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A Survey of Internet of Things based Indoor Positioning Systems based on Bluetooth Low Energy Beacon

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Abstract: The global positioning systems (GPS) and cellular systems face inherent limitations when it comes to enclosed environments like shopping malls, hospitals, warehouses, as they have significant shadowing effects that cause the signals to be distorted. There have been many studies on different technologies and techniques aiming to find the optimum approach to be used for indoor positioning systems (IPS). Among all the technologies adapted by researchers all around the world, Bluetooth Low Energy (BLE) beacons have been a prevalent choice for many, due to its deploying flexibility, low cost, low power consumption and ability to provide very advanced services to users. It is arduous to obtain RSSI values with great accuracy because the signals can be easily intervened by many factors like humidity, temperature, physical barriers, and interference from decoherent signals. In this paper, we presented a comparative analysis of different, fairly recent IPS that are based on BLE beacons by classifying the different proposed approaches in a structured and systematic manner and traversing the issues and challenges that exist with each technique. The accuracy of the results can be enhanced by using the most suitable positioning algorithm, the orientation of the beacon setup, and optimization methods used. A preliminary result from a case study using BLE beacons with K-Nearest Neighbours (KNN) based fingerprinting approach for indoor positioning estimation shows 86.67% accuracy.

Keywords: Bluetooth, Internet of Things, Indoor Positioning System, Relative Signal Strength Index

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1. INTRODUCTION

For years, one of the most go-to location navigation approaches has been the Global Navigation Satellite System (GNSS) such as Global Positioning System (GPS) [1]. However, when it comes to navigating over small distances such as indoors; from room-to-room, corridor-to-corridor, it is necessary to make use of technology that may function effectively and accurately, given the constraints that existing navigating technologies have to face when the line of sight (LoS) is lost [2]. Hence, there is a need for approaches that would be effective and accurate in short ranges such as ZigBee, Bluetooth, RFID, Wi-Fi, and Ultra-Wideband [3]. In [4], researchers have also reviewed technologies based on visible light or Earth's magnetic field. Over the years, since the booming of Indoor Positioning System (IPS), many reviews and surveys have been carried out on different IPS related topics [5-13]. From these reviews, it can be observed that many are missing the latest technologies and techniques while others lack information on future enhancement and trends. Sometimes, the topics they covered were too broad. One very common criterion that most otherwise very detailed, good review or survey papers were missing was the focus of IPS based on Bluetooth Low Energy (BLE) beacons as well as existing and their probable applications based on Internet of Things (IoT).

Thanks to the growing ability of effective data collection over short ranges [14], the challenge to find data for an IoT environment is solved. This enables us to go onto the next phases of information flow in an IoT architecture. There has been a sudden surge in the use of IoT in various sectors including health care [15], automobiles [16], and even in homes [17]. The purpose behind choosing IoT as the architecture is that it allows communication between different devices and modules via the Internet, which consequently enables all the devices to be remotely inter-connected and operate at once as an entire system [18]. For instance, it would allow vendors of a shop to know when exactly a customer is nearby so that promotions may be passed down to him/her, given that both have the mobile application of the respective store installed with the Beacon module on their phones [19].

We shall explore various refining techniques throughout the paper to gain insight on the most suitable and accurate results. For instance, usage of Machine Learning refining algorithms, such as the K-Nearest Neighbors (KNN), may help us filter out ambiguous readings [2], while filters such as the Kalman filter help to smoothen out the values for greater precision [20]. The diagram in Figure 1 illustrates the various techniques proposed for improving the accuracy of the data and the methods shall be further explained in the proceeding section.

Therefore, in this paper, we focus on studies that are related to the use of BLE beacons as indoor positioning systems for IoT based applications. The study is organized as follows: Section 2 presents the background of BLE technology and its potential usage for IPS. Section 3 discusses the state of the art which elaborates on optimization methods focusing on mainly the Kalman filter and Machine Learning algorithms, accuracy of the different proposed systems, and their limitations. Section 4 and 5 elaborate on the architecture of IoT and IoT related applications respectively. Finally, in Section 6 we render our conclusion.

2. BLUETOOTH LOW ENERGY (BLE)

BLE has been a top choice for many working with computing and IoT applications [21-24]. Beacons, first introduced as an incentive to the Bluetooth 4.0 to primarily aid IoT applications [25,26], became a go-to technology for IPS due to its minimum weight, lesser energy consumption, low deployment cost and can provide higher position accuracy than other technologies [27,28]. These miniature wireless devices can provide location-based services to BLE-enabled devices in the working range. Beacons can go as far as 60 meters to transmit data with less than 6ms latency, which has its cost of draining its battery life faster; hence for applications indoors, 2m-5m of functionality is adequate [20]. Transmissions usually take place in intervals, the time between which is known as the advertising interval [20]. The presence of fast-moving receivers may require this interval to be longer in order to provide a steady signal and also compensate for the extended battery-drainage since efficient-energy usage is something beacons have become so popular for [20],[27]. The signals are then used to measure the Received Signal Strength (RSS) and calibrated, using the calculated distances between the receivers and the beacons.

Information about locations collected from the BLE modules using the Received Signal Strength Indicator (RSSI) mainly include the Media Access Control (MAC) address and the universally unique identifier (UUID) which numerically defines the power of the signal that the receiver perceives [3].

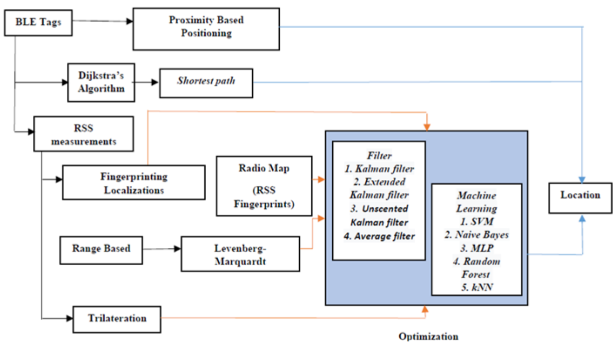

Figure 1. Methods for BLE beacon-based positioning

3. STATE-OF-THE-ART TECHNIQUES

To ensure productive use is made of the trending technology of IoT [27], application of state-of-the-art techniques to handle data must also be ensured. This section summarizes and performs a comparative analysis based on the optimization, accuracy, limitations, and applications of published experimental methods using BLE. The summarized information is tabulated in Table 2.

3.1 Optimization Approaches

The RSSI allows estimation of distances of the receivers from the beacons [20]. Upon receiving the RSSI values containing inaccuracies due to the complex environment surrounding the beacons and the receiver, such as furniture, passers-by, and walls, the need for a filter arises which shall help to minimize the errors caused due to such disturbances [28]. One such example of a fluctuation minimizing tool is the Kalman filter, frequently used throughout BLE-based Indoor Positioning Systems [20], [28], [29], [30].

3.1.1 Kalman Filter

Kalman filter is a recursive algorithm used to minimize noise from RSSI values by calculating a measurement generating matrix (H) and the measurement error covariance matrix (R) to predict the most accurate succeeding values and has been effectively applied in [29] and [30] to improve accuracy. Kalman Filter (KF) can be categorized into many others as used in [31-34]. Because KF is based on linear systems, its use in indoor positioning is justified by researchers in [29] and [30]. Kalman filter seems troublesome for nonlinear relationships [35]. Extended Kalman Filter (EKF) permits nonlinearity between variables and hence serves well in indoor positioning adopting graph optimization method such as in [31] and construction for monitoring use of harness [34]. Researchers in [32] have used the two-tiered Kalman-LULU filter, which is a Kalman filter followed by a layer of non-linear LULU smoother, which leads to the Root Mean Square (RMS) error drops to 2.13 meters (m) from 3.06m.

The Unscented Kalman Filter (UKF) works well for many-to-many nonlinear functions, in contrast to the one-to-one nature of KF and EKF, by mapping a source Gaussian to a target Gaussian and is used in [33] for IPS values optimization.

3.1.2 Machine Learning Algorithm

Machine Learning algorithms have been excellent tools in achieving localization information about receivers [30, 36-39]. However, the effectiveness of the results achieved using each algorithm varies, leading to uncertainty as to which method should be utilized in BLE-based IPS for widespread use. An analysis of the accuracy achieved through each type is provided in Table 1.

Table 1. Summary of Machine Learning Algorithm Accuracy

Paper	[30]	[36]	[37]	[38]	[39]
KNN	99.83 %	-	98.80 %	81.48 %	75.29 %
SVM	-	-	99.00 %	-	-
Decision Trees	-	-	95.60 %	-	-
Random Forest	-	77.20 %	-	-	-
Naive Bayes	-	41.11 %	-	64.81 %	62.67 %
SMO	-	-	-	72.22 %	-
Bayes Net	-	-	-	77.78 %	82.07 %
MLP	-	-	-	-	96.79 %
J48	-	-	-	-	92.00 %

RSSI samples are used to train popular machine learning algorithms to estimate the positions [30], [41-42]. In [37], Support Vector Machine (SVM), KNN, and Decision Trees have been implemented based on the BLE beacon data. Among these three algorithms, SVM was found to be most accurate while in another study [36], the authors found out that the Random Forest algorithm is the most accurate compared to SVM and Naive Bayes (NB). SVM in [37] had a 99% accuracy but in [36], the same algorithm was eliminated as it was proven to be inferior to Random Forest and NB (Naive Bayes). KNN was implemented both in [30] and [37] with recorded accuracies of 99.83% and 98.8%, respectively. The slightly improved accuracy might be due to the Fuzzy Logic approach that was implemented along with KNN, named FkNN, in [30]. Multilayer Perceptron Algorithm (MLP) was used in [41] and it had an accuracy of 78.1%, which was lower than both Random Forest and KNN mentioned previously in [30] and [37]. It can be seen in Table 1 that the claim of the machine learning algorithm with the best accuracy differs from one literature to another. Random Forest was stated to be the most accurate with an accuracy of 77.20% in [36] as compared to NB while in [30, 37,38], KNN is observed to have an excellent accuracy as well. However, it remains inconclusive that KNN had a better performance than other techniques. In [39], KNN had lower accuracy than J48, MLP, NB, and Bayes network even though it consumed the least time for decision estimation. In summary, the disparity of conclusions in the studies highlights that there is no single algorithm that is superior to the others and the performance of each might be subjected to experimental set-ups and the nature of the data collected.

3.2 Accuracy

Accuracy is a term that can be affected by many things such as environment, characteristics of the radio receiver and transmitter [43]. BLE has shown a remarkable contribution to indoor localization since it displays accurate results within the range. Amir Singh et. al [41] discussed the success of Dijkstra's algorithm for continuous movement using the shortest path to his destination in real-time. However, the accuracy among the methods discussed in studies varies in terms of techniques used. Machine Learning and Kalman Filter both serve the purpose of improving the accuracy as seen in [29], [39], and [40]. From the observation of Machine learning algorithms, we concluded that KNN and Random Forest algorithms were most accurate in its purpose as they have shown the accuracy of 99.83% and 77.20% respectively, while by only applying Kalman Filter researchers were able to gain 76.58%-100% accuracy in [20] and 77.58% in [32]. Using Kalman-LULU filter, the authors in [32] had managed to achieve the best of all methods based on range effectiveness which was 9.5m. The accuracy with and without the filter was respectively 77.58% and 70%. Besides that, through the usage of Extended Kalman Filter, the accuracy observed to be improved to 3.25m and 2.78m using Range based and fingerprint-based, respectively [35]. EKF was also introduced by Jesus et. al [34], a system for ensuring safer conditions in construction sites through the method which tried to attach the beacons from the receiver to the worker at the distance of 1m. The method in [29] was satisfyingly accurate under 7m distance from beacons to devices using the same filter. Unscented Kalman filter (UKF) and Gaussian filtering model used together in [33] simultaneously raised the accuracy by reducing the additive noise to an actual error by 2.5 times of the average measurement error and the average location error was only within 4 meters which refers to the accuracy of the user's location. The study in [44] achieves 78.1% accuracy with the precision of 77.7% for pedestrians in an area of 14.0m x 9.0m through MLP algorithm which seems to provide high accuracy with the interfacial effect of Wi-Fi and heavy traffic.

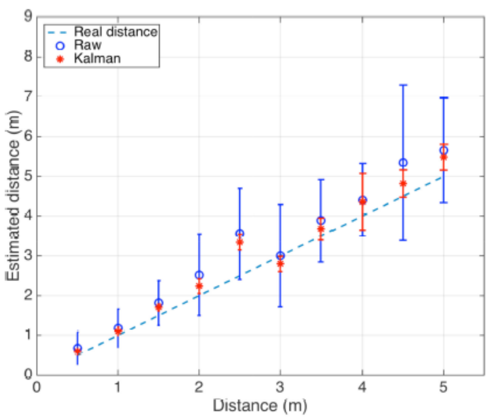

Figure 2. Performance of distance estimation in the laboratory of research conducted in [20].

3.3 Limitations

Despite the possibilities of BLE-based indoor positioning systems, proposed applications in studies have shown observable constraints to suggest that further study in this field may help introduce much more advanced and accurate versions. The project in [41] is incompatible for people with impairments, such as hearing or visual impairments as it provides no facility of text-to-speech, voice input, or braille script. It is not compatible with any other platforms other than Android, has no option for feedback or emergency contact, which is also the case for the smart elderly assisted living home in [37] and may not work for multiple destinations. The hardware used in [36] is not battery efficient and not implementable unless all beacons are replaced twice a year. The smart museum system of [22] works well within short ranges and fewer beacons but fails to remain accurate when several beacons are densely situated. In [31], the system adopting graph optimization and despite its efficiency, loses positioning accuracy as a result of not having a prerequisite surveying process. The values obtained from the process proposed in [32] have a very large standard deviation compared to the difference between mean RSSI connecting each interval. The systems discussed in [33], [37] on the other hand, do not take the necessary measurements to obtain the most ideal results. To get the most optimum results, a minimum number of beacons are required which is not met by the systems of [30], [34], and a reasonable number of RSSI samples which is not met by [30], [44]. A location and motion tracking system for elderly assisted living homes should have the option of medical emergency upon tracking unusual motion, but no such option exists in [45] which makes its purpose of monitoring quite restricting. As evident from the analysis of the projects, specific factors such as a optimum RSSI samples or system design must be regarded when designing an IPS devoid of any restraints.

Table 2. Summary of Investigated Ips

Paper	IPS Approaches	Advantages	Limitations
[20]	Trilateration and Kalman filter	Provide recommendations based on analytics data	Worst accuracy when receiver equidistant from all three beacons. Poor accuracy when receiving >5m away
[29]	Kalman and Average filter	Security and privacy options are available	7m is a poor accuracy if to be implemented in micro-locations
[30]	kNN, FkNN and combining kNN or FkNN with Kalman Filter	Tested in real environmental situation. 10 repetitions of each scenario	For better accuracy, huge numbers of beacons required
[31]	Levenberg-Marquardt algorithm and Graph Optimization	Efficient and no additional time-costly surveying processing required	Lack of prerequisite surveying process
[32]	Trilateration and Kalman LULU filter	Impacts of TX power and interface from the environment taken into consideration	High Standard deviation in RSSI value and intervals
[33]	Gaussian filter and Unscented Kalman filter (UKF)	Purify sample data. Real-time feedback	Necessary measurements not taken to collect the ideal results
[34]	Extended Kalman Filter communication infrastructure.	Robust. No need for calibration. Remote IoT for online monitoring is possible	Higher number of beacons required for better accuracy
[36]	SVM, NB, Random Forest	Locates multiple users in real-time	Not battery efficient
[37]	SVM, Decision Trees, KNN	Wearable device; tested at the real-time location	Emergency feedback facility unavailable
[41]	Dijkstra's algorithm	Real-time shortest path calculation. Efficient and simple	Incompatible multiple destination. Not cross-platform

[44]	Multi-Layer algorithm Perceptron	Tested in the real environment. Superior performance compared to point estimation approach	RSSI samples collected are comparatively low
[46]	RSSI and MQTT	Most work is done on the cloud	Very poor accuracy

4. IOT ARCHITECTURE

The overall phases of information flow can be listed as such: (i) RSSI data collection phase using BLE 4.0 technology (ii) transmitting the data to the central server (iii) processing and using the data according to requirements [14]. Figure 3 shows the sequential steps and Figure 4 illustrates typical IoT architecture implementation. Quite a handful of different IoT architectures and tools have been proposed and used by authors in [20], [29], [32], [36], [37], [46], [47]. A broker service, Message Queuing Telemetry Transport (MQTT), has been used by [37], [46] and [48] for ensuring the RSSI data from the beacons are collected by the BLE scanners and simultaneously pushed to the MQTT server. In [36], an additional proxy server was added for data transmitted to the server and sent back to a MQTT broker. The system begins with several BLE beacons installed throughout a building's hallway, transmitting Eddystone packets and a mobile application is used for scanning them and sending their MAC addresses and RSSI values to the server for processing. In the client-server, the beacons' data is saved, and fingerprinting for location prediction is carried out using a machine learning algorithm. The mobile application and server used for the implementation were based on an open-source project "Find" [45].

Raspberry Pi 3 in [32], [37], a virtual machine based on Linux operating system in [36], ESP32 development board in [46], mobile devices in [29], [47], [49] were hardware devices used for scanning RSSI values. In [20], when an attendee comes in proximity to an exhibit where Beacons are attached, the specific ID and retention time is updated to the control room. If no Wi-Fi signals are detected by the phone, it saves the data locally and only transmits in a batch when the Wi-Fi is available next time. A Python program in Raspberry Pi which decodes the data into binary format to Hex format is used in [32] of which Universally Unique Identifier (UUID) is used to identify the target beacons and RSSI values are generated for estimation of distance. RSSI values are stored in a memory card and is sent to the database using Wi-Fi network for conversion to distance. In [48], the architecture was based on Amazon Web Services (AWS), a Web Application Programming Interface (API) consisting of Gateway API, Lambda and DynamoDB. Their architecture is also inclusive of a mobile application developed with HTML and JavaScript where parameters were received through Web API for distance estimation.

5. INDOOR POSITIONING IN IOT APPLICATIONS

BLE has been a promising technology for functioning within enclosed locations due to its simple nature and popularity compared to other IoT devices [42]. IoT devices have made their way up through applicability in several aspects of society, e.g., smart homes and cities [50], [51], [52], healthcare [53], and several other areas [53-55]. The popularity of IoT devices added with that of mobile devices such as smartphones, makes indoor localization of humans in a detailed context possible which includes motion tracking as well as figuring out the exact location inside a room in real-time [56]. The systems discussed in [31], [36] and [41] all seek to navigate indoors using BLE but do not have any suggested applications. The system of [41] would be better suited for finding the shortest distance on online route-finding map apps, such as Google Maps to describe the indoor structures of public places whereas the systems in [31] and [36] could be used in areas where shortest paths between discrete users need not be found, e.g., for indoor navigation within facilities like an office or school. In [20], Spachos et al. have presented a prototype to build a system for museums such that beacons are assigned to each exhibit so that whenever a visitor is near an exhibit, s/he shall receive information on their phones regarding the specific exhibit. Receipts of signals from different beacons are used to find the approximate location of the visitor and information regarding the visitor's route, retention time, and timestamp of actions are then used to find predictions about the user and recommendations for him/her.

The authors in [32] studied real-time asset localization in terms of accuracy and cost-effectiveness to explore an asset management solution using BLE positioning. Though the work in [33] suggests no applications, due to its utilization of UKF, it is certain that the system proposed would be best applied where inputs are several points from a source Gaussian to be mapped to a target Gaussian. A suggested application can be finding office rooms of all secretaries within an office facility. A successful usage of ephemeral ID which was based on Google's Eddystone-EID frame to improve security measures for the users of the indoor positioning system is presented in [29]. The work did not specify any suitable applications, however, the enhanced security for the user achieved means it can be used in applications which prioritize user anonymity and privacy. The method in [44] was tested in a real environment to ensure novel area estimations, e.g. assigning a subway as a zone. The work in [37] on the other hand, describes a location and motion tracking system for elderly assisted living homes. In a nutshell, the potential applications for IPS based on BLE technology seem promising and offer new possibilities of usage to be explored.

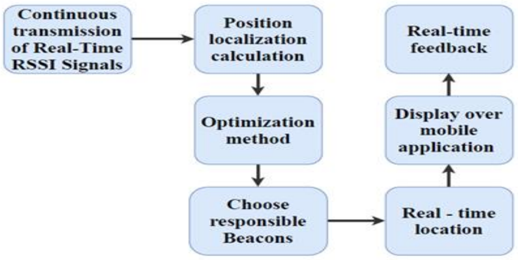

Figure 3. The sequence of action in Beacon based IPS.

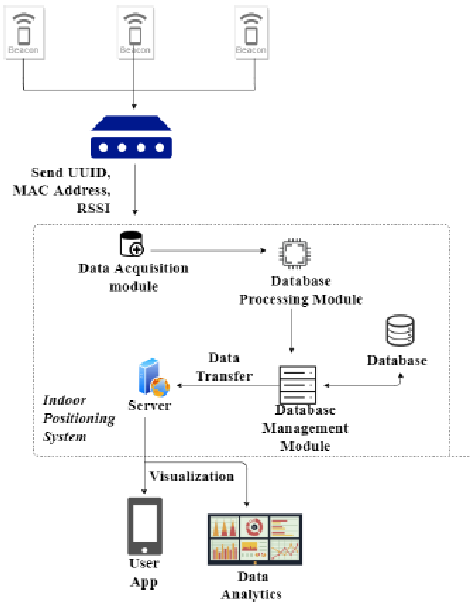

Figure 4. The sequence of action in Beacon based IPS.

5.1 Case Study

In this case study, to estimate the indoor location, the method used is called fingerprinting and KNN algorithm is applied. The experiment is done in a space with 10 beacons that have been placed as shown in Figure 5. Data have been gathered at 30 different locations within space. MATLAB R2022 is used for KNN algorithm computation. Figure 6 and 7 show sample data, calculation, and result for the data analysis of indoor positioning estimation.

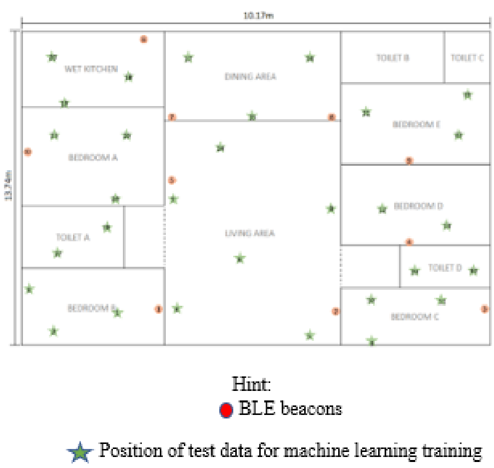

Figure 5. Location of beacons for the experimental setup.

1	beacon_1	beacon_2	beacon_3	beacon_4	beacon_5	beacon_6	beacon_7	beacon_8	beacon_9	beacon_10	location	position
2	-200	-88	-200	-200	-90	-96	-93	-200	-200	-71	BEDROOM A	25
3	-200	-93	-200	-200	-89	-200	-78	-95	-200	-72	BEDROOM A	25
4	-200	-90	-200	-200	-91	-96	-79	-88	-200	-65	BEDROOM A	25
5	-96	-200	-200	-200	-200	-200	-91	-92	-200	-64	BEDROOM A	25
6	-96	-90	-200	-200	-93	-96	-77	-94	-98	-63	BEDROOM A	25
7	-89	-200	-200	-200	-88	-93	-87	-200	-200	-69	BEDROOM A	26
8	-89	-94	-200	-200	-86	-94	-82	-94	-200	-78	BEDROOM A	26
9	-86	-92	-200	-200	-80	-200	-89	-91	-96	-71	BEDROOM A	26
10	-92	-95	-200	-200	-80	-91	-82	-200	-200	-80	BEDROOM A	26
11	-86	-200	-200	-200	-81	-93	-81	-200	-200	-68	BEDROOM A	26
12	-200	-86	-200	-200	-87	-98	-93	-200	-200	-75	BEDROOM A	24
13	-200	-86	-200	-94	-94	-95	-90	-95	-200	-72	BEDROOM A	24
14	-83	-89	-200	-200	-91	-92	-84	-95	-200	-82	BEDROOM A	24
15	-99	-85	-200	-200	-93	-96	-89	-93	-200	-68	BEDROOM A	24
16	-88	-99	-200	-97	-92	-94	-87	-200	-200	-69	BEDROOM A	24
17	-62	-79	-91	-200	-200	-86	-200	-90	-200	-91	BEDROOM B	1
18	-63	-79	-91	-98	-200	-85	-200	-200	-200	-91	BEDROOM B	1
19	-71	-81	-91	-200	-200	-82	-200	-93	-200	-92	BEDROOM B	1
20	-69	-79	-200	-100	-200	-85	-200	-92	-200	-89	BEDROOM B	1

Figure 6. List of RSSI BLE values at different locations.

knn.m

```
X = readtable('data.csv','Range','A1:J151');
Y = readtable('data.csv','Range','K1:K151');
test = readmatrix('test.xlsx','Range','A1:J30');
loc = readcell('test.xlsx','Range','K1:K30');
Mdl = fitcknn(X,Y,'NumNeighbors',5,'Standardize',1);
est = predict(Mdl,test);
compare= cellfun(@strcmp,est,loc);
correct_location = sum(compare);
accuracy = (correct_location/30)*100
```

```
>> knn

accuracy =

   86.6667
```

Figure 7. KNN algorithm-based fingerprinting calculation and accuracy result

From the result, KNN is a promising algorithm to estimate indoor positioning with 86.67% accuracy. This can be improved by using more measurement data for training as well as performance comparison with other machine learning algorithms for indoor positioning estimation.

6. CONCLUSION AND FUTURE WORKS

In this paper, we made a comparative analysis of existing, to-date Indoor Positioning Systems proposed and experimented in different studies. We categorized all the approaches into optimization methods, limitations, accuracy, and IoT based applications, either executed or suggested. Some of the observations from the study were that the method, orientation, and implementation can play a very substantial role in affecting the accuracy and the application. For example, RSSI signals faced too much distortion if beacons were densely packed in less than a meter. It is also an obvious challenge to choose one method or combination of methods of optimization as none of the approaches has not been objectively satisfying so far. It was also observed that among the Machine Learning implemented in many of the studies, KNN and Random Forest algorithm had shown the most promising results in terms of accuracy. Graph Optimization had the most cost-effective solution as it didn't use any surveying process, however, it had a negative impact in terms of accuracy. A conducted case study shows 86.67% accuracy in a fingerprinting method using KNN algorithm.

In the future, it is suggested to take security and privacy into account in the proposed approach. A combination of different technologies can also be merged along with a selected ML algorithm and filter. The IPS based on BLE technology can also be used in commercial properties like a shopping mall. Consumers with a mobile application can find the latest and relevant promotions based on their position to the closest store. Data analytics can be offered by the system too, to help vendors or owners make decisions as required.

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