Improving the Precision of Indoor Positioning Systems

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***Abstract*—Over the last few years, the demand for indoor positioning systems has been increasing at a very rapid pace. This dynamic has been fueled by interest sparking from a multitude of opportunities for ubiquitous connectivity spearheaded by the Internet of Things movement and it has led to the development of numerous devices, systems and applications. The ability to sense data, gather and process information, decide intelligently on how to affect resources, control devices, systems and people is at the heart of such a movement. Industrial, commercial, ludic and scientific spaces want to direct workers, users and resources to certain items or tasks for reasons of security, efficiency, profit, etc. In order to answer this growing need, low-cost, higher accuracy indoor positioning techniques are required. The goal of this thesis consists in assessing currently existing technologies for this task, compare them, propose improvements to their accuracy and provide recommendations regarding their usage. Serving both as a testbed and as a demonstration facility, an indoor positioning system which addresses these requirement has been developed. Clearly it would not be possible to analyze all technologies available that could be used for this task and therefore options had to be made. This is why in this thesis we concentrated on low-cost low-energy Bluetooth solutions. Therefore, prior to system implementation, an analysis of the Bluetooth low energy received signal strength was done over time and distance. In addition, we evaluated the signal coexistence with Wi-Fi, with multiple Bluetooth beacons broadcasting at the same time and in a path experiment. The experimental/demonstration system was implemented on the first floor of INESC-ID in Lisbon, Portugal. An Android application was developed that is capable of calculating and displaying the users position and based on this information to present to the user suggested items previously chosen by the system administrator, via notifications. The position estimation was improved by using the fingerprint method and the weighted k-nearest neighbour comparison method between the online received signal strength measurements and the offline measurements database. A Kalman filter was used to track the users position and thus further improve accuracy. A static accuracy of less than 3m was achieved 95% of the time with a mean error of approximately 1.5m, using 1 fingerprint per $2.5m^2$ and 1 beacon deployed per $5m^2$. The system exhibits a position error of approximately 5.5m when using a reduced fingerprint density (1 fingerprint per $10m^2$) while a reduced density of beacons (1 beacon per $20m^2$) enables a mean accuracy of 1.8m. Kalman filter position tracking improved the correlation of the users positions over time.**

***Index Terms*—Indoor positioning, Weighted k-NN, Kalman filter, Fingerprinting, Android, BLE**

I. Introduction

The Internet of Things (IoT) has been one of the major technology trends in the last years. IoT represents a general concept for the ability of network devices to sense and collect data from the world around us, and then share that data across the Internet where it can be processed and used for various purposes. IoT is considered a revolution in terms of communication between devices.

The ability to determine the position of devices or people inside buildings is one of the most important features in IoT. Bluetooth Low Energy (BLE) is a key building block for the IoT, thanks to its pervasiveness due to the mobile devices support of Bluetooth 4.0, low-power consumption and protocol optimization for low-rate transmission. Even though beacons are very simple, they are a technological advancement because they allow for indoor positioning and subsequently indoor behaviour tracking. They create a new seamless interaction that does not consume a lot of battery power.

Industrial, commercial, ludic and scientific spaces want to direct their workers, users and resources to certain items or tasks for reasons of security, efficiency, profit, etc. Most of the times, those spaces cannot or have difficulty in directing users to their interest. Furthermore, the IoT revolution led to the development of numerous devices, systems and applications, and brought the need to know the position of not only people but also devices. Therefore, arises the need for a positioning system in an indoor environment that can localize both devices and people. Having this in mind, many different solutions for achieving the user's positioning have been proposed. An interesting setting is depicted in Figure 1.

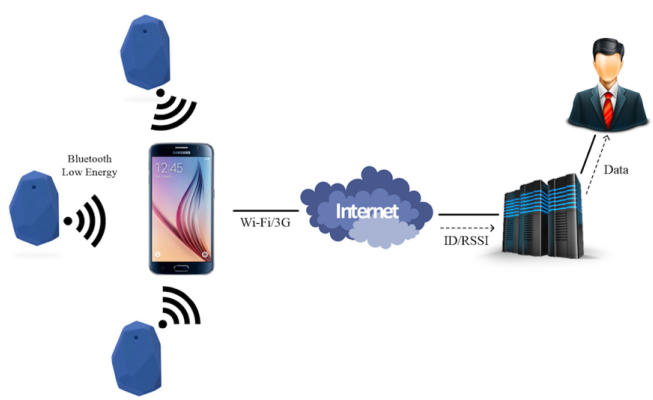


Fig. 1: Architecture of the positioning system.

The basis for our research is to test the capabilities of the technologies in indoor positioning systems. We conducted an analysis of the received signal strength of the Bluetooth low energy advertisements under different conditions which allowed to draw several conclusions.

Having in mind the technology capabilities, we developed a positioning system with a static accuracy of less than 1.5m, 95% of the time using more advanced methods, while

previous work had only achieved a static accuracy of less than 2.5m, 95% of the time [1]. In addition to this static accuracy improvement, the positions correlation was improved over time, enabling path-detection schemes to follow users or resources as they move over time.

II. Background

Technology has evolved in many fronts and certainly in the area of positioning methods. Nowadays, technology is used for both outdoor and indoor environments as well as locating people and devices. Several types of technologies can be used to obtain the position of these devices in an indoor environment.

A. Bluetooth

Bluetooth[1] is a wireless standard technology that connects devices, fixed or mobile, together over short distances and is becoming more and more popular in modern technologies. It can be found in all sorts of devices and areas of consumer goods from mobile phones, headsets, tablets, etc. Bluetooth technology was created as an open standard to allow connectivity between different products leading to cooperation between industries.

B. Bluetooth Low Energy

BLE is intended to provide considerably reduced power consumption and cost, while maintaining a similar communication range, when compared to regular Bluetooth.

a) Advertising and Scanning: BLE Beacons are BLE devices which only use the advertisement mode in BLE. They transmit packets of data at regular intervals of time, which can be then received by other devices like smartphones.

The time between these broadcast events is referred to as advertising interval, which is shown in Figure 2. These events are sent at a fixed rate defined by the advertising interval, which ranges from 20 ms to 10.24 s. Adding to this, a 0-10 ms pseudo-random delay is added to ensure that beacons can coexist, even if they start broadcasting at the same time. The shorter the interval, the higher the frequency at which advertising packets are broadcast, leading to a higher probability of a packet to be received by a scanner. However, higher amounts of packets transmitted also translates to higher power consumption [2].

The specification defines two basic types of scanning procedures, passive scanning and active scanning [3]. In passive scanning, the scanner simply listens for advertising packets.

[1]https://www.bluetooth.com

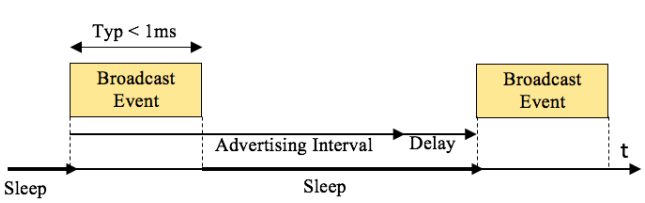


Fig. 2: Advertising Interval.

In active scanning, the scanner issues a Scan Request packet after receiving an advertising packet. The advertiser receives this request and responds with a Scan Response packet.

b) Collisions with Wi-Fi and Bluetooth: The open 2.4 GHz Industrial, Scientific and Medical (ISM) frequency band that is used by BLE is filled with many other wireless protocols, such as Wireless Fidelity (Wi-Fi), as well as potential interference from home appliances, such as microwave ovens. These radio activities may interfere with the BLE activity. The broadcasting of advertisements occurs on three different channels sequentially.

The channels 37, 38 and 39 have been chosen to not collide with the three most commonly used Wi-Fi channels; 1, 6 and 11, as shown in Figure 3. However, Wi-Fi has

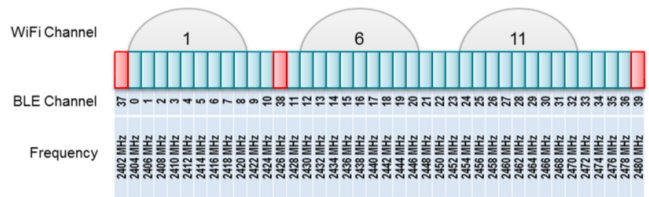


Fig. 3: Frequency Band and Channels.

significantly higher output power, up to 23 dBm compared to the maximum allowed 10 dBm for BLE. This means that placing a beacon very close to a Wi-Fi source will probably distort the transmitted data as spurious emissions on side channels of the Wi-Fi unit will almost always occur on a non-ideal Radio Frequency (RF) device.

Whenever possible, proximity to Wi-Fi sources should be avoided.

c) Advertisement Protocols: The emitted message contains information that the receiving device can use to identify the beacon and to compute its relative distance to the beacon. The receiving device may use this information as a contextual trigger to execute procedures and implement behaviours that are relevant to being in proximity to the transmitting beacon.

The transmitted data from a BLE device is formatted according to the Bluetooth Core Specification and is comprised of the parts shown in Figure 4.

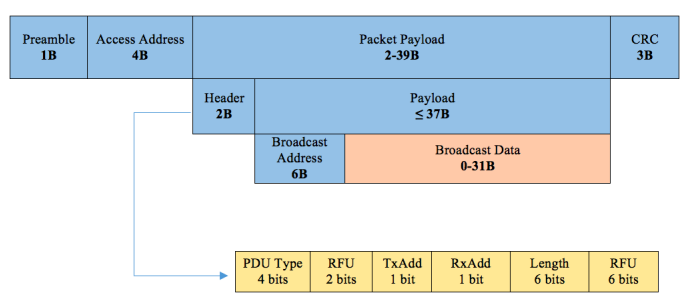


Fig. 4: Bluetooth Link Layer Packet Format.

The broadcast data, inside payload, is used following the rules of one of the next protocols, which define the message format for beacon advertisements: iBeacon, Eddystone, URIBeacon or AltBeacon.

iBeacon[2] is a communication protocol developed by Apple and was the first beacon protocol in the market. iBeacon broadcast segments of data, as shown in Figure 5.

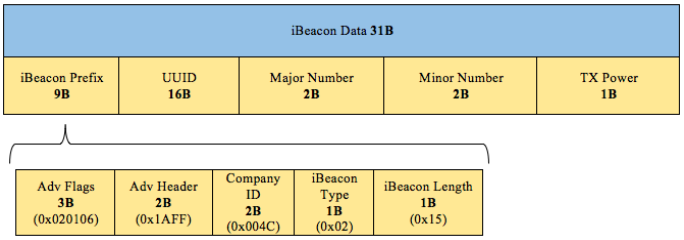


Fig. 5: iBeacon Advertisement Format.

III. Positioning Methods

Several methods can be used to estimate the position of devices. The estimation can use one or more variables and one or more methods. In this section, we introduce the positioning methods we used to estimate the user's position. Fingerprinting was used to obtain a static position estimation and a Kalman Filter was used to extend the previous position estimations to dynamic position tracking.

A. Fingerprinting

Fingerprinting is a localization method and can be divided in two phases. In the first phase or offline phase, it is necessary to collect the Radio Signal Strength Indicator (RSSI) data along the locations where the user is expected to be, in order to construct a map of RSSI values, making this method environment related. These values are then stored in the fingerprinting database so that they can be used later. In the second phase or online phase, the device collects the RSSI values and compares them with the values in the fingerprinting database, to identify which values relate the most to those obtained [4]. These phases are depicted in Figure 6.

Several comparison methods can be used in the second phase, such as: probabilistic methods, k-Nearest Neighbours, neutral networks, support vector machine and smallest M-vertex polygon [4].

K-Nearest Neighbours (KNN) is a non-parametric method used for classification and regression. In fingerprinting, the input consists of the RSSI values vector observed in each trained position in the offline phase. KNN calculates the distance between RSSI vector measured in the online phase and all the others in the offline phase, where unheard transmitters are substituted by zeros. The distance function used in this method is the Euclidean distance described in Equation (1).

[2]https://developer.apple.com/ibeacon/

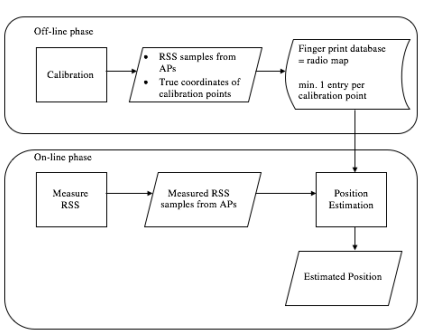


Fig. 6: Fingerprinting Phases.

$$d_i = \sqrt{\sum_{j=1}^{n} (x_{ij} - x_j)^2} \tag{1}$$

Usually in a positioning system, the KNN algorithm provides an estimate based on the average position of the closest k training points in the database. The estimated position can be calculated using Equation (2) [5].

$$P(x,y)_{user} = \frac{\sum_{i=1}^{k} P(x,y)_i}{k} \tag{2}$$

The Weighted K-Nearest Neighbours (WKNN) algorithm is used to improve the accuracy of KNN. This algorithm works following the basic principle of assigning a weighting scheme to the calculation of the estimated position. The weights assigned take in consideration the distance calculated in (1), so that the nearest neighbour contributes more to the estimation of the position when compared to to the neighbours further away. A possible weighting scheme is shown in Equation (3).

$$w_i = \begin{cases} \frac{d_k - d_i}{d_k - d_1} & , d_k \neq d_1 \\ 1 & , d_k = d_1 \end{cases} \tag{3}$$

The value of w_i varies from 0 to 1, depending in the euclidean distance calculated previously. The estimated position can be calculated using Equation (4) [6].

$$P(x,y)_{user} = \frac{\sum_{i=1}^{k} w_i \cdot P(x,y)_i}{\sum_{i=1}^{k} w_i} \tag{4}$$

B. Kalman Filter

Kalman Filter (KF) [7] is widely used in control systems to estimate the state of process in the presence of noisy systems.

State model and measurement model are defined as

$$s_k = \boldsymbol{A}_{k-1} s_{k-1} + v_{k-1} \tag{5}$$

and

$$y_k = \boldsymbol{H}_k s_k + n_k. \tag{6}$$

$\boldsymbol{A}_k \in \mathbb{R}^{N_s \times N_s}$ is denoted as state matrix and includes the linear dependencies between the states at time-steps k and $k-1$. The measurement matrix $\boldsymbol{H}_k \in \mathbb{R}^{N_y \times N_s}$, denoted as measurement matrix, reflects the linear relation between the measurements and the state at time-step k. The matrix s_{k-1} corresponds to the previous position calculated using the Equation (4), which is going to be used to do the prediction. The matrix y_k is the position prediction done by the KF.

The KF algorithm is depicted in Figure 7. The KF is initialized with $s_{0|0}$ and $\boldsymbol{M}_{0|0}$ determined by the a priori distribution of the initial state. In the prediction step, the state of the current time-step is computed taking into account the state of the previous time-step and the knowledge of the state matrix given by A_k,

$$\hat{s}_{k|k-1} = \boldsymbol{A}_{k-1} \hat{s}_{k-1|k-1} \tag{7}$$

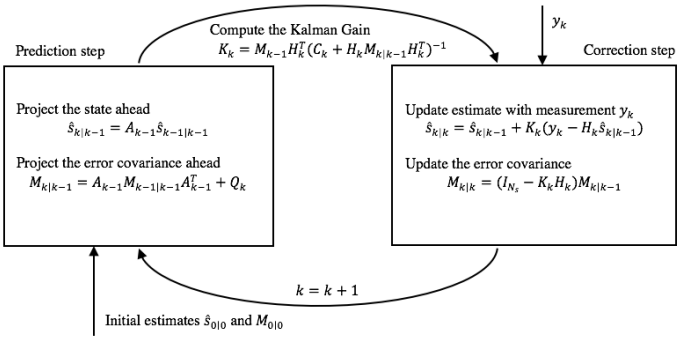


Fig. 7: Kalman Filter Algorithm.

with the estimate of the previous time-step $\hat{s}_{k-1|k-1}$. Additionally, the corresponding Minimum Mean Square Error (MMSE) or covariance matrix after that prediction step can be calculated as

$$\boldsymbol{M}_{k|k-1} = \boldsymbol{A}_{k-1}\boldsymbol{M}_{k-1|k-1}\boldsymbol{A}_{k-1}^T + \boldsymbol{Q}_k \tag{8}$$

where $\boldsymbol{M}_{k-1|k-1}$is the MMSE matrix of the previous time-step.

The Kalman gain matrix includes a weighting between the predicted estimate and the current measurements. It is given as

$$\boldsymbol{K}_k = \boldsymbol{M}_{k|k-1}\boldsymbol{H}_k^T\left(\boldsymbol{C}_k + \boldsymbol{H}_k\boldsymbol{M}_{k|k-1}\boldsymbol{H}_k^T\right)^{-1}. \tag{9}$$

Finally, the correction step combines the predicted estimates with the current measurements weighted with the Kalman gain matrix. This results in the final estimate of the state vector

$$\hat{s}_{k|k} = \hat{s}_{k|k-1} + \boldsymbol{K}_k\left(\boldsymbol{y}_k - \boldsymbol{H}_k\hat{s}_{k|k-1}\right). \tag{10}$$

The corresponding MMSE or covariance matrix after the correction step is obtained as

$$\boldsymbol{M}_{k|k} = \left(\boldsymbol{I}_{N_s} - \boldsymbol{K}_k\boldsymbol{H}_k\right)\boldsymbol{M}_{k|k-1}. \tag{11}$$

IV. Analysis of the BLE Received Signal Strength

Prior to the implementation of the indoor positioning system, we carried out experiments to study the BLE signal. BLE beacons advertisement interval and broadcasting power are set to 100 ms and 4 dBm, respectively, in all experiments. The measurements were collected using an LG Nexus 4 handset running Android 4.4.2.

A. RSSI Measurements over Time and Distance

RSSI is an important component in a positioning system, so it is necessary to study what affects its value in a real world environment. Because of that, experiments related to the reception of the BLE signal were made.

Initially, we need to understand if the RSSI changes over time. To determine this, an experiment was setup where one beacon was placed at one meter distance from the device. Figure 8 shows the RSSI variation over time, more precisely 10 seconds, which resulted from the experiment. From this figure, we deduced that the RSSI vary over time which happens because of multipath losses, also known as fast fading effects.

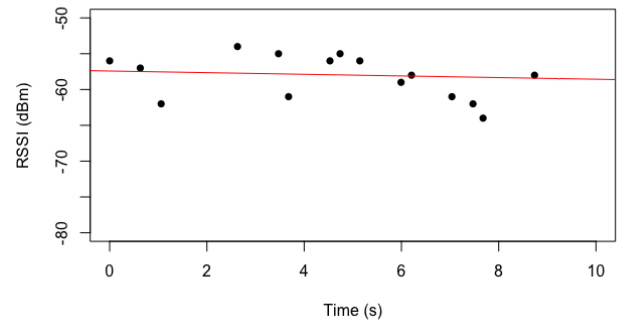


Fig. 8: RSSI measurements with beacon at 1 meter distance.

Since BLE advertises in 3 different channels, centered on 2402 MHz, 2426 MHz and 2480 MHz, the signal received from the receiver device, even though it is sent with the same broadcasting power, may be received with different Received Signal Strength (RSS), because different signal frequencies can suffer different multipath losses [9].

Even though the RSSI is not constant over time, its average value remains constant if the environment and distance to the BLE beacon does not change. In Figure 8, for 1 meter distance the mean of the RSSI, represented by the red line, is approximately -57 dBm.

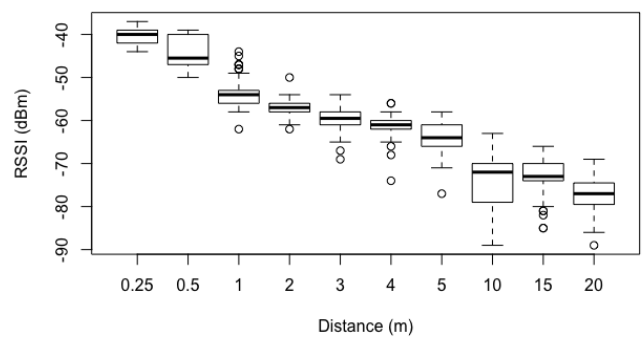


Fig. 9: LG Nexus 4 RSSI variation with distance.

Next, another experiment was setup where the BLE beacon was placed at different distances from the receiving device. The values obtained from the experiments, measured during an interval of approximately 30 seconds, are displayed in Figure 9, from which is possible to corroborate the distance dependency of the RSSI.

B. Human Body Attenuation

BLE devices operate in the 2.4 GHz licence-free band, which is attenuated by the human body leading to a bad range estimation. To assess the effect of such attenuation, an experiment was conducted where one person was obstructing the line of sight of the device. The distance between the receiving device and the BLE beacon is maintained, in order to evaluate how much it would effect in BLE RSS.

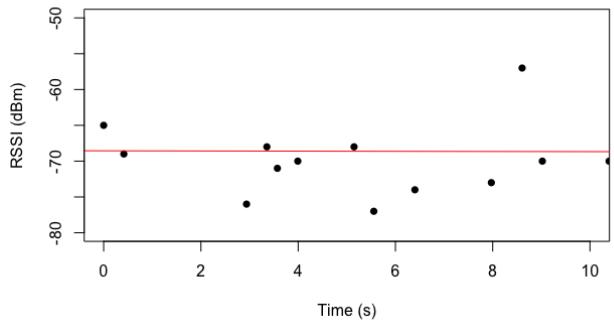


Fig. 10: RSSI received from one beacon at 1 meter distance obstructed by human body.

The experiment results are shown in Figure 10, demonstrating a ∼10 dB signal attenuation when compared with Figure 8. This reduction in RSSI is caused by this body effect, which will still result in a reasonable proximity measurement error when within 10 cm of the transmitter, the body effect can result in a range error estimate of 5-10 m [10].

C. Multiple BLE Beacons

The positioning system is supposed to work with several BLE beacons broadcasting at the same time. Therefore, it is important to known if they affect each other RSSI at the receiving device. To study about the effect that each beacon can have in the RSSI of another beacon at the receiving device, four beacons were placed at 1, 2, 3 and 4 m away from the receiving device, this experiment is depicted in Figure 11.

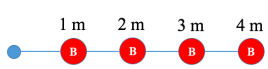


Fig. 11: Experiment Beacons Position.

The results obtained in this experiments are shown in Figure 12, which demonstrates that these signals do not affect each other RSSI in any way, since they appear to be very similar to the results obtained in the experiment depicted in Figure 9. Although the experiment was done with a low number of beacons, it is anticipated that even with a higher number of beacons, around 100 or more in a short space, the strength of the signal will not change. In the worst case scenario, what can happen are collisions between them and making it necessary to broadcast the advertisement again.

D. Wi-Fi Interference

The majority of mobile phones users have the Wi-Fi activated all the time. We need to determine if this activation causes any type of interference with the received signal strength of the BLE radio signal.

In order to evaluate this, experiments with the Wi-Fi connection activated in the mobile phone were made. Initially, the user was placed at 1 meter distance from the Wi-Fi router and 1 meter distance from the BLE beacon. After, the user moved

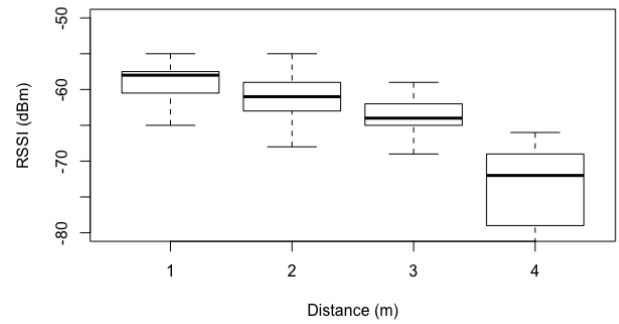


Fig. 12: RSSI received from multiple beacons at 1, 2, 3 and 4 m at the same time.

1 meter away from the Wi-Fi router keeping the distance of 1 m to the BLE beacon moving it too. This experiment is depicted in Figure 13.

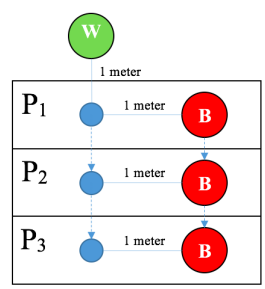


Fig. 13: Wi-Fi experiments Path.

The results obtained from this experiment, where the BLE signal was scanned during 10 seconds in 3 different positions, are displayed in Figure 14.

From this experiment, we observed that there is no correlation with the proximity to the Wi-Fi access point. Although it did not make any difference in this experiment, we need to take into account the possibility that in this experiment the value of Wi-Fi was not high enough to make any difference in Bluetooth RSSI values. In some occasions, such as: Wi-Fi router transmitting with high power close to the BLE receiver, the use of Wi-Fi is not recommended.

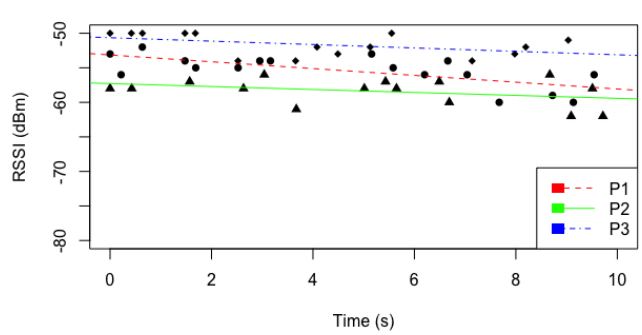


Fig. 14: Wi-Fi experiment Results.

E. Path Experiment

Lastly, an experiment to check if it was possible to detect the exit and entrance in different rooms was conducted. A BLE beacon was placed inside a room and the device was moving away from the BLE beacon starting at a one meter distance and moving approximately 1 meter distance from the previous position every 10 seconds. This experiment is depicted in Figure 15.

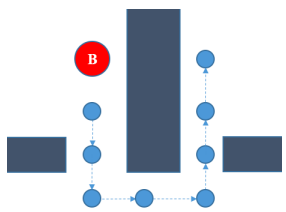


Fig. 15: RSSI measurements Path.

Figure 16 shows the results obtained from this experiment, from which we detected that the user was moving away from the beacon and then was getting closer to it after some time.

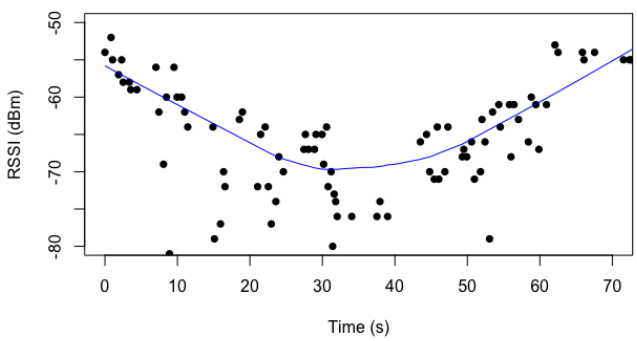


Fig. 16: Path Experiment Results.

In this experiment, the wall does not attenuate much the RSSI because it is a low reflection surface with low reflection coefficient and most of the signal will be diffracted. Adding to this, fast fading effects are evident with drops of 30 dB in power which occur in a little distance variation.

F. Experiments Conclusions

In this chapter, we carried out experiments related to the received signal strength of BLE advertisements under different conditions. Our key conclusions are:

- The BLE RSS measurements vary in time. However, these measurements seem to maintain its average value during a scanning window if the environment does not change. In addition, BLE RSS measurements vary with the distance, decreasing in a nonlinear manner. The device used to receive the signals has influence on the RSS measurements with which they are received, nevertheless the RSS values are similar to the ones received with other devices.
- The existence of multiple BLE beacons does not cause RSS measurements to change. However, collisions may occur if a large number of bluetooth devices coexist in the same area where the receiving device is listening.
- The human body attenuates the BLE signal, mainly when near the receiver or the sender. The attenuation corresponds to approximately 10 dB.
- The Wi-Fi does not interfere with reception of BLE signals. However, this interference may exist if the Wi-Fi signal RSS measurements are 20 dB higher than the BLE RSS measurements.
- Through a path test, we can conclude from the RSS measurements the proximity that a receiving device was moving away or approaching a BLE beacon.

V. Implementation

The positioning system architecture is divided in three components: the BLE beacons, the mobile phone application and the back-end. The chosen beacons are the ones manufactured by Shenzen Sky[3] due to its battery life and four different values of power intensity. These beacons use the iBeacon [4] protocol for the beacon information broadcasting. The mobile phone application is aimed to *android* devices due to previous programming experience in *android* and to the greater number of people using this operating system.

In this section, we describe the conditions to place the BLE beacons and their deployment in our positioning system. Furthermore, the functional specification of the *android* mobile phone application are introduced. After, we depict the design of the application. Lastly, we describe the back-end.

A. BLE Beacons Deployment

The deployment of the positioning system BLE beacons was limited to the area of two corridors and the students room on the first floor of INESC-ID, a non-profit privately owned institution of public interest, in Lisbon, Portugal. This area represents a total of approximately $60m^2$. Ten BLE beacons were deployed evenly through the space so that there are not areas more populated with beacons than others. The space where the BLE beacons were deployed is shown in Figure 17, as well as the BLE beacons deployment layout.

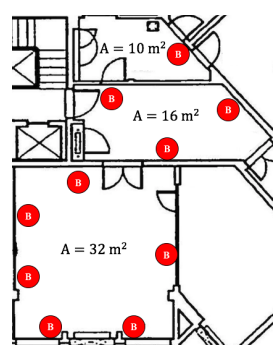


Fig. 17: Positioning System Area.

[3]https://cnsky9.en.alibaba.com
[4]https://developer.apple.com/ibeacon/

B. User's Position Calculation

The user's position calculation is one of the main objectives of this project. Figure 18 depicts the BLE advertisements scanning and filtering processes.

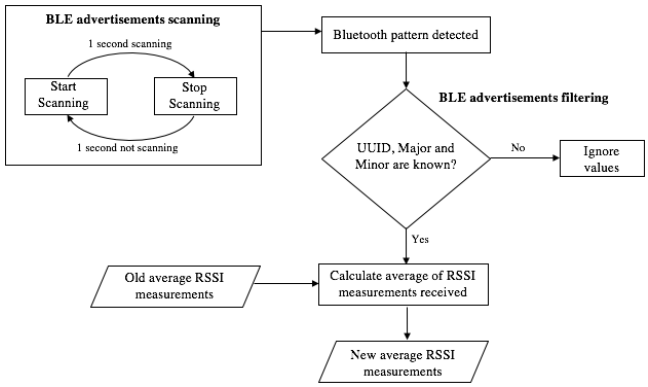


Fig. 18: BLE Advertisements Scanning and Filtering Process.

The position is calculated every 2 seconds. This time is usually called BLE scanning window. The selection of this window is very important because there needs to be a balance between ensuring sufficient samples for multipath mitigation and obtaining sufficient dimensionality in the fingerprint and minimising spatial smearing from handset movement.

For the position estimation method, we used the fingerprinting method as it provides the best accuracy.

In the position tracking implementation, we decided to use the Kalman filter because in a linear system with Gaussian noise, which reflects accurately many systems, the Kalman filter is optimal. In Figure 19, we describe the process to obtain the user's position from the RSSI valid measurements.

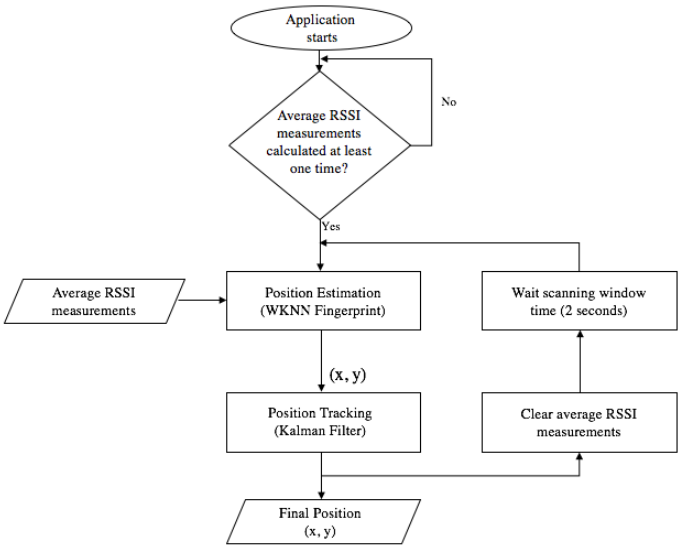


Fig. 19: Position Calculation Process.

C. Back-End Communication

The back-end is contacted for two different reasons. First, to know the value of the latest version of the application.

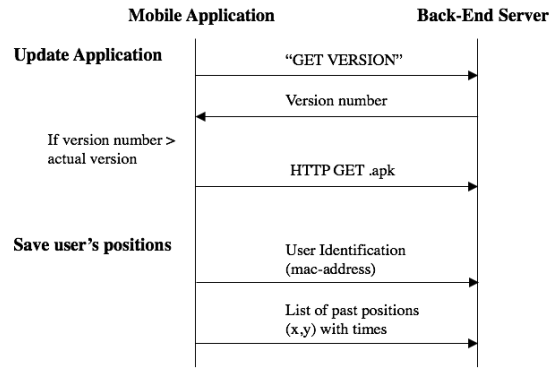


Fig. 20: Back-End Communication Protocol.

Second, to save the values of the computed user positions. The communication protocol between the mobile application and the back-end is depicted in Figure 20.

D. Android Application Design

In this section, we describe the design of the *android* mobile phone application and its storyboard.

Figure 21 introduces the menu of the mobile application. It has two buttons, "View Items" and "View Map" and an INESC-ID Lisbon image as the background image of the main activity. Selecting "View Items" redirects the user to the items list and selecting "View Map" redirects him/her to the map activity.

Fig. 21: Android Menu Activity and Update Available Message Alert.

The list of items introduces to the user all the items present in the system. The image, the title and the description of each item appear in this activity. Selecting one item in the items list introduces to the user its image in greater detail and more information about its description. The list of items and item activity are shown in Figure 22.

The map activity shows the positioning system map and the user's position using a red dot. In this activity the user can only go back to the main activity.

From all the application activities and even in background, the user can receive notifications. The map activity and the notification are depicted in Figure 23.

E. Back-End

The back-end runs a server which is waiting to receive application requests to save the value of the user's position or related to the most recent version number of the application.

Fig. 22: List of Items and Item Activities.

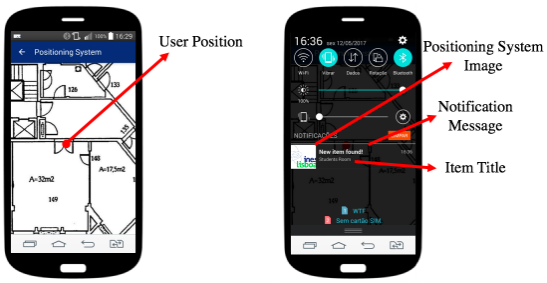


Fig. 23: Map Activity and System Notification.

In addition, the server has the latest version of the application so that we can download or update it. The back-end server request handling algorithm is depicted in Figure 24.

The back-end stores the values of the user's position in a file. Tts name is the mac-address of the mobile phone that sent the values. This file is accessed directly by the server administrator. It may be used later by other programs.

VI. Experimental Results

The fingerprints database was obtained through a static scan of 30 seconds where the values stored in each position are the average RSSI received for each beacon. The experiments were done using a LG Nexus 4 handset running Android 4.4.2 and the BLE beacons advertisement interval and broadcasting power are set to 100ms and 4 dBm, respectively.

A. NN, KNN and WKNN Comparison

The results shown next were obtained from a static test in multiple positions inside the location, where one sample was collected every two seconds for six minutes (total of 183 observations). The cumulative position error probability,

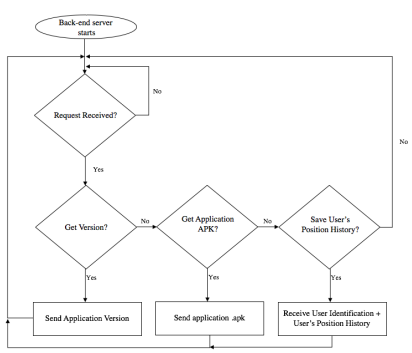


Fig. 24: Back-end Server Request Handling.

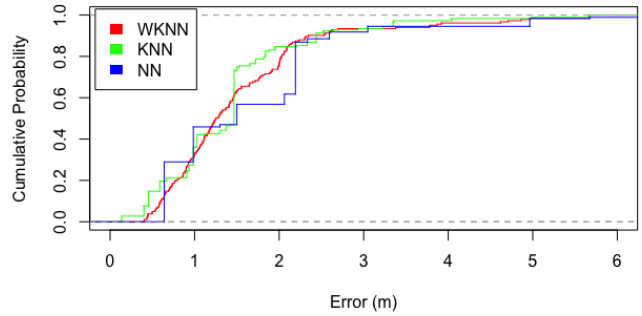


Fig. 25: NN, KNN, WKNN Position Estimation Static Error Cumulative Probability.

in meters, of the position estimation methods are shown in Figure 25. During this test, the highest value of fingerprint and BLE beacons density were used. The k value used in KNN and WKNN was 3 [11].

An accuracy of <3 meters was achieved 95% of the time in all methods with a mean error of 1.5260 meters, as well as an accuracy improvement using WKNN or KNN compared to Nearest Neighbour (NN). On the other hand, KNN values of error are very similar to the WKNN, with a mean error value of approximately 1.5 meters. However, the WKNN curve is much closer to a Gaussian error cumulative probability than the other two methods. This will improve the filtering done with the KF, since it is an optimal filter for Gaussian error.

B. Fingerprints Density

Fingerprint is the set of signal characteristics for a position in the environment. The results obtained previously were made comparing the online fingerprint with all the offline fingerprints. We compared the online fingerprint to the offline fingerprints database associated to each density, in order to determine how the number of fingerprints in the database that are compared to the online fingerprint affect the accuracy of the user's location.

Those fingerprint densities are $1/2.5m^2$, $1/5m^2$ and $1/10m^2$, which will be considered high, medium and low density for the sake of comparison.

The results obtained in this test, using the WKNN position estimation method, are shown in Figure 28. There is a big difference between the high density and the other two densities, since low and medium densities do not have sufficient offline samples to achieve a good position accuracy.

Therefore, we can conclude that the position accuracy is highly dependent on the number of fingerprints. More fingerprints in a positioning system will mean more accuracy. However, we can enter in an endless cycle of constantly changing data because it may never be possible to reach the perfect offline data, since the values are environment dependent and change with the humidity and temperature. The fingerprints database only needs to be recalculated if the environment changes.

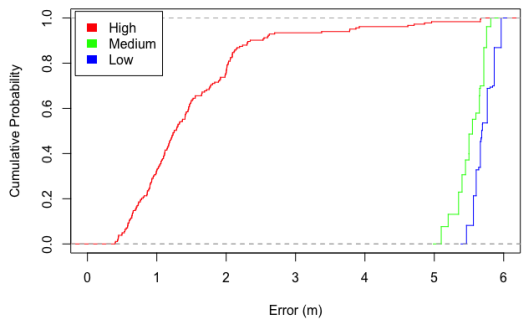
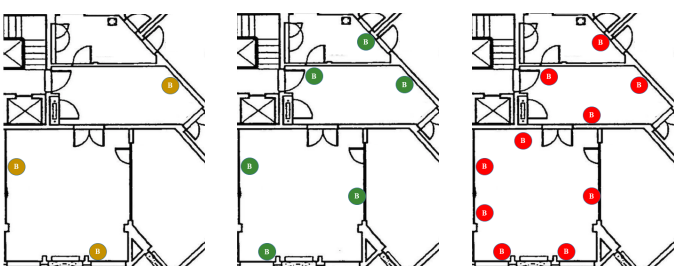


Fig. 26: Cumulative Probability Position Error for Different Fingerprints Densities.

C. BLE beacons Density

After the initial test at the effect of the fingerprinting density, the BLE beacons density was also evaluated in order to see how it can affect the position estimation accuracy of the user's location.

Three different densities of beacons were defined, with densities corresponding to $1/5m^2$, $1/10m^2$ and $1/20m^2$. The location of the beacons at different densities is shown in Figure 27.



(a) Low Density (b) Medium Density (c) High Density

Fig. 27: BLE Beacons Different Densities.

The results obtained in this experiment are shown in Figure 28. For the low density of beacons, a mean error value of 1.7510 meters was obtained. The results show that with the increase in the number of beacons the accuracy of the position also increases. The fact that there are more beacons allows to recognize better the location of the user, because in lower ranges the value of RSSI varies more when compared to higher ranges and having more beacons will permit higher values of RSSI.

Therefore, it may not be worthwhile to use high densities of beacons, since the improvement in the positioning accuracy is not enough to justify this investment. For a mean error of <1.80m requirement, a low density of beacons is enough.

D. Kalman Filter

The values used in the KF were obtained by using trial and error technique in order to find the results that best fit the system. The matrices A, state transition matrix, and H, measurement matrix, are defined as $A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

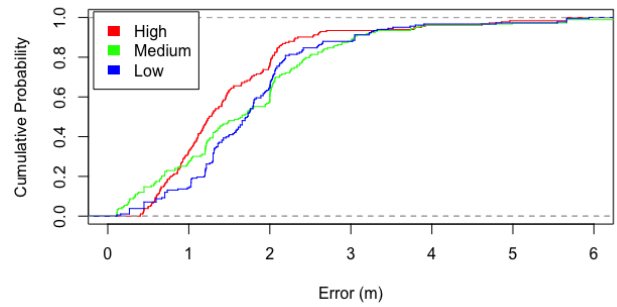


Fig. 28: Cumulative Probability Position Error for Different Beacons Densities.

The input control (B) was set to null. The initial position (x) is unknown because the user can open the application in the position he/she wants to, so it is defined $x = \begin{bmatrix} 0 & 0 \end{bmatrix}$, with a high starting covariance $P = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}$.

The process noise covariance (Q) and measurement noise covariance (R) are defined as $Q = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}$, $R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

In order to test the filter, instead of measuring the positioning error, because it was not allowed to know where the user was at the exact moment his/her position was calculated, a path was defined and the positions obtained were drawn. The defined path is shown in Figure 29.

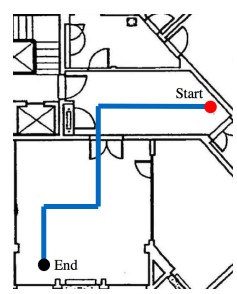


Fig. 29: Tracking Position Experiment Path.

The path test was done using three different velocities to walk through it. The values were drawn using the maximum density of fingerprints, beacons and WKNN position estimation method. The path has 13.4 meters and was travelled at 0.55 m/s .The positions draw in the map, before and after the filter, are shown in Figures 30 and 31.

The drawn positions after filtering are closer to the path which was previously defined, in Figure 29, than the positions that were draw before filtering. Adding to this, the path introduced after the filter is smoother and more suitable to the movement of a person than previously.

Therefore, we can conclude that the application of this filter brings an improvement in the positioning accuracy of the user. One of the relevant factors for this to happen is that the measurement error is Gaussian and the system is linear.

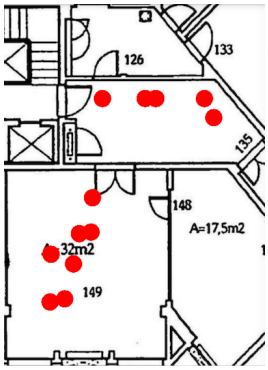


Fig. 30: Experiment Results Before Filtering, at 0.55 m/s.

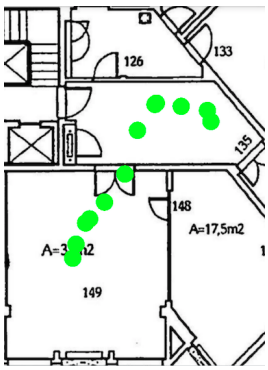


Fig. 31: Experiment Results After Filtering, at 0.55 m/s.

VII. Conclusions

This thesis consisted in testing the capabilities of the existing positioning technologies, which required the elaboration of a system in an indoor environment that uses positioning methods to determine the position of the users in a certain space. We developed a mobile phone application that indicated the position of its user through a fingerprint method, WKNN, and Kalman filtering using BLE beacons.

A BLE signal analysis was performed in order to evaluate the possibility of its use in a positioning system, in which we concluded that:

1) The BLE RSS measurements vary in time due to the use of three advertising channels which relate to different fading. Even though there exists a variation, these measurements seem to maintain its average value during a scanning window. Adding to this, they vary with the distance, decreasing in a logarithmic form. The device used to receive the signals has influence on the RSS measurements with which they are received, nevertheless the RSS values are similar to the ones received with other devices.
2) The existence of multiple BLE beacons does not cause RSS measurements to change. However, collisions may occur if a large number of bluetooth devices coexist in the same area where the receiving device is listening.
3) The human body attenuates the BLE signal, mainly when near the receiver or the sender. It may be detrimental to the calculation of the position if the human body attenuation is not previously considered, which in most cases is not.
4) Through a path test, we can conclude from the RSS measurements the proximity that a receiving device was moving away or approaching a BLE beacon.

An analysis to the experimental results to the system developed was carried out, in which we concluded that:

1) The static position estimation achieved an mean error of 1.52m, while being <3m 95% of the time using WKNN fingerprint method. WKNN improved the position estimation error when compared to NN or KNN method and allowed for a better Gaussian error approximation.
2) The positioning error depends on the density of fingerprints and the low number of these may reflect a larger positioning error. Using WKNN method, was achieved an mean error of 1.52m for one fingerprint per 2.5m^2 and approximately 5.7m of error for 1/5m^2 and 1/10m^2. However, these fingerprints introduced a great loss of time for them to be collected and can lead the implementer to an endless cycle, since the RSS measurements, which constitute a fingerprint, are environment dependent and the environment is constantly changing.
3) BLE beacons densities of $1/20m^2$ are sufficient to ensure a mean error of 1.81m. Higher densities may decrease the error, however, this may not be worthwhile because the positioning accuracy improvement may not be enough to justify the investment.
4) Kalman filter smoothed the positioning estimation done with the WKNN fingerprint, so that the moving position estimated relates to the previous position values. The positions calculated using the Kalman filter adapt more to the path layout, resembling more to an user-made path.

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