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Article

Accurate Indoor Localization with IoT Devices and Advanced Fingerprinting Methods

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Abstract: The Internet of things (IoT) has significantly impacted various sectors, including healthcare, environmental monitoring, transportation, and commerce, by enhancing communication networks through the integration of sensors, software, and hardware. This paper presents an accurate IoT indoor localization system based on IoT devices and fingerprinting methods. We explore indoor localization techniques using Bluetooth Low Energy (BLE) and a Radio Signal Strength Indicator (RSSI) to address the limitations of GPS in indoor environments. The study evaluates the effectiveness of iBeacon transmitters for indoor positioning, comparing the Weighted Centroid Localization (WCL) and Positive Weighted Centroid Localization (PWCL) algorithms, along with fingerprinting methods enhanced by outlier detection and mapping filters. Our methodology includes mapping a real environment onto a coordinate axis, collecting training data from 47 sampling points, and implementing four localization algorithms. The results show that the PWCL algorithm improves accuracy over the WCL algorithm, and hybrid methods further reduce localization errors. The HYBRID-MAPPED method achieves the highest accuracy, with an average error of 1.44 m.

Keywords: location; IoT; internal location; fingerprint algorithm

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1. Introduction

The Internet of things is a promising technology that has already been shown to be useful in sectors such as health, environmental monitoring, transportation systems, and in other commercial applications. The internet, things, and the semantic viewpoint are the three major components of IoT, all of which have significantly enhanced the communication network. The Internet of things is a network of sensors, software, and hardware components that uses shared storage and the internet to gather, store, and manage data. Smart towns that want to utilize more public space may leverage the Internet of things in order to do so. Hospitals, retail malls, libraries, transit systems, and other public institutions may all benefit from using the Internet of things to proactively manage and improve services [1].

Indoor localization can be realized through various IoT technologies, including WiFi, RFID, UWB, and BLE. Each of these technologies offers unique benefits and faces certain limitations. BLE has emerged as a preferred choice for indoor positioning due to its low energy consumption, relatively low deployment cost, and compatibility with most modern devices, including smartphones. This advantage makes BLE highly suitable for real-time localization applications, unlike UWB, which, although more accurate, requires specialized hardware and higher costs [2,3]. Furthermore, BLE provides a favorable trade-off between range and accuracy, outperforming WiFi in environments with significant interference. Comparative studies such as MLTL, IDWPSOInLoc, and EDEEPRFID-IPS have demonstrated BLE's superior performance in terms of scalability and ease of deployment, making it an efficient choice for various IoT applications [4–6].

To address the challenges of indoor localization, our research introduces two novel contributions: the Positive Weighted Centroid Localization (PWCL) algorithm and the

HYBRID-MAPPED method. These approaches are designed to enhance localization accuracy by prioritizing stronger signals and integrating multiple filtering techniques, respectively. This study aims to provide robust solutions to problems surrounding real-world applications by distinguishing our methods from existing studies.

We acknowledge that the original contribution of our work could be further emphasized. To address this, we have revised our approach to clearly highlight the development of the PWCL algorithm and the HYBRID-MAPPED method, which provide significant advancements over existing localization techniques.

In this study, we aim to enhance indoor localization accuracy by leveraging IoT devices, specifically using Bluetooth Low Energy (BLE) combined with advanced fingerprinting methods. The novel contribution of our work lies in the development of the Positive Weighted Centroid Localization (PWCL) algorithm, which prioritizes stronger signals to improve localization accuracy. Additionally, we propose the HYBRID-MAPPED method that integrates multiple filtering techniques, including outlier detection and mapping filters, to further reduce localization errors in challenging indoor environments. These methods distinguish our work from existing studies in this domain.

Various technologies have been investigated for indoor positioning, including Bluetooth Low Energy (BLE) [1,7–10]. In addition to BLE-based methods, the SLAM (Simultaneous Localization and Mapping) approach has been widely used in robotics for simultaneous mapping and localization, and it is highly relevant to indoor localization [11]. Furthermore, while GPS/GNSS technologies are often limited in indoor environments, their integration in hybrid localization systems provides valuable context for the development of more comprehensive solutions [12].

Recent advancements in indoor localization have introduced unified frameworks that integrate multiple localization techniques to improve accuracy and reliability. For example, the work of Zhang et al. presents a unified framework using factor graphs to optimize indoor localization performance by integrating various data sources [13]. Additionally, Kumar et al. have explored the performance improvements achieved through cooperative fingerprint-based localization, highlighting the importance of cooperation in enhancing accuracy [14]. Our study builds upon these foundational works while introducing novel methods to further advance the field.

As they pertain to smart retail complexes like hyperstores, the findings may be investigated further. Imagine having a lengthy shopping list in your hand and entering a shopping center with thousands of things to choose from, and you have to spend hours finishing your list. The presence of an internal location system based on the Internet of things in this instance may show the position of each of the items you desire on your smartphone. Prioritizing the purchase of any goods will undoubtedly result in significant time savings. As a result, based on its current and historical data, this store's smart technology can design a time-based shopping path for you and lead you. Internal positioning systems are also essential for asset monitoring and inventory management applications. Visual–inertial navigation systems have offered dependable methods for indoor and outdoor settings [15], and these systems may substantially improve the efficiency of system responders. VINSs, however, often depend on appropriate illumination and streams of information, while the usage of cameras may create privacy issues [16] that limit their use. Internal positioning systems based on conventional wireless communication technologies have also been investigated as a supplementary option. Environmental obstacles significantly affect radio signals in interior settings, reducing the system's accuracy [17].

The position of a GPS device is always restricted. When the weather is poor, GPS signals cannot be received inside big buildings or in fully enclosed areas such as roads and city tunnels. Unfortunately, the absence of a satellite signal may have a variety of severe consequences in each of these situations. Imagine trying to locate people or objects among structures destroyed during an earthquake or natural disaster, or in a large hospital, showing patients the correct path to their desired location based on GPS. While GPS can easily locate people or objects in open spaces, it cannot send a signal and displays a large vacuum in indoor environments [8].

Because wireless local area networks and Bluetooth Low Energy are so common nowadays, the emphasis of this article is on how to use the Radio Signal Strength Indicator that is accessible through wireless local area networks and Bluetooth Low Energy.

The location of transmitters is addressed first in this article, followed by point finding using the fingerprint technique. A thorough examination of the algorithms used in comparable articles also aids in the development of a unique technique for internal filing by combining various algorithms and applying different filters to the final output.

Because receiving satellite signals in big interior settings is constantly restricted, and people expressly need a different system in these locations, the most essential objective of this research is to identify things in these surroundings. Another aim of this study is to improve the process accuracy in locating and presenting the position of items by taking ambient noise into account.

In this article, we ask the following questions:

How can we locate indoors without the need for GPS using IoT? How can we maximize productivity by locating with a minimum number of transmitters? How can we neutralize the effect of environmental noise with existing algorithms and improve the accuracy and speed of receiver spatial calculations?

To answer the above questions, we consider and test the following hypotheses:

1. It is possible to improve the accuracy and speed of algorithms in indoor environments without the need for GPS signal by replacing Bluetooth-based transmitters instead of Wi-Fi and displaying the location of objects connected to the network on a local map;
2. Using passable point mapping methods, unusable paths can be eliminated in location searches to increase the accuracy and speed of the system response;
3. Based on data processing algorithms in fingerprint methods, noise effects can be neutralized, and accuracy can be increased using the sampled and evolved data of users.

2. Materials and Methods

2.1. Theoretical Foundations

2.1.1. Selection and Placement of Transmitters

Using new wireless standards such as IEEE 802.15.4, low-power Bluetooth, and radio-frequency identification (RFID) helps to develop new positioning technologies in indoor environments [7]. Table 1 represents a good comparison of the performance of these three technologies.

Table 1. Comparison of three different hardware in internal routing.

	WiFi	**RFID**	**iBeacon**
Coverage	50 m	10 m	50 m
Cost	high	Low	A little high
Power Consumption	high	Low	Low
Bandwidth	1.8 G	250 kb	1 M
Battery Life	several Days	1–2 Years	1–2 Years
Positioning Accuracy	2 m–3 m	1 m–2 m	1 m–2 m

iBeacons (iBeacon Estimate location beacons), hardware used.

In this research, hardware called iBeacon will be used to receive the signal, which has the ability to send RSSI signals up to 50 m, and these components can be used for up to 5 years without the need to replace the battery. iBeacon was developed in a collaboration between Apple and the Estimate team and is available to researchers for research projects [18].

iBeacon technology has recently become very popular among researchers, used to position objects and smart devices indoors [19].

In the research that has been conducted in [8], the same transmitters were used as the generator of Bluetooth signal. (Currently, three of these transmitters have been purchased and will be used during the investigation).

2.1.2. Methods for Placing iBeacons

In articles published by the manufacturer of this technology for internal routing, it is easy to see that a large number of iBeacons are needed to cover relatively small environments. One of the challenges for researchers in this field is to design an improved architecture to use the minimum number of iBeacons for the maximum coverage of space and measurement accuracy.

As mentioned earlier, one of the most important issues in research today is to examine the best location for 3 iBeacons in a specific communication range [20]. In the research conducted by Dr. Rezazadeh et al. in 2018, a main reference for this research, this is shown to be an effective method for the proper placement of this technology [7]. Research in Ref. [7] shows that a comparison between the random placement of iBeacons and the placement of the equilateral triangle as a prototype reveals a significant improvement in the latter, with a large error in the random state.

This simple experiment shows the need for optimal placement to achieve the highest accuracy of local location estimation. In addition, other factors contribute to localization error that must be considered. Localization error is a function of factors such as the following:

M: Mapping error

A: Localization algorithm error

B: Type of nodes used by iBeacon

P: Location of iBeacons

$$L_e = f\,(M, A, B, P) \tag{1}$$

Spot Locating of Receivers

Today, there are various ways to estimate the location of objects in the network based on receiving radio signals to finally perform indoor locating by improving the existing methods with iBeacon transmitters, displaying the position of people on smart phones based on received signals from iBeacon, and then guiding those people to their targets in the best path, and in the most time-efficient manner, by using different filters. This is the Internet of things.

2.1.3. Fingerprint Location

One of the most efficient location methods is the fingerprint method. Fingerprint-based wireless indoor positioning is widely used in spatial services, because wireless signals such as Bluetooth and Wi-Fi are used indoors. They are easily accessible [1]. One of the advantages of this method is its simplicity compared to other methods in implementation. Fingerprint-based internal positioning via Wi-Fi or Bluetooth signals has also become a standard method for commercial applications [17]. The basis of this method is to collect a lot of data from different environments such as a room or an entire building so that finally, with the large amount of data collected in the core after implementing the local map, the signals received from each object can be checked with previous data and the location of the object can be displayed on the map.

Fingerprint technology is associated with a high level of accuracy and reliability. Figure 1 provides an overview of the algorithms used in the fingerprint method [1].

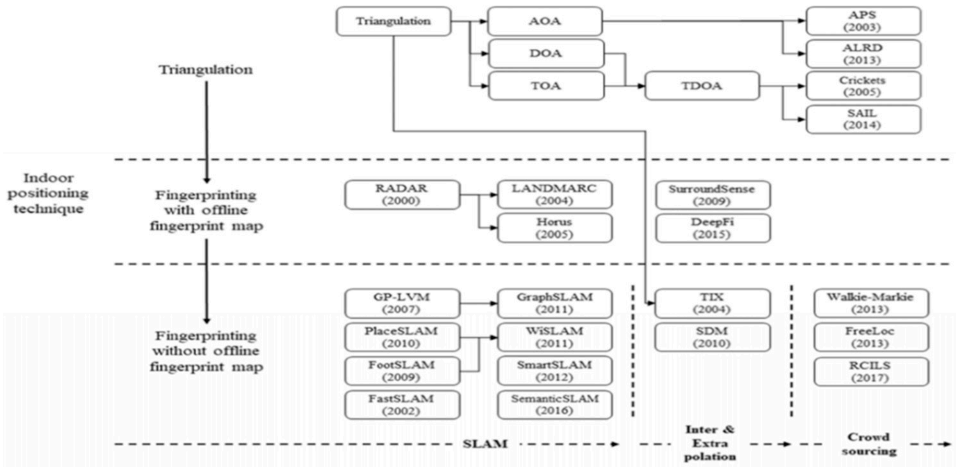

Figure 1. Algorithms used in the fingerprint method.

2.2. Method

Different methods have always been used for internal location without the use of satellite signals or location via the internet. In this study, research is based on the environment and real tools. One of the most efficient location methods is the fingerprint method, which is widely used in commercial applications [7,8,21]. In fact, the main purpose and direction of this research is that first the space of a real environment is mapped on a coordinate axis. The distance between the points of these coordinate axes in the real environment is considered to be 40 cm, according to which the X coordinate axis contains 18 points and the Y coordinate axis contains 30 points. After determining the space by the optimal CiP method, the connection of the transmitters is conducted in the form of an equilateral triangle. After preparing the test space, in the offline stage, with a sampling application in 47 points, the operation of recording and sending training data to the server is performed. The reason for obtaining 47 points is that in the space, a corridor and three passable rooms have been considered for research; if paths are drawn according to the coordinate axis, 47 navigable points will be obtained. After collecting the training data in another phase, the location operation is performed in 4 different ways with another application. In this phase, the complete map of the environment is viewed on the application and by moving in the environment and sending the target point to the server; the server is positioned in 4 ways in exchange for the received signals and the error of the methods is simultaneously registered in another database. Finally, after obtaining the most optimal method from the results of error checking, the best method can be selected as the locating method in the application so that the user can see their location by moving in the environment instantly.

To do this, four main phases are first defined as follows:

1. The first phase: offline section, to collect training data from the environment;
2. The second phase: online section, implementation of locating algorithms;
3. Third phase: online section, combination of second phase algorithms and debugging;
4. Fourth phase: calculation of measurement error.

2.2.1. The First Phase: The Collection of Training Data in the Offline Section

In this section, by collecting training data in 47 points of the environment and sending it to the server, this data is stored in the database to be used in location by the fingerprint method.

2.2.1.1. Selection of the Testing Environment

In this research, As shown in Figure 2, part of a company's workspace has been used. All corridors and rooms of the experimental space are made of glass, which can be considered as a positive point for noise interference in the environment, because the presence of walls made of brick, cement, and plaster can differentiate the received signals and neutralize the effect of noise in different places.

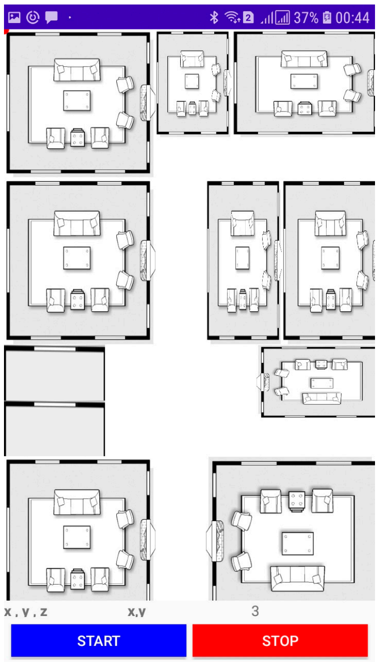

Figure 2. User interface of application based on company's workspace.

In the next step, the space of the research environment is divided into grid layers with a distance of 40 cm from each other, as shown in Figure 3. In the environment, all points of the testing route are labeled for the sampling stage.

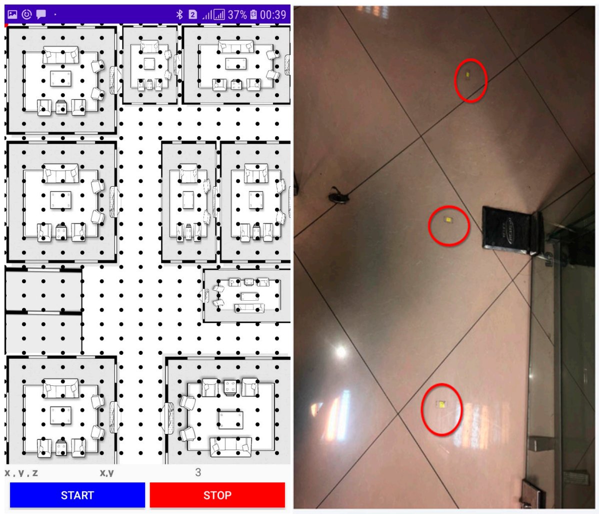

Figure 3. Image on the left: Simulated grid layers, image on the right: the actual space of the environment.

2.2.1.2. Placement of Transmitters (iBeacons) by CiP Method

In this tested space, As depicted in Figure 4, three iBeacons, joint products of Apple and Estimate, have been used and placed in three corners of the space in the shape of an equilateral triangle, which can be seen in the image below.

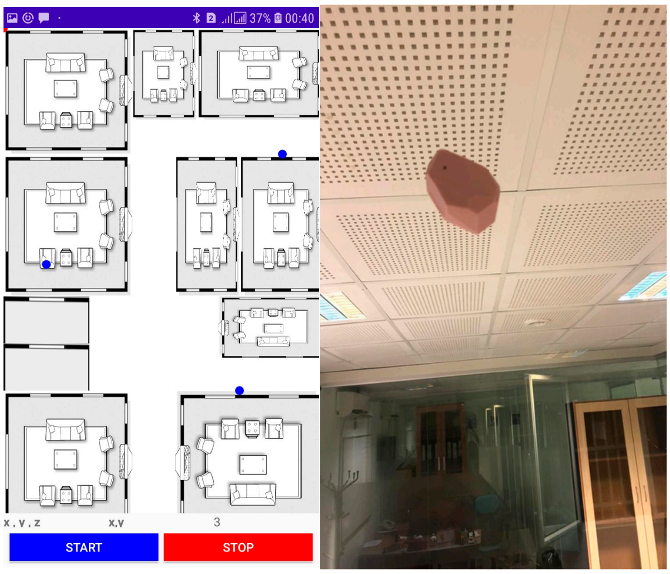

Figure 4. Representation of the transmitters' location.

2.2.1.3. Designing and Implementing Back-End for Receiving and Storing Data

In this section, through the Laravel framework with an Nginx web server, a system has been designed and implemented on the Linux kernel to receive the sample of received signals in the offline section and store them in a PostgreSQL-based database.

In this section, an Android application with Java language is designed and implemented to direct the data received from the transmitters to the server for storage using the following algorithm:

1. Start;
2. Obtain the coordinates of the desired point;
3. Receive 300 signals for each transmitter;
4. Send the data to the server;
5. The end.

The overall architecture of the application, as illustrated in Figure 5, includes both offline and online phases for data collection and localization estimation.

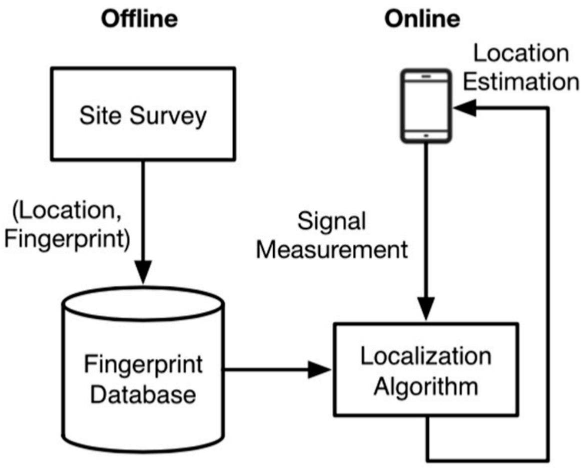

Figure 5. Architecture of application.

2.2.1.4. Sampling

In this section, after configuring the server, creating the back-end structure for data storage, and implementing the sampling application, 47 points including the main corridor of space and 4 rooms are selected as the main sampling points to perform the operation of training data storage. The user interface for the sampling phase, shown in Figure 6, allows the selection of specific points in the environment to capture RSSI values for localization purposes.

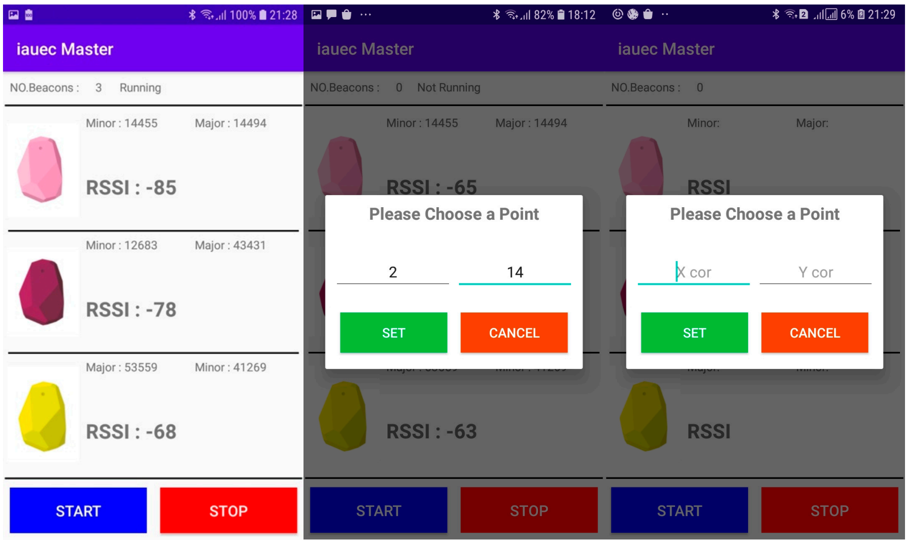

Figure 6. User interface of application in sampling phase.

2.2.2. The Second Phase: The Implementation of Locating Algorithms

In the second phase of the operation, by designing an application and upgrading the back-end methods, internal location is performed in 4 different ways. In the first two methods, location is conducted without the fingerprint method. The other two methods of location are performed in conjunction with the fingerprint method, each of which benefits from a combination of different algorithms. After implementing the location application, the server is ready to implement various methods of location in the desired methods for the target point.

2.2.2.1. Location with Weighted Centroid Localization (WCL) Algorithm

The first location method considered in this research is the WCL algorithm so that it can be used as a benchmark for measuring other innovative methods of this research. Therefore, location using this method is conducted without any change in the structure presented for it in the research [10].

$$p(si) = \frac{\sum_{j=1}^{N_r} (RSS_{ij} \cdot b_j(x,y))}{\sum_{j=1}^{N_r} RSS_{ij}} \tag{2}$$

Equation (2)—Formula for calculating spatial coordinates by the WCL method.

According to this algorithm, the strength of the signals received from each transmitter is multiplied by the transmitter's X and Y coordinates, then added and subtracted. The denominator of the fraction is the sum of the power of the signals. Finally the coordinates of the point found are displayed on the map. To further illustrate the functionality of this algorithm, we tested a sample of the received data.

2.2.2.2. Locating with Positive Weighted Centroid Localization (PWCL) Algorithm

In this section, by improving the WCL method and in fact compensating for the weakness of this method, the tendency of the found points is towards stronger signals. The received RSSIs are inherently negative numbers, and the larger these negative numbers (they tend to zero), the stronger the signal. Therefore, in the WCL method, the final response tends to the center of the triangle. But in the new PWCL method, the received signals are added to the signals before being included in the WCL formula, due to the fact that the received signals fluctuate in the range of −40 to −100. The final response tends to lean towards the strongest transmitter.

$$\mathrm{P(si)} = \frac{\sum_{j=1}^{nr}((\boldsymbol{RSSI}\mathbf{ij} + 100).\boldsymbol{b}\mathbf{j}(\boldsymbol{x},\boldsymbol{y}))}{\sum_{j=1}^{nr}(\boldsymbol{RSSI}\mathbf{ij} + 100)} \tag{3}$$

Equation (3)—Formula for calculating spatial coordinates by the PWCL method.

2.2.2.3. Locating with Fingerprinting Algorithm by Applying Outlier Detection Filter

One of the main challenges of the fingerprint method is the presence of noise. Signals are affected by environmental conditions such as human movement and obstacles that prevent them from reaching the user. The detection of these signals requires filtering to make the received data offline unreliable.

2.2.2.4. Locating with Fingerprinting Algorithm by Applying the Most Frequent Filter Based on Subscription

According to the fingerprint algorithm in the online location section, the data received in the online section is compared with all the data received in the offline section, and finally the customer's location is found. But an examination of the data received in the offline section shows that in different places the power of the signals received from the transmitters can be exactly the same.

2.2.2.5. Locating with the Fingerprinting Algorithm by Applying a Mapping Filter to the Path

In this section, after determining the location point, and before sending the signal to the customer, another filter is applied to the result to check the desired point for possibility or in other words, confirmation of the route point. If the found point is not one of the route points or not valid for people to pass in the environment, then according to a table information application called Maps, the nearest equivalent to that point replaces the result of previous filters and then is sent to the customer.

2.2.3. The Third Phase: Combining Algorithms, Locating and Checking for Errors

In this section, 4 final methods for locating through various implemented algorithms are selected to obtain the final results of the work. These 4 methods are listed as follows:

1. Locating with WCL algorithm;
2. Locating with PWCL algorithm;
3. Locating with HYBRID;
4. Locating with HYBRID-MAPPED.

The first two methods use only the stated algorithms to find the target point, but for the last two methods a combination of filters is selected.

2.2.3.1. HYBRID

In this method, the outlier detection filter is first applied to the training data. Then, with more filters, the frequency of the end point is obtained. But if it is not found in this shared filter, location is performed through the PWCL method.

2.2.3.2. HYBRID-MAPPED

In this method, in addition to applying all the filters of the previous method, the mapping filter is also applied on the passable points on the final result.

2.2.4. The Fourth Phase: Measurement of Locating Error

In the operational phase of user location, at each point the user sends the target point and the signals received from the transmitters to the server; the output of each of the 4 methods of location is stored within a table called trace_logs with the measured error.

The measured error is actually the distance from the target point to the point found by the algorithms, which is obtained by the Euclidean distance method on the Cartesian coordinate axis:

(X_t, Y_t) is the target point and (X_i, Y_i) is the point found by the location algorithms.

$$\boldsymbol{R} = \sqrt{(\boldsymbol{Xt} - \mathbf{Xp})^2 + (\boldsymbol{Yt} - \boldsymbol{Yp})^2} \quad (4)$$

Equation (4)—Euclidean distance measurement.

Then, considering that each unit of Cartesian coordinates is equal to 40 cm, the Euclidean distance is multiplied by 0.4 to convert the error scale into meters. Finally, this process is executed for each point in all 4 algorithms and stored in the table.

3. Results

3.1. WCL Location Results

As shown in Figure 7, The results of this algorithm, which is actually implemented without any changes or improvements, are not very satisfactory and the error rate in some places reaches more than 4 m.

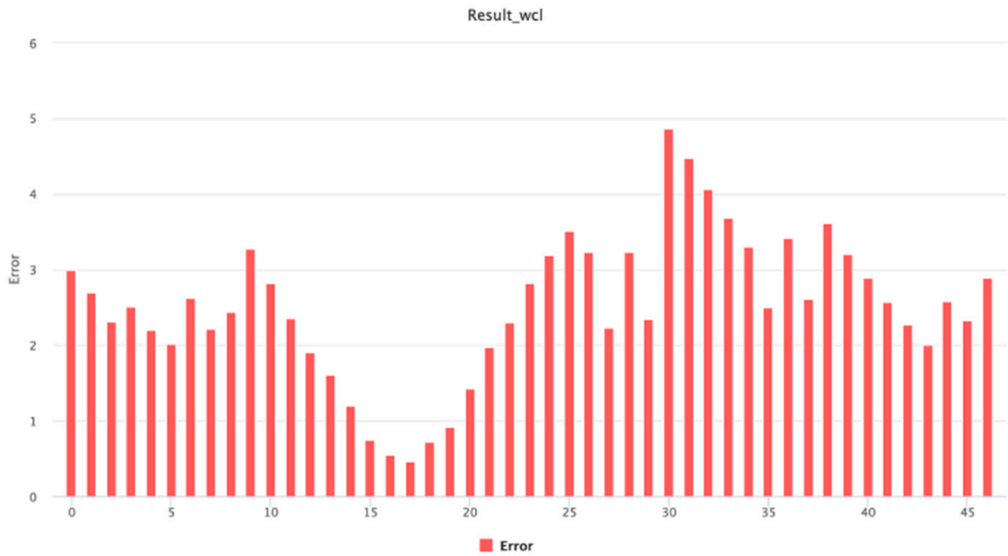

Figure 7. Bar chart of average error (in meters) at 47 points in the WCL method.

If we consider the location of each transmitter as three vertices of a triangle, the points at which the lowest error rates are recorded are the points closest to the center of this triangle. But many other errors have been observed. The average error in this method is 2.51 m. The error variance in this method is 0.92 and the standard deviation is 0.96.

3.2. PWCL Location Results

In this method, many attempts were made to shift the location towards stronger signals. Figure 8 illustrates a complete improvement of the WCL algorithm.

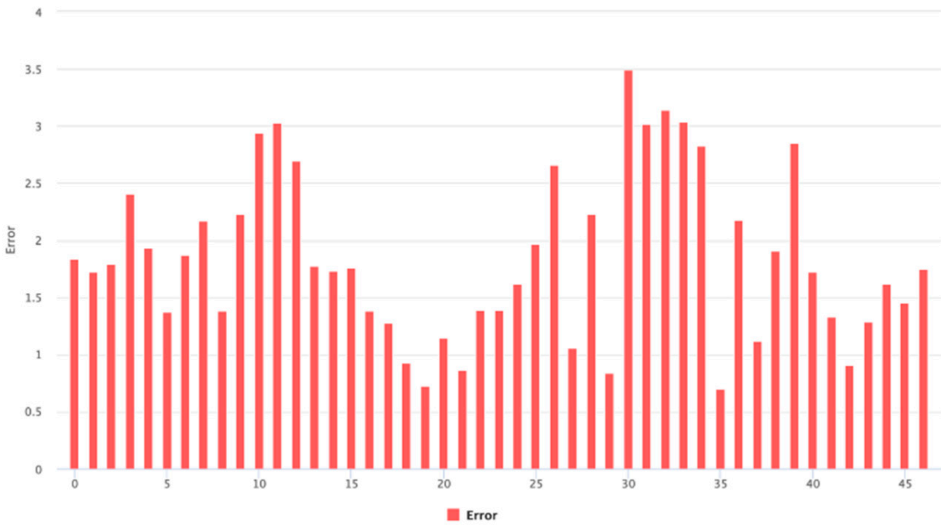

Figure 8. Bar graph of average error (in meters) at 47 points in the PWCL method.

In this method, the closer the user is to a transmitter, the less error is observed; more error is observed in the central points of the transmitter triangle. The average error in this method is 1.84 m. The error variance in this method is 0.52 and the standard deviation is 0.72.

3.3. HYBRID Location Results

In this method, the outlier detection filter is first applied to all data so that the data containing noise is detected and removed from the database as an unreliable point. After that, finding the maximum frequency in the common points of final location is performed using the algorithm. The results of this method show that compared to the PWCL method, there is an improvement in location accuracy. Figure 9 presents the bar graph of average error (in meters) across 47 points using the HYBRID method, highlighting the improvement in location accuracy compared to the PWCL method.

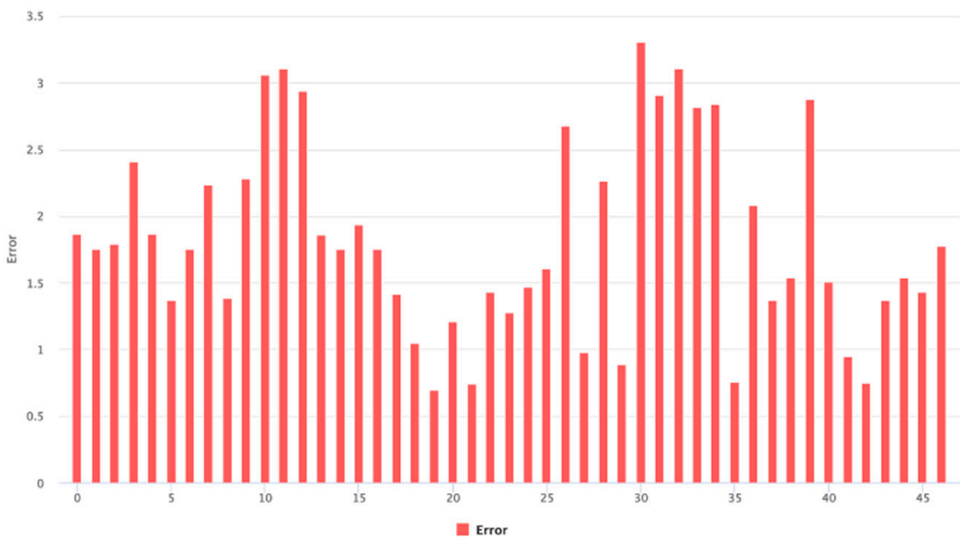

Figure 9. Bar graph of average error (in meters) at 47 points in the HYBRID method.

The average error in this method is 1.82 m. The error variance in this method is 0.53 and the standard deviation is 0.73.

3.4. HYBRID-MAPPED Location Results

Figure 10 illustrates Applying a mapping filter as the final filter had a significant effect on the research results, so much so that the location error was reduced by more than 20%.

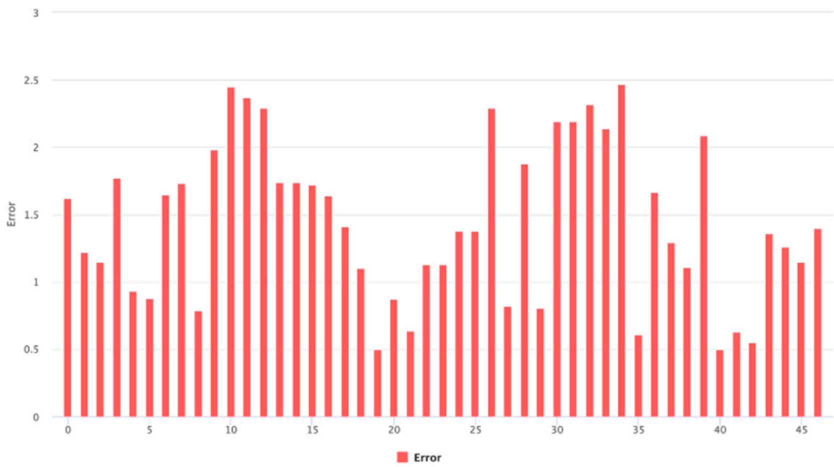

Figure 10. Bar chart of average error (in meters) at 47 points in the HYBRID-MAPPED method.

The average error in this method is 1.44 m. The error variance in this method is 0.34 and the standard deviation is 0.58.

3.5. Comparison

As a conclusion of this research, the results shown in Figures 11 and 12 obtained from four different methods are examined together and can be seen in the diagrams below.

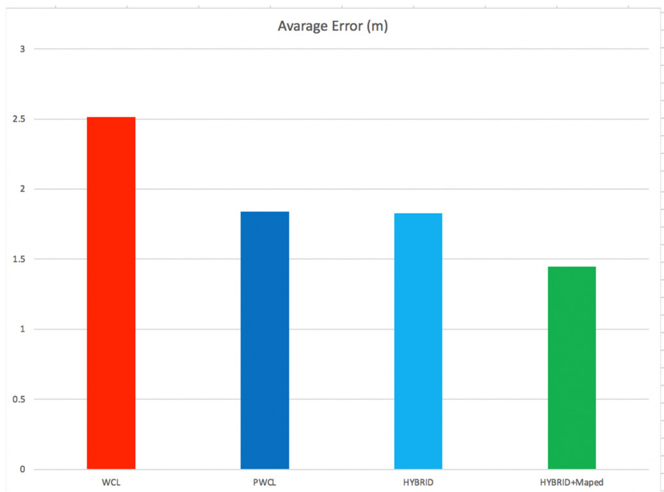

Figure 11. Bar chart of the average total error (in meters) in four different methods.

The improvement demonstrated by the methods used in this research can also be applied in a global contex as shown in Figure 13.

This means that if you are walking on a street and the signals received from the satellite are weakened for reasons such as weather changes, the user's location will never change due to inaccessible or passable points and the program will try to keep the user in the path of the crossing to receive a stronger signal by estimating the user's location.

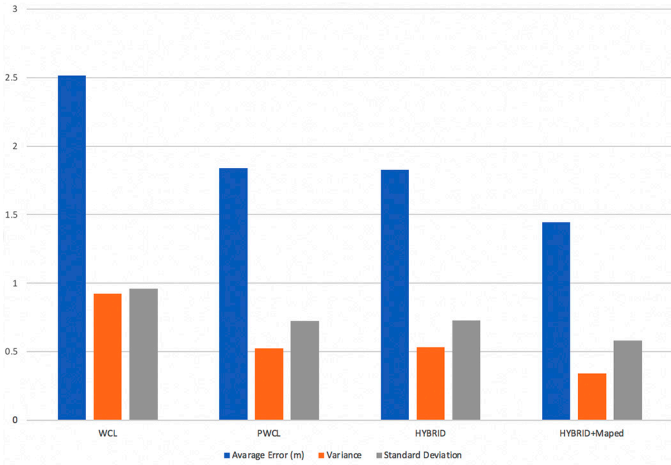

Figure 12. Bar chart of mean total error (in meters), variance and standard deviation in four different methods.

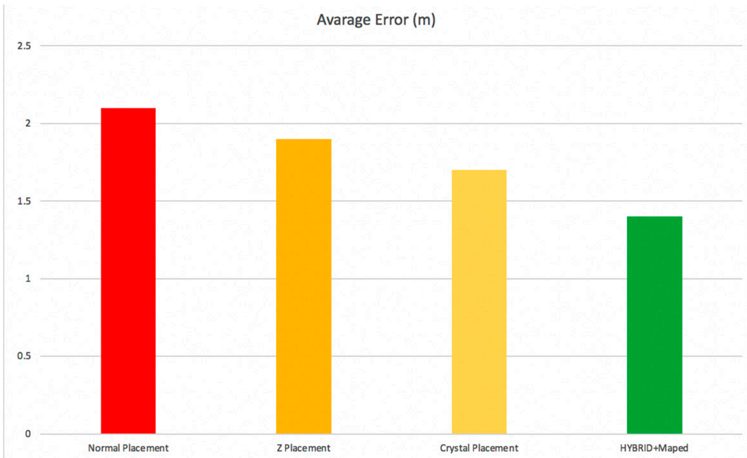

Figure 13. Bar chart of the average total error (in meters) compared to the baseline research.

4. Discussion

The results of our study demonstrate significant advancements in indoor localization accuracy using IoT devices and fingerprinting methods. By integrating Bluetooth Low Energy (BLE) and a Radio Signal Strength Indicator (RSSI), we were able to address the limitations of GPS in indoor environments effectively. Our findings corroborate previous research on the potential of BLE for indoor positioning, highlighting the enhanced accuracy achieved through our proposed algorithms.

4.1. Comparison with Previous Studies

Our study builds upon the foundational work of Dr. Rezazadeh [8], who explored iBeacon placement for indoor positioning. By improving upon their methodology, particularly through the development and application of the Positive Weighted Centroid Localization (PWCL) and HYBRID-MAPPED algorithms, we achieved a marked reduction in localization errors [7,8,21,22]. The average error in our HYBRID-MAPPED method was 1.44 m, which is a significant improvement compared to traditional WCL methods that showed an average error of 2.51 m. This aligns with findings from similar studies that emphasize the importance of algorithmic enhancements and optimal hardware placement for reducing localization errors.

Our HYBRID-MAPPED method demonstrates superior performance when compared to traditional approaches such as the standard Weighted Centroid Localization (WCL) and the recently proposed unified frameworks based on factor graphs [13]. Specifically, our method achieves an average localization error of 1.44 m, a significant improvement over the WCL method with an average error of 2.51 m. Additionally, the integration of cooperative techniques as explored by Kumar et al. [14] has shown promise in further enhancing accuracy, but our approach refines these results by incorporating additional filtering mechanisms to address environmental noise and signal variations. These findings highlight the robustness and applicability of our proposed methods in various indoor environments.

4.2. Interpretation of Results

The success of the PWCL and HYBRID-MAPPED algorithms can be attributed to several factors. Firstly, the use of PWCL allowed for a stronger emphasis on signals closer to the transmitters, effectively minimizing the influence of weaker signals and thus reducing error. Secondly, the incorporation of advanced filtering techniques, such as outlier detection and mapping filters, proved crucial in mitigating the impact of environmental noise and ensuring more reliable signal processing.

Our results also highlight the importance of the physical environment in which the localization takes place. The experimental setup, which included glass corridors and rooms, provided a challenging yet realistic scenario for testing our methods. The positive outcome in such an environment underscores the robustness of our approach in real-world applications.

4.3. Implications and Broader Context

The implications of this study are significant for various sectors relying on precise indoor localization. In healthcare, for example, accurate patient and asset tracking within hospitals can enhance operational efficiency and patient care. Similarly, in large retail environments, improved localization can facilitate smart shopping systems, guiding customers efficiently and enhancing their shopping experience.

The reduction in localization error achieved through our methods also has broader implications for the development of smart cities. Accurate indoor localization systems can support various applications, from efficient space utilization in public buildings to enhanced navigation systems in complex environments such as airports and universities.

4.4. Future Research Directions

While our study has made considerable progress, there are several areas for future research. One potential direction is the integration of mobile phone motion sensors to further refine the localization process. These sensors can provide additional data to predict user movement, thereby increasing the accuracy of location estimates.

Moreover, continuous improvement of the training data through user interaction can enhance the system's performance over time. By incorporating user-generated data into the training process, the system can adapt to changing environments and maintain high accuracy levels.

Future research could also explore the scalability of our approach in larger and more diverse environments. Testing the algorithms in different types of buildings, such as industrial facilities and multi-story complexes, would provide valuable insights into the versatility and limitations of our methods.

In conclusion, this study presents a significant step forward in the field of indoor localization using IoT and advanced fingerprinting methods. The improved accuracy and robustness of our proposed algorithms offer promising potential for a wide range of applications, setting the stage for further advancements in this critical area of research.

5. Conclusions

Given the urgent need for user-located applications in indoor environments, especially very large and nested environments such as department stores, hospitals, and universities, researchers are now increasingly studying indoor location without the need to use satellite signals. Reviewing the results obtained by other researchers showed that the existence of high error in different algorithms has created the need to reduce this error by further investigation using creative methods, and by providing an operational example in the real environment. As shown in this study, the use of combined methods could obtain better results; in the final result in the HYBRID-MAPPED method, the error rate was reduced by about 18% compared to the samples performed in the world.

One way that can reduce the location error in indoor environments in the fingerprint method is to improve the training data over time using the system. This means that users who are in the environment can add the results obtained from the algorithms in the online section to the training data to increase the amount of training data. Applying the most frequent filter based on subscription can provide users with more reliable results. It is also recommended to use mobile phone motion sensors to improve the location of indoor environments in order to predict the user's movement and increase the accuracy of location.

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