

# Using Bluetooth Low Energy Beacons for Indoor Localization

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**Abstract:** Bluetooth Low Energy (BLE) Beacons gain high popularity due to their low consumption of energy and, thereby, long lifetime. Using the BLE protocol, these devices emit advertisement packets at fixed intervals for a short duration. Indoor localization solutions aim to provide an accurate, low cost estimate of sub-room indoor positioning. There are various techniques proposed for this purpose. BLE Beacons are good hardware candidates to assist the creation of such indoor localization solutions. Given the exact position of BLE Beacons, one can attempt to estimate a receiver position according to the received signal power. In this work, we investigated the success of such an indoor localization approach employing multiple BLE Beacons and two different estimation techniques. The results of the experiments indicate that employing multiple BLE Beacons increases the success of prediction techniques considerably.

**Keywords:** Indoor localization, Bluetooth Low Energy, Beacons, kNN

## 1. Introduction

Bluetooth wireless communication protocol is an open specification that facilitate low-power and short-range connections. There are millions of Bluetooth enabled devices such as smart phones, connected cars, electronic cameras, toys, health monitoring systems, etc. on the market already [1]. However, the devices implementing Bluetooth protocol, especially the mobile ones, do not always have excessive energy resources for keeping Bluetooth transceiver running for a long period. Recognizing this important limitation, the Bluetooth v4.0 profile specification is released in June 2011 which introduced very low energy consumption [2]. The Bluetooth v4.0 includes a low energy feature which enables Bluetooth smart devices transmitting very small packets of data at a time, while consuming significantly less power compared to previous Bluetooth versions. Thus, using this special broadcasting feature, Bluetooth devices can function for months or even years on small-sized batteries.

Localization is a process of obtaining location information of a person or an object with respect to a set of reference positions within a predefined space. Depending on the position, various Location based services (LBSs) can be offered to the user including navigation, tracking, healthcare, advertisement, and security [1,3-4]. Localization can be classified into two main groups according to the environment: indoor or outdoor. The techniques to find the location of a client indoors or outdoors differ significantly. The most popular technology for outdoors is Global Positioning System (GPS) [5]. Unfortunately, GPS enabled devices are incapable of tracking indoors [3]. Since people spend most of their time indoors and providing location services within a building has many potential applications, indoor localization has attracted numerous researchers to work on that area. Thus, researchers have proposed different techniques to solve the indoor localization problem efficiently and effectively [6-7]. However,

most of these techniques require expensive infrastructures or specialized devices. Therefore, as introduced above, BLE devices are recently noticed as a potential option to these devices and techniques being cheap, portable and easily applicable to existing systems.

## 2. Reviewed Literature

Indoor positioning systems provide a precise position inside of a closed construction, such as shopping malls, hospitals, airports, subways, etc. [8]. Because of the multifaceted nature of indoor environments, any indoor localization technique faces with several problems emerging from the requirements and the environment. For instance, obstacles such as walls limit the line of sight (LOS); movement of human beings or the furniture cause multipath effect and attenuated signals [4]. As handling all these problems is not straightforward, instead of higher accuracy, applications can accept lower accuracy provided that the cost of the system is low and applicability probability is high.

In the literature, various indoor location detection techniques and location algorithms can be found. These can be classified as Proximity Detection, Triangulation, Angle Based Method, Time Based Method, Signal Property Based Method, Dead Reckoning, Map Matching [4]. Moreover, there are various position systems used for localization: Infrared, WiFi, Ultrasound, RFID, Bluetooth, ZigBee, FM [7]. In this work, we focus on using Bluetooth, especially Bluetooth 4.0, as the position system. Bluetooth is a wireless communication protocol for wireless personal area networks (WPANs). Bluetooth operates in the 2.4 GHz ISM band. Providing high security and using low cost, low-powered, and small-size chips, Bluetooth technology receives high popularity from the electronics market and virtually all WiFi enabled mobile devices, such as mobile phones, tablets, cameras, etc., also equipped with a Bluetooth module.

There have been various proposals to employ Bluetooth as a position system for indoor localization [e.g. 9-14].

Subhan et.al. proposed to employ Trilateration approach for distance estimation using the relationship between the received

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power level and distance following the standard radio propagation model [9]. Similarly, Iglesias, Barral, and Escudero studied on using Bluetooth signal as source of information by introducing a set of algorithms to transform to improve the location process [10]. Johnson and Seeling presented a scheme based on Bluetooth friendly device names to enable power-optimized ad-hoc localization of mobile devices [11]. As the service discovery and connection (including potential pairing) phases in Bluetooth waste time and energy, using friendly device names can remove this burden and help to achieve faster and lower power transmission of location information. Chen et.al focused on developing a constrained Kalman filter to estimate the indoor position depending on the received signal strength indicators (RSSI) [12]. Mair and Mahmoud proposed a collaborative Bluetooth localization method in which each device first stores the location information about discovered Bluetooth devices [13]. Then, whenever the device is to find the location, it first scans the Bluetooth devices around and compares the found devices with the ones in the database. Thus, if the device is able to locate some Bluetooth devices in the database, it can calculate its location from their stored location information provided that these Bluetooth devices do not change their locations. If the device fails to locate any Bluetooth devices in the database, it just uses other services such as GPS to find its own location and stores this location information by associating with the discovered Bluetooth devices. In this work, we aim to use multiple number of BLE devices as the beacons for indoor localization. The BLE devices are fixed and static. The indoor environment is split into grid structure. To locate itself, a mobile user scans the BLE devices. Using the proposed estimating methods and the discovered BLE devices, the user can calculate its position on the grid. In order to estimate the location of the user, we proposed to use a supervised learning based approach. In this approach we first measure the BLE device information and signals strengths at predefined locations. Whenever a new localization is required, the measured signals are compared with the previously measured ones, and based on this comparison a supervised learning based classification is performed to estimate the location. According to our knowledge this approach has not been used for indoor localization before. The details of the proposed method and experiments are provided below.

### 3. The Proposed Method

BLE devices implement the Bluetooth 4.0 or higher specifications. These devices can be standalone devices such as iBeacon or they can be integrated into other devices such as mobile phones and tablets. In general, a BLE beacon device transmits a universally unique identifier with a determined frequency. Other BLE devices can receive these beacon signals and use their signal power to determine their relative location to the transmitting beacon location. Therefore, in this work, we assume a square grid whose corners host the BLE beacons, as given in Fig 1. In the grid, we have labelled 10 positions. The first row is labelled as X and the second row is labelled as Y. All the cells in the grid have a size of 1x1 meters. The corner positions are 1 meter away from the nearest cell. Thus, for the experiment topology, we aim to locate the user's cell correctly comparing signal power levels of BLE beacons located at the corners C1, C2, C3 and C4.

Our method has two phases: *Initiation* and *Service*. In the Initiation phase, BLE beacons are placed in their position and by using a BLE device we record the received signal power level for each cell grid. These readings are stored into a database. In the Service phase, any BLE enabled mobile device visits the grid, reads the

received signal power level of the BLE beacons, and transfers them to the application server. Application server calculates the estimated grid cell and returns the result to the mobile. We do not require knowing the exact location information of the BLE beacons. Moreover, the mobile does not need to do any calculations.

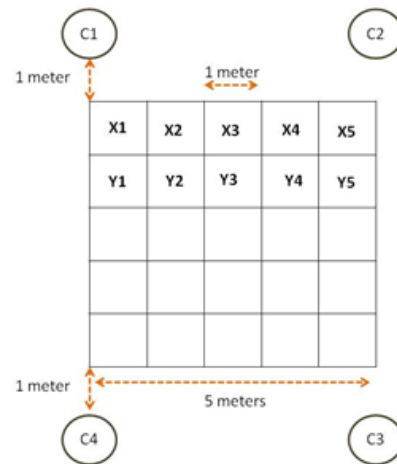


Fig. 1. Test Topology

For calculation of the mobile's location we have implemented two different methods: kNN and Discriminant analysis classifier. K-Nearest Neighbours algorithm (kNN) is a well-known supervised learning based classifier. It was first suggested in 1967 by Cover and Hart [15], and it has been used in many applications such as [16-17]. The algorithm is a non-parametric one, in which first the measured data is compared with all the available data in the training set with a predefined difference metric. Then the measurement is classified to the class with the minimum distance/distances based on this comparison. The details of the algorithm will not be given in here and can be found in the literature [18].

Discriminant analysis is another well-known algorithm that is commonly used in supervised pattern recognition approaches. The algorithm tries to find the feature set or a combination of feature sets that separates the classes of measurements. The number of classes can be two or more. The details of the approach will not be given in here and can be found in the literature [19].

### 4. Experiments

We have executed two sets of experiments. In the first experiment setting, each corner has only one BLE beacon whereas in the second set of experiments, we double this number to observe the effect of increasing number of BLE beacons.

During the Initiation phase, we collected 15 readings from the corners and the labelled grid cells. The total number of readings is 210. In the testing phase, we followed the "leave-one-out" testing approach, in which each measurement is used once in the testing while the others are used in the training set. In this study since we have 210 measurements, we performed this approach 210 times, using each measurement once in testing, and we calculated the estimated classes and compared them with the true ones. The results are provided in Table 1 as the confusion matrix, using kNN Classifier and single BLE Beacon at each corner. For 160 out of 210 test cases, the kNN method estimates the correct grid cell whereas 50 test cases are misclassified. Thus, the location of the user is estimated correctly 76.19% of the cases.

**Table 1.** Confusion matrix showing the classification performance of the proposed method using kNN Classifier and 1 ibeacon at each corner

	C1	C2	C3	C4	X1	X2	X3	X4	X5	Y1	Y2	Y3	Y4	Y5	Correct	Incorrect
C1	13				1						1				13	2
C2		15													15	0
C3			15												15	0
C4				15											15	0
X1					13						2				13	2
X2						15									15	0
X3					1		13				1				13	2
X4								14					1		14	1
X5									14				1		14	1
Y1										15					15	0
Y2	1				1	1					12				12	3
Y3							3	1				11			11	4
Y4													14	1	14	1
Y5	1					1			1			1		11	11	4

**Table 2.** Confusion matrix showing the classification performance of the proposed method using kNN Classifier and 2 ibeacons at each corner

	C1	C2	C3	C4	X1	X2	X3	X4	X5	Y1	Y2	Y3	Y4	Y5	Correct	Incorrect
C1	12				2	1									12	3
C2		15													15	0
C3	1		14												14	1
C4				14			1								14	1
X1					3	4	2		2		2	2			3	12
X2					2	11					1	1			11	4
X3					1	1	11	1			1				11	4
X4							1	13	1						13	2
X5								1	12			1	1		12	3
Y1							2			12	1				12	3
Y2					2	2	2				8	1			8	7
Y3					2	2	2					9			9	6
Y4									1				14		14	1
Y5						2	1							12	12	3

As can be seen from Table 1, a total of 50 measurements are incorrectly classified out of 210 measurements. The main reasons for the incorrect classifications are the measurement noise arising from the measurement devices, classifier errors and environmental differences between the training measurements and testing measurements. As can be seen from Table 1, most of the incorrectly classified measurements are on the 1 meter neighbor cells, which mean that the localization error is 1 meter at most.

When we double the number of used BLE Beacons, we observe an increase in the success of kNN classifier. As can be seen Table 2, the kNN method estimates the correct grid cell for 190 out of 210 test cases. Only 20 test cases are misclassified. Thus, the correction of estimation increases up to 90.48%.

When we double the number of beacons in the corners, the classification accuracy is increased. This is an expected case because when we double the number of beacons, we increase the number of measurements and in the classification phase we take the averages of these measurements. Whenever the average of two independent measurements are averaged, the measurement noise arising are lowered, causing to lower classification errors.

In the following tables, the results of the Discriminant Analysis Classifier are given. Table 3 shows the results of the prediction when a single BLE beacon used at each corner. There are 171 cases classified correctly opposed to 39 misclassified cases. That is, the correctness of the Discriminant Analysis Classifier is 81.43% which is higher than the one of the KNN method (76.19%).

In Table 4, we observe again that increasing the BLE beacons increase the prediction correctness for the Discriminant Analysis Classifier as well. For this case, the correctly classified test cases are 192 whereas misclassified test cases are decreased to 18, which give 91.43% success. The Discriminant Analysis Classifier is slightly better than the kNN Classifier for this case (90.48%).

As can be seen from Table 3 and Table 4, it is seen that when the number of beacons are increased, the classification performance is also increased. This is because when the number of measurements at each corner is doubled, the average of these measurements is used in the classification, which causes lower measurement noise. When the measurement noise is low, it is natural to get a better classification performance.

**Table 3.** Confusion matrix showing the classification performance of the proposed method using Discriminant Analysis Classifier and 1 ibeacon at each corner

	C1	C2	C3	C4	X1	X2	X3	X4	X5	Y1	Y2	Y3	Y4	Y5	Correct	Incorrect
C1	14					1									14	1
C2		15													15	0
C3		1	14												14	1
C4				15											15	0
X1					6	3					3	3			6	9
X2					4	10				1					10	5
X3							13			2					13	2
X4								13					1	1	13	2
X5					2				11			1	1		11	4
Y1							1			14					14	1
Y2					1						12	2			12	3
Y3					3		1					11			11	4
Y4									1				12	2	12	3
Y5								3				1		11	11	4

**Table 4.** Confusion matrix showing the classification performance of the proposed method using Discriminant Analysis Classifier and 2 ibeacons at each corner

	C1	C2	C3	C4	X1	X2	X3	X4	X5	Y1	Y2	Y3	Y4	Y5	Correct	Incorrect
C1	13				1					1					13	2
C2		15													15	0
C3			15												15	0
C4				15											15	0
X1					13	1					1				13	2
X2					3	11				1					11	4
X3					1		14								14	1
X4								14					1		14	1
X5									14				1		14	1
Y1										15					15	0
Y2	1				1		1				12				12	3
Y3						1	1					13			13	2
Y4									2				13		13	2
Y5														15	15	0

When we compare the Table 2 and Table 4, it is seen that both classifiers give nearly the same classification performances (90.48% for kNN and 91.43% for Discriminant Analysis). This means that any of these classifiers can be used for indoor localization based on the proposed approach.

## 5. Conclusion and Discussion

In this work, we propose to employ a new approach as a solution to indoor localization using low cost BLE beacons. In the proposed method, exact locations of BLE beacons are not required. Furthermore, the mobile device does not do any calculations for finding its location. Instead, the mobile device uses the service provided by the location owner. Therefore, the mobile device can save energy and resources. Moreover, since during Initiation phase system collects information according to relative signal power levels with respect to labeled grid location, the location owner can increase the estimation correctness by taking more readings. In the results of experiments, we observed that reading 15 values from each 1x1 meter grid cells and using 8 BLE beacons we can locate the user to the correct grid cell with a success ratio higher than 90% for both classifiers. 1 meter sized measurements are acceptable ranges for many indoor localization requirements such as advertisement and shopping. If we preferred to work on larger sized grids, we could get better results. Besides we showed that whenever the number of beacons at the corners is increased, the performance is also increased. If better performance is required by

a specific application, a larger number of beacons can be used in the corner points of the grid.

In this work, we apply two commonly known classifiers in this study for localization. In a next study different classifiers such as Naïve Bayes, Multi-class SVMs, decision trees or neural network based approaches can be tested for indoor localization.

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