IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 19 July 2023, accepted 8 August 2023, date of publication 15 August 2023, date of current version 23 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3305396

RESEARCH ARTICLE

An Experimental Comparison of RSSI-Based Indoor Localization Techniques Using ZigBee Technology

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This work was supported in part by the Shahid Chamran University of Ahvaz under Grant SCU.EE1401.82, and in part by the Al-Furat Al-Awsat Technical University under Grant Y.L./2P 26085.

ABSTRACT Wireless indoor localization is a significant challenge because of the noise generated by building structures, electromagnetic fields, and distances between connected nodes inside a building. This study compares two main localization methods: fingerprints (real and synthetic) and ranging schemes based on the Received Signal Strength Indicator (RSSI) of the ZigBee network. We followed four steps for the fingerprinting scheme. First, we obtained real data from the transceivers. Second, we computed the path-loss exponent for each device. Third, we produced a synthetic fingerprint dataset. Finally, we used three localization methods: k-nearest neighbor (KNN), multilayer perceptron (MLP), and long short-term memory recurrent neural network (LSTM-RNN). We assessed the performance of the localization methods by measuring their accuracy, precision, error-to-active area ratio, and installation difficulties. The results show that the real fingerprint scheme has the best performance, but it requires more installation time. While the synthetic fingerprint generation is based on the path-loss method that mixes the advantage of both fingerprint and path-loss. Furthermore, we compared the proposed estimated path-loss with that of a state-of-the-art method and demonstrated that the proposed method exhibits superior performance. These results suggest that the proposed method is more precise and suitable for real datasets.

INDEX TERMS Indoor localization, multilayer perceptron (MLS), K-nearest neighbor (KNN), path-loss exponent, RSSI fingerprints, received signal strength indicator (RSSI).

I. INTRODUCTION

The demand for location-based applications has increased significantly with the increase in the number of wirelessly connected devices [1]. Acquiring an accurate location, namely localization, is a central point in wide-scale applications such as smart homes [2], [3] industry [4], surveillance [5], [6], monitoring and control for energy saving in buildings [7], [8], tracking Alzheimer's patients [9], and elderly people fall detection alerts [10].

Localization estimates node-device coordinates (sensors, smartphones, or IoT devices). Generally, localization is divided into outdoor and indoor positioning. Outdoor positioning employs a Global Positioning System(GPS) as an optimum standard solution, which obtains an accurate position within 3.5 meters [11]. However, the GPS approach is inappropriate for indoor localization because of multipath losses, line-of-sight challenges, high costs, and high-power consumption [12].

However, indoor positioning usually demands localization of the nodes within centimeter [13], [14], with the availability of a line of sight, low cost, and low power consumption [15]. Therefore, researchers have focused on handling indoor localization using commercial communication technologies such as Bluetooth Low Energy (BLE) [16], ultrasound [17], infrared [18], RFID [19], WIFI [20], and Zigbee [21] to

The associate editor coordinating the review of this manuscript and approving it for publication was Lorenzo Mucchi.

satisfy the requirements referred to previously. Performing an indoor localization system requires at least three anchors and one movable device [22], [23].

According to network infrastructure, indoor localization techniques can be divided into range-free [24] and range-based [25] methods. In range-free localization, the corresponding distance between the nodes is estimated via hop counting. This method has been adopted in several studies. However, the range-based method is the most realistic cause for the nature of indoor environments. Range-based localization estimates the locations of nodes that initially have unknown positions in the network. It measures the variable characteristics of electromagnetic waves between unknown and reference or anchor nodes. Based on the variable characteristics (amplitude, time, and phase), several ranging schemes have been proposed, such as the Receiving Signal Strength Indicator (RSSI) [26], Time of Arrival (TOA) [27], Time Difference of Arrival (TDoA) [28], and Angle of Arrival (AoA) [29]. AoA can be accurately performed using an array of antennas and additional devices.

ToA and TDoA require accurate clock synchronization for successful performance. However, it requires complex methods to obtain these conditions for real-life applications.

However, RSSI does not require such conditions, where it measures the decay of the signal's power with respect to distance [30]. This approach is considered more suitable for measuring distance without use of additional devices. RSSI can be performed in range-based and map-based model localization (fingerprint-based). The former can estimate the distance between transmitter and receiver by measuring the attenuation of the transmitted signal with respect to the distance, which cannot be calculated correctly without prior knowledge of the exact path-loss model of indoor environment characteristics. These characteristics include noise, attenuation, distortion, fading, multipath loss, and interference. Therefore, range-based model localization systems exhibit significant localization errors. The fingerprint approach consists of two phases: offline and online. In the offline phase, a fingerprint map is constructed by dividing the area into small pieces with known coordinates, and the values of the RSSI are then captured from several access points (APs) in each coordinate to create a fingerprint. The number of fingerprints can be increased to obtain accurate localization. In the online phase, the real position of the node device is calculated using a dataset generated by the localization algorithm. The localization algorithm operates by converting the RSSI values to distance, where it suffers from path-loss impairments. Some studies have been done to overcome this problem, in [31] the authors propose averaging the time-bound collected fingerprint and applying three preprocessing method named instantaneous, averaging and weighted averaging to train cross-correlation algorithm with online data; where the maximum correlation results use to make prediction. Due to their quick learning capability, ease of use, and flexible modeling, machine learning algorithms have been proposed to estimate the position of targeted nodes, such as k-nearest neighbor (KNN) [32], recurrent neural network (RNN) [33], and multilayer perceptron (MLP) [34].

Motivated by the above challenges, we proposed map-based model localization (fingerprint-based) via MLP utilizing Zigbee CC2420.

Our experimental environment was a laboratory with a 5.7 m width and 8.2 m length, and the total area was 46.74 m^2, in which there were two tables and six chairs. The entire lab is divided into a grid with 111 pieces with dimensions of 0.6 m $\times$ 0.6 m; At the vertex of a grid, we take our fingerprint and the distance from nearest points to anchors was 0.63 m, while the distance from the wall to its nearest point was 0.45 m.

We first collected three RSSI at 111 fingerprints; The value of each RSSI was obtained by averaging over 500 reads sampled with 2 ms intervals. These datasets were collected for three different scenarios with different levels of interference. The interference depends on the number of transmitters and persons inside the lab.

In the first scenario, we installed three receivers as anchors to collect the dataset from one movable transmitter, and two persons were present in the testbench. In the second scenario, three anchor transmitters propagated their signal to one movable receiver, and four persons were presented in the testbench. In the third scenario, eleven transmitters were installed in the lab, but only three anchors were tuned with one movable receiver, and the number of persons was variable, two, three and eight persons. All the experiences were done in the morning. Section III-c has more details about our setup.

We also calculated the path-loss exponent for each transmitter. Then, we generated a new fingerprint based on the calculated path-loss exponent. We compared the performance of the proposed approach with that of the trilateration, KNN, and RNN methods in terms of accuracy and precision. For training the algorithm, our offline fingerprints are divided to 70% for training, 30% for testing and the 10 online test points are used for validation. According to the collected real dataset, MLP performed better than the other methods did. Our contributions are summarized as follows:

1) Collection of a unique dataset for our laboratory (SysNet lab).

We collect dataset in the entire of the SysNet lab considering three interference levels based of the signal existing in lab and the number of persons. The details of scenarios are presented as following: (*i*) first scenario, low interference, where has one movable transmitter and three anchors receiver with two persons presented in the lab; (*ii*) second scenario, medium interference, where we use three anchors transmitter and one movable receiver and four persons were presented in the lab, (*iii*) third scenario, high interference, eleven transmitters are presented in the lab but only three anchors of them are tuned with one movable receiver, and variable number of persons. To overcome the RSSI fluctuation problem, we take the average over 500 reads for each RSSI fingerprints.

2) Calculation of the path-loss expands for each anchor.

In the literature, the path-loss exponent was calculated for the technology globally, for example, the path-loss exponent for Wi-Fi in such an environment. In this work, we calculate the path-loss exponent for each device separately; because during the experience, we found that the devices in the same technology have different RSSI values. Furthermore, the method that we used to calculate the path-loss differs from the other studies.

3) Generation of new fingerprints corresponding to the path-loss calculated.

We observed that the fingerprinting process is intensive and takes more time than the path-loss method while collecting the fingerprints. Therefore, we suggested to generate synthetic fingerprint automatically using path-loss equation. The path-loss equation has five variables ($RSSI_d$, d, $RSSI_{dr}$, dr and n). We set the path-loss exponent (n), reference point distance(dr) and $RSSI_{dr}$, then we generated the $RSSI_d$ for different distances.

4) Extensive experiments with averaged readings were performed to accurately calculate the RSSI from each anchor.

Since the RSSI has high fluctuation and suffers from any variation in the environment, we take the average over 500 reads sampled with 2 ms intervals.

5) Propose a new deterministic metric to calculate the error in the active area.

Unlike outdoors, the volume and the size are different from one building to another in the indoor, and the existing evaluation metrics such as RMSE and variance do not consider the testbench extent; for this reason, we propose a new metric that considers the area of interest called Error to Active Area (E/A) ratio in percent. In this metric calculation, we divide the sum of the RMSE by the sum of the distance between test points and anchors. The desired value of this metric is zero percent. Section IV-A. contains more details about this metric.

II. RELATED WORK

Accuracy, precision, complexity, and installation time are important factors in building an indoor localization system, and they are directly related to the location estimation technique. In the literature, the two techniques for the RSSI-based method include range-based and fingerprinting schemes [35]. In this study, we divide the discussion of the previous methods into fingerprinting, range-based, and synthetic fingerprinting approaches. In fingerprinting localization, the environment is divided into small areas. The RSSI from three or more anchors are collected for each small area to create a database containing the RSSIs and corresponding locations [36]. This method is not affected by the anchor's coordinates or environmental characteristics, as long as they do not change after database generation.

Usually, pattern recognition or clustering algorithms are applied to estimate the target location to find the dataset fingerprint closest to the target RSSI [37]. Sadowski et al. [38] proposed that fingerprint-based indoor localization relies on Wi-Fi, BLE, and ZigBee. They compared three well-known localization algorithms, namely KNN, Naive Bayes, and trilateration. Three experimental scenarios were tested: low, medium, and high interference. Regarding the technologies, the authors declare that "the system calculation is not affected significantly by the wireless technology utilized". Regarding the algorithm, the best performance was achieved with KNN followed by Naive Bayes, and the trilateration appears to have the worst overall performance.

Uradzinski et al. proposed the Zigbee Wireless Technology to perform indoor localization based on RSSI fingerprinting [39]. The authors filtered out the interference from the fingerprint database to improve the localization accuracy. To estimate position, they tested three localization algorithms: KNN, weighted KNN, and Bayesian. The results show that the filtered fingerprints outperform natural fingerprints.

V. Bianchi et al. [2] proposed the ZigBee model to perform indoor localization based on the fingerprint method. The authors propose room-level localization with a threshold algorithm and estimate the location of device that has interacted with already installed house devices. If there were more than one person in the environment, the localization estimation gives priority to the more interactive device. The testbench was two rooms and one corridor, the rooms' sizes were equal to 40 m2. In rooms, A and B, 25 fingerprints were gathered, while in the corridor five fingerprints were collected. The authors measure the accuracy of the system by the ratio of the tested point located in the correct testbench; they obtained results with 98% sensitivity and 96% specificity.

Three or more known location anchors are required for range-based localization. The distance between the target and anchors was estimated using a radio path-loss model with the RSSI measured between the target and anchors. Trilateration is a widespread algorithm used to determine the location of target nodes [25]. Earlier studies have primarily attempted to reduce localization errors. The following two references adopt Zigbee technology, RSSI, and trilateration. Reference [40] perform a positioning system for surveillance in a mental health hospital. Owing to its low power, wide range, and high accuracy, the Zigbee model was treated as an optimum solution for this task.

Reference [41] determined the influence of the multipath problem on the indoor and outdoor localization accuracy. The accuracy was below one meter outdoors, while the indoors were highly diverse, with significant fluctuations in the RSSI readings owing to multipath effects.

A. Booranawong et al. [21] used four ZigBee reference nodes to perform RSSI based indoor localization with multilateration algorithm. The accuracy of multilateration method is improved by take the boundary into consideration as well as selection the zone and estimation of the position. Two zones have been tested in this work a 4 m × 4 m lab room and a 22 m × 9.3 m corridor. Theirs estimation errors were 0.682 m for the lab room and 1.776 m for the corridor.

A. Booranawong et al. [42] used the ZigBee module to compare min-max and trilateration methods in the indoor environment. They studied the human presence in two cases with and without human movement. The authors declare that both methods have equal performance in the absent of human movement, while the min-max method perform better for the case of human movement. Also, they propose filtering the RSSI to reduce the variation. After applying the filter, the localization error decreases and the trilateration performs better. Their testbench was a faculty parking with 3.6 m × 6.2 m dimension.

Although the fingerprint method is highly accurate, it is time-consuming and requires challenging installation. Therefore, some studies have proposed generating fingerprints depending on the path-loss equation, and then applying machine learning models to estimate the location to obtain good accuracy and address the problem of installation time and labor. In [43], an enhanced fingerprint-based localization method was suggested to use a path-loss model for fingerprint creation and positioning. The authors proposed a WLAN path-loss model for fingerprint generation with two schemes: dual-scanned fingerprint localization (DFL) and path-loss-based fingerprint localization (PFL). The PFL was more precise than the standard fingerprinting method; however, some tested points were outside the test bench boundary, making the system unreliable. To overcome the unreliable problem, they proposed a DFL that can be realized in two steps to scan first, using the ordinary path-loss equation model, and the second with PFL. The proposed value of the path-loss exponent was fixed at 4, and the associated standard deviation was 5dB. The results show that DFL outperforms the overall results. In [44], the authors proposed a semi-simulated method using Wi-Fi technology to evaluate the cosine similarity of directions to different APs to increase the number of fingerprints inside the test bench environment by generating dense fingerprints from actual spatial RSSI data. The experimental results indicated that the semi-simulated method performed closely to the actual fingerprints. Usually, the performance criteria of any localization system can be summarized as accurate location, low complexity, and rapid installation. As such, the fingerprinting method suffers from a rigid environment, where any change in the obstacle layout and number of connected nodes leads to the regeneration of the dataset. The range-based method suffers from the RSSI fluctuation with time and the not exact path-loss exponent calculation, making the system inaccurate. In this study, we make a trade-off among the above suggestions. Fingerprints were collected from each specific point in the laboratory room to create a real fingerprint dataset and test points, followed by comparing three unsupervised machine learning methods (KNN, MLP, and RNN). Based on the real dataset, we calculated the path-loss exponent for each anchor by assuming that the nearest fingerprint of each anchor is a reference point with high power, and the farthest fingerprint has the lowest power. Moreover, we generated synthetic datasets from the path-loss exponent calculated in the last step. Finally, we compared the real dataset, synthetic dataset, and trilateration in terms of accuracy and precision.

III. METHODOLOGY

The localization process divides into two kinds [45]:

•**Device-based localization:** The target uses anchor node information to find its location, and the primary use of this type of localization is navigation.

•**Monitor-based localization:** The target sends position information to a set of anchor nodes. This type of system is primarily used for user tracking.

Each localization system requires four devices to perform positioning or tracking operations for all methods applied in this study. These devices can be either three transmitters and one receiver group, in this case, the target finds its location for navigation, and it can send the information to an external center fusion for tracking, or these four devices could be three receivers and one transmitter, in which case the receivers send the location information to an external center fusion for monitoring, and can also send the information to the target for navigation.

A. EXPERIMENT ENVIRONMENT

All experiments were effectuated inside the SysNet lab (single room) at the Shahid Chamran University of Ahvaz as illustrated in Figure 1b., the lab's width and length are 5.7 m and 8.2 m, respectively, and the total area is 46.74 m^2. We divided the lab area into a grid of 9 columns and 13 rows, where each column-row intersection is a specific fingerprint (denoted as O_i, i = 1, 2, 3, ….., 111). Note that six fingerprints were neglected because of the slope in one of the corners of the laboratory (depicted with a black triangle in Figure 1a.).

For each fingerprint (O_i), we obtained three $RSSI_{i,j}$ from three transceivers TR_j (i.e., j = 1, 2, 3) located on a dedicated corner in the lab. The setting is shown in Figure 1a.

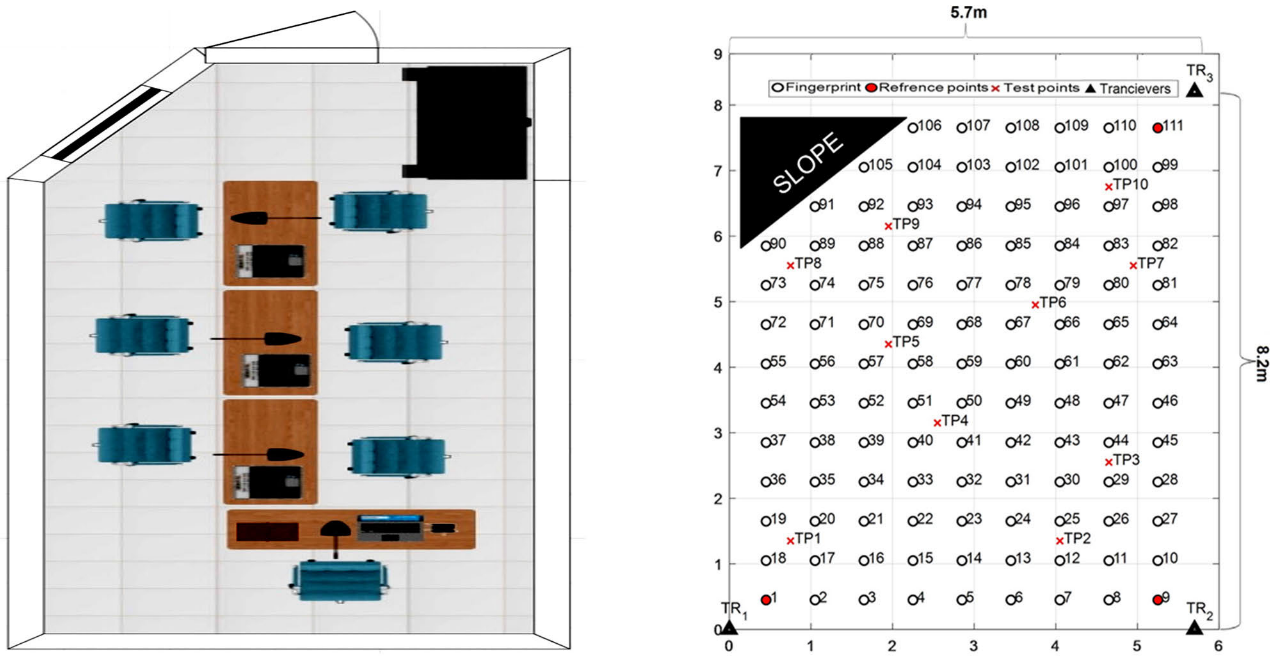
The lab has random Wi-Fi signals acting as attenuation sources that affect the calculated RSSI. Each detected RSSI value around a specific fingerprint varies. As such, we estimated the mean value from the R reads for $RSSI_{i,j}$ as follows:

$$RSSI_{i,j} = \frac{\sum_{k=1}^{R} RSSI_k}{R} \tag{1}$$

where k = 1, 2, 3, …., R, and R = 500. We randomly measured the signal strength in x Test Points (TP) (x =1, 2, …., 10), and marked these points with a red cross sign (x) in Figure 1a.

B. EXPERIMENTAL SCENARIOS

In this section, we explain the details of the experimental scenarios and compare them with state-of-the-art methods. The interference is depending on the number of transmitters and the number of persons presented inside the testbench.



(a) (b)

FIGURE 1. Experimental environment: (a) Actual and (b) General fingerprint representation.

1) FIRST SCENARIO

In this scenario, the environment has low interference, and we installed three receivers as an anchor and one movable transmitter. The movable transmitter propagates a signal at each fingerprint, and the three anchor receivers collect the RSSI. The collected RSSI at each anchor is the mean of the R reads. In addition, two persons have been presented in the environment.

2) SECOND SCENARIO

In this scenario, the environment has medium interference, and we utilized three transmitters as an anchor and one movable node device as a receiver at a time.

Three RSSI were collected for each fingerprint. In addition, four persons were presented in environment two of them are sit and two other moves around.

3) THIRD SCENARIO

In this scenario, the environment has high interference, where we utilized ten devices as transmitters and one node device as a receiver. Three of these ten transmitters were tuned to match the receiver frequency, and the remaining seven were considered noise sources. We collected three RSSI from the anchor points, and considered each fingerprint.

We measured the RSSI at each anchor point for all the fingerprints and test points. In this scenario, the number of persons were variable some time two, three and eight.

C. PROPOSED METHOD

This section presents the proposed framework, dataset generation, and experimental environment. The block diagram in Figure 2. describes the methods presented in this study.

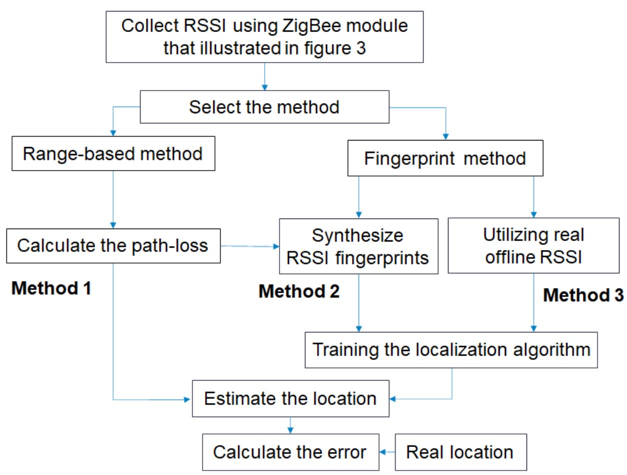


FIGURE 2. Proposed methods.

1) FINGERPRINT METHOD

Localization using a fingerprinting technique requires offline and online phases, which consist of three steps: (*i*) dividing the environment into 111 small pieces with dimensions of 0.6 m × 0.6 m; we take our fingerprint at the vertex of a grid, and the distance for nearest points to anchors was 0.63 m and the distance from the wall to its nearest point was 0.45 m. We sampled the RSSI 500 times with a 2 ms interval. (*ii*) reading the RSSI detected from each anchor at one point of each specific transceiver and (iii) creating a database containing each point's coordinates and three RSSI values. All the experiences were done in the morning. Each point in the database can be identified by either geographic coordinates or RSSI value in the online phase, and the RSSI values of the unknown position are compared with the dataset using an algorithm to find the most likely matched RSSI values. In localization systems, fingerprinting techniques are highly accurate RSSI-based methods. However, mapping an environment may require a lot of time and effort [45]. Multipath effects, reflections, and obstacles significantly affect the RSSI values. The database must be regenerated if the environment undergoes any change. Algorithms used with fingerprinting to perform indoor localization include the MLP [34], KNN [34], [46], [47], and Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) [33]. To train the algorithms, the dataset is divided to 70% around 78 fingerprints for training, 30% around 33 fingerprints for testing, and ten online test points for validation.

The MLP that achieved the best performance in this work for all scenarios with a real dataset has an input layer with three neurons, one hidden layer, four neurons, an output layer with two neurons, and a tangent sigmoid activation function. The optimum LSTM-RNN chosen for this work consists of four layers: three neuron sequence input layers, one LSTM with 20 neuron layers, a fully connected layer with two neurons, and regression output. The most appropriate KNN that achieved the best performance overall utilized in this study was the four nearest neighbors and Euclidean distance calculation.

2) RSSI RANGE-BASED METHOD

The RSSI range-based approach is based on distance estimates. Signal strength measurements at the receiver and reference points (anchor or a point close to the anchor) were used to compute the distance between the transmitter and receiver. Subsequently, the path-loss equation was applied for the distance calculation. As the distance between the transmitter and receiver increased, the power of the signal strength decreased. Once the distance between the anchors and target is calculated, a localization algorithm must be used to determine the position of the target. Localization is not performed unless the position of the anchors is known. Owing to the former procedure, the RSSI-based method can be considered simpler than the fingerprinting method. Lateration is a localization algorithm widely adopted in the literature. The name of this technique is changed based on the number of anchors used. Typically, it operates with at least three anchors; in this case, it is called trilateration [25], [48], [49].When more than three anchors are used, this is called multi-lateration [21], [50], [51]. In this study, trilateration was adopted.

D. PATH-LOSS EXPONENT CALCULATION

The path-loss exponent is a crucial part of the path-loss equation, which is associated with the range-based method for estimating the position of wireless devices. Here, the path-loss exponent is calculated by measuring the RSSI at two points inside the test bench for each transceiver, the nearest

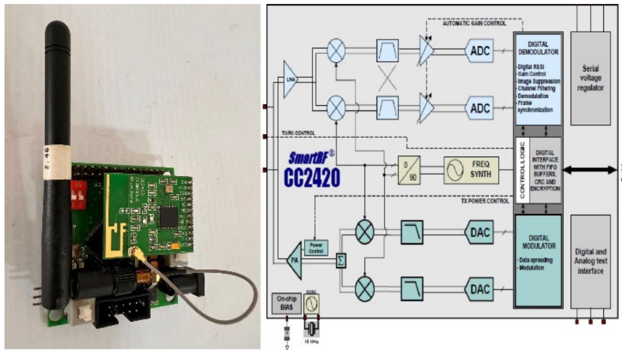


FIGURE 3. ZigBee module.

point to the transceiver $RSSI_{max}$ and the furthest point from the transceiver $RSSI_{min}$, and substituting these real values in the path-loss equation to extract the path-loss exponent. In our setup, we measure the RSSI from RF pins of CC2420 chip which has RSSI built-in register with value of $RSSI_{VAL}$ [52]. The RSS at RF pins is determined as follows:

$$RSS = RSSI_{VAL} + RSSI_{OFFSET} \tag{2}$$

where experimental value of $RSSI_{OFFSET}$ is approximately −45 dBm. The RSSI has proportional relation with power, and as the distance increases, the power decreases. Thus, the path-loss exponent, n, can be computed by substituting $RSSI_{max}$ and $RSSI_{min}$ in the path-loss equation developed in [21]:

$$RSSI_{min} = RSSI_{max} - 10.n.log_{10}\left(\frac{d_{max}}{d_{min}}\right) \tag{3}$$

or

$$n = \frac{RSSI_{max} - RSSI_{min}}{10.log_{10}\left(\frac{d_{max}}{d_{min}}\right)} \tag{4}$$

where, the $RSSI_{min}$ obtained at distance d_{max}. and $RSSI_{max}$ measured at a reference distance d_{min}. We repeat the path-loss exponent calculation for each access point, because we noted that practically the RSSI is different for each access point so the path-loss exponent will also be different.

E. DATASET GENERATION

The datasets utilized in this study were classified as real and synthetic datasets. The dataset generally consists of five values, including a fixed coordinate for each fingerprint $O(x_i, y_i)$ and $RSSI_{i,j}$. The real dataset is obtained directly from each fingerprint (O_i) for each TR_j. Because the coordinate of each fingerprint is fixed for both real and synthetic datasets, we calculated the distance between $O_{i,j}$ to synthesize a new dataset concerning the nearest fingerprint for each TR_j, namely the reference fingerprint Or, where (r = 1, 9, 111). The equation 3 can be represented as follows [42]:

$$RSSI_{i,j} = RSSI_{r,j} - 10.n.log_{10}\left(\frac{d_{i,j}}{d_{r,j}}\right) \tag{5}$$

where $RSSI_{r,j}$ is the measured signal at Or, n is the path-loss exponent that calculated previously for each link, $d_{i,j}$ is the distance between Oi,j and TRj, and, $d_{r,j}$ is the distance between Or,j and TRj. In the literature, $d_{r,j}$ usually equals one. However, to ensure the accuracy in the preparation of our dataset measurement, we selected the nearest O_r (e.g., 1, 9, 111) as the actual distance (0.63 m).

F. ZIGBEE MODULE

This section presents a general overview of the ZigBee Module used in this study. The ZigBee technology allows users to create mesh networks with proper specifications, including efficient power and low cost. The ZigBee communication protocol employs the IEEE 802.15.4 standard to build a personal area network with a small-sized antenna [53]. We used a CC2420 transceiver-wired antenna to build a ZigBee network, as shown in Figure 3.

On the left, the hardware module and on the right, the schematic presented in [54].

The CC2420 module developed by Chipcon [52] can measure the received signal strength via the RSSI parameter indicator, which can be used in our experiment. The CC2420 uses frequency shift keying modulation to send information, and on its physical layer can use the ZigBee protocol version 1 or IEEE 802.15.4 as the MAC layer [55]. This module sends and receives data using the 2.4 GHz frequency band with a transfer rate of 250 kbps. Other features of CC2420 that make it efficient include low cost, high performance, high data transfer speed, multi-channel communication capability, communication via the SPI protocol with the processor, and low power consumption [54].

IV. EXPERIMENT RESULT AND DISCUSSION

A. EXPERIMENTAL RESULTS

This section presents the experimental results. The performance of the measuring system is evaluated in terms of the root mean square of the distance error for all test points (RMSE) [56], variance of error (σ2) [57], and cumulative distribution function (CDF) [58].

Because the indoor environments change in form, area, and allocation of each anchor, we propose a new metric, namely the Error to Active area ratio (E/A), which estimates the mean error of all the involved TP in the area of interest, and can be calculated as follows:

$$\frac{E}{A} = \frac{1}{TP}\sum_{x=1}^{TP}\frac{RMSE_x}{d_{(TR_1+TR_2+TR_3)_x}} * 100\% \tag{6}$$

where $d_{(TR1+TR2+TR3)}$ is the sum of the distances from each transceiver to each test point. Therefore, we considered the entire active area in the error calculations. In the fingerprints tested in this work, as shown in Table 1, there are two types of datasets for training the proposed algorithms: the real dataset collected from the test bench directly, which will be called real fingerprints, and a synthetic dataset built based on the path-loss equation called synthetic dataset.

According to this classification, the algorithms trained with the real dataset will be named (MLP-real, KNN-real, and RNN-real) while the algorithms trained with synthetic dataset will be named (MLP-syn, KNN-syn, and RNN-syn) Figure 4. shows the cumulative errors of the techniques used for each scenario. In contrast, Table 1 summarizes the system behavior for all scenarios and techniques. The CDF results show that the MLP-real has the best overall performance scenarios compared with the other techniques because it reaches 100% at the shortest distance for all test points. Figure 4a. shows the CDF for the first scenario. In this figure, for the entire time response, the first best method is MLP-real with 1.7m error, the second is KNN-real with 2m, the third is RNN-syn with 2.3m, the fourth is RNN-real with 2.6m, the fifth is KNN-syn with 3.5m, the sixth is MLP-syn with 4.7m and the seventh is Trilateration with 5.1m. At the same time, KNN-real appears to have the best performance in 90% of the time with a 1.5m error, followed by MLP-real with a 1.6m error, and RNN-syn with a 2.25m error. The RNN-real comes in the fourth position with a 2.5m error. The MLP-syn had a 3.1m error, followed by KNN-syn with a 3.25m error, and finally the Trilateration had a 4.6m error. Figure 4b. shows the CDF for the second scenario. In full time, the KNN-real and MLP-real share the best accuracy of the other algorithm with 2.5m error followed by RNN-real with 2.6m error, not far from it, RNN-syn with 2.7m error, followed by KNN-syn with 3.5m error. MLP-real had a 5.2m error. At the same time, trilateration has the worst performance with a 6.5m error. Regarding 90% of the time, KNN-real is the best with a 2m error. Not far from this, MLP-real and RNN-syn share the position with a 2.2m error, pursued by RNN-real with a 2.5m error. KNN-syn and Trilateration share the last position with a 3m error. The CDF for the third scenario is shown in Figure 4c. In 100% of time, the MLP-real appears with the lowest error of 2.2m, while KNN-real and RNN-real share the second position with 2.5m error, followed by RNN- syn with 3.1m error, not far from it, MLP-syn with 3.2m error, KNN-syn obtained the fifth position with 3.5m error and in the last position is the Trilateration with 5.1m error. The 90% of time of this scenario is arranged according to the error as follows RNN-real with 1.7m, MLP-real 1.9m, KNN- syn with 2m, KNN-real and RNN-syn with 2.2m, MLP-syn with 3.1m, and in the last Trilateration with 3.5m. Table 1 shows the RMSE, variance, and E/A ratio for all scenarios and techniques used in this work. From the experimental results, MLP-real produced the best overall performance. The estimate computed using KNN-real contrasted the actual receiver by 1.2732m with a calculated variance of 0.6177m, and E/A was 8.19% for all scenarios. Concerning the training dataset, MLP had the best accuracy for each scenario when the real dataset was used for training. Simultaneously, the RNN achieved the best performance when trained with the synthetic dataset for the first and second scenarios. Simultaneously, KNN was the best in the third scenario. Concerning each scenario, in the first scenario, the best performance was achieved by MLP-real, which had an RMSE value of 0.9280m with a variance of

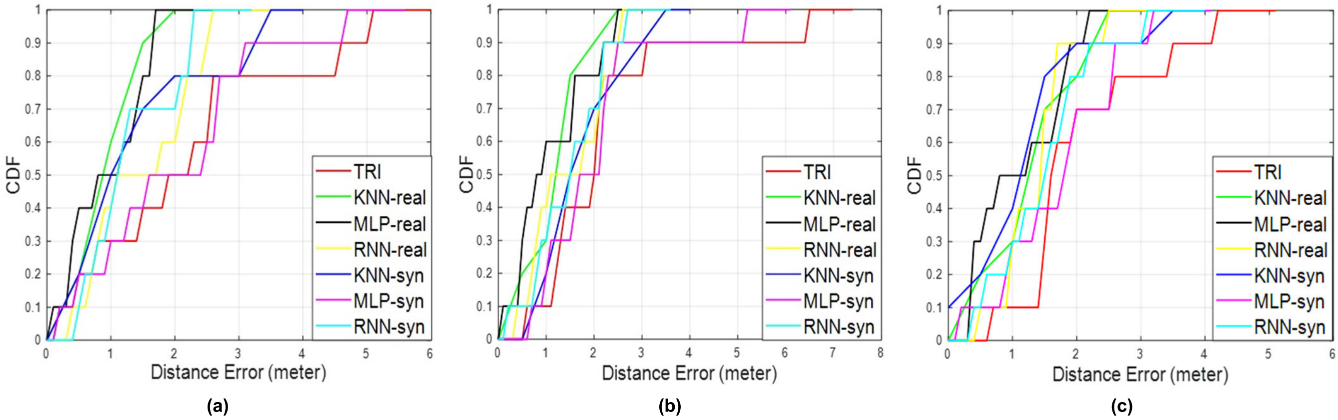


FIGURE 4. CDF response: (a) First scenario, (b) Second scenario and (c) Third scenario.

TABLE 1. Accuracy and precision of each scenario.

	KNN			MLP			LSTM-RNN		
	RMSE	$\sigma 2$	E/A (%)	RMSE	$\sigma 2$	E/A (%)	RMSE	$\sigma 2$	E/A (%)
Fingerprint method algorithm trained with real dataset									
1^{st} Scenario	0.9525	0.1970	6.13	**0.9280**	0.3741	5.97	1.4606	0.6794	9.39
2^{nd} Scenario	1.1497	0.3187	7.39	**1.0982**	0.6246	7.06	1.3553	0.7640	8.71
3^{rd} Scenario	1.2265	0.4731	8.42	**1.0990**	0.5191	7.07	1.3470	0.3186	8.67
Average	1.1096	0.3296	7.31	**1.0417**	0.5059	6.69	1.3876	0.5873	8.92
Fingerprint method algorithm trained with synthetic dataset									
1^{st} Scenario	1.3310	1.0816	8.6	1.9843	1.8332	12.76	**1.2639**	0.4719	8.13
2^{nd} Scenario	1.6698	0.7746	10.73	1.9955	1.5456	12.83	**1.4579**	0.6075	9.37
3^{rd} Scenario	**1.3100**	0.8611	7.89	1.7121	0.8308	11.01	1.4791	0.6031	9.51
Average	1.4369	0.9058	9.07	1.8973	1.4032	12.20	**1.4003**	0.5608	9.00
Path-loss method – Trilateration									
scenarios	1^{st} Scenario			2^{nd} Scenario			3^{rd} Scenario		
metrics	RMSE	$\sigma 2$	E/A (%)	RMSE	$\sigma 2$	E/A (%)	RMSE	$\sigma 2$	E/A (%)
value	2.1557	2.6544	13.86	2.1957	2.7006	14.12	**2.0351**	1.1051	13.09

0.3741m and E/A of 5.97%. The second-best algorithm is KNN-real. It achieved an RMSE of 0.9525m, a variance of 0.1970m, and an E/A of 6.13%. The third-best algorithm is RNN-syn. It achieved an RMSE of 1.2639m, a variance of 0.4719m, and an E/A of 8.13%. The fourth-best algorithm is KNN-syn with 1.3319m of RMSE, 1.0826m of variance, and 8.6% of E/A. The fifth-best algorithm was RNN-real with 1.4606m of RMSE, 0.6794m of variance, and 9.39% of E/A. The sixth-best algorithm was MLP-syn with 1.9843m of RMSE, 1.8332m of variance, and 12.76% of E/A. The algorithm with the worst performance was Trilateration with 2.1557m of RMSE, 2.6544m of variance, and 13.86% of E/A. In the second scenario, MLP-real had the best algorithm with RMSE of 1.0982m with a variance of 0.6246m, and E/A equal to 7.06%, followed by KNN-real, with 1.1497m of RMSE, 0.3187m of variance and E/A of 7.39%, next to RNN-real with 1.3553m of RMSE, 0.764m of variance and E/A of 8.71%. Consequently, RNN-syn with 1.4579m, 0.6075m of variance, and an E/A of 9.37 %. Subsequently, KNN-syn with 1.6698m, 0.7746m of variance, and E/A of 10.73%. The MLP-syn with 1.9955m, 1.5456m of variance, and E/A of 12.83%. The last is Trilateration with 2.1957m of RMSE, 2.6544m of variance, and E/A of 13.86%. In the third scenario, the first position of accuracy was MLP-real. It's RMSE was 1.0990m, with a variance of 0.5191m and an E/A of 7.07%. The algorithm in the second position was KNN-real, with an RMSE of 1.2265m, variance of 0.4731m, and E/A of 8.42%. The algorithm in the third position was KNN-syn; its RMSE was 1.31m, it had variance of 0.8611m, and its E/A was 7.89%. The algorithm in the fourth position was RNN-real; its RMSE was 1.347m, its variance was 0.3186m, and its E/A was 8.67%. The algorithm in the fifth position was RNN-syn, its RMSE was 1.4791m, its variance was 0.6031m, and its E/A was 9.51%. The algorithm in the sixth position was MLP-syn, its RMSE was 1.7121m, its variance was 0.8308m, and its E/A was 11.01%. The algorithm in the last position

TABLE 2. Classification of algorithm according the nearest estimation for first scenario.

	E(m²) <=1m	E(m²) <=1.5m	E(m²) <=2m	E(m²) >2m	E(m²) High
MLP-real	8	2	0	0	0
KNN-real	7	3	0	0	0
KNN-syn	6	0	2	2	0
RNN-real	5	3	2	0	0
RNN-syn	5	3	1	1	0
MLP-syn	3	2	1	3	1
trilateration	3	2	1	2	2

TABLE 3. Classification of algorithm according the nearest estimation for second scenario.

	E(m²) <=1m	E(m²) <=1.5m	E(m²) <=2m	E(m²) >2m	E(m²) high
MLP-real	6	2	1	1	0
KNN-real	5	4	1	0	0
KNN-syn	4	1	3	2	0
RNN-syn	4	2	3	1	0
RNN-real	3	5	1	1	0
trilateration	2	1	4	2	1
MLP-syn	2	1	3	3	1

TABLE 4. Classification of algorithm according the nearest estimation for third scenario.

	E(m²) <=1m	E(m²) <=1.5m	E(m²) <=2m	E(m²) >2m	E(m²) high
KNN-syn	6	2	1	1	0
MLP-real	5	3	1	1	0
RNN-syn	4	4	0	2	0
RNN-real	4	2	3	1	0
KNN-real	3	6	0	1	0
MLP-syn	3	4	0	3	0
trilateration	1	5	1	2	1

TABLE 5. Utilization reference dataset.

Method	Wi-Fi		ZigBee		BLE	
	RMSE	σ2	RMSE	σ2	RMSE	σ2
Curve fitting	2.3529	0.4536	3.5016	7.1631	2.2734	4.1409
min-max	2.1467	2.5633	1.8481	0.7021	1.5435	0.3932

TABLE 6. Utilization our dataset.

Method	Scenario 1		Scenario 2		Scenario 3	
	RMSE	σ2	RMSE	σ2	RMSE	σ2
Curve fitting	2.5518	2.7637	12.3211	60.5897	12.1343	18.262
min-max	2.1557	2.6544	2.1957	2.7006	2.0351	1.1051

was Trilateration; its RMSE was 2.1288m, its variance was 2.1534m, and its E/A was 13.69%. For better presenting the results, we classify the algorithms depending on the number of estimated points nearest to ground truth points. Five cases are taken into consideration in the classification including the number of points that lie in an area less than one square meter in both coordinates, the number of areas that lie in less than 1.5 square meters, the number of estimated points that lie far from ground truth by two square meters or less and the number of estimated points that lie in more than two meters finally the number of points that lie out of testbench. Tables 2, 3, and 4 classify the localization algorithm for the first, second, and third scenarios, respectively.

B. DISCUSSION

As demonstrated by the experimental results, when comparing various indoor localization algorithms in specific environments, the algorithms trained using the real dataset had the lowest RMSE and variance. It is essential to mention that low RMSE and variance imply high accuracy and precision, respectively. MLP was the best overall for the three scenarios tested. The results are expected because fingerprinting techniques can compute the location of the device based on the real RSSI collected directly from the test bench. Despite the high accuracy of the real fingerprint method, it suffers from limitations, such as installation costs. The estimated RSSIs must exist inside the training dataset, and the change in the number of anchors or environment must recreate the dataset and retrain the algorithms. By contrast, trilateration did not suffer from such limitations. It can estimate any possible location by knowing the transceiver's position and the environment path-loss; however, it has poor accuracy and precision. The dataset generation method exhibited moderate accuracy. Its installation is as easy as trilateration and needs to know the coordinates of the anchor and create a dataset for training the algorithms. However, all of these issues are more straightforward than the laborious process of fingerprint installation time and improvement in accuracy. Table 2, 3 and 4 classify the localization algorithm according to the nearest distance to the ground truth test point. Table 2 illustrates the classification of algorithm of first scenario. In this table we remark that the best algorithm in this scenario was MLP that trained by real dataset; it can estimate 8 points in 1 m^2 around the ground truth and two point less than 1.5 m^2 which mean that algorithm can estimate 80% of point in less than on meter distance while KNN is has 70% of its estimation in less than one meter of estimation.

In table 2, we remark that the trilateration and MLP-syn have some points outside the boundary of the test bench and near each other, which does not produce an accurate estimation, and the MLP has detected the path-loss equation.

Regarding the algorithm used with the fingerprint method, The MLP and RNN algorithms generate a fixed infrastructure after training to operate on specific data. Using this method with other data is impossible, as it produces a non-flex system. Simultaneously, the KNN retrained itself with every run, passing through the data and computing the Euclidean distance between the test point coordinates and all points in the dataset, and the lowest k point distances averaged to estimate the test point location. One of the advantages of KNN is that it is easy to add and remove anchors and change the environment, whereas increasing the number of fingerprints and anchors requires more computation time for every run of the KNN algorithm.

C. COMPARING THE PATH-LOSS EXPONENT CALCULATION METHODS

The path-loss exponent is a substantial part of the path-loss equation. The performance of localization by lateration improves with a more exact value of the path-loss exponent. This section compares the proposed method explained above and the curve fitting method presented in [46], [47], [59], which calculates the path-loss exponent for the environment depending on a fixed distance and reads the RSSI at some points to draw a curve used to extract the path-loss exponent. We compared our results with the curve fitting method explained in [60]. In brief, the authors of [60] placed the transmitter and receiver separated by 5 meters. To apply the logarithmic fitting method, they divided the 5 meters into two parts. Part A is one meter divided into nine points separated by 0.1 meters. Part B is four meters divided into eight points separated linearly by 0.5 meters. Subsequently, the data is collected and a curve fitting technique is used to extract the approximate value of the path-loss model variables.

The comparison was made in terms of accuracy and precision in two steps: (i) applying the two methods to scenario one from the dataset presented in [61] and also used in [38]. This dataset has utilized three technologies Wi-Fi, BLE and ZigBee. As illustrated in Table 5; and (ii) applying the two methods to our dataset, as shown in Table 6.

As illustrated in the Table 5 and 6, the proposed method of calculating the path-loss exponent using two reference points and the path-loss for each link outperforms the curve-fitting method. Remarkably, it is possible to calculate the path-loss for the environment for a technology that consumes high power (Wi-Fi) because it appears near the accuracy of our method. According to the results, the first scenario in our dataset appears to have acceptable accuracy when using the curve fitting method.

V. CONCLUSION

This study examines four This study examines four localization techniques, KNN, MLP, LSTM-RNN, and trilateration, to perform indoor localization tasks. The criteria for comparing these techniques are accuracy, precision, and distance error-to-coverage area ratio. In the first step, we collected real fingerprints from the site of interest to perform an indoor localization system based on the mapping method. In the second step, to overcome the problems of installation time and labor of the fingerprint method, we generate fingerprints using the path-loss equation. A single laboratory room with three interference levels was used to conduct the experiments.

The best results were obtained using real fingerprints, synthetic fingerprints, and ranging methods. The real fingerprint method was best than the other method due to the data collected in the actual environment and compared with the real test point by consequence it will be the best. The synthetic fingerprint is based on the path-loss exponent of each link but the algorithm compares online RSSI with the offline 111 pre-saved fingerprints.

Concerning the localization algorithms, the results demonstrated that the accuracy obtained from best to worse was MLP (single hidden layer and four neurons and tangent sigmoid activation function), KNN(k=4), RNN-LSTM (with twenty hidden neurons), and trilateration, respectively. The MLP has a nonlinear (activation function) part in each neuron which can detect the mathematical model of the indoor environment best than the KNN which contains only the linear Euclidean mathematical model that can perform better with synthetic data. For the LSTM, this kind of algorithm considers sequential data which appeared not very useful with the RSSI-based system. The trilateration calculates only one time with the path-loss equation that affects highly by the environment. The experimental results provided an indicator for selecting a suitable indoor localization system.

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