Fingerprint-based indoor positioning system using BLE: real deployment study

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ABSTRACT

There are a myriad of applications where the localization of interior surroundings is vital in the era of smart cities Bluetooth low energy (BLE) technology is designed for short-range wireless communication, low energy consumption, low cost hardware design and simple deployment with respect to other technologies. This paper presents a low cost BLE fingerprint-based indoor positioning system, where a minimum number of Beacons are deployed in different test bed subareas with different conditions. Collected measured received signal strength indicator (RSSI) signals received from all beacons in each grid cell of all areas of interest are stored. We experimented two deterministic matching algorithms: k-nearest neighbors (KNN) and weighted algorithm (WKNN), to match previously collected RSSI readings with the RSSI at mobile unknown location, to determine where the user is. Experiments results show that WKNN algorithm manages to obtain less mean and standard deviation positioning error for all subareas, that experiencing different conditions of obstructions, reflections, and interferences.

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1. INTRODUCTION

There is a myriad of applications where the localization of interior surroundings is vital in the era of smart cities. Generally, indoor localization not only adds safety and security to the workplace, but it can also boost productivity. Indoor localization systems are based on a variety of positioning technologies and methodologies, which makes them useful for certain applications but cumbersome for others. The technologies available for indoor positioning systems (IPS) include Wi-Fi-based positioning systems (WPS), Bluetooth low energy (BLE) solutions, radio frequency identification (RFID)-based systems, ultra-wideband (UWP), and Zigbee technology [1] but they all have their own properties and considerations. The Wi-Fi technology has two main advantages: it is already installed in many areas, obviating the need for new network equipment and it has a larger range than alternative options. When positioning is based on signal fingerprinting, the fundamental disadvantage of Wi-Fi solutions is their low precision, which ranges from 5 to 15 meters. In order to improve its positioning accuracy, more access points are required to be deployed, which raises the deployment cost. Within the lifespan of RFID systems, its accuracy is the finest among all other technologies of a typical error less than 0.1 m without a need for a battery in the RFID tags. The narrow range (below 1 m) and the substantial and costly installation of many RFID readers to cover huge regions are its key drawbacks.

BLE technology operates on a frequency range of 2400 MHz to 2485 MHz, which split into 40 channels with a spacing of 2 MHz. For beacon-based applications [2], BLE hops across three frequencies such that there's less likelihood of noise on all three. Also, the advertising period is very short, typically taking 1 or 2 ms, making the coincidence of the noise and the advertising less likely than would be the case of a longer transmission. In comparison to other technologies, BLE is designed for short-range wireless communication of 20–30 meters, low energy consumption, low-cost hardware design, and simple deployment.

In the case of the ultra-wideband (UWB) technology, the most important features are the precision (error is minimized below 0.3 m) and range over 150 m. While its key drawbacks are its excessive power consumption and high cost. The IEEE 802.15.4 standard, which defines the operational point for wireless personal area networks (WPANs) with low-data-rate, provides the foundation for Zigbee technology. Employing carrier-sense multiple access with collision avoidance (CSMA/CA), devices using IEEE 802.15.4 can manage the flow of information and prevent data loss. Features like link quality and energy monitoring are included into Zigbee devices, allowing metrics like the received signal strength indicator (RSSI) to be easily establish. Zigbee has a higher range than BLE because it can transfer data over a longer distance utilising a mesh network of relay nodes. Because of its low power consumption, Zigbee is commonly used in specifying nodes location in wireless sensor networks, in spite of additional required hardware. Although Wi-Fi solutions were once popular, BLE technology offers such a low-cost and low-power solution which they have proven appealing in situations where Wi-Fi infrastructure is not accessible. Although Wi-Fi allows for significant data rates to be transmitted, the type of data normally required for a positioning system does not necessitate high throughput, hence BLE's data transmission speed of 1 Mbit/s is sufficient [3].

Signal measurements like travel time, direction, and the relative strength [4] are commonly used in the RF-based positioning techniques. The common models used in signal evaluation include: angle of arrival (AoA), time of arrival (ToA), time difference of arrival (TDoA), and RSSI. RSSI is the most popular and simplest methods for measuring distances in localization [5], [6]. RSSI estimates the distance between the transmitter and receiver by evaluating the signal strength on the receiver. RSSI-based techniques have a low implementation cost and are easy to be implemented because It does not require any additional hardware and also is available on any device that uses wireless technology. Earlier methods used algorithms requiring extensive calibration and energy consumption [6].

Moreover, RF signals encounter impairments, such as interference and multi-path propagation, which change the received signal causing inaccurate estimations of the relative distance using RSSI. RF interference is caused by other wireless devices working on the same frequency channel and phase in the area. Other obstructions in indoor environment such as walls, furniture and people may block or distort the BLE signals due to possible multi-path propagation of the signal. To obtain a better positioning accuracy, many RSSI-based research works use fingerprinting methods which calibrate the RSSI values in the environment in an offline stage and compare it with the obtained RSSI in positioning. Sp¨ork *et al.* [2] explained the reliability of using BLE RSSI to estimate the location. In order to validate the reliability of RSSI readings, it compared a set of alternative mathematical methodologies, such as the moving average method or the weighted average method, with a theoretical reference curve.

This paper proposes a fingerprint-based indoor positioning system using BLE. It utilizes learning techniques based on K-nearest neighbor (KNN) and Weighted (WKNN). The KNN and WKNN algorithms are used in classifying the RSSI values obtained in an unknown location by matching them to the RSSI fingerprint constructed for the area of interest. These algorithms are chosen due to their simplicity, accuracy and lowest time complexity with respect to other machine learning algorithms. Moreover, the proposed IPS is implemented and evaluated in a building of the Faculty of Computer Science and Information at Ain Shames University. Experimental results show the system suitability of indoor positioning with low cost and implementation complexity and high accuracy. The paper is organized as follows: the related work along with systematic literature studies are discussed in section 2. The proposed fingerprint-based indoor positioning system using BLE is explained in section 3. The test-bed area and BLE devices deployment are described in section 4. Experimental results and analysis enlisted in section 5. Section 6 concludes the paper.

2. RELATED WORK

This section reviews recent research works, and algorithms that find the accurate indoor position using RSSI and Bluetooth technology. Generally, existing RSSI-based indoor localization algorithms can be classified into two main categories: i) deterministic mathematical model-based algorithms and ii) fingerprint estimation based on machine learning algorithms. The first category includes the trilateration approach, as well as its modifications, is the most often used mathematical model in localization. The trilateration technique is a trigonometric methodology in which the distances between three known access points (APs) are determined using the selected the propagation model. The positions of the node can be determined using the positions of the APs and the estimated distances of the mobile nodes from each of them. The fundamental disadvantage of this method is the impact of the environment on RSS values, as well as the necessity to use complicated propagation models to provide such a mathematical formulation of the environment. Furthermore, in centroid localization method, N nearest APs are selected based on RSS values, and node positions are computed using the centroid formula [7]. In a complex scenario, trilateration could be described by three circles intersecting at a single point, which would be the object's original position. However, in real-world situations, we find that this does not occur, and that distances are frequently overestimated or underestimated, resulting in circles that do not intersect or that are too big with extensive overlapping sections. To address this issue, different methods have been developed, such as wall-adapting local eddy (WALE) [8], discrete choice experiment (DCE) [9], which entail resizing the circle dependent on whether it is an overestimation or underestimation. This challenge can be tackled by recasting it as a minimization problem that can be addressed mathematically to obtain the best likelihood. Mathivannan *et al.* [10] proposed a novel calibration-free, adaptive, weighted trilateration technique that uses the characteristics of dual-band Wi-Fi, and an iterative heuristic approach to estimate the most likely position of a smart phone. To improve the time complexity of this technique, additional optimization techniques are implemented. Experiment results in various indoor environments show better accuracy than other calibration-free RSSI-based approaches.

To improve the precision of a BLE indoor locating system, Jiang *et al.* [11] used three deterministic modeling methodologies on series: channel diversity, Kalman filter, and a weighted trilateration algorithm. The primary purpose of channel diversity is to reduce the inherent dispersion of RSSI readings in such systems. Kalman filtering is used to reduce the consequences of implausible or unattainable location predictions caused by inaccurate RSSI observations, allowing for more precise tracking of a device's location. Because the three measurements of fundamental trilateration do not always converge to a single point, the weighted trilateration technique is its enhancement version. The results show that when all of the proposed strategies are used together, precision increases by 43.47% in a medium-size room scenario and 38.33% in a large-size room scenario, compared to precision without using any of the approaches proposed. Although mathematical deterministic models based on trilateration have a low computational complexity and requires less Beacons, it was not applied in wide range of problems because the complexity of the model in some topologies and architectures. In addition, this category of models is inaccurate in Bluetooth positioning due to the instability of signal strengths. On other hand, the machine learning models to find fingerprint estimation is preferred on most research works [12], [13].

Fingerprint-based indoor localization techniques place some beacon nodes (BNs) in key locations and periodically broadcast beacon packets or heartbeats containing the BN's ID, location, and other information in order to locate an unknown target device (TD) [14]. The RSSI values and other information of beacon packets can be easily obtained by devices receiving the packets. Indoor fingerprint localization methods typically have two phases: offline and online. For each reference point (RP) with a known location, the offline phase collects beacon packet RSSI values from various BNs. The online phase involves collecting beacon packet RSSI values from various BNs as a TD's fingerprint and comparing them to those in the database. A matching algorithm is used to identify the RPs with the most similar fingerprints to the TDs. Then, based on the locations of the identified RPs, the TD's location is estimated.

There are a number of machine learning algorithms for classification that are applied in many situations to improve the location accuracy. In other words, for identifying the position of object, we use the RSSI values as fingerprints or features of the environment. Fingerprints have been read by the Bluetooth receivers and sent to a centralized node where the accurate position of object will be identified based on these values received from all the Bluetooth devices using a machine learning algorithm. Artificial neural networks (ANN) is also evaluated where they are trained for localization using the RSSI values and related coordinates obtained during the offline phase [15]. After the ANN has been trained, it can be used to determine the user's location using online RSSI measurements. One of the most often used ANN for localization is the multi-layer perceptron (MLP) network with one hidden node layer [16]. An input vector of RSSI measurements is multiplied by the input weights and added to an input layer bias in MLP-based localization, assuming that bias is selected. The result is then passed through the transfer function of the hidden layer. The hidden layer bias is increased by the product of the transfer function output and the training hidden layer weights (if bias is chosen). The estimated user location is the result received. Support vector machine (SVM) is an attractive approach for classifying data as well as regression. SVM is primarily used for machine learning (ML) and statistical analysis and has high accuracy. As highlighted in [17], SVM can also be used for localization using offline and online RSSI measurements. Random forest learning algorithm used also for accurate determination of location. Wang *et al.* [18], used the random forest learning approach in real-time trials to conduct indoor localization in a simulated IoT environment. The authors put up a 13-beacon IoT-based space. The random forest model was trained using the signals from these beacons, which were based on the user's changing position.

KNN techniques used root mean square error (RMSE) to determine the k-nearest matches (based on offline RSSI measurements recorded in a database) of known locations using online RSSI. The device/ approximate user's location is then calculated by averaging the closest matches. A weighted KNN is also utilized where the distances are used as weights in the signal space. To perform indoor localization, Pasha *et al.* [19] used graph optimization and achieved an error of 1.27 m in the best scenario. Jiang *et al.* [20] used Gaussian Kernel-based fingerprinting to do indoor localization and achieved errors of less than 1.5 m at around 90% of test cases. Altini *et al.* [21] used a two-step fingerprint-based detection approach that resulted in a 1.05 m localization error. Ganti *et al.* [22] used an eight-neighborhood template-matching technique to anticipate the target device location and achieved a localization error of 1.0 m. Some recent papers concentrated on the applications of IPS. Zafari *et al.* [23] built a low-cost BLE Beacon-based indoor positioning system and tested it in a real grocery store with two levels with varied layout characteristics for shoppers' placement during shopping excursions. The goal of this research was to apply and compare various indoor positioning approaches in order to determine the most efficient position determination for moving clients in a retail store. The fundamental innovation of this study is the context (i.e., the retail store) and the fact that it is not a controlled laboratory experiment.

Varma and Anand [24] proposed IPS system to improve knowledge about museum visitor. BLE beacons are strategically placed throughout the museum. The software installed on the museum visitor's mobile phone detects the signals sent by beacons. Using the trilateration approach and the Kalman filter, the application calculates the position of visitors. The localization data is then mapped on the museum map so that the layout of the items on display can be evaluated.

The work presented in this paper proposes an improved fingerprint-based indoor positioning system using BLE. KNN and WKNN algorithms are utilized to classify the RSSI values obtained in an unknown location by matching them to the RSSI fingerprints constructed for the area of interest. These algorithms are adopted due to their simplicity, accuracy, and lowest time complexity.

3. PROPOSED FINGERPRINT-BASED POSITIONING SYSTEM

This section presents the proposed fingerprint-based indoor positioning system using BLE. The BLE technology is chosen, since it is designed for short-range wireless communication, low energy consumption, low-cost hardware, and simple deployment with respect to other technologies. Also, most mobile devices already have BLE interfaces.the proposed positioning system consists of several BLE beacons deployed in the indoor area that need to be covered. These beacons broadcast heartbeats with their identifier (e.g., MAC address) every short period (1 s). The Raspberry Pi 3 Model B board is used as a BLE beacon for developing the prototype, however low-cost BLE beacons can be used in the real deployment. When a user navigates in the covered area, her smartphone receives heartbeats from the surrounding BLE beacons with different RSSI values. The received BLE identifiers found in the heartbeats with their corresponding RSSI values are then matched with the BLE fingerprint of the area to estimate the user's position. The BLE fingerprint of the covered area is constructed in an offline scanning phase and stored in a cloud server. The proposed positioning system consists of two phases: BLE fingerprint construction and online indoor positioning, as discussed next. Figure 1 shows the system block diagram illustrating its phases. The offline data scanning module is responsible for the acquisition of RSSI values from the BLE devices, performs some data preprocessing prior for construction RSSI fingerprints, and transmits the received processed data to a cloud-hosted database where RSSI training data is stored. The online position identification matches previously collected offline RSSI readings with the RSSI at the user's unknown location to determine where the user.

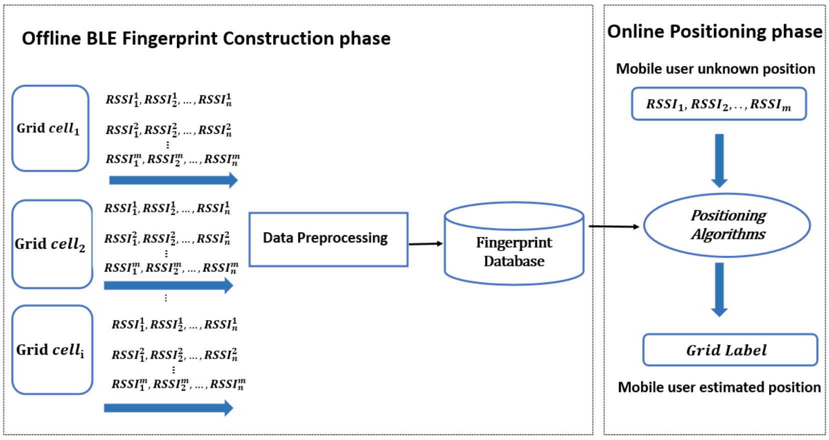


Figure 1. System block overview

3.1. Offline BLE fingerprint construction phase

In the BLE fingerprint construction phase, BLE beacons are placed and distributed over the area of interest. They are configured to periodically broadcast heartbeats. The transmission power and frequency of the beacon are tuned since they are crucial factors that significantly affect the positioning accuracy. Since a Raspberry Pi 3 board (BLE 4.2) is used as a BLE beacon, it could be dynamically configured with the desired values of transmission power and frequency based on the condition of the indoor environment. It is configured to broadcast its MAC address with 1 Hz frequency, and default transmit power set to 0 dBm which covers up to 40 meters. For BLE beacons placement, the approach presented in [25] is followed which avoid putting the beacons in the positions around obstacles such as wall and furniture. Also, it ensures that all BLE beacons are placed with the same height, orientation and in line of sight between the transmitter and receiver. The area of interest is composed of two rooms and a hallway corridor. Each indoor subarea is divided into grid cells of 50x50 cm, which referred as G_i, i = 1, 2... n where i represents the grid index, and n is the total number grid cells. Each indoor environment has a BLE beacon placed on a table. Next, a smartphone is used to build a training dataset by collecting the measured RSSI for heartbeats received from all beacons in each grid cell. A mobile app is developed to scan the area and store the grid cell information with the received RSSI. For each indoor subarea, a user enters the name of subarea, and the grid index where the RSSI are collected. The user is required to rotate her smartphone inside every grid cell for a specific number of seconds. Therefore, various RSSI measurements are collected from each beacon which grantee that the collected RSSI measurements represent different positions of the user inside every grid cell. Thus, the fingerprint for a grid cell is presented as a vector of RSSIs collected from several beacons V_i = ($RSSI_1$,$RSSI_2$,....,$RSSI_m$), where m is the total number of beacons received at this grid. The mobile app stores temporary all measured RSSI values from beacons at a grid cell, for a specific period. To reduce RSSI variations, the average RSSI is computed for a period of time, forming a vector of filtered RSSI values, as shown in (1).

$$a_i = \frac{\sum_{i=1}^{T}(\,RSSI_1, RSSI_2, ..., RSSI_m)}{T} \tag{1}$$

Where m is the number of the beacons, and a_i is the averaged vector T measurements received from beacons at a known grid location.while the mobile app scans the area of interest, it sends the filtered RSSI values with the subarea label and grid cell index to a cloud database for further analysis necessary for the indoor positioning. Firebase cloud service is used as the cloud database where data is stored as JSON and synchronized in real time to every connected user. Thus, all users can share one real-time database instance and automatically receive updates with the newest data.

3.2. Online positioning phase

In this phase, the mobile app matches the RSSI values received at the user's unknown location with the previously collected RSSI readings (i.e., BLE fingerprint). Two deterministic matching algorithms are studied: KNN and WKNN.

3.2.1. K-nearest neighbors

The KNN chooses the k-nearest neighbors from the stored RSSI values in comparison to the users received RSSI values using the Euclidean distance (2). It estimates the user unknown position as the area and grid cell index with the most frequent grid cell out of the k nearest neighbors.

$$D_i = \sqrt{\sum_{j=1}^{n} (RSSI_j^i - RSSI_j^u)^2}, (i = 1, 2, 3...M) \tag{2}$$

Where D_i is the distance between the measured RSSI value ($RSSI_j^u$) of access point j of the unknown location u and the recorded fingerprint ($RSSI_j^i$) at grid number i, n is the number of BLE beacons, and M is the number of entries for each grid fingerprints in the whole database. The k-nearest matches are selected and the final estimate of the receiver's location is obtained in terms of indoor subarea label and the grid cell index inside that subarea.

3.2.2. Weighted K-nearest neighbors

To enhance the accuracy of KNN, another variant of KNN is implemented which is based on the inverse weights technique. For the WKNN classifier, we assign a weight to each grid index in the selected K nearest matches. To calculate the weight, we compute the sum of the distance inverses for the k nearest matches based on (2), then divide each inverse by the sum (3).

$$W_i = \frac{\frac{1}{D_i}}{\sum_{i=1}^{K} \frac{1}{D_i}} \tag{3}$$

Each calculated weight is a vote for its associated grid cell in the selected K nearest matches, hence different weights which are associated to a multiple occurrence of the same grid cell are added together formulating a final weight for each distinct grid number in K nearest matches (4):

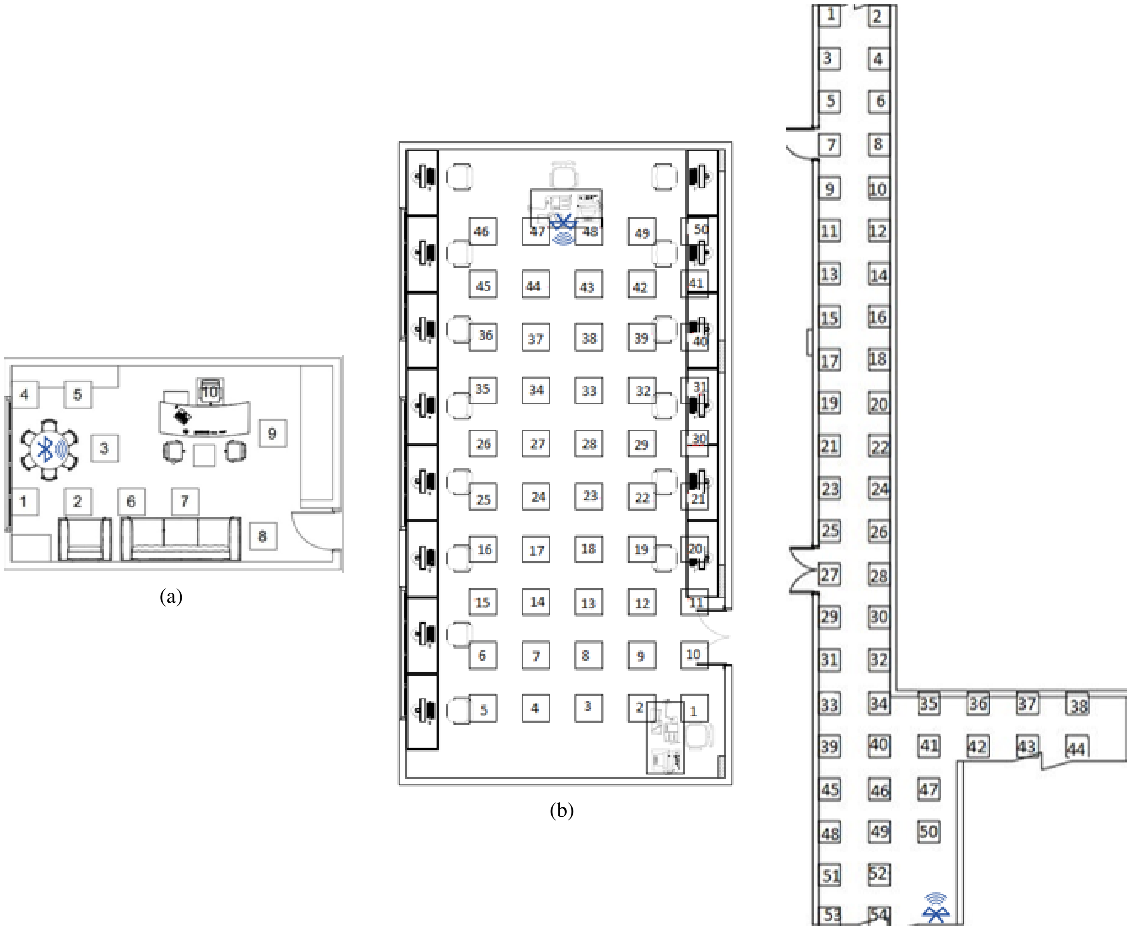
$$W_{final} = \sum_{i \in C} W_i \tag{4}$$

where C is set of the different weights that are belong to the same grid cell, (4) is repeated for all grid cell that has multiple occurrences in the selected K nearest matches. Finally, we estimate the unknown location U by assigning it to the grid cell G that has the highest weight among the selected K nearest training matches along with the subarea label that is this grid belongs to.

$$U = W_{max(W_1, W_2, ..., W_k)} \tag{5}$$

4. ENVIRONMENT SETUP

The proposed system is deployed at the second floor of the Faculty of Computer and Information Science (FCIS) building at Ain Shams University. The area of interest is composed of two offices and a corridor divided into grid cells of size 0.5 m×0.5 m. The grid layout is shown in Figure 2. The first subarea is a small meeting room of size 4×6 m, as shown in Figure 2(a), where signals are experiencing high obstructions and reflections due to the dense existence of tables, chairs, and other transmitting devices. The second subarea, shown in Figure 2(b), is a wide student's laboratory of size 14x6 m, where many objects such as tables, chairs, and Wi-Fi-enabled computers are placed in the area. Hence, signals are experiencing obstructions, interference, and reflections. The third subarea, shown in Figure 2(c), is a corridor of an L shape, and connecting the other two subareas. The most significant noise source in this subarea is the Wi-Fi AP which shares the 2.4 GHz bandwidth. Three BLE beacons are placed in the above-mentioned area, one at each subarea (antenna symbol in Figure 2. They were installed at a height of 40 cm from the floor. The Beacon deployment process followed the recommendations in [25], [26]. During the fingerprint construction phase, the RSSI readings are recorded and stored for every grid cell in each subarea for 20 seconds, with 1 Hz heartbeat transmission frequency. A BLE fingerprint map is created with 200 recordings for the meeting room, 1,040 for the corridor, and 1,000 for student lab.



(a) (b) (c)

Figure 2. Layouts for the three subareas (a) subarea1-meeting room, (b) subarea2-lab, and (c) subarea3-corridor

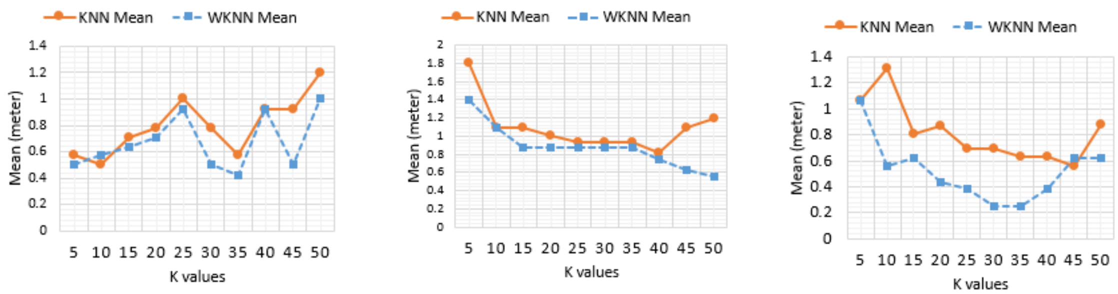
5. RESULTS AND DISCUSSION

This section presents and analysis the results of the proposed BLE fingerprint-based indoor positioning system using two classification techniques: KNN and WKNN algorithms. We measured the accuracy of both algorithms with different values of K that ranges from 5 to 50, using the following metrics: mean error and standard deviation error. Figures 3(a)-(c) show the mean positioning error for KNN and WKNN for subarea 1-3, respectively. Figures 4(a)-(c) show the standard deviation positioning error for KNN and WKNN for subarea 1-3, respectively. It's clearly shown that WKNN algorithm manages to obtain less mean and standard deviation positioning error for all subareas compared to KNN.

For subarea 1, shown in Figures 3(a) and 4(a), the WKNN algorithm has the minimum mean error at K=35 and standard deviation at K=5, while the KNN algorithm has the minimum mean error at K=10 and minimum standard deviation at K=5. For subarea 2 shown in Figures 3(b) and 4(b), the WKNN algorithm got the minimum mean error occurred at K=50 and minimum standard deviation at K=10, followed by KNN algorithm that has both minimum mean error and standard deviation at K =40. For subarea 3 shown in Figures 3(c) and 4(c), the minimum mean error and standard deviation for WKNN algorithm occurred at the same K value which is 30, whereas KNN algorithm has minimum mean error and standard deviation at K=45.

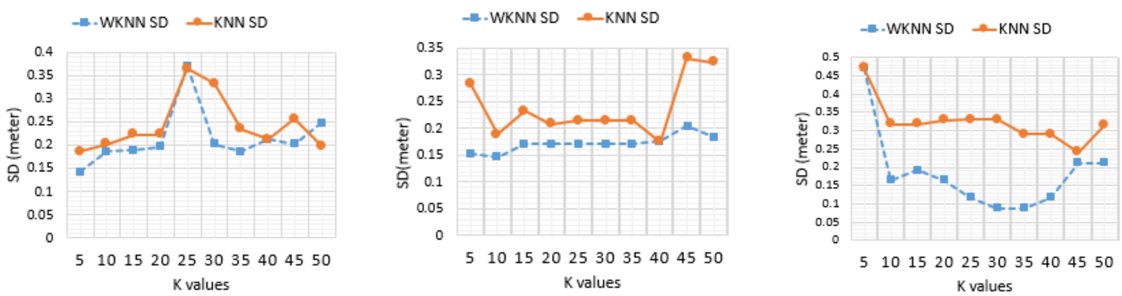
Performance of KNN and WKNN algorithms depends mainly on choosing the right value of K. When the results are analyzed and compared for WKNN over the different testing subareas with different environmental conditions, several interesting conclusions can be drawn. The minimum mean error calculated in subarea 3 (corridor) was 0.25 m with a minimum standard deviation of 0.089 m, in subarea 1 (meeting room), the mean error was raised to 0.50 m with a standard deviation of 0.14 m, and in subarea 2 (lab), the mean error was raised to 1.1 m with a slightly higher standard deviation of 0.15 m.

The observation in subarea 3 was found to be better than those in subareas 1 and 2. While the error in subarea 2 was the highest. The results in subarea 1 can be ascribed to multipath effects caused by the narrow area. Because subarea 3 is significantly longer, reflections from the sidewalls did not have the same impact on the accuracy as those did in subarea 1. Several transmitting devices were already deployed in subarea 2, causing extra interference. As shown in the current analysis, the environmental interference played a part in the variability of the RSSI values in all the environments, and the accuracy of positioning results. Besides the indoor localization algorithms employed in this work, evaluating the results between different testing subareas, a consistent error between all the different subareas was determined. The errors were not only uniform, but the results were also considered as reliable and robust. This is due to BLE technology. BLE technology divides the frequency band into smaller 40 channels and rapidly hops between those channels when transmitting packets, also Bluetooth adapts its hopping sequence so that noisy and busy channels are dynamically tracked and avoided, reducing the probability of interference and figuring a clear transmission path. This implies that the level of noise and interference between the different environments had almost no significant effect on the results.



(a) (b) (c)

Figure 3. Mean positioning error for KNN and WKNN (a) subarea1-meeting room, (b) subarea2-lab, and (c) subarea3-corridor



(a) (b) (c)

Figure 4. Standard deviation positioning error for KNN and WKNN (a) subarea1-meeting room, (b) subarea2-lab, and (c) subarea3-corridor

6. CONCLUSION

The paper proposes a low cost BLE mobile indoor positioning system based on two different fingerprint techniques: KNN and WKNN algorithms, using Euclidean distance. Mean error, standard deviation of both fingerprint algorithms with different k nearest neighbors values are measured and analyzed. Experiments results show that WKNN algorithm manages to obtain less mean and standard deviation positioning error for all subareas, that experiencing different conditions of obstructions, reflections, and interferences. Position accuracy of subarea with most significant noise and interference is highly improved using WKNN, compared to other subareas.

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