Bluetooth Beacon Based Accurate Indoor Positioning Using Machine Learning

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Abstract - The objective of this work is to develop an indoor location system with high precision and continuous position monitoring in real time with the use of a mobile phone without any special hardware using only commercially available low-cost sensors. Finding the location is done using the measured Received Signal Strength Indicator (RSSI) value of Bluetooth beacons received from mobile phones combined with measurements from other phone sensors. For the development of our model, we collected measurements for the RSSI values from Beacons which we placed in a space of 30.75 sqm and the values from the mobile accelerometer in motion. We divided the space into 16 subareas of 1.45m x 1.35m and used our measurements to develop a machine learning model using the open source TensorFlow framework to predict the correct subarea of the user. Through experiments, we show that our model can reach an accuracy of 0.7209 which means that our system can predict the correct user location in 72% of the cases with accuracy less than 1 meter.

Keywords—indoor localization, Bluetooth, beacons, machine learning

I. INTRODUCTION

With smartphones becoming ubiquitous and equipped with a wealth of sensors, applications that are able to harness information such as position become increasingly powerful. While GPS has traditionally been used as the main location tracking technology, GPS is available only at outdoor locations and with a maximum accuracy of 5 meters. At the same time systems for indoor positioning with high accuracy are becoming an upcoming trend and they cannot rely on the GPS due to the reasons mentioned above.

Indoor positioning systems can be used to estimate the location of a subject in areas like malls, airports, libraries, hospitals, etc. and can be exploited by services such as context-based advertising, indoor navigation, robotics applications, emergency response, assisted living, etc.

An indoor location system must meet the requirements listed below.

- **Accurate and continuous representation of the position.** It is important to be able to have a consistent and accurate representation of the position for a user who is moving in a two-dimensional space. For example, limited accuracy yielding a deviation greater than two meters could guide some user to the wrong door of a corridor or on the wrong shelf in a supermarket. User location identification must be continuous with no lag. So, it is important to use high signal monitoring frequency and the execution time of estimation algorithms must be small.
- **Work in a complex/hard indoor environment.** Indoor environments have many challenges to overcome. First of all, in most cases, they present the features of dynamic environments that change continuously so any indoor location system must be able to adapt to changes. In some cases, especially in public places, environments can be completely different when they are crowded. Indoor environments are full of obstacles such as walls, shelves, stalls, etc. And last, in most of the cases, indoor environments must be represented in three dimensions including different floor levels.
- **Using standard technologies that are available on modern mobile phones.** It is important that an indoor location system makes use of sensors that are available in smartphones such as GPS, WiFi, Bluetooth, etc. with no need for any special hardware.

Indoor localization approaches today based on RSSI of wireless signals such as WiFi and Bluetooth are the most popular [1], [2], [3] due to their low infrastructure cost, their use in all smartphones and potential high accuracy. The majority of approaches used today are based on Wi-Fi signals to estimate indoor locations. Additionally, most usually they are using algorithms to estimate the distance from a known position.

Machine learning is a field of artificial intelligence dealing with algorithms and statistical models used to effectively perform a specific task without using explicit instructions. This allows building models based on the attributes that best fit the correct value. Machine learning algorithms provide excellent solutions for building models that generalize well given large amounts of data with many attributes by discovering patterns and trends in the data. A task that is often difficult by other means. In our case, addressing the problem of finding the location of a user by using the Bluetooth RSSI values, machine learning is a good solution because RSSI values are fluctuating and are not stable even within the same distance. Thus, we need an algorithm that handles a model with many attributes such as RSSI values and accelerometer attributes with no specific pattern or trend.

The remainder of the paper is organized as follows. In section II we review the related recent work in the literature. In section III we present our approach and expected benefits. Section IV describes our experimental evaluation method, the data collection process we implemented and the development and training of our machine learning model. Finally, the paper concludes with presenting the results in Section V, a discussion and conclusions in Section VI and our future directions for research described in Section VII.

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II. Related Work

Finding indoor location is one of the issues that has been addressed by many researchers in recent years [4], [5]. There have been several approaches focusing on different technologies, different application areas and scenarios and exploiting different methods. Most approaches are based (at least) on the measurement of the RSSI value from wireless signals such as WiFi and Bluetooth [2]▪ , [3]. In addition to RSSI-based methods, other techniques that use RFID have been developed [6]▪ , UWB signals [7]▪ , ultrasounds [8]▪ , etc., with most of these methods requiring specialized hardware for both the infrastructure and the user devices. Recently, methods exploiting the Channel State Information (CSI) in WiFi networks have also been researched to achieve greater accuracy (~1m) [9], [10]▪ . Unfortunately, CSI is not available on smartphones and therefore cannot be used in our case, where we want to develop a system with no use of any special hardware.

Although the proposed solutions discussed above address many different technologies the most widespread are those using WiFi and Bluetooth due to the use of these technologies in modern smartphones, the high-precision they offer and the relatively low cost of implementation. Indoor positioning methods based on the Bluetooth technology can be broadly classified into the following major categories based on the techniques they use: proximity [11]▪ , triangulation [2], [10] and fingerprinting [2]▪ , [12]. RSSI-based tracking methods can be divided into two categories: fingerprint and model-based methods. Methods based on fingerprinting are the predominant solution for achieving higher accuracy [1], [13]▪ . It is usually conducted in two phases: the phase of training where you use data collections with RSSI values and the actual position and the phase of the operation to assess the position of a user's mobile device. Model-based methods assume a model for the propagation of radio waves and the estimation of RSSI in different locations [14], [15]▪ . Although model-based methods require far less training data than fingerprinting methods, they are also less accurate.

WiFi fingerprinting methods have been extensively studied to locate indoor position by using the RSSI signal. Although WiFi access points (APs) are installed in most buildings, they have many disadvantages versus Bluetooth [16]▪ ▪ . WiFi broadcast frequency is lower than Bluetooth. WiFi scan Data are not allowed from all mobile platforms, for example, Apple's iOS allows only RSSI readings from the connected access point, which prevents third-party WiFi fingerprinting. The WiFi specification does not require the signal strength value to be reported in any specific unit. Consequently, cross-device positioning can be challenging if the devices do not share a frame of reference for the fingerprint values [5].

Instead, positioning based on Bluetooth has many advantages after introducing the Bluetooth (currently in its latest 5.1 version) standard and the commercial spread of beacons. Power draw at mobile devices is lower for Bluetooth than WiFi. Bluetooth beacons are more easily deployed (especially if battery powered) and not constrained by the need to provide uniform communications coverage [3], [5], [17], [18]▪ .

Additionally, machine learning algorithms for indoor positioning by using the RSSI values from the WiFi has widespread usage. In [19] selected machine learning algorithms are compared in terms of positioning accuracy and computation time. However, similar studies have not been researched enough in the case of using Bluetooth beacons.

In the following section, we describe our approach that builds on top of the proposals described above and results in a methodology to exploit position and smartphone sensor data for estimating the user position in indoor locations.

III. Machine Learning Based Indoor Positioning

Our positioning method introduces a system for finding indoor locations with high precision and in real time by making use of the Bluetooth RSSI values obtained from smartphones and values from the smartphone sensors. Below we summarize the basic motivation behind our approach.

A. Exploiting the benefits of Bluetooth technology

Our positioning method is based on the use of RSSI from Bluetooth beacons. Bluetooth beacons have many advantages versus any other localization technique.

1) Bluetooth is supported by the majority of smartphones these days.
2) Bluetooth devices are small, inexpensive and can run for a very long time on batteries with no special maintenance.
3) In the near future, it is expected that Bluetooth devices will be contained in many buildings.
4) Bluetooth is designed for machine-to-machine communication with the 'Internet of Things' in mind.

Bluetooth on mobile devices as smartphones is a wireless technology standard for exchanging data between devices over short distances using short-wavelength UHF radio waves bands, from 2.400 to 2.485 GHz, and building personal area networks (PANs).

A beacon is a Bluetooth radio transmitter, powered by batteries. Beacons are similar to a lighthouse in functionality. These small hardware devices incessantly transmit Bluetooth Low Energy (BLE) signals that broadcast their identifier to nearby portable electronic devices. The technology enables smartphones, tablets, and other devices to perform actions when in close proximity to a beacon. Bluetooth beacons transmit a universally unique identifier picked up by a compatible app or operating system. The identifier and several bytes sent with it can be used to determine the device's physical location, track customers, or trigger a location-based action on the device such as a check-in on social media or a push notification.

The difference between classic Bluetooth and Bluetooth Low Energy to appreciate in Bluetooth beacons is: Classic Bluetooth consumes high power and transmits to long ranges, which is suited for Bluetooth headsets and speakers. However, Bluetooth Low Energy transmits fewer data over a smaller range, hence consuming much less power. Bluetooth beacons transfer small amounts of data at regular intervals of time.

We expect in next years that beacons will be widespread in all buildings. The main reasons for that are that beacons can be used in many places as retail outlets, sports arenas and stadiums, concert venues, airports, trade shows, and conference halls, schools, hospitals, museums, etc. They can be applied in many use cases as proximity marketing, hyperlocal check-in, asset tracking, indoor navigation, etc.

and they can be used to Track shopping patterns (e.g. determine how long a shopper has lingered in a given section, or see real-time data on which in-store displays and services customers are focusing on). Such applications, for example, can be used to:

- Target customers based on time and place (e.g. send custom promotions just to people in the beer aisle at a supermarket at happy hour, or transmit messaging in a tourist hotspot specifically to devices that are registered from distant places to weed out locals).
- Reduce transaction friction with built-in payment systems (e.g. PayPal beacons, Apple Pay, etc.).
- Influence point-of-purchase decisions with advertising and promotions.
- Provide information and entertainment (e.g. directions and free content such as games and videos).
- Solicit feedback from users. Reward customers with loyalty points or other bonuses.

Today all new smartphones have the ability to connect to Bluetooth beacons. One of the major issues that beacons face is that many smartphone users leave their Bluetooth radios off for security reasons or to save battery life. But things are changing. As more cars include Bluetooth functionality, users are increasingly dropping the cord and leaving Bluetooth on. Additionally, Apple's decision to remove the 3.5mm headphone jack from the iPhone 7 and promote wireless, Bluetooth headphones instead will only further drive Bluetooth adoption. Standalone beacons are also fairly inexpensive, usually costing between 5-30€, and prices continue to drop. Some companies are also offering them free of charge, such as Facebook, which provides free Bluetooth beacons to business with a Facebook page.

B. *Exploiting the widespread use of Bluetooth enabled smartphones*

One of our main goals in the development of this method is that it can be easily applied in any modern smartphone and has no further need for any special equipment. Today smartphones are equipped with Bluetooth and accelerometer. So, our model will be easy to deploy in a mobile application that can be downloaded and installed.

C. *Exploiting latest advances in the field of neural networks*

Our method makes use of a neural network model to estimate the user location. The problem of finding a position by making use of the RSSI values is a very complex problem because RSSI values are not stable as discussed above. Neural networks are best suited to solve such complex problems.

Artificial neural networks (ANN) are a set of algorithms, modeled from the human brain, that are designed to recognize patterns. They interpret data through a kind of machine perception, labeling or clustering raw input. The patterns they recognize are numerical, contained in vectors, into which all real-world data, be it images, sound, text or time series, must be translated.

Nowadays ANNs application has become popular in the various area of human needs. A good advantage of ANNs application is that it can make models easy to use and more accurate from complex natural systems with large amounts of inputs. ANNs have seen massive use in specific domains, such as speech recognition, interpretation of multi-language messages, three-dimensional object recognition, texture analysis, facial recognition, and hand-written word recognition. Thus, ANNs can learn by example like people. In some cases, ANNs can be designed for a specific application like data classification or pattern recognition through the learning process [20].

D. *Proposed positioning method*

For finding the location our system uses a model from machine learning neural networks. As input parameters in our model we use the RSSI values of Bluetooth beacons spread around in the area of interest, measurements from the mobile accelerometer and the user's previous estimated location. The target of the neural network is to predict the current user's position.

For the deployment of our model inside buildings where users are expected to move around in a 2-dimensional space, we assume that beacons are pre-installed forming a dense enough network of nodes placed at known locations of the building area. After beacon installation (and their placement on a 2D map), for our method to apply, the area of the building must be split up in subareas where a number of measurements need to be carried out so that the ANN we use can be trained before entering into an operational state. Some manual work is required in order to cover the area and measure received RSSI values to train the model for the specific building (collecting an adequate number of measurement points per subarea).

After having the ANN trained, in a practical implementation, when a user enters into a building for the first time, he could, for example, download and install an application in his smartphone. This initial step would be required so that he could authorize the system to collect his position information and other data that could be considered sensitive private information and use the internal positioning service supported by the proposed method. In the entrances of the buildings, QR codes, for example, could be placed with which the user can interact as a starting point for using a navigation/positioning application. In such a case, the user can scan these QR codes, directing him/her through an appropriate link to download the navigation/positioning application, the training model for the specific building and initialize his/her starting position for the application to start tracking his position from that point on. Having gone through the initial installation of the application in one building, for the first time, the user will then have to load only the training model of each specific building that uses the same application, at all later times.

IV. Experimental Evaluation

A. *Collecting data for our model training.*

The first step in developing our system was to create a data collection to train and evaluate our neural network model.

Fig. 1. Bluetooth beacons used in our experiments

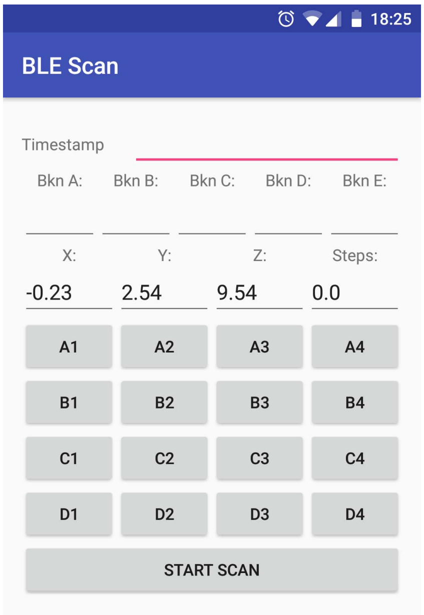

Fig. 3. Smartphone application screen for collecting measurements for data-set

To create the data collection, we used five Bluetooth beacons iBKs105 of Accent Systems that we placed in a 31m^2 apartment "Fig. 1". The space of the compartment has been divided into 16 equal areas (1.45m x 1.35m) where each area was named from the column (A, B, C, D) and the row in which it is located (1, 2, 3, 4) "Fig. 2".

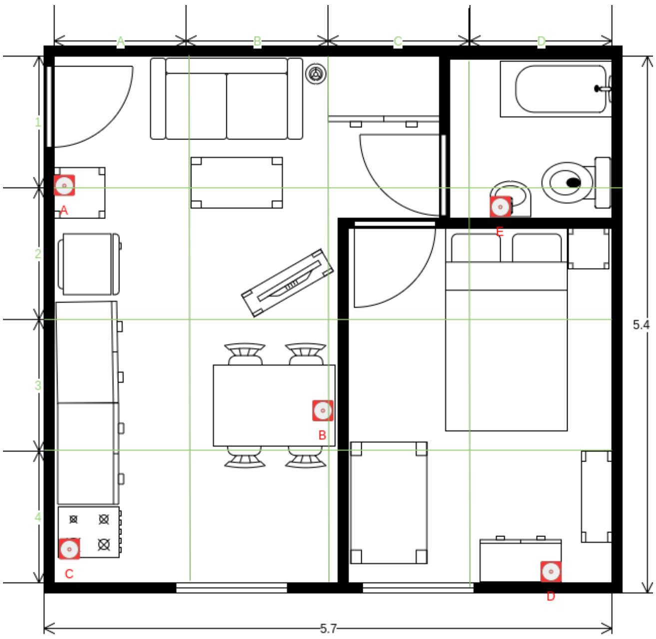

Fig. 2. Apartment map with BLE beacon locations and subareas.

Then by using the application, we have developed for a smartphone (a screenshot from the application is given in "Fig. 3") we started to move into the space of the apartment and take measurements. For each measurement, we record the current position in the space (by pressing the corresponding button from the application), the RSSI values from the beacons, the accelerometer sensor values for the three axes (X, Y, and Z) and the timestamp of the moment we took the measurement. The mobile phone we used to collect the data is a Xiaomi Mi A1.

In total, we have gathered 3699 measurements to train and validate our model.

B. Development and training of our machine learning model.

The development of our machine learning model to predict the position was done using the TensorFlow framework [21].

We divided our 3699 measurements into two groups, one for the training and one for the validation. For the training of our model, we used 2959 measurements out of the 3699 in total and for the validation the remaining 740. We used the cross-validation technique to test our model, in order to flag problems like overfitting or selection bias and to give an insight on how our model will generalize to an independent dataset. So, we partitioned our dataset into complementary subsets (training set and validation set). To reduce variability, we performed five rounds of cross-validation using different partitions and for the validation, we took the average over the five rounds.

Our neural network model consists of three layers "Fig. 4". The architecture of the layers is densely-connected [22]. with the first having 128 nodes the second 32 nodes while the latter has 16 SoftMax nodes which return us a series of 16 rankings with a probability summing at 1. Each node contains a score indicating the probability that the values of the current measurements correspond to the specific area of the apartment space.

```
model = keras.Sequential([
    keras.layers.Dense(128, activation=tf.nn.relu),
    keras.layers.Dense(32, activation=tf.nn.relu),
    keras.layers.Dense(16, activation=tf.nn.softmax)
])
```

Fig. 4. Our neural network model in TensorFlow framework.

We develop our model with densely-connected layers because it is a very simple neural network architecture and easy to deploy, yielding at the same time high accuracy and reduced training time.

Then we trained our model by giving the 2959 measurements we retained for training and set training in 100 epochs. "Fig. 5" shows that accuracy (y-axis) growing of our model in relation to the training epochs (x-axis).

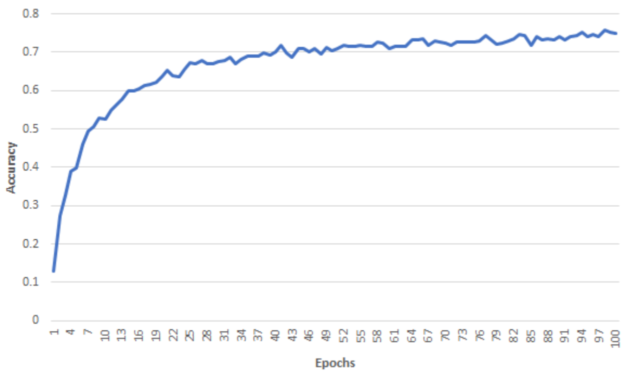

Fig. 5. Our model training process. Accuracy per training epoch

To evaluate our model, we used the group of the collection (740 measurements) that we retained for testing. As mentioned above the experiments where repeated five times, where in each execution we used different values for the training and evaluation groups. Additionally, during each experiment, we repeated the training and evaluation process for 20 times in order to estimate a statistical average result. The average accuracy for each iteration is shown in "Fig. 6".

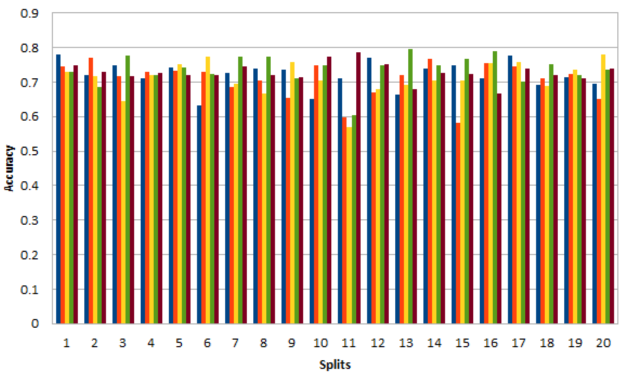

Fig. 6. Our model accuracy per execution, dataset split and iteration.

V. Results

A. Results Analysis

From the results, we can conclude that our system, even when trained with a relatively small collection of data, has been able to achieve good accuracy in predicting the correct position of the user. In "Fig. 7" below, we present the accuracy of our model per split as well as the average accuracy across all splits, which is 0.72089.

This means that our system can predict the correct user location in about 72% of all cases. Since in our system, we have divided the experimental area into a grid with a granularity of 1.45m x 1.35m, the above result also indicates that in 72% of all cases, our system yields an accuracy better than 1 meter.

Our model accuracy per training/testing split	
Split accuracy 1	***0.72034***
Split accuracy 2	***0.70736***
Split accuracy 3	***0.71135***
Split accuracy 4	***0.73736***
Split accuracy 5	***0.72804***
Average accuracy	***0.72089***

Fig. 7. Our model average accuracy per split.

Finally, it was interesting to estimate the time lag introduced by our system to return the position estimation. In this respect, the response time during operation (i.e. after the application has been installed and the model has been trained) is expressed as the time for the system to calculate and return the current position. Throughout our experiments, the time lag was found to be negligible.

VI. Conclusion

To find indoor locations for individuals with the use of smartphones, it is essential to develop a localization system that can achieve high levels of accuracy in building-scale real-world environments. In this paper, we considered the challenges of developing a system by using RSSI from Bluetooth beacons and the values from smartphone accelerometer in a neural network model. We create a data-set with values from Bluetooth RSSI and smartphone accelerometer and train a neural network model. Our model was shown to achieve an average accuracy of 0.72089, which in turn expresses the probability that the user position is estimated with localization error better than 1 meter.

VII. Future Work

Our next steps will be to create a data-set with a higher number of measurements. We are planning to test our model in a larger area with a more complex environment and with more Bluetooth beacons deployed and to experiment with different neural network architectures. To this end, it will be interesting to investigate the effect of grid partitioning and the possibility to introduce smaller subareas even in larger areas in relation to the overall range of Bluetooth. A potential approach to increase scalability would be to split the total area into smaller subareas where each subarea will have its own grid and training mode. In this way, a central system for all subareas can be used to locate the user into a subarea and then loading the corresponding training model for this subarea for final accurate positioning. Finally, we will investigate the effect of the new Bluetooth 5.1 standard and its impact on our positioning methodology.

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