Indoor Localization Techniques in Location-Based Business Applications and Services

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ABSTRACT

Indoor localization in multi-floor buildings is an important research problem in recent years. The development of location-aware applications can be promoted by the increasing popularity of smartphones and huge demand in different business sectors based on the localization services. In this paper, we are going to use location fingerprinting based algorithms instead of modelling the propagation of the WiFi signal. The fingerprinting-based localization using Received Signal Strength (RSS) measurements coming from indoor networks, such as WiFi and BLE (Bluetooth Low Energy) is one of the most widely spread techniques for indoor localisation in multi-floor buildings. But it needs to store and transmit a huge amount of fingerprinting data which is a great drawback for mobile devices like smart phones, tablets, etc. which have limited memory, power and computational resources. Alternative methods, which have lower complexity and is faster than the fingerprinting is the Weighted Centroid Localization (WCL) and Log-Gaussian algorithms. All the simulations have been conducted by MATLAB software to test the performances of the methods. All the experiments have been carried with the given dataset of RSS and coordinate values that has been stored from smartphones in typical building environment. The errors have been obtained by computing the similarity between current estimated and the stored true fingerprints for every new location. The size of the dataset can be decreased by storing only the values of the coordinates and their corresponding floor labels.

Keywords: Indoor Localization, WiFi, Fingerprinting Based Algorithms, Weighted Centroid Localization (WCL), Log-Gaussian Algorithm, Received Signal Strength (RSS).

1. INTRODUCTION

Accurate localization in indoor is very important like outdoor because of the fact that people stay most of their time indoors for example at home, at workplace or in stores etc. Everyday life can be benefited by proper indoor localization. Some practical implementations of indoor localization are- tracking the elderly old people in their homes, tracking people who need special attendance in the hospitals, finding specific items in warehouses, and in emergency situations locating policemen and fire fighters quickly inside the buildings (Stella, Russo, & Begusic, 2012).

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Due to less availability of satellite signals with weak signal powers the Global Navigation Satellite System (GNSS) fails to offer an accurate location estimate indoors. For this reason, during the last decade different attractive solutions have been proposed and developed with the help of smartphones including built-in sensors and WLAN technologies. The positioning results are changeable with the changes in the layouts of building (or room) and the number of people inside (Seco-Granados, Lopez-Salcedo, Jimenez-Banos, & Lopez-Risueno, 2012). With the increasing size of the infrastructure of the buildings (such as hospitals, shopping malls or offices) the indoor localization technique is becoming more and more difficult.

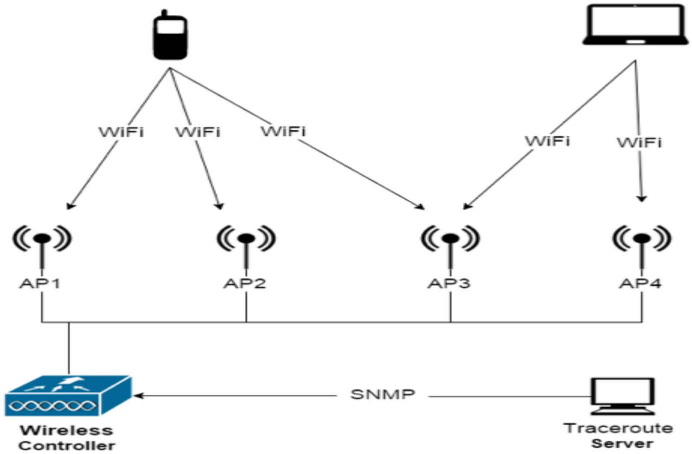


Figure-1(a) WiFi Access Points (APs) (Seco-Granados, Lopez-Salcedo, Jimenez-Banos, & Lopez-Risueno, 2012)

Nowadays, WiFi Access Points (APs) have become quotidian, whether in the offices, museums, hospitals, shopping malls or airports shown in Figure-1(a). In the meantime, smartphones are playing the most important roles in people's daily life. In the present wireless world indoor localization in multi-storied buildings are becoming more and more challenging task. People can easily access navigation in a museum, or airport terminal, finding specific merchandise or promotion information in a shopping mall, or locating themselves whenever they get lost with the help of an accurate indoor localization system.

Global Positioning System (GPS) is commonly used for navigation in the outdoors. But it lacks enough accuracy when functioning in indoor environment. People are trying to develop WiFi based Positioning System (WPS) to fulfil the indoor localization task (Chan & Baciu, 2012). Users' search time can be saved by finding the correct floor, in a fast and efficient manner, in a shopping mall or an unknown university building that can enable a myriad of Location Based Services (LBS) in the future.

Huge number of services including indoor localization are improving in last few years because of the wide-scale proliferation of different wireless devices especially smart phones. Indoor localization can be defined as the process of obtaining the position of mobile device or user in an indoor environment of a large building. It is shown in Figure-1(b).

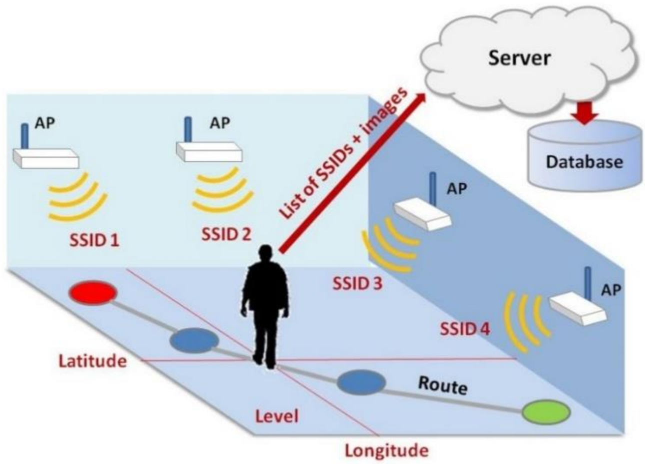


Figure-1(b) WiFi based indoor positioning system (Chan & Baciu, 2012)

A WiFi based localization system has several advantages- first, existing infrastructure can only be relied by WPS without the necessity of any modification to the environment. Second, only the Received Signal Strength (RSS) and the Basic Service Set Identifier (BSSID) can be included for doing localization using the required WiFi information. Third, simply by sniffing the wireless traffic in the air, the information can be collected easily. Fourth, WiFi is extremely suitable for the use in indoor environment where there are a lot of walls and obstructions as WiFi signals do not require line-of-sight (LOS) (Chan & Baciu, 2012).

For the last few decades one of the most extensively investigated research areas is indoor localization, because in the big industrial and official buildings it is very much important to know the locations of the employees and other devices. However, this area has been developed less than a decade ago since there was no smart phone and wireless communication technologies before that. These technologies have enabled the ways of tracking users and devices in industry, health sector, disaster management and wide range of other related applications and services (Liu, Darabi, Banerjee, & Liu, 2007).

Convolutional Neural Network (CNN)-based image retrieval method was proposed by Chen, et al., (2018) that makes use of visual indoor positioning system. In accordance with a given local coordinate system and scene labels, images captured from each scene have been contained in the system database and its CNN features. Absolute coordinates and quaternion have also been provided. Using the pre-trained deep learning VGG16 network, the CNN features of the images have been extracted in the offline phase which are related to each scene. The proposed system consists of the following two online phases: (1) image retrieval task based on CNN and (2) pose estimation task. When the image retrieval phase is being used, the most similar images (two images) will be recovered by CNN with respect to the query image.

At low frequency magnetic based technology can be used for indoor localization. The magnetic field radiated from at least three reference magnetic stations has been received by the magnetic sensor and the location of the sensor has been estimated by trilateration. This technology can be implemented accurately at low frequencies. However, this process is sensitive to conductive and ferromagnetic materials (Diaz, Ahmed, & Kaiser, 2019). Recently, Bluetooth Low Energy (BLE) based indoor localization has been utilized in smartphones as iBeacons (Apple) and Eddystone (Google). The most significant point is that smartphone can be used for indoor localization within airports, train stations, big markets, malls and restaurants. Here the area map has been sent to the smartphone and then localization is performed using the BLE (Zafari, Gkelias, & Leung, 2019).

In (Chen S. , 2020) fingerprint clustering method has been proposed as an indoor localization system. Two phases have been included here- i) offline phase and ii) online phase. Received Signal Strength (RSS) signal has been collected in the offline phase. For creating the fingerprint database this signal has been pre-processed with the Gaussian model. After that to cluster the fingerprints the K Means++ algorithm has been used and the fingerprints have been grouped with similar signal strengths into a clustering subset. On the other hand, weighted K-Nearest neighbour (WKNN) algorithm has been used in online phase to classify the measured RSS for calculating the localization error.

Because of large bandwidth, high-speed communication, high time resolution, high data rate, and short-wavelength Ultra Wide Band (UWB) signals can be used for indoor localization combining with Wi-Fi infrastructure as a hybrid method. This can reduce the cost and the accuracy can be higher by implementing this algorithm. Typical UWB systems proposed in (Groβwindhager, Stocker, Rath, Boano, & Römer, 2019) can localize a limited number of tags. This UWB localization system is called SnapLoc which is able to localize an unlimited number of tags.

A review of an article on indoor localization techniques and technologies has been introduced in (Obeidat, Shuaieb, Obeidat, & Abd-Alhameed, 2021). Here different detection techniques of recent indoor localization systems have been discussed. Then a comparative overview has been shown between these systems based on accuracy, cost, advantages, and disadvantages. Finally, few indoor localization methods and algorithms, including Angle Of Arrival (AOA), Time Of Arrival (TOA), and Received

Signal Strength (RSS) have been introduced. The concepts, requirements, and specifications for each category of all the methods and algorithms have been considered during the study of this paper.

2. Background Study And Literature Review

2.1 Brief History

At the beginning of the 20th century the development of radio transmission systems paved the way for a new era regarding location systems. In a Global Navigation Satellite System (GNSS), signals from known locations transmitted by satellites are used as localization marks (Samama, 2008). It is shown in Figure-2(a). In terms of availability, coverage, and accuracy the use of satellites for positioning resulted in real improvements. In 1958 the first satellite navigation system was launched under the name of TRANSIT project. In 1964 this system became operational for the U.S. Navy.

The obtained accuracy was in the range of 200-500m. Then to overcome the limitations of the previous system in 1973, the NAVSTAR-GPS project was launched by the U.S. Direction of Defense (DoD). In 1978 the first four GPS satellites were launched and in 1994 the 24th was launched(Hegarty & Chatre, 2008). Initially, the highest quality of service was reserved for military use, and the signal available for civilian use was intentionally degraded (selective availability). In the year of 2000 the selective availability was turned off improving the precision of civilian GPS from 100m to 20m. The Galileo system is currently built by the European Union (EU) and European Space Agency (ESA) and aims at providing a high precision positioning system upon which European nations can rely on. The initial service of this system is expected around 2014 and completion by 2019(ESA, 2011).

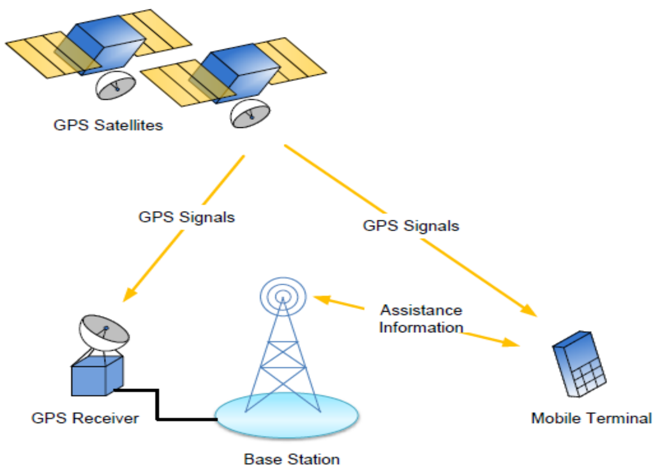


Figure-2(a) Global Navigation Satellite System (GNSS)(Samama, 2008)

2.2 Indoor Localization Systems

In developing the indoor localization systems, extensive research has been done all over the world, such as Radio Detection and Ranging (RADAR) (Bahl & Padmanabhan, 2000), Horus (Youssef, 2004), and Compass (King, Kopf, Haenselmann, Lubberger, & Effelsberg, 2006). However, laptop platforms have been used to develop most of which are equipped with better antennas than on the smartphone. Moreover, only room level accuracies have been achieved by the recent work on developing smartphone indoor localization apps. Therefore, by using smartphone proper indoor localization remains a remarkable problem. By introducing peer assisted localization approach, Liu et al., (2012) tried to solve this problem. But only the public areas with high densities of smartphones present at the same time can use this approach. An accurate smartphone based indoor pedestrian localization system using WiFi including the camera on the phone has been described by Lokesh et al. Agarwal & Toshniwal, (2013).

Researchers have been working on different possibilities for the last decade on how to make the mobile device a navigation tool in addition to using it as a communication tool. Navigation system is making our life easier and more comfortable and becoming more and more important in our everyday life. During the last generation, most people bought mobile phone with in-built Global Positioning System (GPS). The most prominent contribution in determining the position of users and in routing any person to the desired destination is GPS. Satellites have been used by the system to triangulate the location of the GPS device.

For outdoor positioning, this system has given a good performance in terms of accuracy and is the most preferred location-based system. But when it is needed to be used in indoor environment, GPS has proved to be inefficient. The device needs to be in the line-of-sight from the satellites in order for GPS to perform a triangulation and this is the main reason for its inefficiency. Moreover, low precision is another factor for GPS system to make it unsuitable for indoor areas (Garcia, Martinez, Tomas, & Lloret, 2007). Therefore, when it comes to use in indoor localisation system, other alternatives such as Bluetooth, WiFi, RFID and Infrared Red are preferable.

Typically, Nearest Neighbour (NN) method has been used to achieve the floor estimation via fingerprinting approaches that can solve the indoor localization problem locally (Zhang & Feng, 2012). But these solutions to be used worldwide are very expensive and computationally rather more expensive. In the fingerprinting-based methods (Roos, Myllyma"ki, Tirri, Misikangas, & Sieva"nen, 2002), a fingerprint database has been constructed by the location service providers and then this database has been transferred to the Mobile Station (MS). Then its location and corresponding floor estimation can be computed by the MS. The fingerprint databases do include (RSS's) coming from various Access Points (APs). For this reason, they are typically very large in many points or coordinates within a building.

Based only on the known or estimated positions of the transmitters or Aps, an alternative floor estimation approach has been used with less complexity. The simplest of such approaches is Weighted Centroid Localization (WCL) (Sharma, 2006). Thus, as the solution of the problem of the large sized databases and to increase the estimation speed, this method can be used as its complexity is much less than the one of the NN fingerprinting.

2.3 Algorithms for Indoor Localization

There are many algorithms that have been proposed by various researchers in recent years. Some important algorithms are described below.

2.3.1 Received Signal Strength Indicator (RSSI)

Received Signal Strength Indicator (RSSI) is very simple and popularly used technique for indoor localization. This algorithm only depends on the Received Signal Strength (RSS). The power which is actually received by the receiver is called RSS. The unit for RSS is usually decibel-milliwatts (dBm) or milliWatts (mW). The distance between a transmitter (Tx) and a receiver (Rx) device is highly dependent on the value of the RSS. If the distance between Tx and Rx is smaller, then the value of the RSS is higher between them. Different signal propagation models can be used to determine the absolute distance can be estimated using a known transmission power at a reference point (Yang, Zhou, & Liu, 2013). It is shown in Figure-2(b).

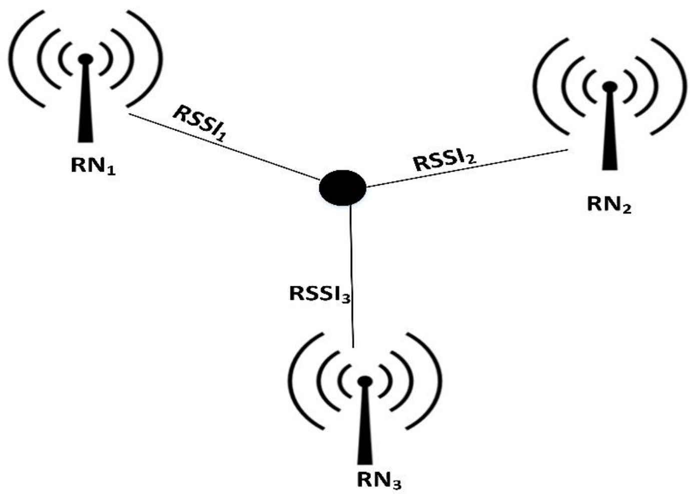


Figure-2(b) RSSI based localization [21]

2.3.2 The weighted centroid algorithm

For the estimation of the indoor position the complexity of this algorithm is the lowest. An estimated AP position is the major factor only on which it depends. The estimation of the position can be measured by the weighted centroid of the AP positions. The observed Received Signal Strengths (RSSs) are used to derive the weights. The training data, in their turn, is the basis to estimate the AP positions (Razavi, Valkama, & Lohan, 2015).

2.3.3 The log-Gaussian probabilistic

Normally distributed noise is mainly assumed by this algorithm. Using the training positions the probability of the RSS measurements is evaluated. By measuring the highest probable value(s) the position estimate can be determined Cramariuc, Huttunen, & Lohan, (2016) Srestha, Talvitie, & Lohan, (2013).

2.3.4 Clustering

This method can be categorised in two versions:

i) To match the RSS, modified log-Gaussian metric and affinity propagation is used for RSS clustering

ii) K-means method is used for 3D coordinate clustering with the modified log-Gaussian metric.

In case of both algorithms, the average over the three training positions is calculated to get the final position. Three best matches should be coherent with this value (Cramariuc, Huttunen, & Lohan, 2016).

2.3.5 The UJI kNN algorithm

The k-Nearest Neighbour (kNN) algorithm is the base for this deterministic rule. To find out the number of floors in the feature space from the k-Nearest fingerprints (kNN) set, voting procedure has been used which is included in this rule. All the fingerprints are discarded from the kNN-set if they do not belong to the estimated floor. The geometric centroid of the remaining fingerprints is then used to determine the final estimate. Various types of data representations and distance metrics are considered by this algorithm to pretend the behaviour of radio propagation. It is also used to avoid the usage of unit-less values in RSSI and also to consider the physical underpinning (Torres-Sospedra, Montoliu, Trilles, Óscar, & Huerta, 2015).

2.3.6 The RTLS@UM System

This Real Time location System (RTLS) algorithm has been proposed by a team from the University of Minho (UM) who had participated in the Evaluating Ambient Assisted Living (EvAAL) competition. An iterative procedure has been introduced in this algorithm to obtain the coordinates floor and building based on k-Nearest fingerprints (kNN) and Weighted k-Nearest fingerprints (wkNN).

In this paper five alternative algorithms have been mentioned that are slightly different from each other. Among these five, only two algorithms have been tested in this paper and all the results of these two have been provided in the competition. Marginal gain has been reported by the authors. For this reason, in this database the proposed diversity devices filter was not applied (Moreira, Nicolau, Meneses, & Costa, 2015)(Torres-Sospedra, et al., 2015).

2.3.7 Rank-Based Fingerprinting (RBF)

In this algorithm at the operational stage the RSS values have been measured and ranked according to their values. In this ranking the first position has been given to the AP that provides the strongest signal. Then the operational rank vector and the radio map have been used to generate the reference ranks. Finally, the Spearman’s footrule has been used to perform the rank comparison which is described by Machaj, Brida and Piché (2011). Since RSS rank doesn’t change with biasing and scaling, this is more convenient for the algorithm. So, in this case the RSS values are replaced by the RSS ranks.

2.3.8 Coverage Area-Based Algorithms

In the simplest form of this algorithm, the information of the signal strengths is not required. It depends only on the observance of which ASs are heard. The pointwise defined knowledge has been used in the probabilistic coverage map. The coverage areas have been defined as the distribution which is introduced in this algorithm. By taking the average of the points where the AP is heard, the location of the coverage area can be defined that are based on distribution. By adjusting the shape or covariance parameters of the probability distribution function of these points, the size and shape of the coverage area can be defined. For example, an elliptical shape can be found in Gaussian and Student distributions and the coverage area can be defined using this (Leppäkoski, Tikkinen, & Takala, 2010).

3. METHODOLOGY

In this paper the location fingerprinting based algorithms have been used instead of modelling the propagation of the WiFi signal. It assumes that similar signal strength can be received by a WiFi enabled device at a certain location, such RSS and coordinates would serve as a unique “fingerprint” of that particular location. The stored dataset that includes all the values of RSS and coordinates can be used to estimate the locations of the mobile devices. For every new location, the Wi-Fi signal strength is detected and the error can be estimated by measuring the difference between current and stored values of the fingerprints.

Two algorithms have been implemented in this paper-

I. Weighted Centroid Localization (WCL) algorithm

II. Log-Gaussian Probability algorithm

All the implementations have been done using MATLAB software.

3.1. Weighted Centroid Localization (WCL) Algorithm

In wireless sensor networks, Weighted Centroid Localization (WCL) is the first proposed approach for estimation of the position. For determining the indoor position, it is one of the lowest complex algorithms, and it relies only on the estimated AP positions. The weighted centroid of the AP positions has been used for the position estimation, where the weights can be derived from the observed RSSs. So, the AP positions can be estimated based on the training data.

In the WCL approach the position of the MS can be measured as the weighted average of the positions of APs heard by the MS. The set of all hearable APs can be denoted by H and the (known) coordinates of APs by c_{ap} ≡ (Xap, Yap,Zap), where ap = 1,...,|H|. Then the WCL-based estimate of mobile station coordinates can be computed as follows (Wang, Urriza, Han, & Cabric, 2011),

$$C_{MS,wc} = \frac{\sum_{ap=1}^{H} w_{ap} c_{ap}}{\sum_{ap=1}^{H} w_{ap}} \tag{1}$$

Here the values of weights have been denoted by w_{ap}. For nearer APs, to weight shorter distances more than higher distances, w_{ap} may be chosen as (Wang, Urriza, Han, & Cabric, 2011),

$$w_{ap} = \frac{1}{(d_{ap})^g} \tag{2}$$

where d_{ap} is the distance between ap-th AP and the MS, and degree g is to ensure that remote APs still impact the position estimation.

Since the RSS heard from AP is inversely proportional to d_{ap} and the distances d_{ap} are not readily available, the weights w_{ap} can be replaced by RSS to obtain the following RSS-based formula for WCL (Wang, Urriza, Han, & Cabric, 2011),

$$C_{MS,wc} = \frac{\sum_{ap=1}^{H} m_{MS,ap} C_{ap}}{\sum_{ap=1}^{H} m_{MS,ap}} \tag{3}$$

Where $m_{MS,ap}$ is the measured test RSS of AP number ap by MS.

For each coordinate of above-mentioned equation can be written independently. For instance, for the height coordinate Z_{ap}, that matters in floor estimation task, it can be written as follows (Wang, Urriza, Han, & Cabric, 2011),

$$Z_{MS,wc} = \frac{\sum_{ap=1}^{H} m_{MS,ap} Z_{ap}}{\sum_{ap=1}^{H} m_{MS,ap}} \tag{4}$$

For commercial and privately-owned buildings, such as shopping malls or blocks of flats, the deployed APs are typically owned by various owners. For this their locations are decentralized and unknown in totality. The AP location may be known to some extent for industrial and university buildings, but such information should be typically stored in incomplete or inexact form, because from the communication point of view it is not considered important. Due to these reasons, it has been assumed that the location of APs is not known in advance and is estimated based on the available fingerprint data. So, it can be noticed that to perform the WCL algorithm only the number of coordinates at the mobile device needs to be stored making the WCL approach a promising one from complexity point of view.

3.2 Log-Gaussian ProbabilityAlgorithm

Traditional fingerprinting without clustering is the method of this algorithm that has been used in this project. The current training coordinates has been compared to the estimated positions of the mobile stations that has been measured by using the K Nearest Neighbours (KNN) algorithm.

Here for the current location a set of fingerprints has been selected as possible candidates. Then the average of the positions of these fingerprints has been used as the estimated positions for the current positions (Cramariuc, Huttunen, & Lohan, 2016). The average of the mobile station positions can be found by using the following RSS-based equation for Log-Gaussian algorithm (Fan, Guo, Zheng, & Hong, 2019)-

$$S'_j = \frac{\sum_{j=1}^{k} w_{i,y_j} s_{y_j}}{\sum_{j=1}^{k} w_{i,y_j}} \tag{5}$$

Here k is the total number of access points, w_{i,y_j} are the values of training RSS and s_{y_j} are the values of training coordinates that has been found from the given dataset. MATLAB built-in function "knnsearch( )" has been used to get the outputs of the estimated positions between the measured positions from the above equation and the given training coordinates.

For K-NN algorithm, user-defined neighbour parameter is K. The classification accuracy and the interference to the data are highly dependent on the value of K. The accuracy will be reduced and the interference will be increased for both higher and smaller values of K.

Eventually, the neighbour data points are very important for the estimation results. There may be an increase in the estimation error if the value of K is not correct. Therefore, the value of k is often set as a relatively small value in normal applications of the K-NN algorithm. But it must be an integer (Fan, Guo, Zheng, & Hong, 2019).

The location of the target mobile device can be estimated by this fingerprinting method using a pre-defined fingerprint database. In case of a deterministic network, by seeing the measured RSS and the corresponding location coordinates, the specific fingerprint can be found. The comparison between the target mobile device and the collected fingerprint can be measured just after getting the target measurements. Afterwards, the most matching fingerprint can be used to find out the target location. In other way several most matching fingerprints can be taken as a weighted linear combination (Bshara, Orguner, Gustafsson, & Van Biesen, 2010).

3.3 Error Calculation

For the both algorithms explained above the estimation error has been calculated by using the following equation-

For vectors,

$$E = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x}_i)^T (x_i - \overline{x}_i)} \tag{6}$$

For scalars,

$$E = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x}_i)^2} \tag{7}$$

Here n is the total number of total access points (APs), x_i is the true position and $\overline{x}_i$ are the estimated positions of mobile stations (MS). We have got the true positions from the given dataset of test coordinates that has been used for Weighted Centroid Localization algorithm. For the Log-Gaussian algorithm the true positions have been taken from the given dataset of training coordinates. The estimated positions have been calculated by using the equations described in 3.1 and 3.2 sections.

3.4 Dataset Description

The database and supporting software have been deposited in the Zenodo repository, created within the EU-funded project OpenAIRE (Open Access Infrastructure for Research in Europe). It was initially meant for EU-funded projects, but now it has been used by the entire research community coming from various research fields, such as telecommunication, physics, chemistry, etc. Because of its ease of access and use, reliability, and supportive attitude towards BigScience tools the Zenodo repository has been chosen. The required dataset has been found at the following link (Lohan, et al., 2017).

All the files in the database are provided as ‘csv’ files. Four ‘csv’ files for the training data and four ‘csv’ files for the test data are available. These are as follows-

Coordinates files: Two files-one for test data and another for training data. In these files according to the measurement the (x, y, z) coordinates (in meters) have been showed in each row. For the positioning studies these files can be used directly.

RSS files: Two files-one for test data and another for training data. These files are very large in size. The number of columns is equal to the number of Access Points (Aps) showing the RSS level of each measurement point at which each of the MAC addresses of the Access Points were heard. One measurement has been corresponded to each row.

4. RESULTS AND DISCUSSIONS

In this paper all the results have been found by using MATLAB software. After downloading, all the datasets have been saved in the same folder where the main code for this project has been saved. At the beginning of the code all data files have been loaded by using the MATLAB function ‘importdata()’ so that all the values can be used for all implementations.

The input files are as follows-

I. Test_rss_21Aug17.csv
II. Test_coordinates_21Aug17.csv
III. Training_rss_21Aug17.csv
IV. Training_rss_21Aug17.csv

4.1 OUTPUTS AND GRAPHS IN MATLAB

Figure-4(a) shows the locations of the training coordinates data that has been loaded from the “Training_coordinates_21Aug17.csv” file.

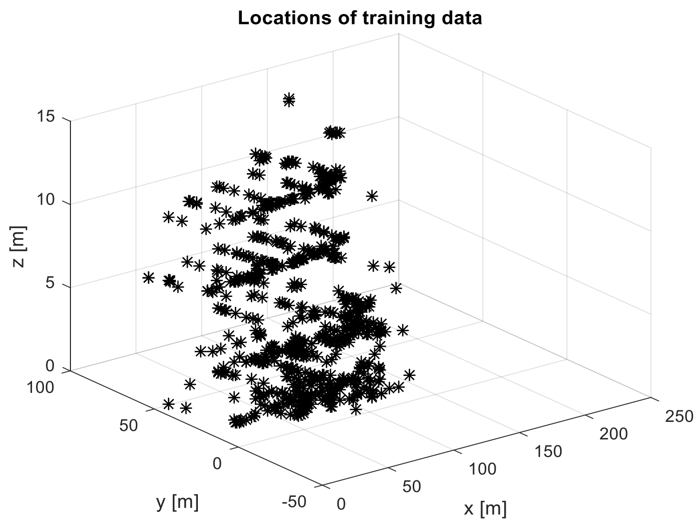


Figure-4(a) Locations of training data

Figure-4(b) shows the locations of the test coordinates data that has been loaded from the “Test_coordinates_21Aug17.csv” file.

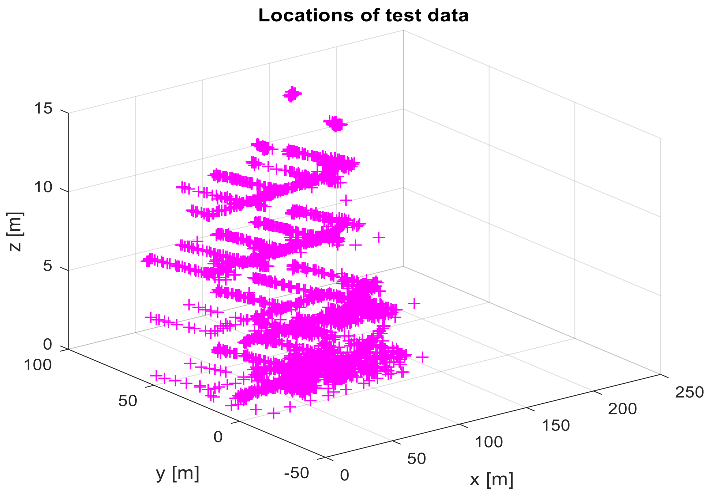


Figure-4(b) Locations of test data

The formula for Weighted Centroid Localization (WCL) has been implemented in MATLAB software. The estimated locations of the Mobile Station (MS) using the WCL based algorithm with respect to the access points are shown in Figure-4(c)

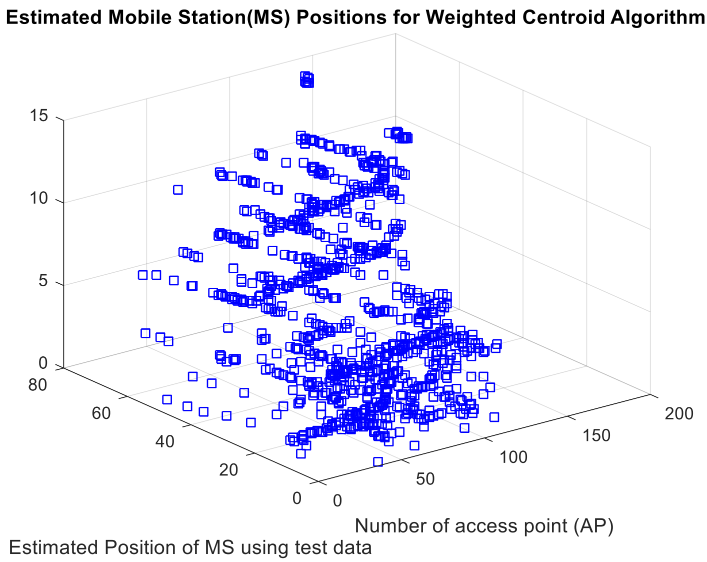
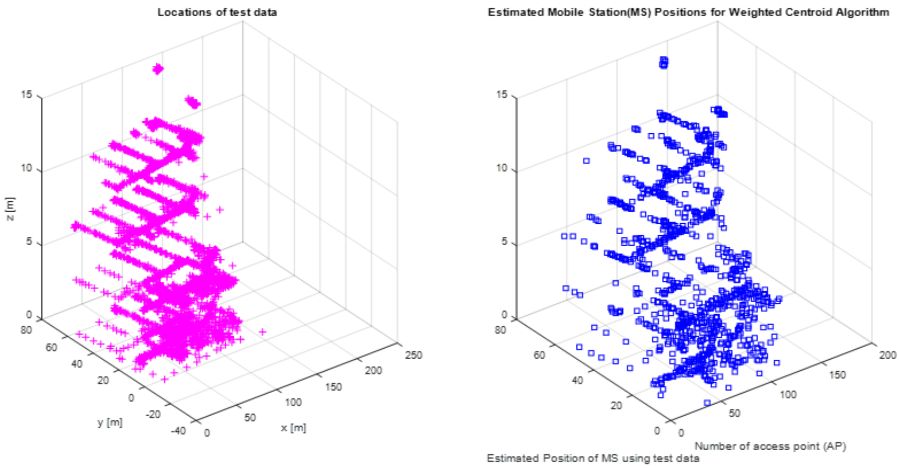


Figure-4(c) Estimated MS positions using WCL algorithm

The true positions for this algorithm are the positions of the test coordinates that have been found in the given dataset. After getting the estimated positions the error formula has been implemented in MATLAB. The value of the mean error has been found 18.0686m for WCL algorithm. A combined figure for the true and estimated positions for WCL is given bellow in Figure-4(d).



(i) (ii)

Figure-4(d) (i) True locations for WCL, (ii) Estimated locations for WCL

Figure-4(e) shows the output for the estimation error with respect to the number of Access Points.

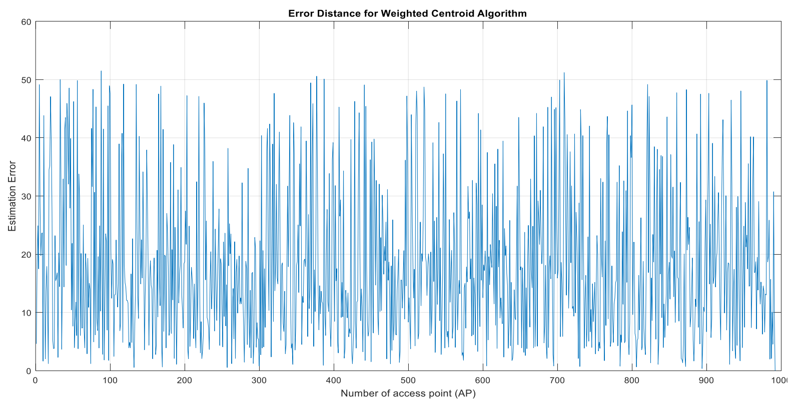


Figure-4(e) Estimation error using WCL algorithm

The formula for Log-Gaussian algorithm has been implemented in MATLAB software. The estimated locations of the Mobile Station (MS) using the Log-Gaussian based algorithm with respect to the access points are shown in Figure-4(f)

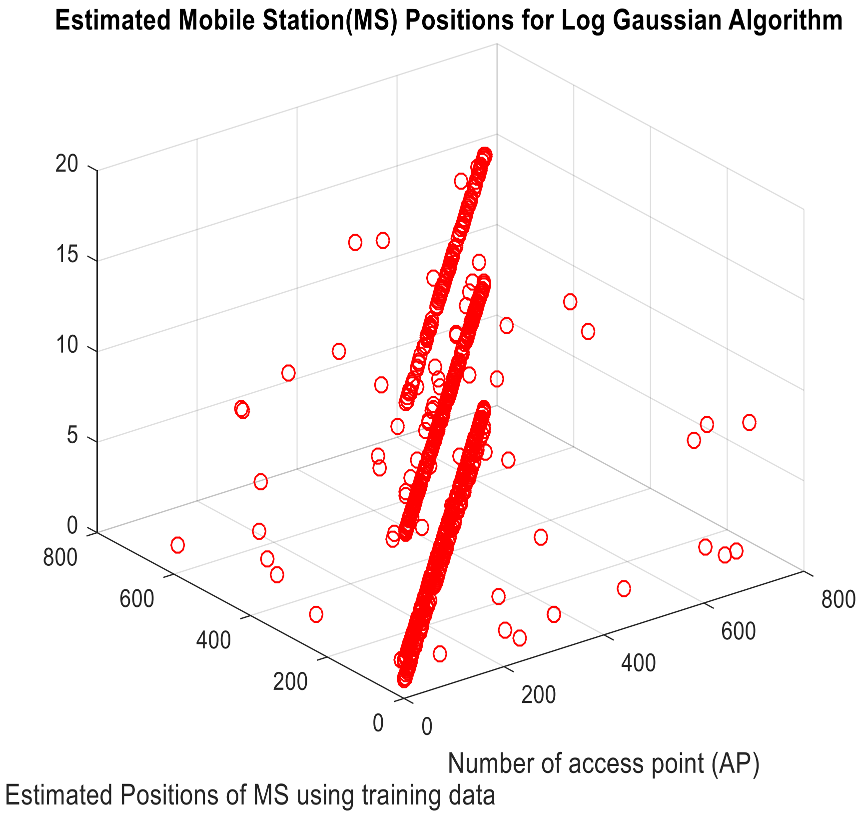
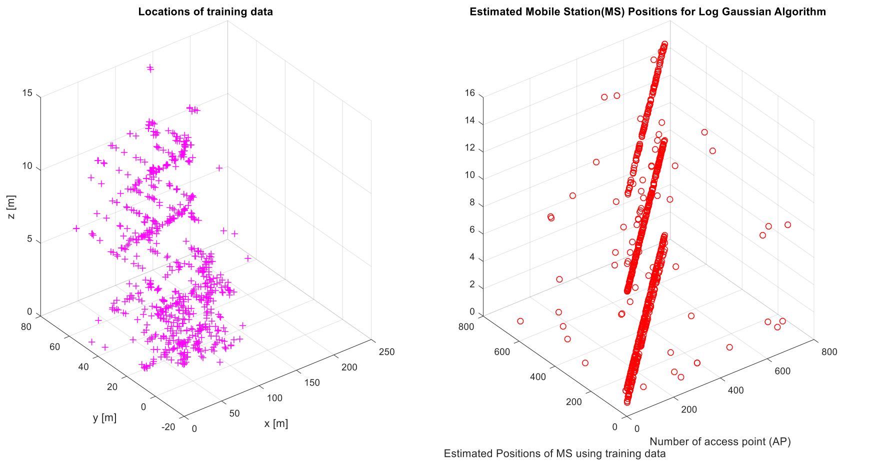


Figure-4(f) Estimated MS positions using Log-Gaussian algorithm

The true positions for this algorithm are the positions of the training coordinates that have been found in the given dataset. After getting the estimated positions the error formula has been implemented in MATLAB. The value of the mean error has been found 15.2667m for Log-Gaussian algorithm. A combined figure for the true and estimated positions for Log-Gaussian algorithm is given bellow in Figure-4(g).



(i) (ii)

Figure-4(g) (i) True locations for Log-Gaussian, ii) Estimated locations for Log-Gaussian

Figure-4(h) shows the output for the estimation error with respect to the number of Access Points.

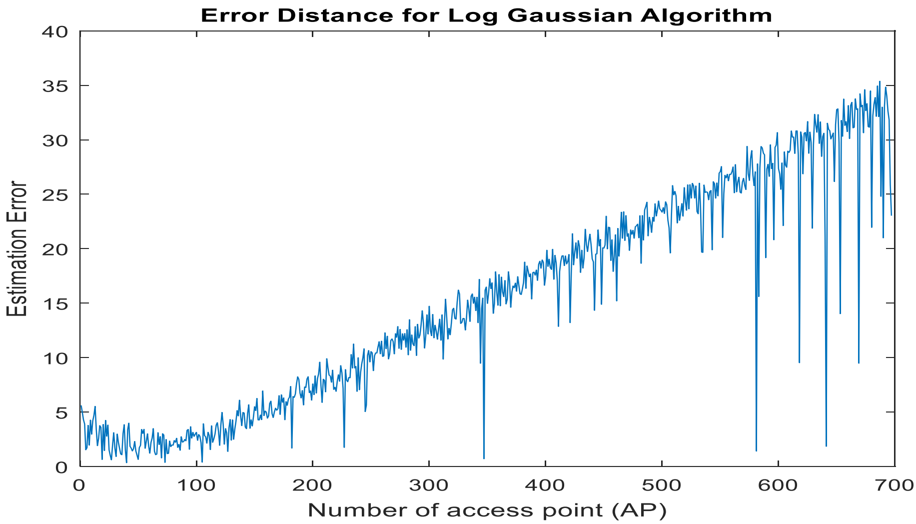


Figure-4(h) Estimation error using Log-Gaussian algorithm

The location of access points is a major factor for the number of coordinated per access point. In the centre of the building the access points are easily hearable and users frequently pass by these points. But for the access points that are located outside the building may only be heard marginally at an edge of the building and the amount of information is less.

5. PRACTICAL CONTRIBUTIONS

The recent advancement and developments in localization-based technologies have led to a growing business interest in location-based applications and services. Today, locating or real-time tracking of physical belongings and other necessary equipment inside the buildings accurately have become the most important requirement in technological innovation in business. Thus, the demand for indoor localization applications has become a key prerequisite in present markets. In addition, indoor localization technologies have overcome the limitations of Global Positioning System (GPS) inside any closed environment, like buildings, big markets or shopping malls. So, this paper aims to provide the idea of the recent advancements in wireless indoor localization algorithms to deliver a better understanding and motivation to the new researchers in this rapidly developing field. The Localization techniques mentioned in this paper can be used for accurate indoor positioning capabilities to locate all important equipment necessary for big industrial buildings and factories. Wi-Fi positioning signals can be utilized to accomplish position tracking in places where GPS cannot reach.

6. CONCLUSION

In this paper two of the different indoor localization algorithms using WiFi have been discussed in detail and implemented in the MATLAB software so far. Estimated positions of the mobile stations and the estimation errors have been obtained using the downloaded training and the test datasets. The test dataset for both coordinates and RSS have been used to estimate the positions of the mobile stations using the Weighted Centroid Localization (WCL) algorithm. In the Log-Gaussian algorithm for both coordinates and RSS the training dataset have been used to estimate the positions of the mobile stations.

All the calculations have been done using a new database for WiFi-based indoor positioning. The estimation error has been calculated for both algorithms using Root Mean Square method. The value of the mean error for Weighted Centroid Localization (WCL) is 18.0686m and for Log-Gaussian algorithms it is 15.2667m. Both the values are quite similar to the previously implemented values.

For the processing and evaluation of the RSS data, some additional software can be provided. The indoor positioning technology and the indoor navigation community are being benefited by this dataset. Significant advances might be done in this project by more comprehensive studies in many different scenarios that can be performed with many other available databases.

Because of the accelerating demands on Location Based Services (LBS), indoor positioning using wireless systems are receiving remarkable importance in various sectors of business. There are lots of infrastructures for wireless network are available like-cellular radio networks (LTE and5G), Wi-Fi networks, Bluetooth Low Energy (BLE) networks etc. The most convenient and competent option is to use the Received Signal Strength (RSS) for indoor localizations. Because for most of the existing networks they are easy to obtain for all the positioning measurements.

With the improvement of the WiFi finger-print localization algorithms the stability and accuracy of the positioning results will be improved. The high demand of indoor localization can be fulfilled by this way. In different sectors of e-commerce and business indoor environment has a great importance for wireless network applications.

6.1 LIMITATIONS

There is no doubt that GNSS has achieved enormous success in outdoor positioning. But some factors should be considered in case of indoor localizations like - Non-Line-Of-Sight problem in indoor environment, problems of multipath propagation, blockage of signals, intentional and unintentional interferences, etc. The main problem of these factors is the attenuation of signals that fails to get the locations in indoor environments. Thus, all those LBS fail when going indoors. By implementing the indoor localization algorithms properly, accurate indoor localization can be ensured.

6.2 FUTURE SCOPES

As a future enhancement, by applying various techniques such as backtracking, the accuracy of the system can be improved. Using this technique, the system will be able to avoid choosing one between two similar measurements. By applying backtracking, the system will go back to the user’s previous location if any ambiguity occurs, and then user’s next location between the candidate locations might be compared by the system.

Using other signal sources like Bluetooth and Global System for Mobile Communication (GSM) wireless technologies can be another future improvement for this project. The accuracy of the system can be increased by having more signal sources so that the system can be used in bigger scale. As the future research, motion sensors can be combined on the smartphone. By using motion sensors more location-related information can be provided by multimodality of the smartphone. To improve the indoor localization performance, it will help to develop a sophisticated motion model.

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REFERENCES

Agarwal, L., & Toshniwal, D. (2013). Smart Phone Based Indoor Pedestrian Localization System. *13th International Conference on Computational Science and Its Application*, (pp. 678-724).

Bahl, P., & Padmanabhan, V. (2000). RADAR: An in-building RF-based user location and tracking system. *IEEE International Conference on Computer Communications (INFOCOM' 00)* (pp. 775-784). IEEE.

Bshara, M., Orguner, U., Gustafsson, F., & Van Biesen, L. (2010). Finger-printing localization in wireless networks based on received-signal-strength measurements: A case study on WiMAX networks. *IEEE Transactions on Vehicular Technology*, 283–294.

Chan, E., & Baciu, G. (2012). *Introduction to Wireless Localization.* Singapore: John Wiley & Sons Singapore Pte. Ltd.

Chen, S. (2020). Indoor Localization Based on Fingerprint Clustering. *Network and Communication Technologies: Canadian Center of Science and Education*, 40-45.

Chen, Y., Chen, R., Liu, M., Xiao, A., Wu, D., & Zhao, S. (2018). Indoor Visual Positioning Aided by CNN-Based Image Retrieval: Training-Free, 3D Modeling-Free. *Multidisciplinary Digital Publishing Institute (MDPI)*.

Cramariuc, A., Huttunen, H., & Lohan, E. (2016). Clustering benefits in mobile-centricWiFi positioning in multi-floor buildings. *International Conference on Localization and GNSS (ICL-GNSS).* Barcelona, Spain.

Diaz, E., Ahmed, D., & Kaiser, S. (2019). A review of indoor localization methods based on inertial. *Amsterdam: Elsevier*, 311-333.

ESA, G. (2011). *What is galileo ?* Retrieved from European Space Agency: http://www.esa.int/esaNA/galileo.html

Fan, G., Guo, Y., Zheng, J., & Hong, W. (2019). Application of the Weighted K-Nearest Neighbor Algorithm for Short-Term Load Forecasting. *Multidisciplinary Digital Publishing Institute (MDP)*.

Garcia, M., Martinez, C., Tomas, J., & Lloret, J. (2007). Wireless Sensors selflocation in an Indoor WLAN environment. *International Conference on Sensor Technologies and Applications*, (pp. 146-151).

Groβwindhager, B., Stocker, M., Rath, M., Boano, C., & Römer, K. (2019). SnapLoc: An ultra-fast UWB-based indoor localization system for an unlimited number of tags. *18th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN)* (pp. 61-72). IEEE.

Hegarty, C., & Chatre, E. (2008). Evolution of the Global Navigation SatelliteSystem (GNSS). *Proceedibgs of the IEEE*, 67-108.

King, T., Kopf, S., Haenselmann, T., Lubberger, C., & Effelsberg, W. (2006). Compass: A probabilistic indoor positioning system based on 802.11 and digital compasses. *Proceedings of the 1st international workshop on Wireless network test beds, experimental evaluation & characterization*, 34-40.

Leppäkoski, H., Tikkinen, S., & Takala, J. (2010). Optimizing radio map for WLAN fingerprinting. *International Conference on Ubiquitous Positioning Indoor Navigation and Location Based Service*, (pp. 1-8). Helsinki, Finland.

Liu, H., Darabi, H., Banerjee, P., & Liu, J. (2007). Survey of wireless indoor positioning techniques and systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 1067-1080.

Liu, H., Gan, Y., Yang, J., Sidhom, S., Wang, Y., Chen, Y., & Ye, F. (2012). *Push the Limit of WiFi based Localization for Smartphones.* ACM MobiCom.

Lohan, E., Torres-Sospedra, J., Richter, P., Leppäkoski, H., Huerta, J., & Peng, Z. (2017). WiFi Crowdsourced fingerprinting Database and Benchmark Software for Indoor Positioning. *Multidisciplinary Digital Publishing Institute (MDPI)*, 1-16.

Machaj, J., Brida, P., & Piché, R. (2011). Rank based fingerprinting algorithm for indoor positioning. *International Conference on Indoor Positioning and Indoor Navigation.* Guimaraes, Portugal.

Moreira, A., Nicolau, M., Meneses, F., & Costa, A. (2015). Wi-Fi fingerprinting in the real world -RTLS@UM at the EvAAL competition. *International Conference on Indoor Positioning and Indoor Navigation (IPIN).* Calgary, AB, Canada.

Obeidat, H., Shuaieb, W., Obeidat, O., & Abd-Alhameed, R. (2021). A Review of Indoor Localization Techniques and Wireless Technologies. *Springer: Wireless Personal Communications*, 289-327.

Razavi, A., Valkama, M., & Lohan, E. (2015). K-Means Fingerprint Clustering for Low-Complexity Floor Estimation in Indoor Mobile Localization. *IEEE Globecom Workshops (GC Wkshps).* San Diego, CA, USA: IEEE.

Roos, T., Myllyma"ki, P., Tirri, H., Misikangas, P., & Sieva"nen, J. (2002). A probabilistic approach to WLAN user location estimation. *International Journal of Wireless Information Networks*, 155-164.

Samama, N. (2008). *Global Positioning : Technologies and Performance. Hoboken.* New Jersey: NJ, USA, John Wiley.

Seco-Granados, G., Lopez-Salcedo, J., Jimenez-Banos, D., & Lopez-Risueno, G. (2012). Challenges in Indoor GNSS: Unveiling its core features in signal processing. *IEEE Signal Processing Magazine*, 108-131.

Sharma, N. (2006). A weighted center of mass based trilateration approach for locating wireless devices in indoor environment. *4th ACM international workshop on Mobility management and wireless access (MobiWac '06)* (pp. 112-115). New York: USA.

Srestha, S., Talvitie, J., & Lohan, E. (2013). Deconvolution-based indoor localization with WLAN signals and unknown access point locations. *International Conference on Localization and GNSS (ICL-GNSS).* Turin, Italy.

Stella, M., Russo, M., & Begusic, D. (2012). RF Localization in Indoor Environment. *Redioengineering*, 557-567.

Torres-Sospedra, J., Montoliu, R., Trilles, S., Óscar, B., & Huerta, J. (2015). Comprehensive analysis of distance and similarity measures for Wi-Fi fingerprinting indoor positioning systems. *Expert Syst. Appl.*, 9263–9278.

Torres-Sospedra, J., Moreira, A., Knauth, S., Berkvens, R., Montoliu, R., Belmonte, O., . . . Costa, A. (2015). A realistic evaluation of indoor positioning systems based on Wi-Fi fingerprinting. *The 2015 EvAAL-ETRI competition*, 263–279.

Wang, J., Urriza, P., Han, Y., & Cabric, D. (2011). Weighted centroid localization algorithm: theoretical analysis and distributed implementation. *IEEE Transactions onWireless Communications*, 3403–3413.

Yang, Z., Zhou, Z., & Liu, Y. (2013). From RSSI to CSI: Indoor localization via channel response. *ACM Computing Surveys (CSUR)*, 25.

Youssef, M. (2004). HORUS: A WLAN-based indoor location determination system. *Department of Computer Science, University of Maryland*, 76-84.

Zafari, F., Gkelias, A., & Leung, K. (2019). A survey of indoor localization systems and technologies. *IEEE Communications Surveys & Tutorials* , 2568–2599.

Zhang, N., & Feng, J. (2012). Polaris : A fingerprint-based localization system over wireless networks. *International Conference on Web-Age Information Management* (pp. 58-70). Springer.