figure 1. Two example points demonstrating how the identified access points might be used to create the appropriate position vectors RSS

3. Methodology

In the experimental design section, the dataset collection process is meticulously detailed to ensure transparency and reproducibility. A total of 33,300 RSS (Received Signal Strength) data points were collected to develop the proposed model. The data acquisition was carried out using a Dell Inspiron N5050 laptop equipped with an Interactive Scanning Driver tool, which recorded RSS measurements from five Access Points (APs) operating on the 2.4 GHz frequency band. The APs were strategically positioned at a height of two meters (2 m) and configured with adjustable power settings, including LOW (≤-43 dBm), MEDIUM (≤-30 dBm), and HIGH (≤-18 dBm), to simulate varying signal strength conditions. The experimental area spanned approximately 350 square meters and included 74 Reference Points (RPs) distributed in a grid pattern at intervals of 1–1.5 meters. At each RP, 30 RSS samples were collected at a sampling rate of 1 Hz, ensuring a robust and consistent dataset. The RPs were maintained at a constant height (ground floor level) to minimize variability. The dataset was gathered during the offline learning phase, with RSS readings systematically recorded to maintain consistency. During the online phase, 11,100 data points (33% of the total dataset) were introduced to test the model, ensuring a rigorous evaluation of its performance under real-world conditions. The layout of the RPs and APs is illustrated in Figure 2, while Table 1 summarizes the key experimental parameters, including RP density, AP density, and power configurations.

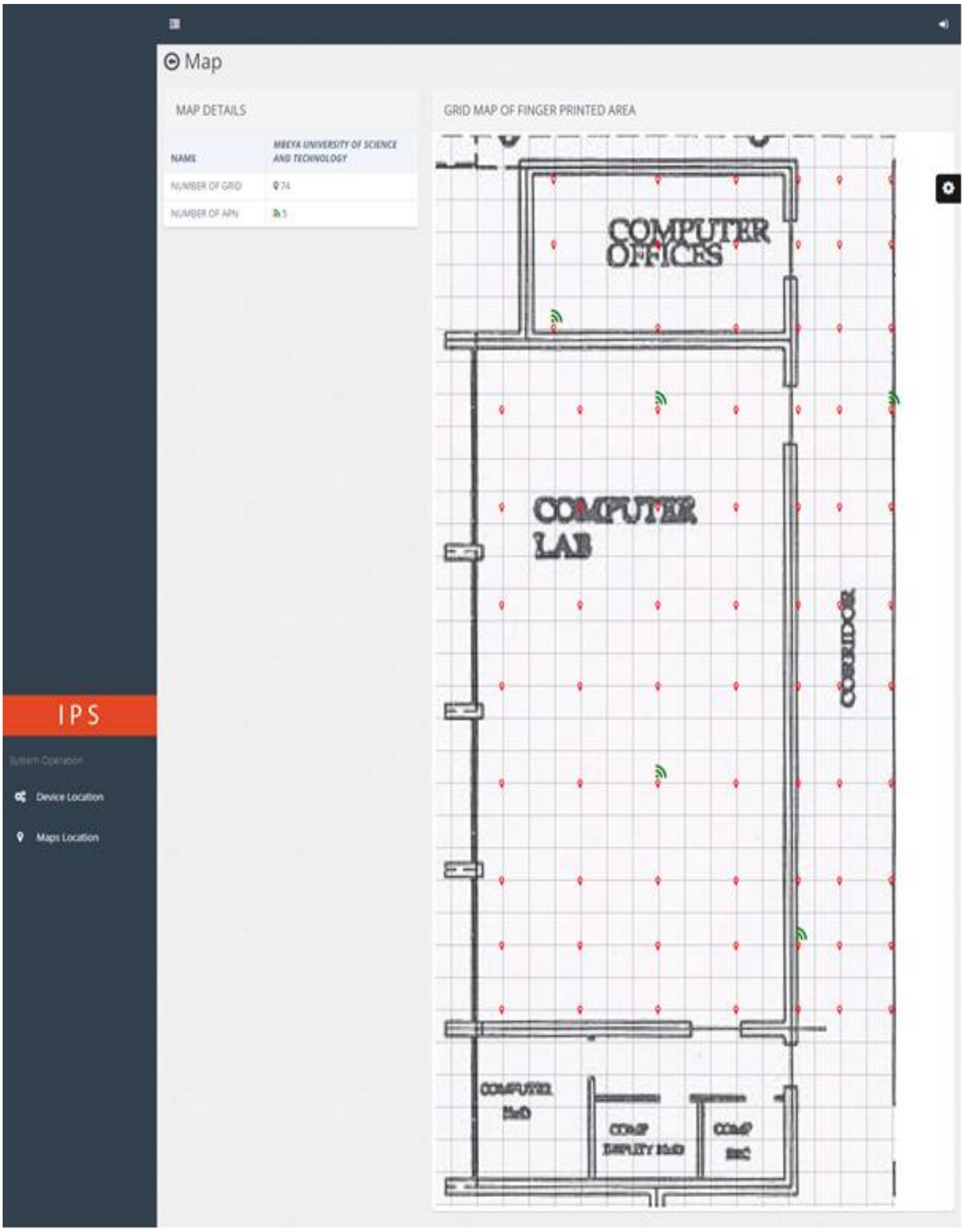

Figure 2. Grid and fingerprinted reference location on a map

Table 1. Illustrations of the experiment settings assumptions

Factors	Options
Sampling rate	1 Hz
RPs heights	Constant (at ground floor level)
RPs distribution	1-1.5m
Number samples	30 per reference point
RPs density	74
APs density	5
Receiver model	Inspiron N5050
APs power	HIGH(≤-18*dBm*), MEDIUM(≤-30*dBm*), LOW (≤-43*dBm*)

3.1 Mathematical model

In the process of estimating a mobile user's location, two primary vectors are employed. The first vector, denoted as the RSS (Received Signal Strength) sample vector, is crucial for real-time location determination. This vector is composed of RSS samples collected from N Access Points (APs) during an active online session within the designated area. For the purposes of this study, the RSS sample vector is mathematically represented as: $R = [r_1, r_2, \ldots, r]$ where r_i represents the RSS value received from the *i-th* AP. The indoor localization system utilizes this RSS sample vector to infer the mobile device's position through a sophisticated amalgamation process. Each component of the RSS vector is considered a random variable, subject to specific assumptions that are fundamental to the accuracy of the localization algorithm. Two key assumptions are made regarding the statistical properties of these random variables which are Independence and Normal Distribution.

In independence, the random variables r_i (measured in dBm) are assumed to be mutually independent for all *i*. This assumption allows for simplified mathematical modelling and analysis of the RSS data. In normal distribution, each random variable r_i (in dBm) is assumed to follow a normal (Gaussian) distribution. This assumption is based on empirical observations and theoretical considerations of signal propagation in indoor environments.

These assumptions play a critical role in the development and implementation of robust indoor localization algorithms, enabling the system to estimate the mobile user's position with a high degree of accuracy and reliability. The normal distribution assumption, in particular, facilitates the application of various statistical techniques and machine learning algorithms for location estimation.

The secondary vector, integral to the creation of location fingerprints, is composed of the empirical means derived from the Received Signal Strength (RSS) random variables collected within a specified area from N Access Points (APs). This comprehensive information is meticulously recorded and organized within the position database. Throughout this paper, this vector is interchangeably referred to as position fingerprints, location fingerprints, or the RSS vector, and is symbolically represented as μ: $\mu = [\mu_1, \mu_2, \ldots, \mu]$ where μ_i represents the mean RSS value from the *i-th* AP. The assumption that the RSS follows a normal distribution is not arbitrary but is substantiated by multiple research studies [20]. This theoretical foundation provides a robust basis for the utilization of RSS in location fingerprinting techniques, enhancing the reliability and accuracy of positioning systems that rely on these signal strength measurements. The normal distribution of RSS can be expressed as: $P(RSS) =$

$(1 / (\sigma\sqrt{(2\pi)})) * e^{(-(RSS - \mu)^2 / (2\sigma^2))}$ where: P(RSS) is the probability density function of the RSS, μ is the mean RSS value, σ is the standard deviation of the RSS, e is the base of the natural logarithm These equations form the mathematical basis for the RSS-based location fingerprinting technique, allowing for precise and reliable position estimation in various indoor positioning systems.

The aim of this study is to optimize the WLAN fingerprinting indoor positioning system by reducing computational complexity while improving accuracy. The proposed approach involves selecting three Reference Points (RPs) with the lowest mean average signal strengths before comparing the signal relationships between online and offline Access Points (APs). At its core, the model adopts a probabilistic method that utilizes AP signal strength relationships and a mean average filter, departing from the traditional Received Signal Strength (RSS) approach.

To clarify the concept of the mean average filter and its relationship to signals, consider the following example:

Let $\bar{x}_1$ represent the offline RSSI (Received Signal Strength Indicator) mean at Reference Point 1 for various Access Points (APs), and $\bar{y}_1$ represent the online RSSI mean at Reference Point 1 for the same APs.
The Average Mean Filter (AMF) for Reference Point 1, considering N Access Points, is expressed by Equation 1:

$$AMF = (1/N) * \Sigma(\bar{x}_1 - \bar{y}_1) \qquad 1$$

This equation calculates the average difference between the offline and online RSSI means across all N Access Points at Reference Point 1. The AMF provides a measure of how the signal strength at a specific location compares to previously recorded values

In the subsequent stage, the radio map is utilized to select the three K points exhibiting the lowest Average Magnitude Function (AMF) values. These points are then employed to establish signal relationships. This selection process effectively eliminates other Reference Points (RPs) from further consideration, thereby reducing the computational burden associated with the model.

The intensity of the relationship is modulated by amplifying the signal correlation. This correlation is evaluated by comparing the relationships between user-transmitted values and their corresponding database entries within the algorithm's assessment framework. For instance, if $\alpha = 70$ and $\beta = 68$, the relationship can be expressed as:

$$\gamma = \alpha - \beta = 70 - 68 = 2 \qquad 2$$

his equation demonstrates how the difference between two signal values (α and β) is used to quantify their relationship (γ).

It is an established fact that the signal strength values received by a terminal device at a specific reference point are significantly greater than those encountered in any other location. This conceptual framework is employed to formulate the algorithmic model. When the signal strength from an access point is sufficiently elevated, it indicates that the terminal's position is in proximity to that access point, thereby enhancing the likelihood of that position being selected. In cases where two signal strengths, X and Y, exhibit Gaussian distributions, the probabilistic relational approach employs a random variable Z, defined as the difference between these strengths: $Z = X - Y$. This resulting variable Z also follows a Gaussian distribution. The mean of Z is subsequently expressed by Equation 3.

$$\mu_z = \mu_x - \mu_y \qquad 3$$

And variance is defined by Equation 4

$$\delta_z^{\ 2} = \delta_x^{\ 2} - \delta_y^{\ 2} \qquad 4$$

The approach's operational mechanics enable the calculation of probability density function values for each prevalent association between user-retrieved and database beacons corresponding to candidate locations. The term, "prevalent" refers to relationships with identical MAC addresses. The probability density function values are then aggregated for each location and normalized by the total number of relationships. To be considered a candidate, a database location must have a sufficient number of common user signal relationships. This method allows for the exclusion of positions that lack an adequate number of signals in the appropriate configuration before applying the probabilistic equation. The methodology is implemented through an iterative process. For instance, if *k=3* during the initial relationship computation, *k=k+3* is applied in the subsequent iteration. Ultimately, as shown in Equations 5 and 6, the normal difference distribution's density function serves as the definitive probability density function approach.

$$f(z) = \frac{e^{\left(-\frac{(\mu_x - \mu_y)^2}{2(\delta_x^{\ 2} + \delta_y^{\ 2})}\right)}}{\sqrt{1 + (\delta_x^{\ 2} - \delta_y^{\ 2})}} \qquad 5$$

$$P(L) = \frac{\sum_{i=1}^{n} f(z_i)}{n} \qquad 6$$

4. RESULTS AND DISCUSSION

4.1 System Parameter Dynamics and Their effect on Performance

This segment explores how varying access point (AP) power settings impact the accuracy of the Indoor Positioning System (IPS) model, considering both signal relation and non-signal relation approaches. The study aims to test whether integrating the signal relation method can improve IPS model accuracy as AP power configurations change. To reach a conclusive finding, the IPS model's performance is assessed before comparing it with relevant studies in the field.

4.1.1 Effect of WLAN Access Points Power on Accuracy Performance Based on Signal Relation Technique

Figure 3 elucidates the performance concerning position estimation measured in terms of Root Mean Square Error (RMSE) across various Test Points (TPs). The investigation revealed that the power setting of the WLAN Access Point (AP) resulted in RMSE values of 0.8596 m, 0.8653 m, and 1.1986 m, respectively. This observation indicates that the RMSE recorded under the "low" power configuration is comparatively minor in relation to that observed under the "high" setting. As the power level escalates, there is a related increase in the RMSE. This outcome signifies that the "low power" AP arrangement is capable of providing a more precise representation of interior positioning in comparison to the configuration utilizing a high-power signal.

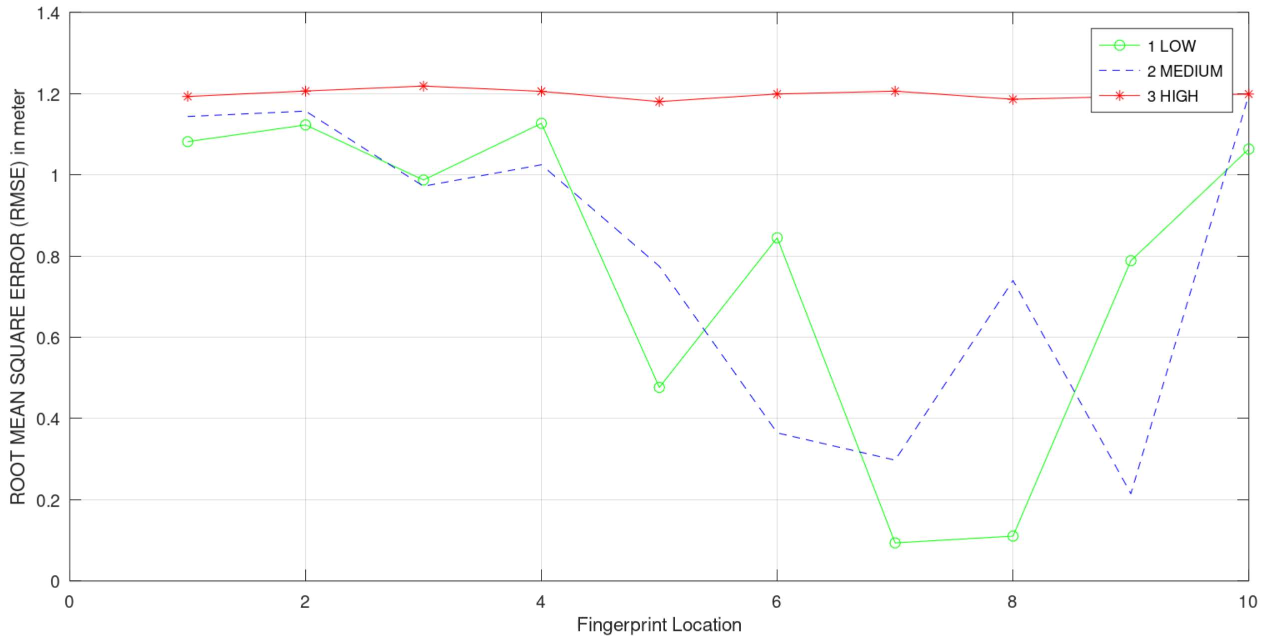

Figure 3. Performance of location estimation in meter over different test points (TPs) when height 2 meter

4.1.2 Effect of WLAN Access Points Power on Accuracy Performance Based on None-Signal Relation Technique

Figure 4 depicts the position estimation performance in terms of Root Mean Square Error (RMSE) across various Testing Points (TPs). The analysis revealed RMSE values of 1.1507 m, 1.086 m, and 1.2201 m for different Access Point (AP) power configurations. After power setting adjustments, the RMSE showed no clear trend of increase or decrease, likely due to the complex interplay between low and high signal relationships affecting position estimation. Notably, the observed RMSE is higher than that achieved using the signal relation methodology. This suggests that the signal relationship approach may offer improved accuracy in indoor positioning compared to none-signal relation methods. Figure 4 specifically illustrates the position estimation performance in terms of RMSE across different TPs without employing a signal relation technique.

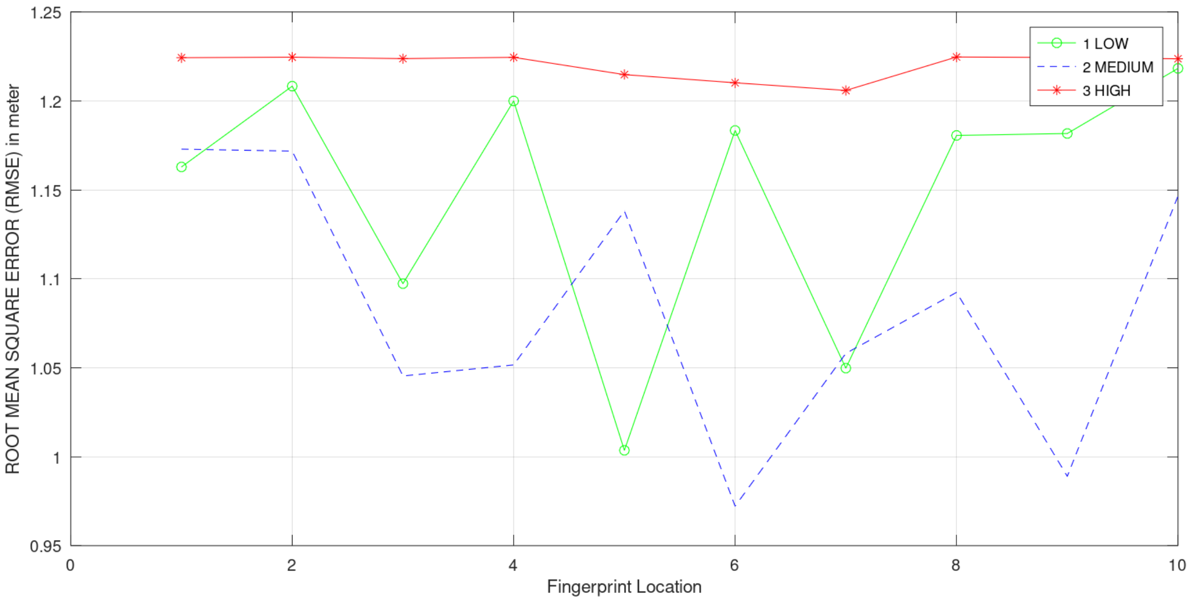

Figure 4. Performance of location estimation in meter over different test points (TPs) when height 2 meter

4.1.3 Performance Comparison of Indoor Positioning Systems

As noted earlier in the introductory portion of this paper, the fundamental purpose of this research is to construct an innovative algorithm tailored to reduce the adverse consequences of lowered signal correlation instigated by access point power configurations on WLAN fingerprinting indoor localization systems, consequently enhancing accuracy. This investigation has commenced at a pivotal juncture; notwithstanding the plethora of research endeavours yielding substantial accuracy, numerous studies have failed to acknowledge the influence of reduced signal correlation attributable to transmitter power settings on overall accuracy [6]. The empirical results delineated in this research contribute to a novel theoretical framework regarding the WLAN fingerprinting methodology in localization, particularly in tackling the challenges associated with accuracy in indoor positioning performance.

Previous research has explained the influence of access point power and significant signal fluctuations as barriers to the performance of the WLAN fingerprinting technique in enhancing indoor localization accuracy. Notwithstanding these efforts and numerous additional initiatives, achieving high accuracy in indoor positioning through WLAN-based fingerprinting techniques continues to pose a significant challenge.

The investigation provides valuable insights into the impact of transmitter power settings on indoor positioning accuracy using WLAN fingerprinting. The study's findings highlight the significance of these settings in determining positioning accuracy, emphasizing the need for careful consideration of power configurations in indoor positioning systems. The study also demonstrates the effectiveness of clustering techniques, particularly signal correlation, in enhancing indoor positioning accuracy. This observation aligns with and reinforces the conclusions drawn by [21], lending credibility to the study's findings. The consistency with other international studies [22], [23] further strengthens the validity of the results. However, it is important to critically evaluate the conflicting findings presented in [24] and [25]. While [24] supports the impact of access point power on positioning accuracy, [25] claims no substantial effect when power variations are minimal. The discrepancy in these findings warrants further investigation to determine the specific conditions under which power settings significantly influence accuracy. The methodology employed in [25], which involved altering the mobile device's orientation rather than directly manipulating transmitter power, raises concerns about the study's validity. The authors' conclusion may be uncertain due to the limitations imposed by human body interference during orientation measurements. This approach fails to account for the complexities of real-world scenarios and may not accurately represent the true impact of power settings on positioning accuracy. Furthermore, the study overlooks the crucial role of antenna sensitivity and manufacturer-specified antenna gain in determining transmitter power limitations. These factors can significantly influence the relationship between power settings and positioning accuracy, and their omission may lead to incomplete or potentially misleading conclusions.

Moreover, to elucidate the enhancement in percentage accuracy, Equation 7 has been employed to calculate the percentile. Table 2 demonstrates that the proposed model achieves a mean accuracy improvement of 15.794% in a two-meter configuration upon the introduction of the high signal relation concept. Additionally, the mean accuracy was determined utilizing Equation 7. The percentage accuracy improvement (H_p) using the signal relation algorithm can be expressed as:

$$H_p = \left[\frac{H_{ns} - H_{ws}}{H_{ns}}\right] * 100\% \qquad 7$$

Where H_{ws} is the accuracy with the signal relation algorithm, and H_{ns} is the accuracy without the signal relation algorithm.

Table 2: Performance Accuracy Comparison of Non-Signal and Signal Relation Techniques Configuration

Power Settings	LOW	MEDIUM	HIGH
Highest RMSE Value Achieved by Signal Relation-Aware Algorithm (in Meters)	0.8596	0.8653	1.1986
Highest RMSE Value Achieved without Signal Relation-Aware Algorithm (in Meters)	1.1507	1.086	1.2201
Relative Improvement in RMSE Performance with Signal Relation-Aware Algorithm in meter (%)	25.297	20.322	1.762
Average Relative Improvement in RMSE Performance with Signal Relation-Aware Algorithm in meter (%)	15.794		

The overall performance of the proposed model demonstrates significant improvement with the introduction of the high signal relation concept, as evidenced by the data presented in Table 2. The model achieves an average accuracy enhancement of 15.794% in a two-meter configuration, calculated using Equation 7, which quantifies the percentage accuracy improvement (*Hp*) by comparing results with (*Hws*) and without (*Hns*) the signal relation algorithm. Additionally, the signal relation-aware algorithm shows notable reductions in Root Mean Square Error (RMSE) across low, medium, and high-power settings, with relative improvements of 25.297%, 20.322%, and 1.762%, respectively. These results highlight the effectiveness of the signal relation algorithm in enhancing both accuracy and precision, particularly in low and medium power configurations, where the improvements are most pronounced. Overall, the integration of the signal relation concept significantly boosts the model's performance, making it a valuable enhancement for practical applications.

5. CONCLUSIONS AND FUTURE WORK

This investigation has examined the influence of access point (AP) power configurations on the accuracy of indoor positioning systems (IPS) that employ WLAN fingerprinting techniques. The study has analysed the significance of high signal relations while minimizing the repercussions of low signal variations. The proposed probabilistic analytical algorithm has demonstrated its efficacy in enhancing IPS accuracy, as substantiated by a notable decline in the Root Mean Square Error (RMSE). Experimental results indicate that the proposed method achieves an average accuracy enhancement of 15.794% in terms of RMSE, reinforcing its effectiveness in mitigating signal degradation effects and improving localization precision. The findings highlight the potential benefits of varying AP power levels to augment the functionality of WLAN-based localization systems, particularly within environments characterized by elevated wall density and significant signal attenuation. The incorporation of AP power into the fingerprinting technique presents a promising strategy for addressing various intrinsic challenges associated with indoor positioning, ultimately resulting in more dependable and precise location determinations.

Although this investigation has revealed the advantages of integrating AP power into WLAN fingerprinting-based IPS, additional scholarly inquiry is imperative to resolve several unresolved issues. Future study could investigate the real-time dynamic modulation of AP power levels to accommodate variations in environmental conditions, such as changing user density or the emergence of new physical barriers. Furthermore, an exploration of the scalability of the proposed methodology within larger and more intricate indoor settings, such as multi-story structures or areas with a high concentration of access points, would yield significant insights. In addition, the amalgamation of other localization methodologies, such as machine learning techniques or sensor fusion, with the proposed framework could further enhance positioning precision. Lastly, it would be essential to assess the implications of forthcoming WLAN standards and technologies on indoor positioning efficacy to ensure the continued advancement of robust and future-oriented IPS solutions.

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