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Radio map generation approaches for an RSSI-based indoor positioning system

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ABSTRACT

The use of Radio map fingerprinting, which relies on a received signal strength indicator (RSSI), is a popular indoor positioning method that offers high accuracy and cost-effective deployment. However, the generation of an RSSI radio map requires significant time and effort. This paper presents three methods for generating radio maps, with the aim of reducing the time required. The first method involves a dedicated mobile application that collects experimental RSSI data, while the second method uses biharmonic spline interpolation (BSI) to expand a prerecorded experimental radio map. The third method, the Wireless InSite simulator-based method, generates a fully simulated radio map. All three methods are studied in detail to evaluate their effectiveness in reducing the time required for radio map generation. Location estimation is then carried out based on the prerecorded radio maps. The combined method presented in this study increases the efficiency of building indoor positioning mobile applications. Experiments using combined real and simulated datasets collected at An Najah National University and University of Dubai campuses demonstrate that the model outperforms similar methods, improving the localization accuracy to approximately 0.45 meters. This level of accuracy is suitable for a variety of location-based applications, including critical ones such as evacuating people from buildings during emergencies.

1. Introduction

The rapid development of contemporary wireless sensor network (WSN) applications has created an urgent need for accurate data collection and location specification. Position estimation is a critical requirement for many WSN applications, including vehicular networks where location information is necessary for providing highly accurate and reliable localization information anytime, anywhere [1]. In the health sector, biomedical sensor nodes attached to a patient's body are used to monitor their activities [2]. Location information is also important for several Internet of Things (IoT) applications, such as monitoring daily activities in smart cities, municipal solid waste management [3], and smart manufacturing [4]. It is essential to study various localization methods while carefully addressing users' privacy and security concerns through appropriate techniques [5]. The Global Positioning System (GPS) is a common outdoor positioning solution that achieves localization accuracy within a few meters. However, its main disadvantage is that it does not work efficiently in environments where the line of sight is unavailable, such as indoor settings [6,7].

Indoor positioning systems have used different wireless technologies such as ultra-wideband (UWB), Bluetooth low energy (BLE), and Wi-Fi. Wi-Fi has become the simplest option for indoor environments due to the widespread use of Wi-Fi access points in buildings [8]. Various methods for measuring wireless signals [9], such as the angle of arrival (AOA), time difference of arrival (TDOA), time of arrival (TOA), and Received Signal Strength Indication (RSSI), are available. Among these methods, RSSI-based localization systems are widely adopted due to their high accuracy and the prevalence of wireless technologies. The basic techniques used for RSSI-based localization are fingerprinting, triangulation, and trilateration methods [10]. Fingerprinting is the most commonly used technique due to its accuracy, robustness, and simplicity, particularly in environments affected by factors such as multipath [11].

The RSSI-based fingerprinting method involves two stages: the *training* and *estimation* stages. In the *training* stage, the RSSI data collection process is performed to create a radio map that will be utilized in the *estimation* stage to estimate the user's location using a specific positioning

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algorithm. Nonetheless, constructing an RSSI-based fingerprint radio map in the *training* stage requires a considerable number of reference points (RPs) to be surveyed to collect the RSSI fingerprint measurements at each RP, which consumes a significant amount of time. Thus, RSSI-based fingerprinting is a time-consuming and labor-intensive technique, necessitating the identification of methods to overcome the drawbacks of the *training* stage. Moreover, the accuracy of the estimated locations is the most crucial performance metric used to evaluate any positioning system and can be evaluated using various performance criteria [12].

Generating an RSSI-based fingerprint radio map is a critical step in implementing the fingerprinting indoor positioning method. To mitigate the time required for radio map generation, various approaches have been proposed in the literature. For example, Ni et al. [13] proposed a semi-supervised self-adaptive local linear embedding algorithm, which reduced the number of required RSSI values and achieved a localization error of around 3 m. Crowdsourcing was used in [14], while [15,16] discussed a path loss model-based approach. Additionally, Zhou et al. [17] introduced some efficient interpolation methods that significantly reduce the amount of labor required for the radio map generation process.

Indoor positioning methods that rely on Radio map fingerprinting, which utilizes a received signal strength indicator (RSSI), are commonly used due to their high accuracy and cost-effective implementation. Nonetheless, creating an RSSI radio map necessitates substantial time and effort. To overcome this issues, this paper introduces three methods for generating radio maps more efficiently. The first method involves using a mobile application to collect experimental RSSI data, while the second method expands a prerecorded experimental radio map using biharmonic spline interpolation (BSI). The third method generates a fully simulated radio map using the Wireless InSite simulator. Each of these three methods is carefully analyzed to assess their effectiveness in reducing the time required for radio map generation. The resulting radio maps are then used for location estimation, which is critical for building indoor positioning mobile applications. Moving forward, the three methods are combined to create a more efficient approach to building indoor positioning mobile applications. Using real and simulated datasets collected from An Najah National University and University of Dubai campuses, they conducted experiments that demonstrated the superiority of their model over similar methods. This model achieved a localization accuracy of approximately 0.45 m, which is suitable for a variety of location-based applications, including emergency evacuations. Overall, the main contributions of this study can be summarized as follows:

- The proposed system is validated using actual location coordinates and RSSI measurements collected at An-Najah National University [18]. To gather accurate RSSI fingerprints values and corresponding records (RSSI Fingerprint, SSID to the AP, Mac address (MA) of the AP, etc.), a mobile application was developed and verified at the University of Dubai [19].
- Three different radio maps are introduced for the same indoor environment: (i) an effective mobile application is developed to collect RSSI values for generating an experimental radio map; (ii) to reduce the complexity of the RSSI fingerprints radio map generation during the Wi-Fi fingerprinting training stage, two different solutions are introduced: (a) an efficient interpolation method called BSI [20] to generate an efficient semi-interpolated radio map, and (b)) a fully simulated radio map using Wireless InSite Simulator [21] that takes into account the effect of building materials.
- A comprehensive comparison of the three radio map generation methods is presented, including the advantages and disadvantages of each one. The generated radio maps are also statistically evaluated.
- A tradeoff between the reduction in effort in terms of the time required for the radio map generation process during the training stage and the desired accuracy in the estimation stage is identified.

This paper is structured as follows: Section 2 presents previous research related to this study. Section 3 outlines the approaches used in the proposed indoor positioning system. The implementation of the indoor positioning system is detailed in Section 4, followed by the presentation of results and discussion in Section 5. The paper concludes with Section 6.

2. Related works

Fingerprinting is widely used in RSSI-based indoor positioning techniques due to the ubiquity of Wi-Fi infrastructure, the widespread use of mobile devices, and its ability to achieve satisfactory accuracy [18]. Many research studies have focused on RSSI-based indoor positioning techniques. For instance, one study provided an overview of Wi-Fi fingerprinting-based indoor positioning, and another study discussed the trilateration algorithm for RSSI-based indoor localization [19,20]. Additionally, [21] conducted a comparative analysis of different fingerprint-matching algorithms for Wi-Fi RSSI signal-based localization systems.

To simplify the radio map generation process for indoor localization systems, researchers have proposed various methods. For example, one approach involved a probabilistic framework to analyze the performance of Wi-Fi fingerprint-based localization and reduced the sampling size from a theoretical perspective, in addition to using the crowdsourcing method [22–24], interpolation methods [8,25,26], and others.

To collect data during the training stage in the Wi-Fi fingerprinting method, various techniques have been proposed in the literature. For instance, the author in [27] used an RSSI prediction model for data collection. In [28,29], different propagation models were proposed to predict signal strength values and generate radio maps. A genetic algorithm-based approach was used in [30] for indoor positioning, which avoided explicit efforts for the deployment process, and the median error of their system was 2 and 7 meters for small and large environments, respectively. Similarly, the experiment in [31] was conducted in an indoor environment, where a rank-based localization method was used that relied only on the rankings of the RSSI values, and the mean localization error was 4 m.

The primary contribution of our method is achieving a balance between reducing the required effort, in terms of time, and achieving desired localization accuracy. To accomplish this balance, we utilized a radio map that consists of both real and interpolated values. The real values were gathered using our specially designed mobile application, while the interpolated values were generated using one of the most advanced interpolation methods, BSI, which overcomes the limitations of other interpolation methods. BSI uses a mathematical function that minimizes overall surface curvature, resulting in a smooth surface that passes exactly through the input points and produces a very small prediction error. We analyzed the effect of the number of real measurements used during the interpolation, which has been overlooked in most existing studies. Furthermore, we introduced a simulated radio map generated using the Wireless InSite simulator, and we conducted a comprehensive and detailed analysis and comparison of the results.

3. Overview of the approaches used for the proposed indoor positioning system

This section gives an overview of the method used for indoor localization systems: the fingerprinting method, the BSI, and the simulation using the Wireless InSite simulator.

3.1. Fingerprinting localization method

The proposed localization method involves two main stages: the fingerprinting *training* stage and the fingerprinting *estimation* stage, as illustrated in Fig. 1.

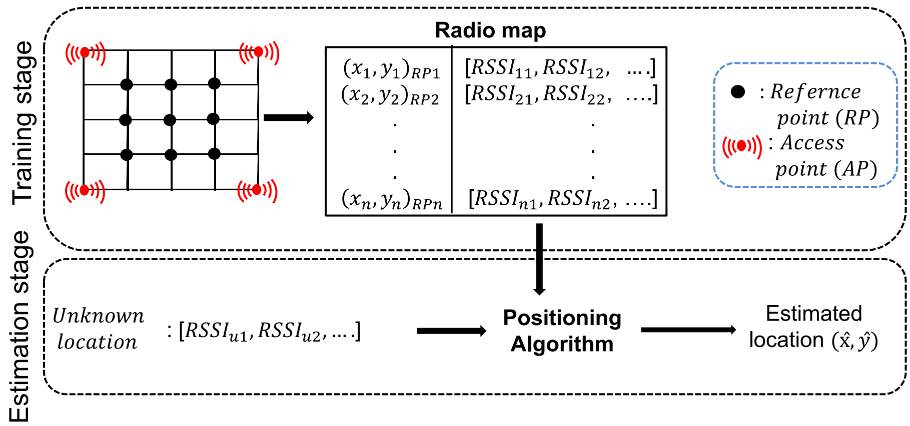


Fig. 1. Fingerprinting method.

section name	RP name	SSID AP	RSSI	MA	time	sample Number	RP [x,y]
a	a1	ExtraB	-49	64:70:02:5d:c0:f5	1/25/2020 8:00	1	[3,4]
a	a8	ExtraB	-55	64:70:02:5d:c0:f5	1/25/2020 8:00	2	[3,16]
b	b4	Najah	-40	f0:5c:19:47:6e:d0	1/25/2020 11:26	3	[2,7]
b	b7	OutdoorD	-94	e8:de:27:bc:ae:e2	1/25/2020 11:26	5	[2,10]
b	b13	OutdoorD	-97	e8:de:27:bc:ae:e2	1/25/2020 11:26	4	[2,16]
c	c2	Tplink2GA	-60	60:e3:27:7a:0d:76	1/25/2020 11:26	6	[4,51]
c	c8	IndoorA	-76	64:70:02:5d:c2:aa	1/25/2020 11:26	7	[8,51]
d	d2	OutdoorA	-87	e8:de:27:bc:92:b0	1/25/2020 11:26	8	[49,49]
d	d5	Najah	-77	f0:5c:19:47:60:d0	1/25/2020 11:26	9	[49,46]
d	d14	Najah	-30	f0:5c:19:47:60:d1	1/25/2020 11:26	10	[49,37]

Fig. 2. Sample of radio map training data.

3.1.1. Fingerprinting training stage

During the *training* stage of RSSI-based fingerprinting, RSSI samples were collected at predefined points called reference points using a mobile application installed on a device, in order to generate a radio map. This involved scanning the area for access points (APs) based on beacon frames periodically sent by the AP for synchronization, in order to construct a database (radio map). To collect the RSSI samples, the user was required to remain stationary at specific calibration points (reference points) using the proposed mobile application. The mobile application required the user to select the point name and the section containing the reference point, and then choose the number of RSSI samples to be gathered from each deployed AP at each reference point. The radio map was generated on the server as a comma-separated values (CSV) file. Fig. 3 provides a screenshot of the proposed mobile application used to perform the data collection process.

Moreover, during the training phase, the RSSI samples in (dBm) were collected along with other related information to construct the radio map. The collected data consisted of the section name, which is the area's name that contains a given RP; the $SSID$ to the AP, where $SSID$ is the network identifier; the AP MAC address, which is a physical address used as a unique identifier for the AP; the time, which is the timestamp when each $RSSI$ sample is collected; and the sample number, which is the number of recorded $RSSIs$ at a specific RP from the detected APs, and (x, y) are the coordinates of the APs. Table 1 illustrates the structure of the recorded radio map, and Fig. 2 displays a screenshot of a sample of radio map training data.

Averaging the samples of the RSSI values to store the average in the radio map is a common processing step [32]. Eq. (1) is used to find the average of the RSSI values from the j^{th} AP to ith AP.

$$\overline{RSSI}_{ij} = \frac{1}{m}\sum_{t=1}^{m} RSSI_{ij}^{t}, \tag{1}$$

where m is the number of $RSSI_{ij}$ values read from a specific AP, and $RSSI_{ij}^{t}$ is the tth element from the $RSSI_{ij}$ radio map.

3.1.2. Fingerprinting estimation stage

In the location estimation process, the nearest neighbors algorithm was employed to determine the distance between the received signal strength indicator (RSSI) values of the reference points (RPs) and the testing points. The nearest neighbor point was designated as the estimated location. The mean square error (MSE) metric was used as the distance measure, which estimated the desired location by finding the nearest position based on the RSSI values that give the minimum MSE. Alternatively, the Euclidean distance could be used in the fingerprinting estimation stage, where it computes the distance between two points. However, the MSE method is also a suitable choice because it calculates the deviation between the pre-recorded RSSI at a specific RP and the observed RSSI at the testing point [33]. Eq. (2) illustrates the application of the MSE-fingerprinting method.

$$MSE = \frac{\sum_{i}^{n}(RSSI_{unk,i} - RSSI_{p,i})^2}{n}, \tag{2}$$

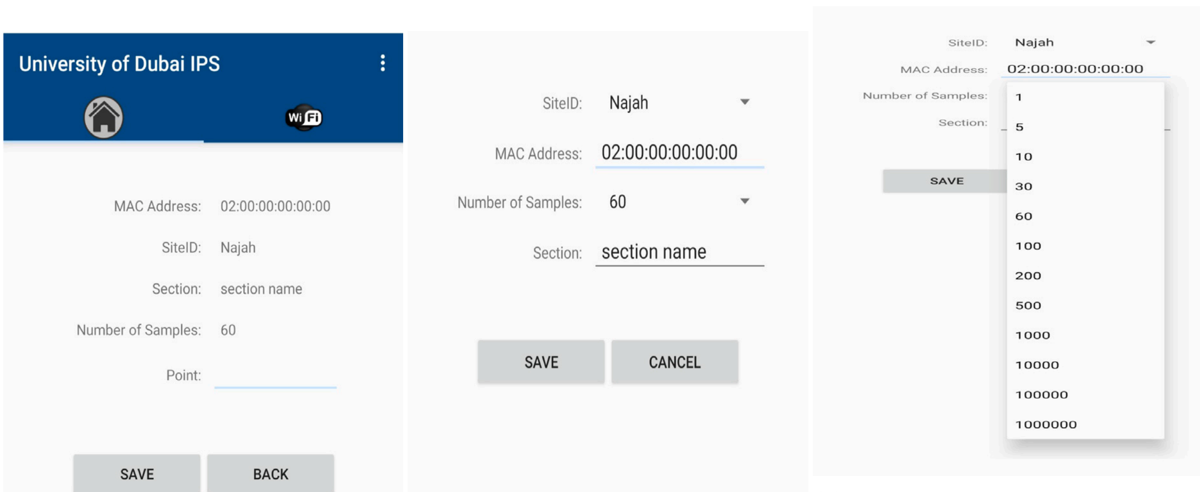
where $RSSI_{p,i}$ represents the prerecorded $RSSI$ values stored in the radio map. The $RSSI_{unk,i}$ is the observed $RSSI$ value at i location, and n is the number of the total RSSI measurements at i location, in other words, the value that states the number of APs detected by the user involved in the localization process.

3.2. Biharmonic spline interpolation method

This section provides an overview of one of the most advanced and crucial interpolation methods, the biharmonic spline interpolation method. As mentioned earlier, the first stage of fingerprinting involves

Table 1
Radio map structure.

Section name	RP name	SSID AP	RSSI value	AP Mac Address (MA)	Time	Sample number	X-Y coordinates
section	$P_{i=1}$	$AP_{j=1}$	$RSSI_{i,j}$	MA_j	day/month/year, hour: minutes: seconds, hour: (am/pm)	1	(x_{P_i}, y_{P_i})
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	$P_{i=n}$	$AP_{j=q}$	$RSSI_{i,j}$	.	.	.	.



(a) main page (b) section input page (c) choose the number of samples page

Fig. 3. Mobile application interface.

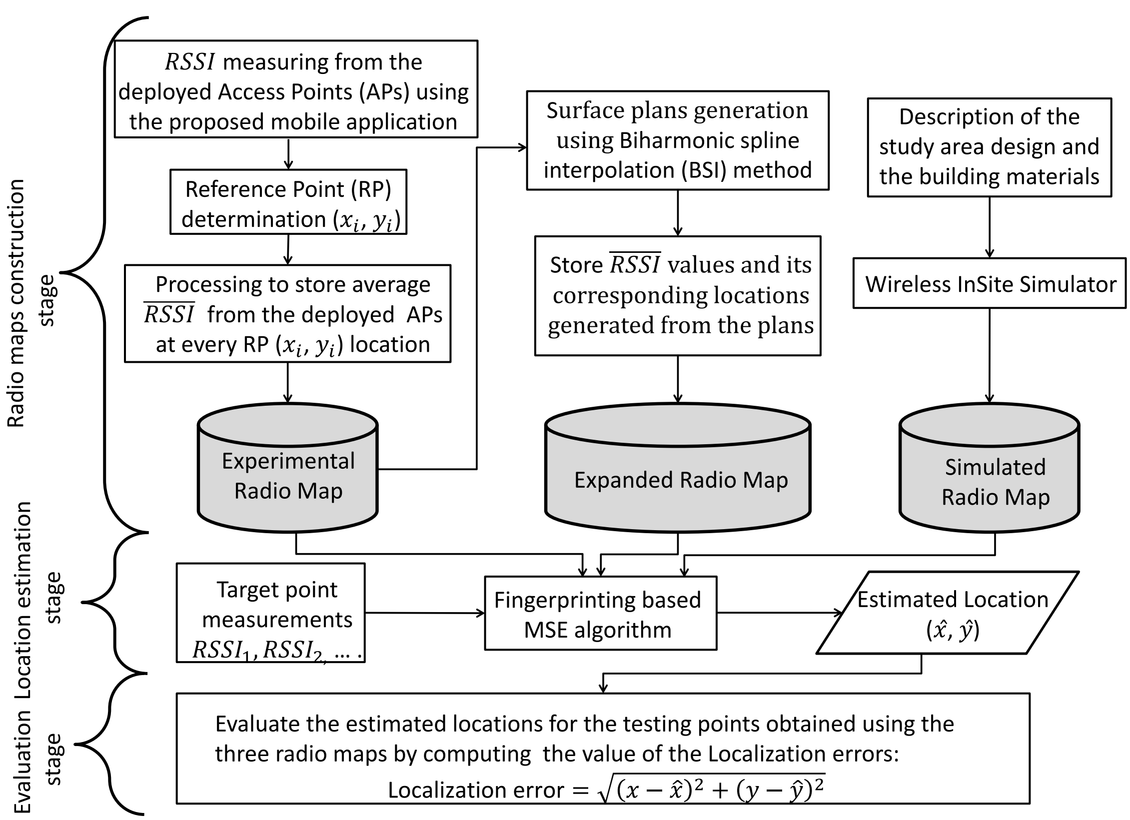
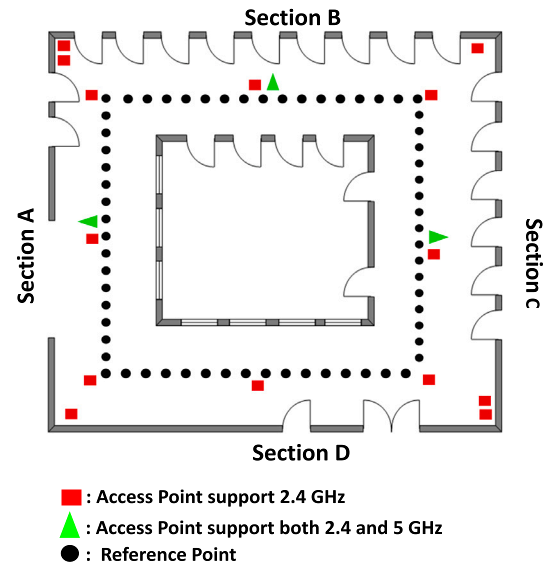


Fig. 4. Proposed indoor positioning system.

(a) Corridor photo



(b) Sections map

Fig. 5. Corridor photo and sections map.

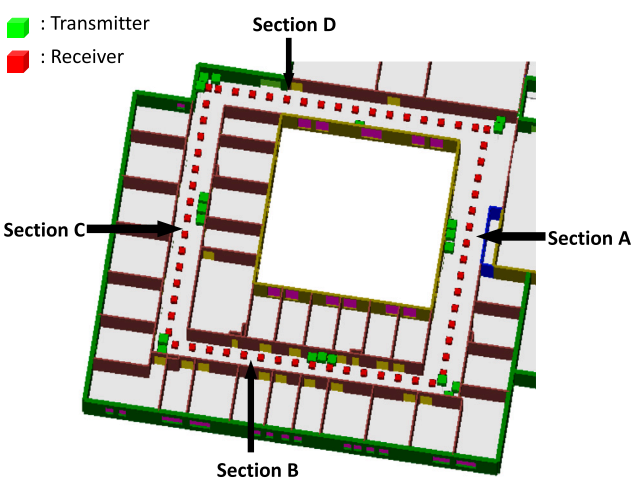


Fig. 6. Map of the simulated study area.

collecting RSSI values at different reference points (RPs), while the second stage (testing stage) involves applying the MSE-fingerprinting localization method to estimate the user's location. The accuracy of the location estimation process is primarily influenced by the size of the radio map. A larger radio map typically results in a more precise positioning estimation [34]. However, creating a large radio map can be time-consuming and is considered the primary drawback of the fingerprinting training stage. To overcome this limitation, interpolation methods are used to estimate a portion of the RSSI values, thereby generating a larger radio map and improving the accuracy of the location estimation process.

Several interpolation methods have been developed to generate a smooth surface for predicting new data across various domains. MATLAB software offers several interpolation methods, including nearest neighbor, linear, cubic, and biharmonic spline. However, except for the biharmonic spline, these methods have several drawbacks. For instance, they often return NANs (Not-A-Number) for points located exactly on or near the convex hull. Furthermore, the linear and nearest interpolation methods exhibit discontinuities on the first and zeroth derivatives, respectively [35,36]. Hence, the most suitable method for producing accurate results is the biharmonic spline (BSI), which Sandwell and David described as a linear combination of Green's functions centered at each data point [37]. Additionally, the BSI method is flexible and can use both values and slopes to generate surfaces. Therefore, in the fingerprinting training stage, the BSI was used as an efficient method to create a denser radio map.

3.3. Wireless InSite Simulator

This section outlines the use of the Wireless InSite Simulator for RSSI prediction in the study area. Wireless InSite is a powerful electromagnetic modeling tool that enables robust radio wave propagation modeling at high speeds. It achieves this by combining 3D models with propagation models, including empirical and deterministic models. The tool is capable of predicting signal strength in both indoor and outdoor spaces while accounting for the impact of building materials. With its advanced plotting system, users can specify the locations of transmitters and receivers, as well as the building design. The Wireless InSite software output can be leveraged for localization purposes.

4. Implementation of the proposed indoor positioning system

This section outlines three different methods used for generating radio maps in the fingerprinting *training* stage. The first method involved conducting an experiment to gather actual RSSI measurements using the proposed mobile application. The second method involved using Wireless InSite 3D Wireless Prediction Software to simulate the case study and generate a radio map containing simulated RSSI measurements. The third method involved using the BSI method to predict new RSSI values and expand the prerecorded radio map generated from the experiment. The MSE-Fingerprinting Localization method was then used in the *estimation* stage to predict the user's location based on the three radio maps. Finally, the localization accuracy was evaluated by computing the estimated results. The proposed indoor localization system is illustrated in Fig. 4.

4.1. Experimental methodology

The used indoor environment was a part of the second floor in the engineering college at An-Najah National University, which covers

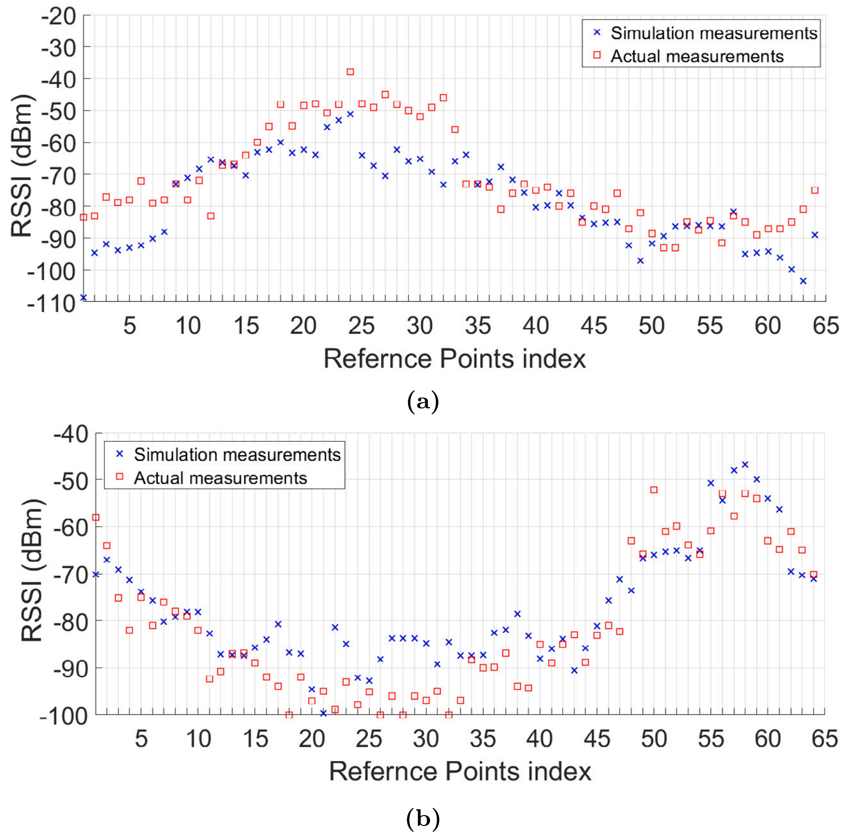


Fig. 7. (a) Actual and Simulation Measurement Results for AP_1; (b) Actual and Simulation Measurement Results for AP_2.

approximately 37 × 32 m^2. Fig. 5 (a, b) show a section map and a corridor photo of the area under study, respectively.

The study area was equipped with 17 access points that supported various IEEE 802.11 standards, including a, b, g, and n, out of which three access points supported dual-band at both 2.4 GHz and 5 GHz. The map in Fig. 5(b) illustrates the placement of these access points, with 14 of them supporting 2.4 GHz marked by red square symbols, and the remaining three supporting dual-band marked by green triangles. For the fingerprinting *training* stage, a mobile phone was used as a receiver to gather RSSI values at each of the 64 reference points (marked by black dots on the map) along a specific route with a separation of $1.35m$ between each point. Additionally, during the *estimation* stage, 16 testing points were randomly selected, and their RSSI values were collected.

To construct the experimental radio map, 60 RSSI samples were collected from each deployed access point at each of the reference and testing points using the proposed mobile application. These samples were averaged to generate the radio map, which consisted of the actual RSSI measurements. The MSE-Fingerprinting method was then applied to estimate the locations of the 16 testing points using the generated radio map containing 64 RPs with their corresponding RSSI values from the deployed access points. The minimum and maximum localization errors were found to be 0 and 0.76 m, respectively.

4.2. Simulation method

A 3D Shoot and Bouncing Ray (3D SBR) technique was used to perform a simulation model in the Wireless InSite Simulator, which allowed for the evaluation of different types of building materials and their impact on the RSSI values. Concrete material was found to have a greater attenuation effect on the RSSI values than glass material, while wooden and metal doors were also used in the simulation. The study area was simulated with receivers (reference points) located in the same positions as the APs in the experiment and transmitters (access points) represented by red and green points, respectively, as shown in Fig. 6.

To generate an accurate simulated radio map, the simulation was run five times to provide a stable prediction of the performance [38], and the average RSSI values from each run were collected at each receiver from each detected transmitter. A comparison was then made between the radio maps consisting of the actual and simulated measurements. For simplicity, two random APs were selected to describe the RSSI behavior in the simulation and actual cases, as shown in Fig. 7.

To determine the strength of the relationship between the simulated and actual measurements, the Pearson correlation coefficient (R) was used, as shown in Eq. (3). A high value of R close to 1 indicates a good fit. In this case, the value of R was found to be 80

$$R = \frac{n\sum_{i=1}^{n} p_i\hat{p}_i - \sum_{i=1}^{n} p_i \sum_{i=1}^{n} \hat{p}_i}{\sqrt{(n\sum_{i=1}^{n} p_i^2 - (\sum_{i=1}^{n} p_i))(n\sum_{i=1}^{n} \hat{p}_i^2 - (\sum_{i=1}^{n} \hat{p}_i)^2)}}, \quad (3)$$

where p represents the actual RSSI measurements, $\hat{p}$ represents the simulated RSSI measurements, and n is the total number of RSSI values.

4.3. BSI method

This section presents an efficient BSI method to reduce the required time and effort in generating radio maps during the fingerprinting *training* stage, while also producing accurate estimated locations during the fingerprinting *estimation* stage. Interpolation is a crucial technique for predicting values of a surface at unsampled points and optimizing the size of the radio map. By using the experimental $RSSI$ values at each RP from the detected AP, a surface was generated to predict new $RSSI$ values for new RPs in the area of interest. The BSI method was used to form an expanded radio map, consisting of both actual and interpolated RSSI measurements.

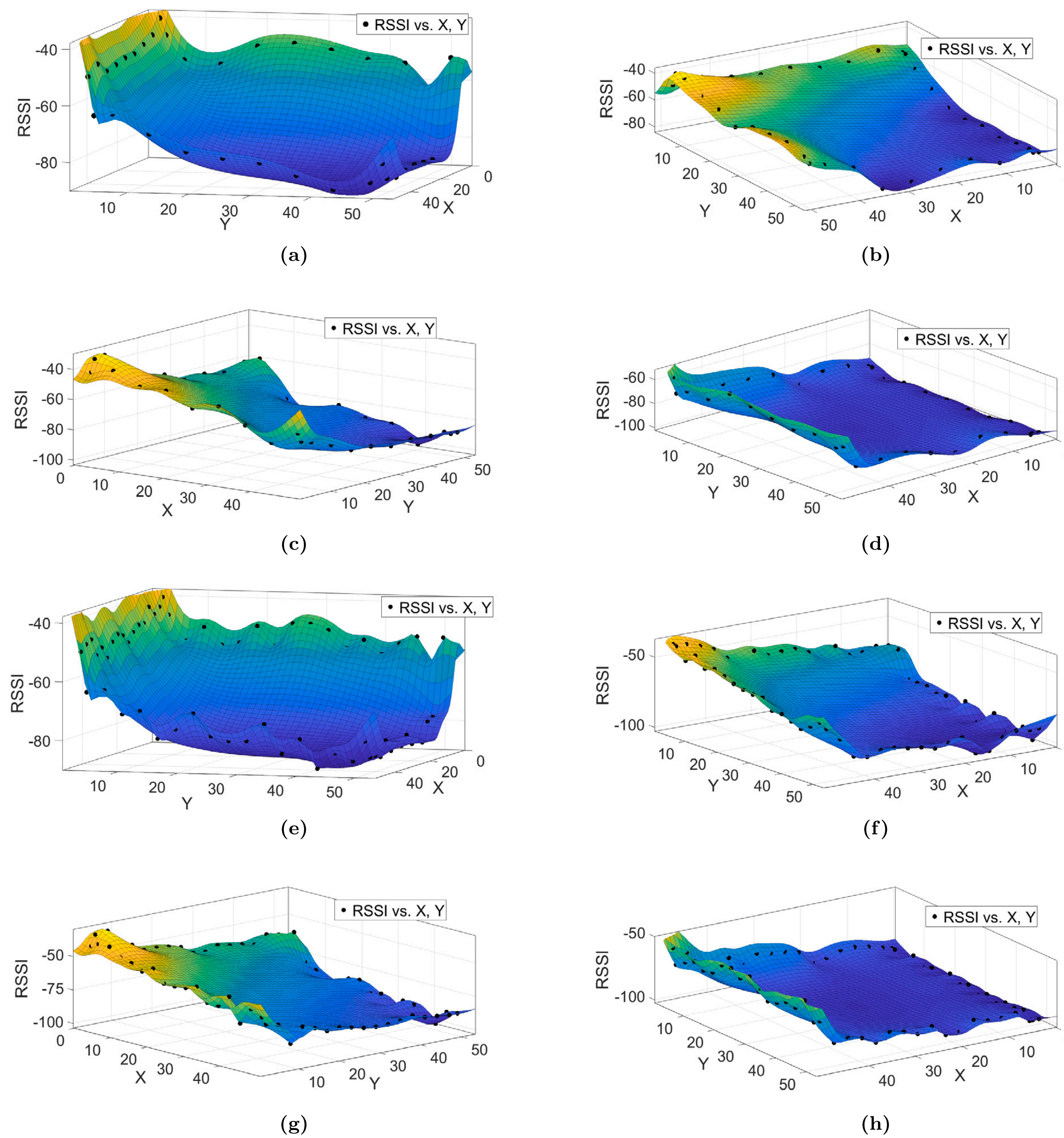


Fig. 8. The interpolated surfaces of the RSSI values generated by the BSI method based on the corresponding APs. a–d The interpolated surfaces generated using 50% of the original RPs based on AP_1, AP_2, AP_3, and AP_4, respectively. e–h The interpolated surfaces generated using 100% of the original RPs based on AP_1, AP_2, AP_3, and AP_4, respectively.

The BSI method was applied to two different numbers of actual RSSI measurements. In the first case, approximately 50% of the RPs were removed from the experimental radio map generated using the proposed mobile application in Section 4.1. The remaining 50% of actual RSSI measurements were used to plot a BSI surface for each deployed AP. Fig. 8(a–d) shows the interpolated surfaces using the RSSI values corresponding to 50% of the original RPs for four different deployed APs, for the sake of simplicity.

The results obtained from the interpolated surfaces led to the generation of the first semi-interpolated radio map, consisting of part of the experimental $RSSI$ measurements. This radio map corresponded to 50% of the original access points marked by black dots in Fig. 8, with the remaining part being the interpolated measurement value. The first semi-interpolated radio map was constructed by spacing 190 reference points at $0.45m$ intervals. Out of these, 32 reference points corresponded to actual $RSSI$ values, while the other 158 corresponded to interpolated $RSSI$ values.

Increasing the number of access points used to generate interpolated surfaces resulted in a reduction in the interpolated error for the BSI method. This is not always the case when using other interpolation types, such as polynomial interpolation [39]. Therefore, another semi-interpolated radio map was generated using more values of experimental $RSSI$ measurements than in the first semi-interpolated radio map. The second semi-interpolated radio map was constructed using BSI surfaces, and the experimental $RSSI$ values corresponded to 100% of the original reference points, i.e., 64 reference points. Fig. 8 (e–h) illustrates the generated BSI surfaces with the $RSSI$ values corresponding to 100% of the original reference points, marked by black dots.

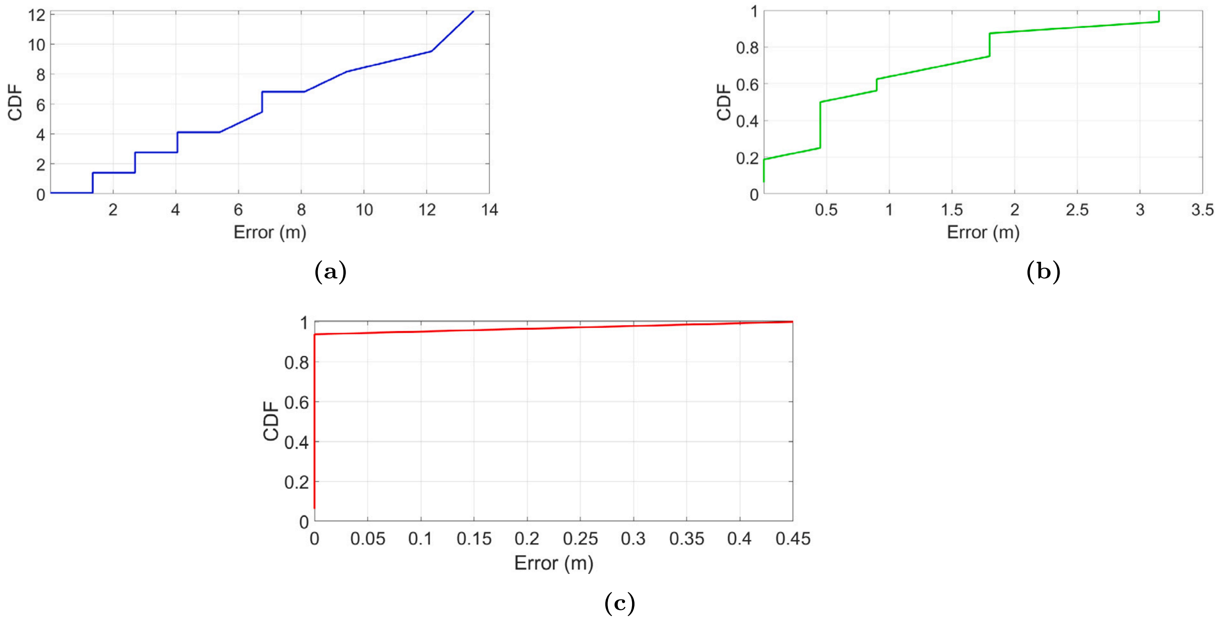


Fig. 9. CDF of the positioning error: (a) CDF of the simulated positioning error, (b) CDF of the first semi-interpolated positioning error, (c) CDF of the second semi-interpolated positioning error.

5. Discussion and results

The accuracy of the location estimation process was evaluated using three radio maps: the experimental, simulated, and semi-interpolated radio maps. The estimation error (e) was measured as the distance between the actual and estimated locations, which was calculated using Eq. (4):

$$e = \sqrt{(x - \hat{x})^2 + (y - \hat{y})^2}, \tag{4}$$

where x, y are the actual coordinates, and $\hat{x}, \hat{y}$ are the estimated coordinates.

- The location estimation process based on the experimental radio map: The MSE-Fingerprinting method was based on the experimental radio map consisting of 64 RPs with their corresponding RSSI values. The obtained results had minimum and maximum localization errors equal to 0 and 0.76 m, respectively, and the average error for all the testing points was 0.084375 m.
- The location estimation process based on the simulated radio map: The MSE was used to estimate the locations. For instance, 38%, of the testing points had an error in the range $(0, 2.7)m$ with an average of $1.65m$, while 37% of the testing points had an estimation error higher than $2.7m$ up to $7m$ with an average of $5.2m$, and the remaining 25% of the testing points were estimated with an error up to approximately $13.5m$. The cumulative distribution function (CDF) of the simulated positioning error is shown in Fig. 9(a), and a comparison between the estimated location for the testing points obtained from the simulated and experimental radio map is illustrated in Fig. 10(a). The location estimation was performed using MSE, and the resulting errors were analyzed. Specifically, the analysis revealed that for 38% of the testing points, the estimation error was within the range of $(0, 2.7)m$ with an average error of $1.65m$. For 37% of the testing points, the estimation error was higher than $2.7m$ up to $7m$ with an average of $5.2m$. The remaining 25% of the testing points were estimated with an error of approximately $13.5m$ or less. The cumulative distribution function (CDF) of the simulated positioning error is shown in Fig. 9(a), while Fig. 10(a) compares the estimated location for the testing points obtained from the simulated and experimental radio maps. As seen from Fig. 10(a), the simulation error for the testing points was higher than the experimental error, meaning there was no tradeoff between the required effort and the desired accuracy when the localization system was based on the simulated radio map.
- The location estimation process based on the semi-interpolated radio map.

1. The first semi-interpolated radio map, with 50% of the original RPs: The MSE method was utilized to estimate the positions of 16 testing points, with the outcomes indicating that 50% of these points had a localization error ranging from $(0, 0.45)m$, with an average of $0.28m$. The remaining 50% of points had an error range of $(0.9 - 3.2)m$, with an average of around $1.8m$. The cumulative distribution function (CDF) of the first semi-interpolated positioning error can be found in Fig. 9(b), while a comparison of the estimated locations for the 16 testing points based on the first semi-interpolated and the experimental radio maps is illustrated in Fig. 10(b). Fig. 10(b) demonstrates that the localization error dependent on the first semi-interpolated radio map increased when compared to the experimental error, but still remained within an acceptable range. Specifically, ten testing points exhibited an error of less than $1m$, while the other six testing points resulted in a low-accuracy localization.
2. The second semi-interpolated radio map: The process of estimating the locations of 16 testing points resulted in exact estimation for 94% of the points, with a localization error of $0m$. For the remaining 6%, the localization error was $0.45m$. The cumulative distribution function (CDF) of the second semi-interpolated positioning error is presented in Fig. 9(c), while a comparison between the estimated locations for the 16 testing points using the first semi-interpolated and experimental radio maps is depicted in Fig. 10(c). The results obtained from the second expanded semi-interpolated radio map provided more precise measures for location estimation. When compared to the results obtained from the experimental radio map, 13 testing points exhibited identical localization errors in both cases. Additionally, two testing points demonstrated a reduction in localization error when compared to the actual scenario.

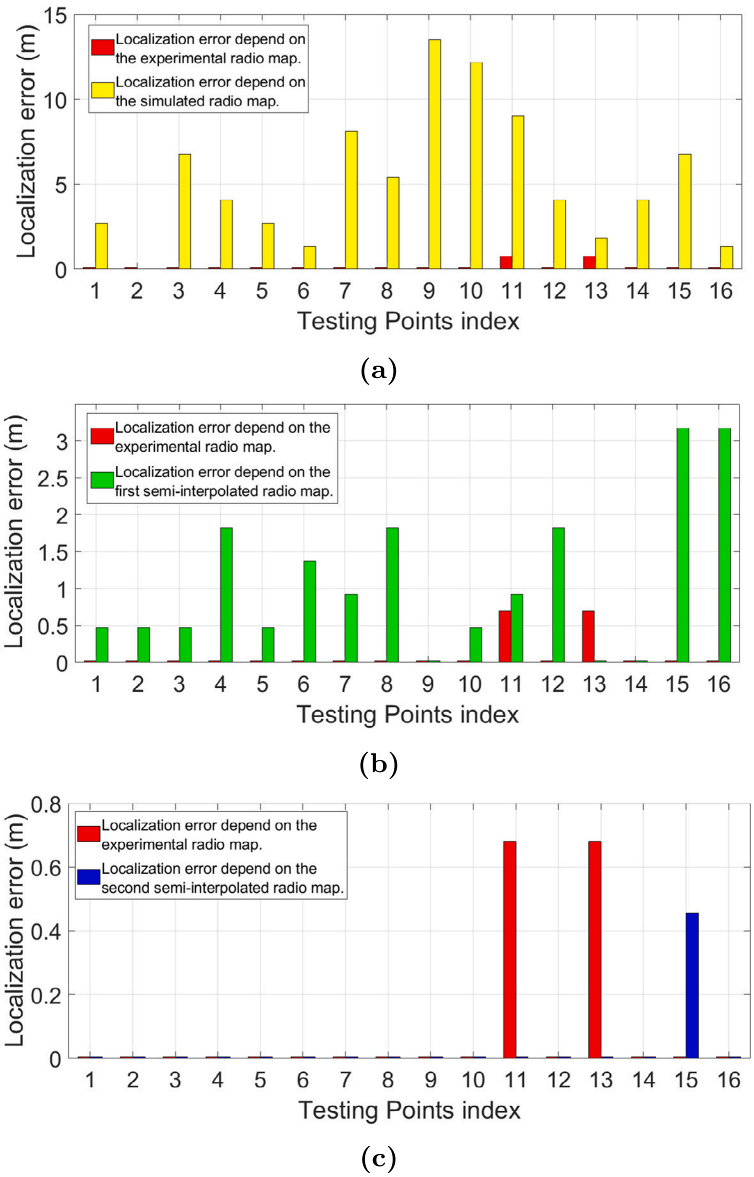


Fig. 10. Localization errors for the testing points obtained from the three generated radio maps: (a) experimental radio map vs. the simulated radio map, (b) experimental radio map vs. the first semi-interpolated radio map, (c) experimental radio vs. the second semi-interpolated radio map.

Lastly, it is worth noting that the BSI method optimized the accuracy of localization by utilizing an adequate number of actual Received Signal Strength Indicator (RSSI) measurements to form a dense radio map consisting of both the experimental and interpolated RSSI values. The map was then optimized through the BSI method to generate a more intricate radio map, balancing the reduction in complexity during the radio map generation process with the desired localization accuracy. In summary, Table 2 indicates that the BSI method outperformed the other two methods by achieving a tradeoff between the required time and effort with localization accuracy, as well as between the minimization of effort and the desired accuracy. Therefore, it is evident that the actual data collection process is a critical and efficient means to construct the initial radio map. Based on our understanding, this groundbreaking research successfully combined three distinct methods to develop indoor localization systems based on RSSI values.

A comparison with different methods used in the state-of-the-art studies was conducted to clarify the contribution of this study. Typically, linear interpolation methods were used in [40] to reduce the time needed for radio map creation. An advantage of this method was that there was no rounding error at the checkpoints. An increasing number of the used checkpoints led to mitigating the interpolation error value, which is not always true in other interpolation methods, such as polynomial interpolation. On the other hand, the BSI method used in this study found the smoothest surface passing through the data. Therefore, in the offline fingerprint phase, the BSI is a suitable method to construct a more dense database of RSSI fingerprints.

Table 2
Comparison of the indoor localization system depending on the three radio map generation methods.

Method	Time and effort	Localization accuracy
Experiment	High	Medium
BSI	Medium	High
Wireless InSite Simulator	Low	Low

Moving on, in [14], the missing values in the fingerprint map were reconstructed using two interpolation methods: the k-nearest neighbor (KNN) interpolation method and the inverse distance weight (IDW) interpolation. A comparison between the two methods was provided. In contrast, this study introduced three distinct radio maps and utilized two different methods to interpolate the missing values of the RSSI readings, ensuring accurate RSSI predicted values. The study provided a comprehensive analysis of an advanced interpolation method, resulting in more precise outcomes, and detailed comparisons for each case.

Compared to the aforementioned works, our proposed radio map generation system comprehensively addresses several issues, exhibiting superior performance in terms of localization accuracy, simplicity, and effort. Moreover, the methods we introduced have the potential to be employed in large-scale heterogeneous practical environments, functioning as a reliable and efficient database for indoor localization systems in future studies.

6. Conclusions

The BSI method was proposed as an improvement for indoor positioning systems by expanding an experimental radio map to generate a more dense map with increased numbers of reference points for efficient location estimation. Machine learning algorithms can be applied to further increase the size of the experiment environment and generalize the proposed model to multi-floor buildings. In this paper, three approaches were used to generate $RSSI$ radio maps for indoor localization: an experimental radio map generated by a mobile application, a simulated radio map generated by the Wireless InSite Simulator, and a semi-interpolated radio map generated by the biharmonic spline interpolation method. The results demonstrated the effectiveness of the proposed mobile application and the BSI method when a sufficient number of $RSSI$ values were used. Moreover, radio maps with larger sizes were proven to be more efficient for indoor positioning systems. The average localization accuracy was approximately 1.65 for 37% based on the fully simulated radio map and less than 0.45 m for the semi-interpolated radio map. A detailed comparison of the suggested methods confirmed the superiority of the semi-interpolated radio map using the BSI method with a sufficient number of reference points. In future work, the three generated radio maps can be used to apply indoor positioning systems using traditional localization methods.

Declaration of competing interest

There is no conflict of interest.

Data availability

Data will be made available on request.

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