An Assessment of Bluetooth Low Energy Technology for Indoor Localization

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Abstract
Buildings have a large share in the total energy consumption of the world and a considerable amount of this share is wasted for operating the building services in unoccupied spaces. In order to ensure energy efficient and people oriented built environments, it is necessary to detect the existence and location of occupants in buildings. The process of determining the position of occupants in indoors called indoor localization. The aim of this research is to assess the technological applicability of Bluetooth Low Energy (BLE) technology for indoor localization. BLE technology is already embedded in most of the mobile devices and its properties such as ultra-low power consumption, low cost, and low latency in data exchange make it a good alternative to currently available technologies. In order to determine the viability of the proposed framework, multiple field experiments were carried out in an office building at Middle East Technical University. Location fingerprinting method and k-nearest neighbor algorithm were utilized in the experiments. The results show that BLE technology can be used as a reliable solution for indoor localization as it gives better accuracy and precision results when compared to existing approaches in the industry.

1 Introduction

With the breakthrough of Global Positioning System (GPS), location-based services has shown a widespread emergence in the world within a wide scope such as on-road navigation, tracking of valuable assets, and route monitoring. Although GPS technology is a universally accepted solution for finding position in outdoors, since satellite signals cannot penetrate through structural obstructions (*i.e.,* walls, floors, roofs), it cannot be adapted for localization in indoor built environments. Indoor localization is an important area of research for the construction industry, and it is used for various purposes such as security, emergency, hospitality, commerce, and building operation optimization. In order to satisfy the comfort needs of occupants and ensure energy efficiency in buildings at the same time, it is important to have the knowledge about the existence and number of occupants in the spaces. Occupancy information could have a crucial effect in enabling energy savings of buildings as well as providing a comfortable environment for habitants if it is monitored in real-time simultaneously and implicated in facility management systems.

There are some existing technology based approaches for detecting the location of people in indoors, such as image detection systems, Passive Infrared (PIR) sensor based systems, CO_2 sensor based systems, and radio frequency based (wireless) systems. However, a reliable and precise location detection framework is still missing due to certain shortcomings

of the current technologies including uncertainties in detection, time latency and privacy issues, inability for multiple detection, and high expense of deployment and maintenance.

The main aim of this study is to assess technological applicability of Bluetooth Low Energy (BLE), which is already equipped in most current mobile devices, for indoor localization in office buildings. Although BLE is not designed specifically for indoor positioning or occupancy detection purposes, its properties such as ability to penetrate through walls, ultra-low power energy consumption, low cost, low latency in data exchange, uniqueness of each BLE tag make it a potentially appropriate technology for utilization in localization frameworks (Lodha et al., 2015). The deployment of BLE for indoor localization is based on the analysis of the radio signal propagation characteristics, such as power, attenuation, and interference. As mobile devices such as smartphones, tablets or smart watches has become essential objects in people's daily lives and shows a rapid evolvement, there is a potential for using them as an enabler for the integration of BLE in indoor localization systems.

2 Background Research
In order to propose a BLE based indoor localization framework, wireless based localization approaches and localization techniques for wireless based detection systems including proximity, triangulation, trilateration, and fingerprinting in the literature are reviewed. In this section, the related studies about these subjects are covered.

2.1 Wireless sensor based approaches for indoor localization
Despite the popularity of GPS for locating people and positioning objects in outdoor environments, the system does not work for indoors properly due to attenuation of electromagnetic waves by the walls and obstacles due to obstruction of line of sight between the satellites and receivers (Farid et al., 2013). Since radio waves have the capability of penetrating walls, obstacles, and human body, radio frequency based technologies are suitable for indoor localization with their wide coverage area and less hardware necessity (Vorst et al., 2008). Radio Frequency (RF) based localization systems are generally composed of transmitters and receivers, which interact with each other through radio signals. The very first RF based occupant localization system was named RADAR, developed by Bahl and Padmanabhan (2000). The goal of the authors was to locate and track occupants in indoor built environments through gathering Received Signal Strength Index (RSSI) data at multiple receiver locations and using collected information for position estimation. In the light of the research of Bahl and Padmanabhan (2000), many other studies have been conducted for establishing a reliable and accurate real-time indoor localization solution based on RF technologies including radio frequency identification (RFID), WLAN, Ultra-wideband (UWB).

One of the most popular methods studied for detecting occupancy is RFID sensor based models. An RFID system is composed of a number of readers and generally a large number of tags adjusted according to intended building size. What separate RFID from the other sensor technologies are its benefits such as RFID tags' features of having unique identity numbers and light, portable designs, its effectiveness in non-line of sight and longer detection range compared to infrared, ultrasound, and WLAN technologies (Pradhan et al., 2009). Despite the capability of RFID sensor based detection systems to provide comprehensive fine-grained occupancy information for demand driven applications in buildings (Li et al., 2012), it has some limitations such as the multipath effect for signal propagation, changing environments' negative effects on RSSI, and unwillingness of occupants to wear RFID tags (Ekwevugbe, 2013).

As the infrastructure of WLAN is already deployed in many indoor environments including office buildings, educational facilities and public areas, the interest towards using WLAN for detecting occupancy has become a popular issue for researchers (Ismail et al., 2008). In WLAN based location detection models, position of every Wi-Fi compatible mobile device can be located through the use of existing Wi-Fi infrastructure with the aid of a positioning server. In this application line of sight is not required between access points and the target units (Farid et al., 2013). Moreover, the coverage area of a WLAN based localization system is expandable since it can bear additional access points, and any mobile target can be tracked unless it goes

out of the covered range (Ismail et al., 2008). Despite its potential for gaining occupancy information, WLAN based systems have their shortcomings and limitations, such as the negative effects of possible changes (*i.e.* moving furniture) in the environments on Received Signal Strength (RSS), high initial deployment cost, variations in Wi-Fi signal strength by time and possible interferences with other appliances (Mautz, 2012). However, WLAN based occupancy detection solutions are still preferred over PIR based or ultrasound based systems since they need fewer transmitters and provide higher confidence in real-time positioning accuracy (Pradhan et al., 2009).

Ultra-wideband technology is based on data transmission technique through sending and receiving ultra-short radio pulses. For an UWB based detection system, multiple unique tags for target units, stationary receivers covering signal map of the area, and a location management platform are required (Torrent and Caldas, 2009). UWB system has the capability of high accuracy indoor localization with low power consumption even in non-line-of-sight conditions. Since signals transmitted from UWB tags use a wider radio spectrum than the other RF-based tools, it is not affected by the interference of other signals in the environment and it has resistance to multipath effects. In addition, large bandwidth of UWB provides high resolution in both time and location for positioning and tracking, and it is suitable for utilizing positioning techniques including time of arrival and time difference of arrival (Mautz, 2012). There are several studies in the literature for developing an applicable UWB based localization and tracking system, yet there are no widely accepted solutions. Although UWB based location detection models have the highest accuracy and precision (with a location error of 15 cm) among all other indoor localization solutions, a comprehensive receiver-transmitter infrastructure is required and the necessary initial deployment is so expensive that it is not in wide-scale use (Mautz, 2012).

2.2 Overview of wireless localization techniques

Localization with wireless based detection systems is defined as the process of gaining location data of a mobile unit using pre-located reference nodes within a defined space and localization techniques for wireless systems can be classified under four main categories; proximity, triangulation, trilateration, and scene analysis (Farid et al., 2013).

Proximity method, which may also be called as connectivity based localization, basically provides relative position information (Farid et al., 2013). This method relies on a dense grid of antennas whose positions are recognized by the system. If a mobile unit is detected by one simple antenna in the test-bed, its position is assumed to be collocated with that antenna. When more than one antennas detect the mobile unit, the one that receives the strongest signal is considered as collocated with the mobile unit (Liu et al., 2007) . However, proximity method is not robust to noise in radio signal propagation. Pu et al. (2011) claim that, since the locations of surrounding sensor nodes can be obtained instead of exact location coordinate of mobile units, this method is not suitable for location tracking applications. Yet, it can be beneficial for location detection in large-scale sensor networks (He et al., 2005).

In triangulation technique, the position of a mobile unit is estimated through computing angles relative to multiple reference nodes and angle of arrival (AoA) of wireless signals received at the base. Assumed that line of bearings of reference nodes or angular separation between the mobile unit and reference nodes can be obtained, the position of a mobile unit can be determined by using triangulation method (Amundson and Koutsoukos, 2009). Although two reference nodes are enough for location estimation with this method, in most studies, three or more reference nodes are used in order to improve accuracy (Farid et al., 2013). In the situations where there is a direct line of sight between the mobile unit and reference nodes, triangulation works properly. However, since multipath effect and reflection of signals from interior objects may significantly change the direction of signals arrival and decrease the accuracy, this method becomes barely usable as an indoor positioning system (CiscoSystem, 2008). Moreover, the cost of the system implementation increases with the use of additional antennas with the capacity to measure the angle of arrivals of signals (Farid et al., 2013)

Trilateration is a distance-based method that differs from triangulation in the information provided into the process of location detection. The coordinates of the target unit is estimated by measuring its distances from multiple reference nodes (Pu et al., 2011). In this method, at least three reference nodes are necessary. The distances among the target unit and each reference node, which is computed by multiplying the travel time and radio signal velocity, may be represented as the radius of circles and the target unit is estimated to be located at the intersection of those three circles (Amundson and Koutsoukos, 2009). Trilateration technique may be reviewed under two sub-headings; time of arrival and time difference of arrival. Trilateration was stated to be suitable for localization in large-scale outdoor spaces rather than indoor spaces where high levels of overall obstruction exists.

Location fingerprinting, which is also called scene matching in literature, is claimed to be the most accurate and popular method for indoor positioning and object tracking (Subhan et al., 2011). It consist of two phases as offline phase and online phase. In off-line phase, first reference node beacons are placed providing a complete signal coverage of the intended area. Then the area is divided into grids of suitable ranges and in each grid cell, RSSI fingerprints are collected and labelled on that (x, y) coordinate in order to create a radio map of the area. In online phase, where the position of the target estimated, current time RSSI measurement of the mobile unit is matched with the closest pre-defined location fingerprints and the estimation position is detected (Taneja et al., 2012). Although it has serious drawbacks of being highly time-consuming and not tolerant of any possible changes in the indoor environment, as Subhan et al. (2011) argue, the accuracy obtained by this method is higher than any other RF based positioning techniques.

2.3 Bluetooth Low Energy Technology

BLE was established in 2010 and its core objective is claimed by Collotta and Pau (2015) as to run with an ultra-low power consumption. While former versions of Bluetooth are mostly used for transmitting huge amount of data such as audio or files, BLE is designed to exchange small data pieces such as pings, temperature or humidity readings. This makes the technology convenient for devices requiring long battery life rather than high data rates (Andersson, 2014b). Latencies in connection and data transfer is also much smaller in BLE when it is compared with former technologies.

BLE has adapted itself into the mobile device industry very rapidly and most of the smart device producer companies, as Townsend et al. (2014) observe, including Apple, Samsung and Google are putting significant efforts into embedding this technology into their products and publishing design guidelines around it. The reason behind this uncommonly rapid adoption rate is that it is an extensible framework for exchanging data and it allows little task-specific and innovative devices to talk to smartphones or tablets, which potentially open the gates for new ideas and improvements in the market (Townsend et al., 2014). Another driver for the rapid adoption rate is the concept of Internet of Things (IoT). The visionaries of the IT sector propose a future where every tool, device, component will have the ability to connect to internet and form a network of devices. Easy-to-deploy, cost efficient and low power wireless solutions are the key requirements for the IoT concept, and BLE was shown to be a well-suited technology with its ultra-low power sensors and low-cost deployment needs (Andersson, 2014a).

Although BLE is not specifically designed for indoor positioning and occupancy detection, it has a significant potential (Ionescu et al., 2014). BLE uses tiny circuit boards, widely known as Bluetooth tags, in which radio frequency and microprocessor technologies are combined for creating a robust system and this system can be used for both identification, monitoring and maintenance of building assets, and indoor positioning of people through communicating with a tag reader (Lodha et al., 2015). As this low energy and low latency data exchange technology is increasingly popular in the device industry, almost all mobile devices such as smartphones, smart watches, tablets, or laptops equipped with BLE are able to communicate with Bluetooth tags and can be used as readers. These Bluetooth tags can send small data pieces to the readers, which can be any mobile device, and the distance can reach up to 50 meters (Ionescu et al., 2014). Besides its pervasive availability in mobile devices (which

people readily own and carry), relatively low cost and ultra-low power consumption of BLE tags when compared to other technologies can be claimed as the main advantages for utilizing it for locating people in indoor environments.

3 Research Approach

The research approach is shown in IDEF0 diagram in Figure 1. As it is claimed as the most accurate localization technique for wireless detection systems in an indoor environment (Lin and Lin, 2005) and since the signal parameters of Bluetooth are not very convenient for other techniques like triangulation (Hossain and Soh, 2007), location fingerprinting was selected as the indoor positioning technique of this research.
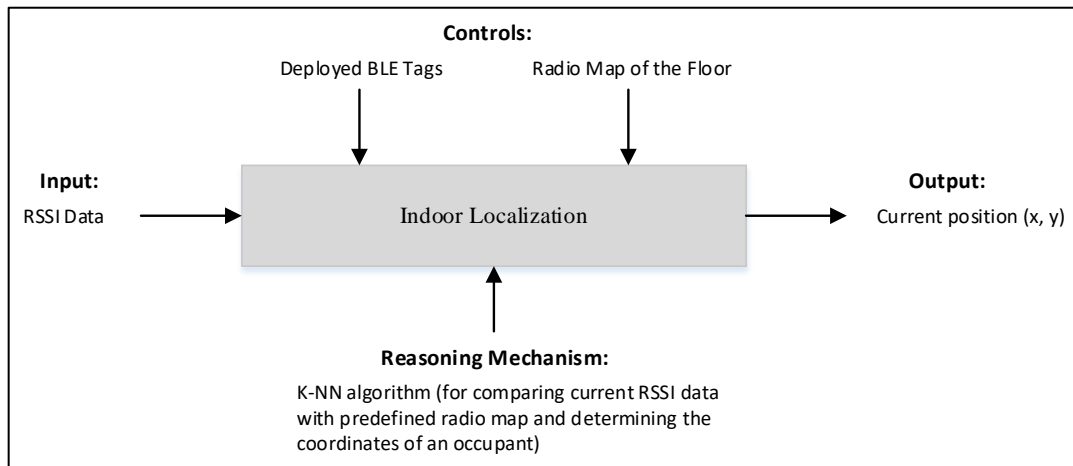

Controls:

Deployed BLE Tags   Radio Map of the Floor

Input:

RSSI Data → Indoor Localization → **Output:**

Current position (x, y)

Reasoning Mechanism:

K-NN algorithm (for comparing current RSSI data with predefined radio map and determining the coordinates of an occupant)

Figure 1: IDEF0 diagram demonstrating the research approach

In order to assess the applicability of BLE for indoor positioning, field experiments were carried out in the second floor of a reinforced concrete office building at Middle East Technical University. The experiment floor has a gallery space, steel super-structure, many concrete masonry walls and obstructions that may affect the proposed system's performance. The selected area consists of six personal offices, two restrooms and a corridor, and has an approximate area of 240m^2. The materials of the proposed system is composed of BLE tags as signal transmitters and a mobile computing device as reader. RSSI is taken as the parameter for assessing the technological appropriateness of the BLE for indoor localization. Although signal strength is claimed to be inversely proportional to distance between the transmitter and the reader (Çalış et al., 2013), experiments show that there is not a regular decrease in RSSI values as the distance increase, due to the attenuation and reflections of the signals in the environment (Ergen et al., 2007). In order to overcome this nonlinearity, an algorithm to manage this noisy data is needed. The most commonly used and widely accepted solution is claimed as k-nearest neighbor algorithm by the researchers (Bahl and Padmanabhan, 2000, Pradhan et al., 2009, Taneja et al., 2010). In this study, k-NN algorithm is used as it was asserted to be the most effective classifier for handling large sets of radio signal strength data (Han et al., 2012).

In the offline phase, first, twelve BLE tags were placed in certain locations on the floor, considering the actual signal range of the tags and possible signal attenuations. A Samsung Galaxy Note 10.1 2014 tablet with Android 4.4.2 operating system was used as the reader and signal data was collected at 46 different points for creating fingerprints and radio map of the floor. Iglesias et al. (2012) emphasize that since variability of signal strength values causes instability in the measurements of particular positions, there should be significant distances between fingerprint points in order to minimize the inaccuracies. Considering this, the distance between two consecutive points was determined as 1.8 meters, and data was collected in all four directions (North, West, South, and East) for 46 distinct points (Figure 2). A total number of 184 training data sets were created. Then these data sets were correlated with the coordinates on the defined two-dimensional space and a radio map was constructed. The signal strength data were collected using the same software application in material selection

process and the duration for each record was determined as one minute. Although there are twelve tags deployed in the test bed environment, due to signal attenuation and limited coverage range of BLE tags, the number of detected BLE tags vary in different data collection points. It was recorded that, at least two BLE tags were detected for every predefined location, whereas the maximum number of detected tags within all data sets was found to be ten. Data collection process was repeated two times with one-month time interval and the former was used as the training data set whereas the latter was used as test data set.
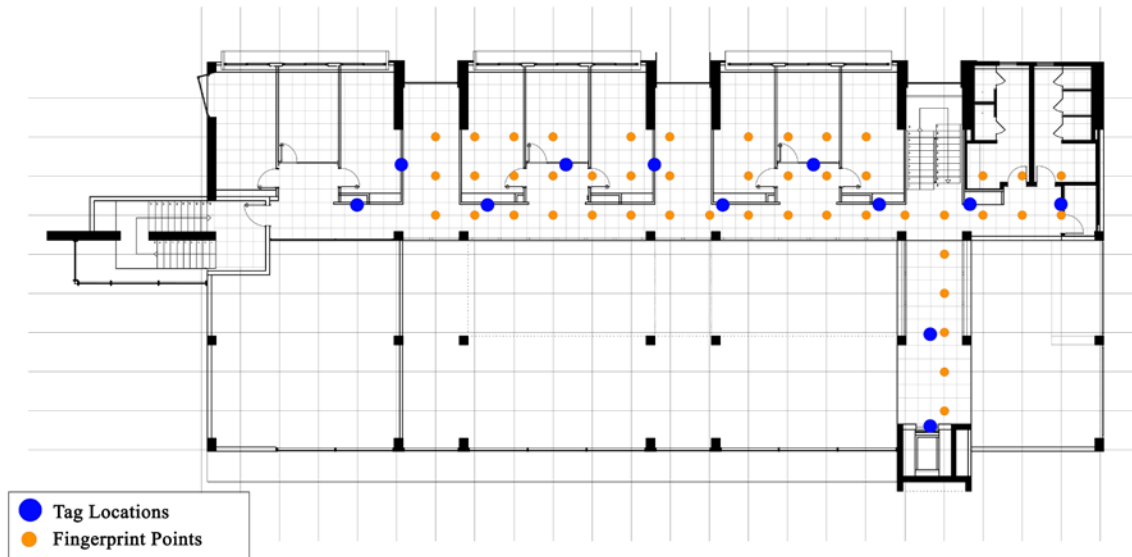

Figure 2: Tag locations and fingerprint points on floor plan

In the online phase, 184 test data samples were processed separately. First, a test data sample was selected and inquired in the pre-established radio map. In the radio map, the closest RSSI data match was derived through using k-NN algorithm. The position of the test data sample was identified as the coordinates of the closest training data sample (Figure 3).
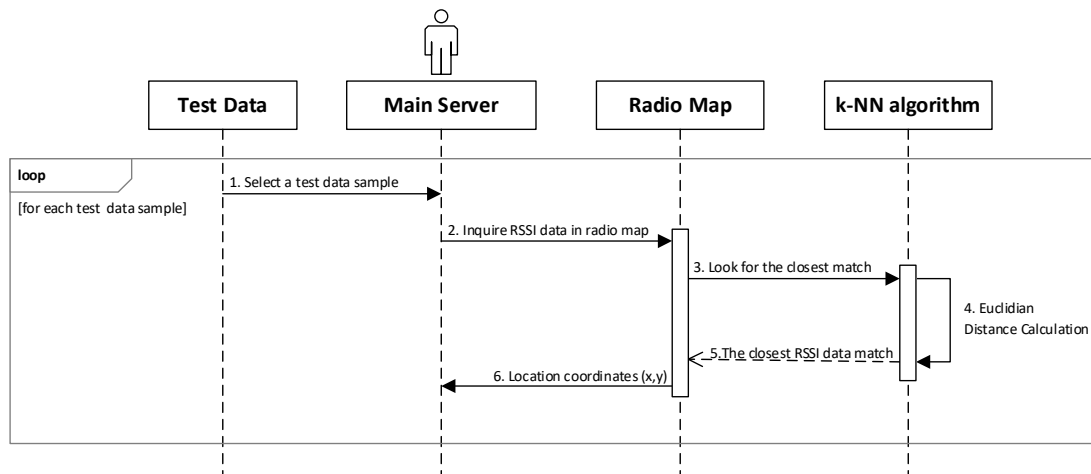

Figure 3: UML Sequence Diagram of the Experiment Analysis

K-NN algorithm was used to locate a test sample, in 184 (46 points x 4 directions) training data sets of signal strength values that were created in the offline phase of location fingerprinting. Accordingly, the Euclidian distance in signal space between the given test sample (ss1, ss2, ss3…ss12) and the each training data sample (ss'1, ss'2, ss'3…ss'12), where ssi represents the signal strength value of tracked BLE tag i (i ∈ 1,12), was calculated (2).

$$\text{Euclidian Distance}(p_1, p_2): \sqrt{\sum_{i=1}^{n=12}(ss_i - ss'_i)^2} \tag{2}$$

After the calculation of the Euclidian distance between the test sample and each training data sample, calculation results were sorted from the smallest to the largest, and the coordinates of the closest match was identified as the position of the test sample, in the case that k=1. If k is set as 2 or 3, or even higher, the location of the test sample is calculated through determining closest k-number of training data sets, and calculating the average of their coordinates. Han et al. (2012) state that, the most effective value for k, in which give the minimum error rate is achieved, can only be determined through experimental trials. Similar to what Bahl and Padmanabhan (2000) propose in their study and the preference of Taneja et al. (2012), the error distance for the estimated location in this research was defined as the Euclidian distance between the location coordinates identified by k-NN algorithm and the true location coordinates of the test sample.

4 Results and Discussion

The main parameters for location detection systems are clearly described in the literature as spatial accuracy and precision (Bahl and Padmanabhan, 2000, Elnahrawy et al., 2004). Spatial accuracy and precision are interdependent localization metrics and they are used to define the effectiveness of any location detection solution. The accuracy metric in this research is given in percentage, which reveals the probability of locating the intended unit within a defined range. Division of the number of successful location detection attempts for a determined precision to the all localization trials, when multiplied with 100, gives the percentage of the accuracy. The interpretation of localization precision is defined in meters and it is calculated as the location error. If it is assumed that $P_t (x_t, y_t)$ be the true location of a unit and $P_e (x_e, y_e)$ be the estimated location, the precision is defined as the Euclidian distance between these two points (1).

$$\text{Precision} = \sqrt{(x_t - x_e)^2 + (y_t - y_e)^2} \tag{1}$$

Referring to the fingerprinting grid size in the field experiments, four values, namely 1.8 meters, 3.6 meters, 5.4 meters and 7.2 meters were taken as the precision levels to analyze the accuracy of the proposed location detection framework.
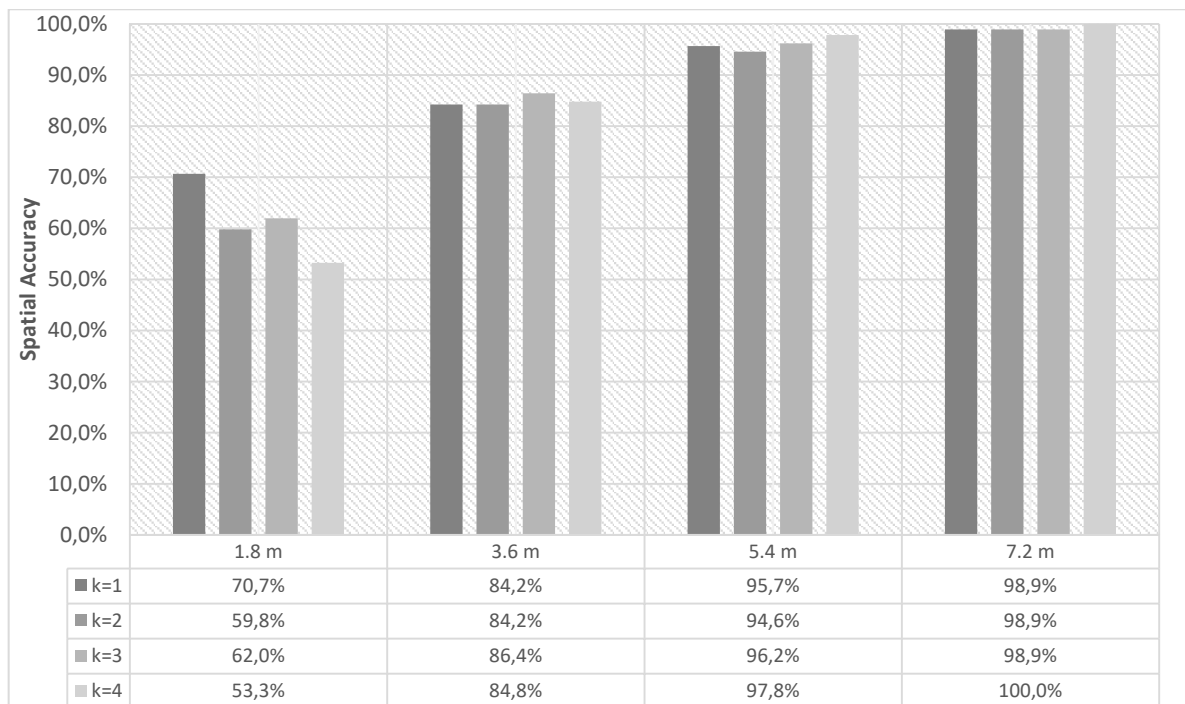
	1.8 m	3.6 m	5.4 m	7.2 m
k=1	70,7%	84,2%	95,7%	98,9%
k=2	59,8%	84,2%	94,6%	98,9%
k=3	62,0%	86,4%	96,2%	98,9%
k=4	53,3%	84,8%	97,8%	100,0%

Figure 4: Spatial accuracy and precision results

According to the results, at the highest specified precision, which is 1.8 meters, an accuracy of 70.7% is achieved at k=1 (Figure 4). There is not a regular variation in the accuracy level as the k value gets higher, yet the worst accuracy level for 1.8 meters precision is achieved in the case where k=4, with a percentage of 53.3. Since predetermined minimum grid size is 1.8 meters, for 1.8 meters of precision, the spatial accuracy decreases as the k value increases, where for all other precision levels it is not the case. For a precision of 3.6 meters, the spatial accuracy levels for different k values are almost the same, ranging between 84.2% and 86.4%. Since room level precision, which is claimed as meaningful for many indoor localization based applications in the literature, is defined as about 5 meters (Bargh and Groote, 2008, Dahlgren and Mahmood, 2014, Li et al., 2015), the indoor localization solution proposed in this research can be claimed as successful considering the results for a precision of 5.4 meters. Accordingly, at k=4, an accuracy of 97.8% is achieved for room level location detection. In this research, the lowest precision level is determined as 7.2 meters, for which full accuracy (100.0%) is gained. It can also be inferred from the results that, as the precision level gets low, the change in the k value does not affect the accuracy results in a considerable manner.

5 Conclusion

The main objective of this research was to determine the applicability of utilizing Bluetooth Low Energy in indoor localization and experimenting with the different parameters of this radio frequency based technology. The results of the experiments outlined an accuracy of 70% with 1.8 meters precision and 98% with room level precision, which is 5.4 meters. The achieved accuracy and precision levels show that BLE technology can be taken as an alternative to current approaches with its low complexity, good scalability and low cost properties. Considering the extensiveness of BLE adoption in mobile devices, it can be deduced that a mobile device integrated indoor localization framework is technologically feasible.

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