Journal of Ambient Intelligence and Humanized Computing (2020) 11:3907–3919
https://doi.org/10.1007/s12652-019-01626-2

ORIGINAL RESEARCH

Improving bluetooth beacon-based indoor location and fingerprinting

Pedro Martins[1] · Maryam Abbasi[2] · Filipe Sá[1] · José Cecílio[3] · Francisco Morgado[1] · Filipe Caldeira[1]

Received: 24 July 2019 / Accepted: 30 October 2019 / Published online: 10 December 2019
© Springer-Verlag GmbH Germany, part of Springer Nature 2019

Abstract
The complex way radio waves propagate indoors, leads to the derivation of location using fingerprinting techniques. In this cases, location is computed relying on WiFi signals strength mapping. Recent Bluetooth low energy (BLE) provides new opportunities to explore positioning. In this work is studied how BLE beacons radio signals can be used for indoor location scenarios, as well as their precision. Additionally, this paper also introduces a method for beacon-based positioning, based on signal strength measurements at key distances for each beacon. This method allows to use different beacon types, brands, and location conditions/constraints. Depending on each situation (i.e., hardware and location) it is possible to adapt the distance measuring curve to minimize errors and support higher distances, while at the same time keeping good precision. Moreover, this paper also presents a comparison with traditional positioning method, using formulas for distance estimation, and the position triangulation. The proposed study is performed inside the campus of Viseu Polytechnic Institute, and tested using a group of students, each with his smart-phone, as proof of concept. Experimental results show that BLE allows having < 1.5 m error approximately 90% of the times, and the experimental results using the proposed location detection method show that the proposed position technique has 13.2% better precision than triangulation, for distances up to 10 m.

Keywords Beacon · Wireless · GPS · Indoor location · Block-chain · Crowd learning · Bluetooth · BLE · WiFi · Fingerprinting

1 Introduction

An important issue related to mobile devices is the challenge of applications strictly based on indoor location detection. The main purpose of knowing such location is to offer information (e.g., promotions, bathroom locations, elevators, garden location) and guide instruction (e.g., emergency evacuation, or help people with special needs). In all possible scenarios related to location pinpointing, an inaccurate location can lead to dangerous situations and serious consequences (e.g., inaccurate stairs detection for a blind person).

Since a couple of years ago, a relentless market explosion of mobile devices, like smart-phones, attracted endless applications and services in business and infotainment. All this information relies on location and mobility.

GPS signal allows positioning outdoor, but this signals cannot penetrate inside buildings, so other methods must be used for indoor positioning. WiFi fingerprinting is a used technique to determine users positioning, however, other alternatives can be used for the same purpose, such as Bluetooth 4.0 signals. Moreover, with new WiFi Access Points (AP) power-saving techniques, fingerprinting is no longer a straightforward approach.

In this paper, a location proof of concept is demonstrated, based on fingerprinting signals such as Bluetooth beacons vs. WiFi. Let's assume the following example for indoor location: inside a shopping center, there are several beacons and hundreds of WiFi signals. The proposed system will use installed Bluetooth beacons, within distinct

✉ Pedro Martins
pedromom@estgv.ipv.pt

Maryam Abbasi
maryam@dei.uc.pt

Filipe Sá
filipe.sa@estgv.ipv.pt

José Cecílio
jmcecilio@fc.ul.pt

Francisco Morgado
fmorgado@estgv.ipv.pt

Filipe Caldeira
caldeira@estgv.ipv.pt

1 Department of Computer, Polytechnic Institute of Viseu, Viseu, Portugal

2 Department of Computer Sciences, University of Coimbra, Coimbra, Portugal

3 Department of Computer Sciences, University of Lisbon, Lisbon, Portugal

locations, to pinpoint users location. On works (Dong and Dargie 2012) and (Chen et al. 2015) other nearby locations are estimated. Collected information is shared using a block-chain strategy (Decker and Wattenhofer 2013) for storing and validate results with other nearby devices. So, as more users pass in the same location (marked with the beacon), the more accurate the location estimation using surrounding networks will be.

Additionally, since a couple of years ago, a relentless market explosion of mobile devices, like smart-phones, attracted endless applications and services in business and infotainment. All this information relies on location and mobility. Many academic (Chawathe 2008; Palumbo et al. 2015; Zhuang et al. 2016), articles propose techniques based on the mathematical formulation to calculate the distance. However, the distance estimation depends on many variables that cannot be accounted using these methods, for instance: different hardware's have different behaviors; the wrapping material surrounding the beacon affects the signal strength; winds; electronic interference; battery power level; and many others.

Having in account the available signals, in this paper it is also proposes a signal distance measuring technique dedicated to each beacon. For each device, the respective distance curve is determined. This way distance measurements have the lowest error possible, even if there are signal reflections. Then battery power attenuation over time is also accounted. All data is treated and stored in a database. This data is then used to feed each device with the signal power measurements vs. distance, for each beacon in range.

To minimize measurement errors, data is collected in preset locations. This way even if objects are interfering with the measures, the location will be precise. For this purpose, a communication architecture, a mobile app, and a database server, were developed and tested.

Based on received signal strength indicator (RSSI), results using a prototype implemented in Java (J2SE and Android), show that indoor location, within 3 m distance estimation is precise with low error margins (1.5 m or less). Above, 3 m range, distance estimation have high error margins, sometimes reaching 5 m or more. More, our scientific results, show that the proposed location method in this paper is 13.22% better than the traditional triangulation of signals, which does not ponder the beacons that are more near.

The paper is organized as follows. In Sect. 2 is discussed the main motivation that led to this work. Section 3, states the main contributions. Section 4, describes the related-work on location dissemination. Section 5 describes how the experimental method was implemented, and a proposed position determination technique based on pre-trained signals. Section 6 describes the used test-bed. Section 7, describes the obtained results. Finally, Sect. 9, concludes the work and introduces future work guidelines.

2 Motivation

Making use of the 2 GHz unlicensed radio frequency, BLE uses 40 channels separated by 2 MHz distance. Similar to BLE there is also WiFi, but, as shown in Fig. 1 with fewer channels and a bigger separation. Note that, BLE only advertises the network on channels 37, 38 and 39. With blue filling is represented WiFi networks channel 1 and channel 6.

BLE method is used to reduce battery consumption, it relies on using concise messages (Heydon 2013), which are data, or network advertising messages, sent in the broadcast. These advertising messages, forwarded in broadcast, carry a payload, which can be used to determine the position. In this case, the strength of the broadcast signals can be used to create a fingerprint signature of all surrounding networks.

In Fig. 1, it is clear that WiFi and BLE use the same frequency width. However, when choosing one (BLE or Wifi) to determine location, there are important differences to account:

- WiFi has long waiting times for the Service Set Identifier (SSID) broadcast, where each broadcast helps pinpointing the location. Thus if the broadcast rate is slow, the location determination will require more time. New WiFi band, in the 2.4 GHz and 5 GHz, have intervals of 100 ms giving a low positioning update rate.
- If a user is moving WiFi location is not optimal, because, WiFi access points buffer information in a single report update, before sending. This way, long scans limit the update-rate, which affect radio fingerprinting if the user is not standing in the same place.
- Privacy might be a concern when repeatedly scanning the networks to obtain signal strength statistics. Moreover, this process also reduces WiFi throughput, by increasing network traffic.
- WiFi does not use continuous signals strength values, therefore making fingerprinting harder.
- New WiFi power-saving techniques, reduce the signal power when a low amount of users are connected, and increases the signal power when users load increases. This power-saving policy, makes WiFi fingerprinting very inaccurate for location determination.

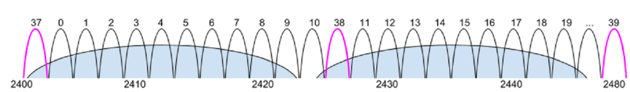


Fig. 1 40 BLE channels and two commonly populated WiFi channels (channel 1 and 6)

On the other hand, BLE uses standard units of dBm, and packages are reported immediately, offering clear benefits:

- Power consumption of BLE is lower than WiFi, this happens due to the WiFi associated regular radio scanning, and because WiFi was not designed for continuous scans. On the other hand, BLE simpler protocols and optimized scan operations are more suited for low power consumption.
- It is easier to deploy a BLE beacon because they can be battery powered and not limited to provide communication coverage. Meanwhile, WiFi access points need to provide communication, meaning, minimum frequency range overlap, and most of the times without concerning WiFi access point geometry positioning.

3 Contributions

In this work BLE fingerprinting is evaluated assuming static BLE beacons distributed in a controlled environment, in contrast with the WiFi system that is randomly distributed across rooms, halls, stairs.

The BLE high advertising rates, 50 Hz, transmission power, and post-processing was investigated to achieve a good positioning.

The contributions for the state-of-the-art of BLE positioning are:

- BLE positioning study using fingerprinting;
- A study on critical parameters that affect accurate indoor positioning;
- Impact of the variation of the channels used in BLE;
- Tests to protect against channel overlapping.
- Experimental validation;
- Identification of accuracy distances;
- New future work challenges based on Big-Data.

4 Related work

Position detection is already a popular research field where many approaches and technologies can be found, each one with comprehensive overviews (Al Nuaimi and Kamel 2011; Koyuncu and Yang 2010; Liu et al. 2007; Ciabattoni et al. 2019). Special relevance is given to BLE positioning fingerprinting, that avoid complex models that require a pattern match with previously surveyed radio strengths mapped signals, as happens with WiFi signals (Bahl et al. 2000; Honkavirta et al. 2009; King et al. 2006; Youssef and Agrawala 2005). Nevertheless, these techniques have been initially developed for WiFi technology and later adapted to BLE.

With some relevance, the work (Duarte 2014) tests beacons to determine the indoor location using a traditional approach based on the RSSI signal strength. In this work the author limits to detect the proximity to a single beacon, and no major triangulation or other beacons signals are used to determine the user in door location.

Classic Bluetooth (before version 4.0) has many proposed proximity techniques (Chawathe 2008; Forno et al. 2005; Fu et al. 2019) oriented to triangulation (Chawathe 2008; Subhan et al. 2011), and, fingerprinting (Chen et al. 2013; Subhan et al. 2011). Although there are important limitations, one of them is the necessary time for a device to search and find close Bluetooth beacons, in the worst case scenario takes 11 s, while during that time the user can travel more than 15 m. As a consequence, positioning using classic Bluetooth was not adopted.

With BLE the classic Bluetooth latency issues are no longer present. The BLE standard incorporates the concept of “micro-location”, which is nothing more than a proximity technique (Bluetooth 2010).

Another path in fingerprinting literature combines WiFi fingerprinting with other sources, based on the idea of simultaneous location and mapping (SLAM), applied to pedestrian location prediction (Faragher et al. 2012; Huang et al. 2011; Harle 2013). In SLAM automatic search is exploited with machine learning techniques, to correct user’s path during navigation. This approach makes use of Gaussian Process regression to estimate signal maps from discrete WiFi RSS information. (Ferris et al. 2007).

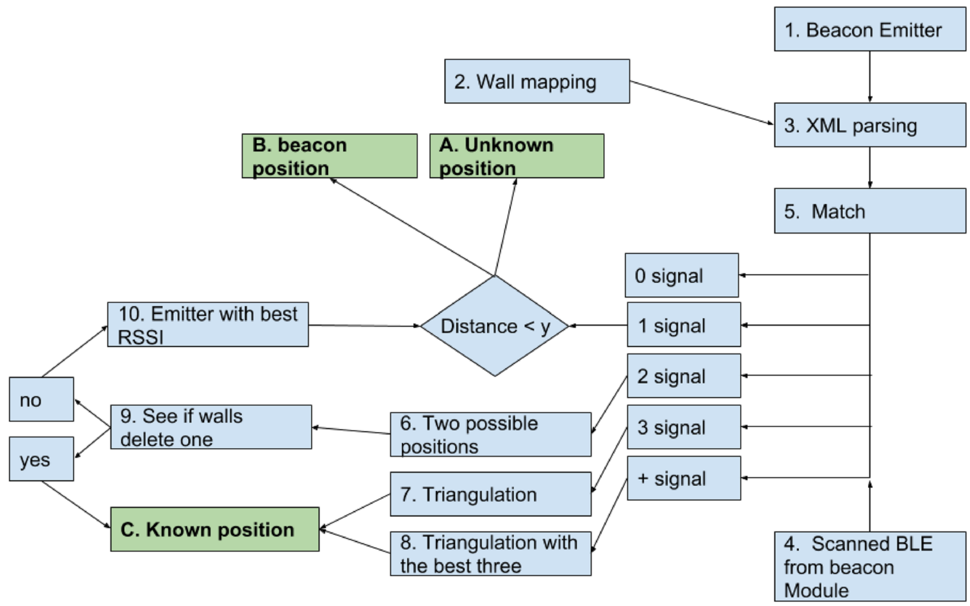
5 Experimental method

Based on our previews developed work in this field (Cecílio et al. 2015, 2018), in Fig. 2 is shown the diagram for the proposed position detection generic algorithm, using both BLE or/and WiFi signals. Before any location detection/navigation it is necessary for the proposed system to load all beacons identifiers and wall conditions, this is, relative location of the walls to the beacons (Fig. 2, steps 1, 2, 3).

During navigation and position detection, beacons RSSI and identifiers are matched with a list of beacons, existent on the beacon XML file. If the signal does not match any of the known emitters, then the position cannot be estimated, and goes to “A. unknown location”. However, if one match is found, the distance to the emitter is determined. If the distance is less than y (by default set to 2 m) the algorithm returns the estimated position relative to the beacon. If the distance is larger than y, the algorithm returns “B. Unknown position”, since the significant distance to the beacon means that the person can be in a very disparate location.

When two signals match, the proposed approach first calculates the two possible positions (Fig. 2, step 6), which

Fig. 2 Location flowchart



correspond to the intersection of the two circumferences, centered on the beacon, with a radius equal to the distance.

The wall conditions are checked (Fig. 2, step 9), and if only one position is possible it is returned "Known position", else, the algorithm chooses the beacon with strongest RSSI (Fig. 2, step 10), and processes as a single signal.

When three or more beacons signals are matched, the algorithm determines the position based on triangulation (Fig. 2, step 7 or 8). If more than three RSSI measures are identified, only the ones with better RSSI ratios will be used.

5.1 Position determination over BLE

A Bayesian estimator is used to determine positioning during a walk. The entire area of interest was divided into cells, each with 1 m, and then the probability of each fingerprinting to correspond to a cell was estimated. In order to accomplish this, distance was calculated as a group of signal values captured inside a cell. Then the fingerprint of the radio signals was measured by the device and the distance (d) computed as follows:

$$d(beacon, fm, map) = \sqrt{\sum_{i=1}^{N} \frac{\left(fm\left(be_i\right) - map\left(be_i\right)\right)^2}{N}} \quad (1)$$

In Eq. 1, fingerprint *fm*, includes beacons ID measures $beacon = \left\{be_1, \ldots, be_n\right\}$ and the group of beacon maps, *map*. Based on a Gaussian Kernel model, this metric is used to calculate a score for each individual cell.

Cells with moderate or high variance thresholds were ignored during these computations. After, to each cell was assigned a probability:

$$p = \exp\left(-\frac{d^2}{2\sigma^2}\right) \quad (2)$$

In Eq. 2, σ, represents the standard deviation associated to the fingerprint measurement noise.

Other used method to estimate the distance and validate results was the same as used on sensors from Sun Microsystems, integration 802.15.4 radio (cc2420) with 2.4 GHz antenna. Each RSSI value was obtained by averaging over 8 symbol periods (128 µs) in the register (Instruments 2006). The distance estimation model radio is given as:

$$RSSI = -(10 \times n)log_{10}(d) - A \quad (3)$$

where in Eq. 3, *RSSI* represents the radio signal strength in dBm, n represents the signal propagation constant or exponent, d represents the relative distance to the beacon, A is the received signal strength in dBm (i.e.: the RSSI value when the separation distance from the beacon is less than 1 m).

These two last combined techniques were used to obtain an average distance from the beacon position, measured in the next sections.

5.2 Proposed position detection

Traditionally the distance from the beacon measuring is given by an expression similar to:

$$d = 10^{\left(\frac{P-RSSI}{10n}\right)} \quad (4)$$

where, in Eq. 4, n ranges between 2 and 4, and it is used to adjust the signal pondering. Then, *RSSI* represents the measured signal strength. Usually, this value is negative and is always changing. In the formula, P is the TxPower which beacons are transmitting as part of the package and RSSI from the beacon device. The most common value of P is 2–2.5.

Never the less the distance accuracy is quite “unstable” and with large variations. The values variation can be mitigated by collecting a few values over time and use the average, with a low standard deviation. Another issue is the interference.

In this paper, is proposed a different method to determine position. Let’s use as an example the distances in Fig. 3, where P is the actual position, B1 to B4 are beacons, and d1 to d4 are the distances.

5.2.1 First step

For each beacon (Bi), at a given distance (e.g., 1 m, 2 m, etc.), the RSSI values are collected using different exposure times (i.e., 10 s, 30 s, 60 s, 120 s), and the average of the averages is calculated. This process is repeated for different distances. By doing so, for each beacon, the charted RSSI distance curve of the beacon is created (with a minimum standard deviation), and stored into a central database. Note that, even if a beacon is suffering interference, that is accounted in the distance calculation, overcoming a limitation in Eq. 4.

Figure 4, shows some examples of charted measures that can be obtained from the proposed fingerprinting method. However, these show some distance measuring problems and concerns. How to ponder, more or less a measured distance, to make it more accurate? For instance, B1 and B4 should have more weight on the distance measurement, since they are more near the position P. How to overcome multiple different reads for different distances (mostly due to interference noise in the signal)? The B2 and B4 represent equal RSSI measures that reference two different distances.

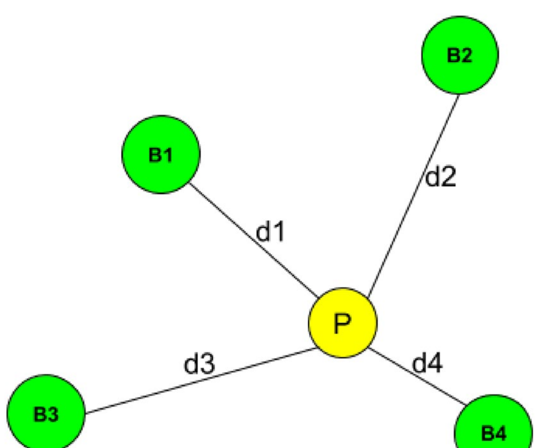


Fig. 3 Example, beacons distance

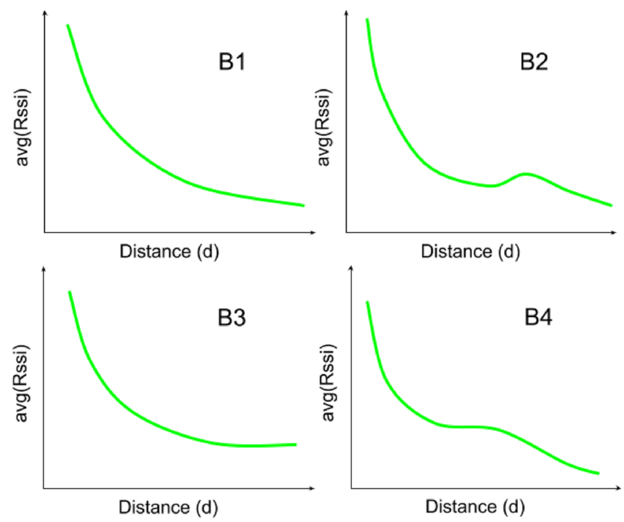


Fig. 4 Example charts (RSSI, distance)

5.2.2 Second step

Ponder the measured distances accordingly with the position *Pos* to the beacon. The main objective is to consider that a near distance beacon has more weight on the position determination than a further distance beacon. Based on that, determine the x, y, z, current position.

$$Pos_{(x,y,z)} = \frac{\sum_{i=0}^{N} \left(Bi_{(x,y,z)} \times P_i\right)}{\sum_{i=0}^{N} P_i} \tag{5}$$

Equation 5, is used to give the positioning coordinates in *x, y, z,* referential. Where, $Pos_{(x,y,z)}$, represents the position on the given referential. $Bi_{(x,y,z)}$ is each beacon position in *x, y, z*. The *P*, represents the ponder for each measured distance.

$$P_i = \frac{1}{d_i} \tag{6}$$

Each beacon ponder, P_i, is represented by the inverse of the distance, d_i, to each beacon.

$$Pos_{(x,y,z)} = \frac{\sum_{i=0}^{N} \left(Bi_{(x,y,z)} \times \frac{1}{d_i}\right)}{\sum_{i=0}^{N} \frac{1}{d_i}} \tag{7}$$

Therefore, the equation to determine the position, Eq. 6, evolves to Eq. 7. However, there is the need to be able to modify how each measured distance will be pondered when the position is being estimated.

$$P_i = \frac{1}{A + d_i^B} \tag{8}$$

Equation 8, introduces values A and B that can variate as needed to ponder the distance, depending on how far or near, in relation to the current position, each beacon is.

$$Pos_{(x,y,z)} = \frac{\sum_{i=0}^{N} \left(Bi_{(x,y,z)} \times \frac{1}{A+d_i^B} \right)}{\sum_{i=0}^{N} \frac{1}{A+d_i^B}} \tag{9}$$

This way the final positioning equation, with pondering, takes the form represented in Eq. 9. So, even if for a given beacon the charted curve is not the most correct at a given distance, adjusting A and B is possible to give more or less weight to the measurements obtained by a given beacon.

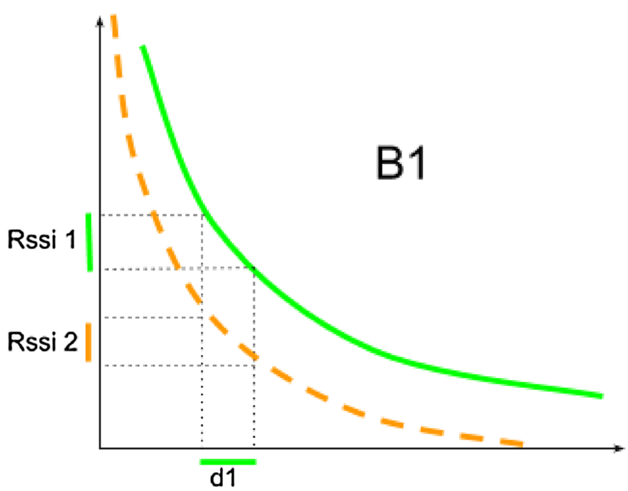


Fig. 5 Example charts, pondering effect

Considering the Char B1 represented in Fig. 4, with represented Eq. 9, it is possible to give more relevance to a distance of a given RSSI, or vice-versa, as represented in Fig. 5.

5.2.3 Third step

When analyzing Fig. 4, chart B2 and B4, for different distances the same RSSI was measured. This happens because of signal interference's and reflections. This issue is overcome by keeping a historic window of the dislocation. So, if for a given RSSI the distance measures point to $\{d_3, d_4, d_5\}$ the past information will help deciding the next distance position. Based on previously measured values, $d_0, d_1, d_2, \{d_3, d_4, d_5\}$, the next logical position will be d_3.

Based on proposed methods, Fig. 3, B4 and B1 have more importance/relevance (because they are more near P), than B3 and B2 (which are further from P).

6 Experimental testbed

Figure 6, shows the testbed floor plan, covering in total 8000 m^2 (200 m by 40 m). Space included offices, daily classrooms, and green spaces at the Viseu, Polytechnic Institute, PT. Red dots mark in total 20 WiFi access points that can be detected in upper and down floors. Beacons, streaked with pink triangles, were deployed, totaling 45 beacons used by class entrance doors and green areas. The majority of the beacons were installed a high of approximately 1.50 m from the floor.

Two mobile devices, Samsung J5 with Android, were used with an app developed to capture the signals data. One device captured WiFi signals, while the other captured BLE beacons signals.

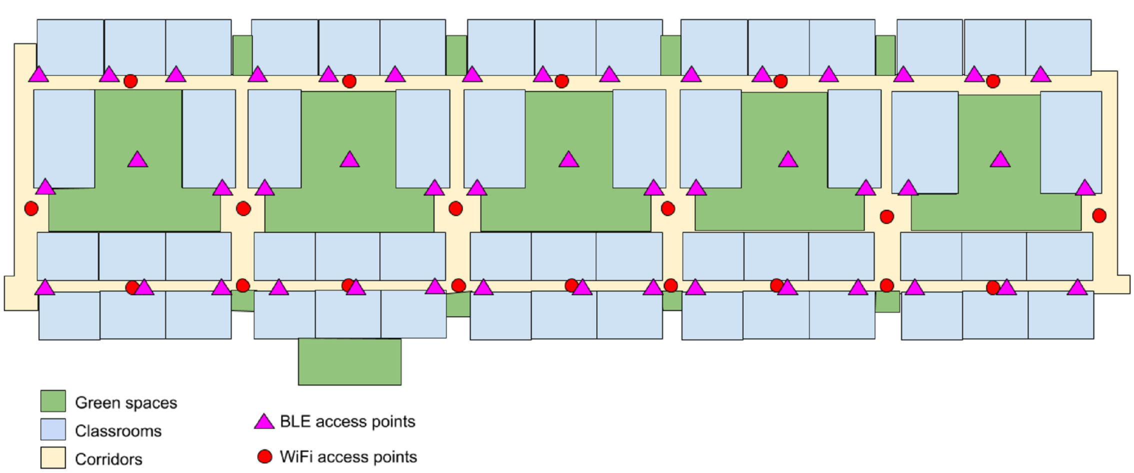


Fig. 6 Plan of a building floor

When using WiFi, the access points broadcast their identification (SSID) using 20 MHz radio channel frequency. However, BLE signal broadcast is in a smaller frequency, 2 MHz, with faster succession. Each one of the channels is numbered with a label (e.g., 37, 38, 39), and spaced in frequency (e.g., 2402 MHz, 2426 MHz, 2480 MHz), this way, minimizing overlapping and interference with WiFi signals.

Each fingerprint is created from the signal sampling within a time window. The windows must have the right size, to capture each signal only the desired number of times. Variation of the windows size allows to define the number of captures of the signal and reduce the redundancy.

6.1 Proposed position detection technique test-bed

To evaluate the performance of the proposed solution were performed two different types of tests in the library of the Polytechnic Institute of Viseu, Portugal. First using the proposed method, based on pre-trained signals fingerprints for different distances. All information, generated by beacons is continuously stored into a database for later querying and location estimation. In the context of this proposal, queries to the database, for getting recorded sensors data, were set to execute with a fixed size of results, 100 rows per beacon, and fixed time intervals, every 1 s. The second test was performed using signal triangulation of the three (or more) most powerfully beacons signals.

The space used for testing had two large rooms, one per floor, each with approximately 400 square meters, with a circular shape. Eight beacons were distributed in the room as shown in Fig. 7, marked with green circles, letters A to H. At the bottom and top of each stair, is a beacon aiming to help determine a position change in axis Z (moving upper or down in the floor). The Z-axis allows to ignore the upper and lower floor beacons signals, and consider only the ones within the present floor. This beacon filtering allows to consider only X and Y beacons positions. Marked with red color, letters P1 to P5, are the user positions, which were used to perform the positioning tests.

The training process of the proposed positioning method consisted of fingerprint measurements of the distance to each beacon, variation + 1 m, for each iteration, around the beacon.

All beacons devices were of the same type and brand, Estimote. Note that: standard deviations for the trained measurements were minimized as much as possible for each beacon so that the training accuracy approaches 1 (one).

For comparison purposes, the traditional triangulation method is also used. The distance to each beacon (minimum 3 beacons) is calculated using Eq. 4, the circumferences are calculated, and finally, their intersection coordinates represent the measured location.

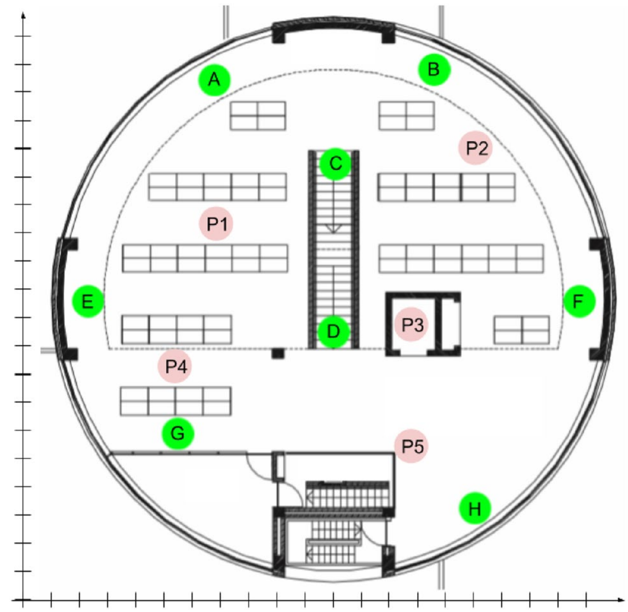


Fig. 7 Library floor layout, with beacons

7 Results analysis

The presented results were obtained from a set of walking experiments performed by a group of students. Each walk had a duration of 5 to 20 min, and the entire test-bed area (all beacons) was covered without having a pre-defined route. Measures included visits with and without movement.

WiFi access points broadcast their SSID in distinct radio frequencies with widths of 20 MHz. On the other hand, BLE works with more narrow frequencies, with a width of 2 GHz, allowing faster broadcasts. BLE frequencies variate channel to channel, for instance, channel 37, 38, and 39 are spaced at 2402 MHz, 2426 MHz, and 2480 MHz. This separation, allows reducing the interference's with other channels, as well as, with WiFi networks.

Figure 8 shows BLE RSSI values, measured in a static position, 3 m away from the beacon. The measures were performed for the three broadcast channels, 37, 38 and 39. Based on obtained results, it is possible to conclude that the mean levels of the tested channels is different (channel 37, avg: − 68, stdev: − 1.8 dBm; channel 38, avg: − 64.5, stdev: − 2 dBm; channel 39, avg: − 68, stdev: 5 dBm). Antennas do not always have a stable signal transmission across the 2.4 GHz band. The variation that occurs on these results has two main reasons: the channel strength variations, and multi-path interference due to wall reflections. Note that, with WiFi working on 20 MHz, this issue is not a problem. Regarding the multi-path, this raises an additional problem related with signal strength which fade in environments with several obstacles (e.g., walls).

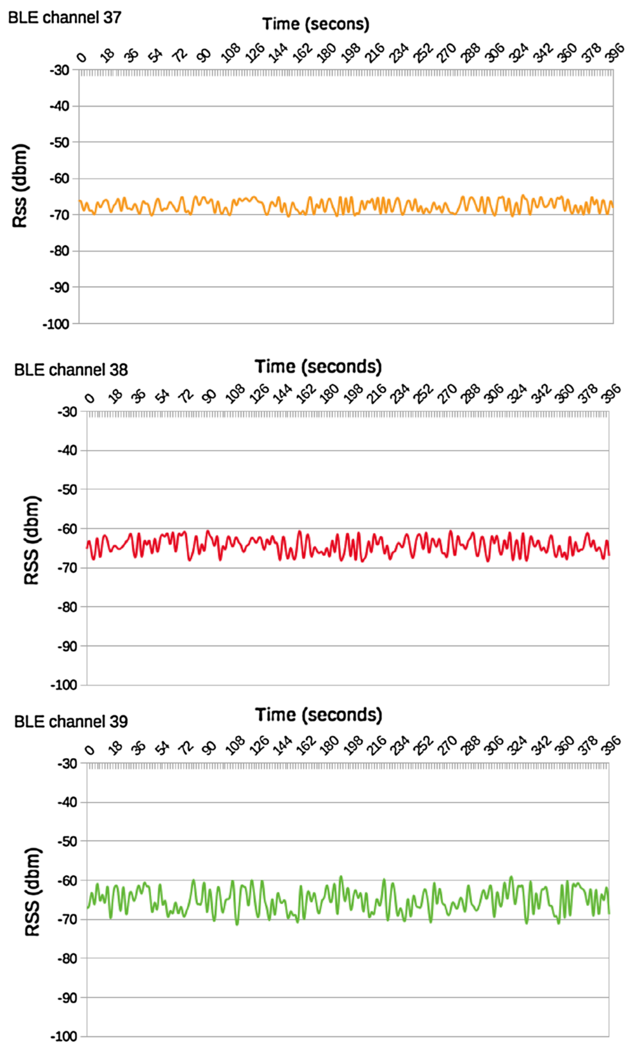


Fig. 8 Broadcast channel 37, 38 and 39, signal measure, static position

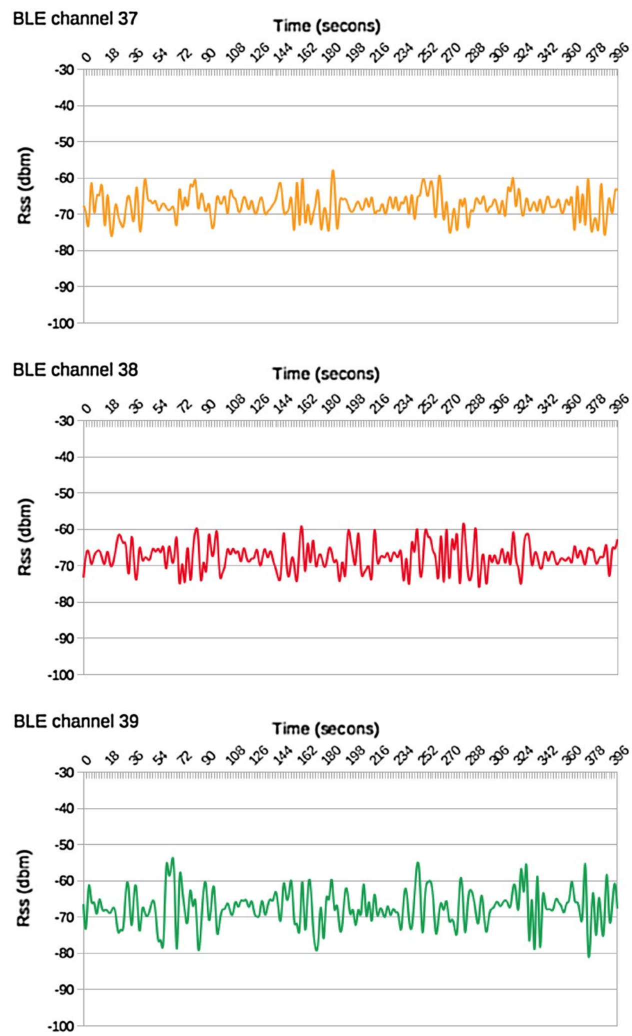


Fig. 9 Broadcast channel 37, 38 and 39, signal measure, moving position

Figure 9 shows how BLE signal variate when walking in a circular shape with 3 m radius of the BLE beacon. Signal fading is visible in both experimented channels, a loss of 20 dB in power was detected after just 50 cm. This variation observation is considered during the position estimation. These preliminary results impact the positioning estimation, helping to reduce the noise and variations of the signal.

In Fig. 10 is shown RSSI signal strength measures to create a heat-map relative to a specific position in the test-bed map. These measures were performed using a Gaussian Process regression (Eq. 2). With this results, it is possible to better estimate the impact of walls regarding signal strength and reflections, for position fingerprinting to determine location inside buildings.

On open space, without movement, inside the testbed building, the distance error was measured when moving away from the BLE beacon. Figure 11, shows how the measured error distance (in meters) increases as the measuring device (smart-phone) moves further away from the BLE beacon. Only by observing Fig. 11, it is possible to conclude that until 3.5–4.0 m distance the measured error margin is shallow, around 0.5 m. However, as the distance from the beacon increases the measured distance error also increases, up to the point that the measures variation goes up to 11 m error within a real length of 20 m from the beacon.

Using the presented test-bed, beacons were deployed, with 100% of the test-bed coverage, using transmission power between − 10 and − 20 dBm. This range of values was selected since they do not have an impact on accuracy. In the results from Fig. 12, is represented a baseline position accuracy using the same algorithms as WiFi. Note that, for all results, WiFi or BLE, the proximity is calculated based on the most powerful signals at a given location.

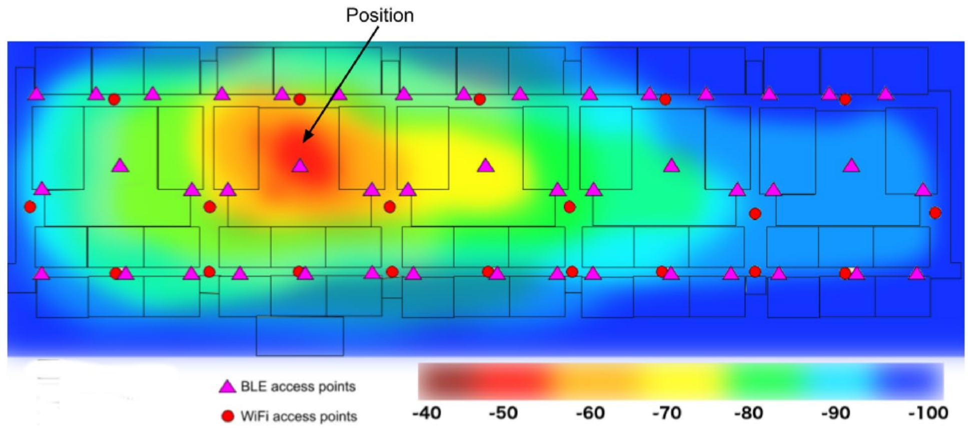


Fig. 10 BLE signal strength heat-map (200 m by 40 m)

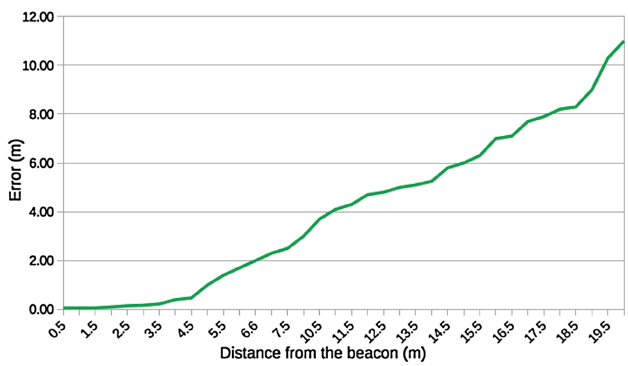


Fig. 11 Real error vs. distance from the beacon

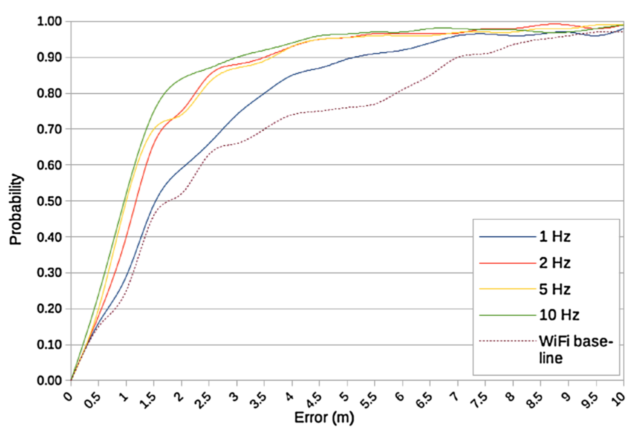


Fig. 12 Cumulative probability of Error distance measuring (m)

Figure 12 results were obtained from eight different walks. These results show that the BLE beacon system, in general, is better than the WiFi system. When using the WiFi, it was obtained an error of < 9 m, 96% of the times (this was expected, since an opportunistic method is being used, instead of dedicated beacons). Note that, results with WiFi were even worse than when using 1 Hz beacon rates.

Table 1 BLE beacon, commercial supplier configurations

Supplier	Power in dBm	Broadcast rate (Hz)
CSR	[– 18; + 4] (default – 18)	[0.1; 50] (default 4)
Estimote	[– 30; + 4] (default – 12)	[0.5; 20] (default 5)
Kontakt	[– 20; + 4] (default – 16)	[0.1; 50] (default 2)

A significant improvement is achieved when using BLE beacons with frequencies of 10 Hz, < 3 m, 94% probability.

Table 1, presents the commercial suppliers default parameters configurations and trade-offs for good positioning performance. Based on previous tests and usage experience, the transmission power of – 12 dBm was configured, matching the default of the popular Estimote beacons.

7.1 Proposed detection technique experimental results

The experimental evaluation compares the proposed positioning method, versus, the traditional triangulation based on the distance to the beacon from positions P1 to P5, Fig. 7.

In Table 2 is shown the real position in the axis x and y of the beacons position (beacon A to H) and the user positions (P1 to P5). P1 to P5 locations were used to determine the position of the user using the proposed positioning method, and with the triangulation method.

Table 3 shows the position, for P1 to P5 locations, using the proposed positioning method. Positioning precision averages 97.5% which we consider an excellent precision. In the case of the proposed method, the beacons act as an analogy to magnetic fields, the nearer Px is from the beacons, the more relevant for the positioning determination it will be (i.e., there is a more significant attraction), resulting on more relevant information for the positioning determination.

Table 2 Real positions (beacons and user)

	X	Y
Beacons real position		
Location A	6.5	18
Location B	15	18
Location C	10.5	15
Location D	10.5	9
Location E	2	10.5
Location F	19	10.5
Location G	5.5	5.5
Location H	16	3
User real position		
Location P1	16	13
Location P3	7	15.5
Location P2	13.5	10
Location P5	5.5	8
Location P4	13.5	5

Table 4, shows the experimental results using the traditional triangulation methods (i.e., interception of circumferences). Given this method, the global accuracy was 84.2%, which is good.

Comparing both methods to determine the position using Bluetooth beacons, the positioning method proposed in this paper is 13.2% better than the traditional triangulation of beacon signals.

8 Application interface—proof of concept

As proof of concept, an application was developed (for Android OS) where the beacons are mapped, and the before mentioned proposed approach is used to determine the user location. The following screenshot figures represent:

Table 3 Proposed method, beacons real positions

	Precision of proposed method			
	X	Y	X (%)	Y (%)
Location P1	7.6	12.8	91.4	98.5
Location P2	15.9	16.1	99.4	96.1
Location P3	13.1	10	97.0	100.0
Location P4	5.4	7.8	98.2	97.5
Location P5	13.3	5.1	98.5	98.0
	AVG accuracy		96.9	98.0

Table 4 Proposed method, experimental results, positioning and precision

	Precision of triangulation method			
	X	Y	X (%)	Y (%)
Location P1	5.4	11.7	77.1	90.0
Location P2	15	17.6	93.8	86.5
Location P3	10	12.8	74.1	72.0
Location P4	5.2	8.4	94.5	95.0
Location P5	11	3.9	81.5	78.0
	AVG accuracy		84.2%	84.3

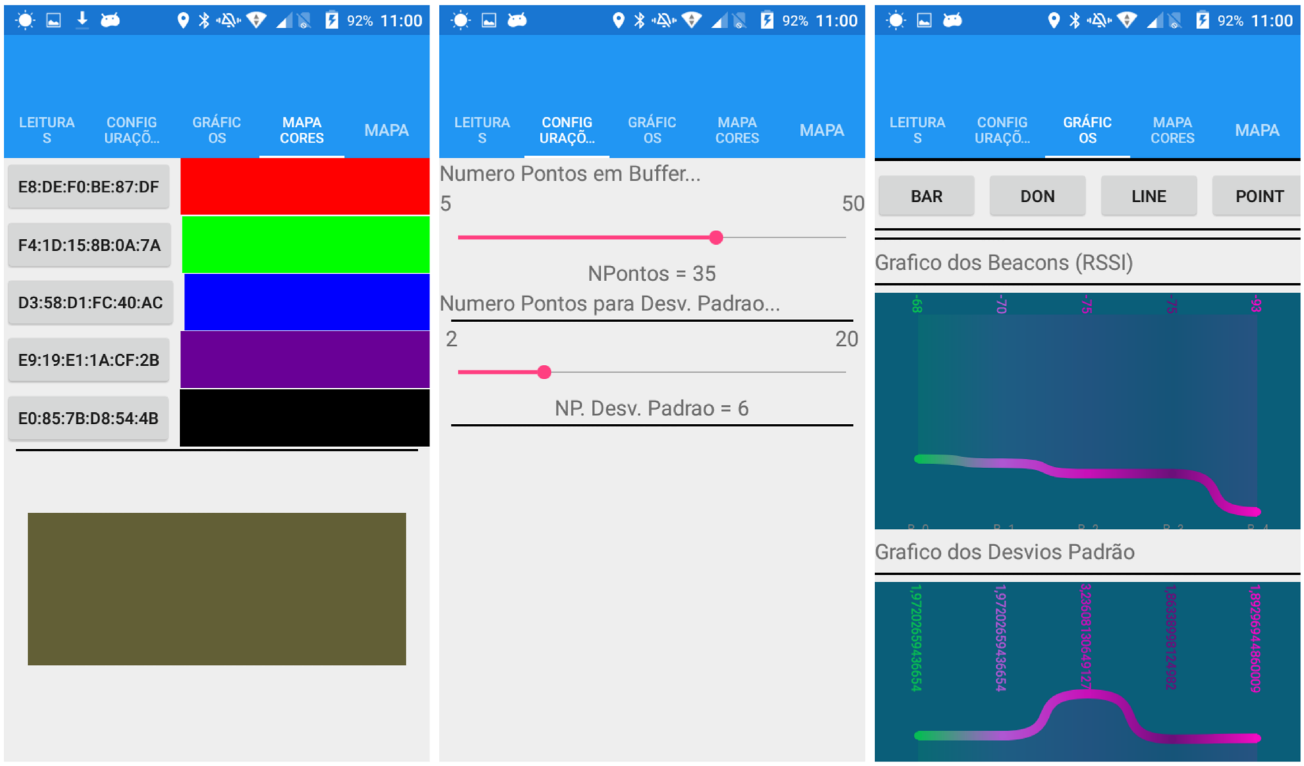
- In Fig. 13a is represented the application interface to edit beacons, (x, y, z) position, and identification color by their MAC address.
- In Fig. 13b are shown the configuration parameters for the number of samples to consider and their trust interval.
- In Fig. 13c is represented the application charts measuring the RSSID and STDev for a given beacon when the user is getting further away.
- Figure 14 show the configuration parameters for the values A and B, present in Eq. 8. At the same time the beacons positions are represented in colors (in the corners and center of the map), and it is visible the movement of the user (fading green dots).

9 Conclusions and future work

In this paper was explored the Bluetooth low energy (BLE) beacons for position determination, based on fingerprinting. Based on experimental results, it is proven that significant improvements can be obtained when comparing BLE with WiFi.

The main conclusions of this study are:

- The tested BLE broadcast channels have different transmission gains, and different reflection effects. This happens because of the small frequency width.
- With BLE, long listening periods are necessary, to filter beacons measurements. If the user is moving, multiple Hertz are necessary to eliminate noise.
- As the number of detected beacons increases, up to 10, the positioning error decreases. Beyond ten beacons, no improvement in the positioning accuracy was detected.
- Depending on the beacons deployment distance, accuracy measures can be improved significantly. For instance, when deploying the beacons approximately each 40 m^2 apart, we detected accuracy's of < 3 m 94% of the times.



(a) Definition of the beacons color mapping **(b)** Chart configurations (number of points, standard deviation) **(c)** Chart representing the historic RSSID and STDev

Fig. 13 The application interface

When placing the beacons 100 m^2 apart the accuracy degraded to < 5.

- BLE demonstrates a significant improvement in positioning detection, compared with WiFi.
- WiFi signal variations as more users connect (due to power-saving policies), make impossible to use only fingerprinting to determine the position at any time.

Given the proposed location techniques, experimental results, comparing the proposed method with triangulation, show that the processed method was able to achieve 97.5% vs. 84.2% for the triangulation. An improvement of 13.2% of the average positioning precision.

As future work this study opens several doors and new ideas, such as sharing location metadata across users and storage servers using a block-chain p2p concept, for data mining, dissemination, and validation. One of the research works already going on, recurring of this, consists of collecting as much WiFi measures over the day, for one or more years. Since new WiFi access points variate the energy of the signal depending on the number of connected users (for power saving purposes), fingerprinting with WiFi becomes more complicated. For instance, if only one user is connected, the signal power is weak and can be interpreted as a certain distance. As more users join the signal power increases, leading to a different signal interpretation for the same position. Based on data mining techniques, of several users, over data collected over several years, our next work, researches how to improve position fingerprinting over WiFi based on the knowledge of how space is used.

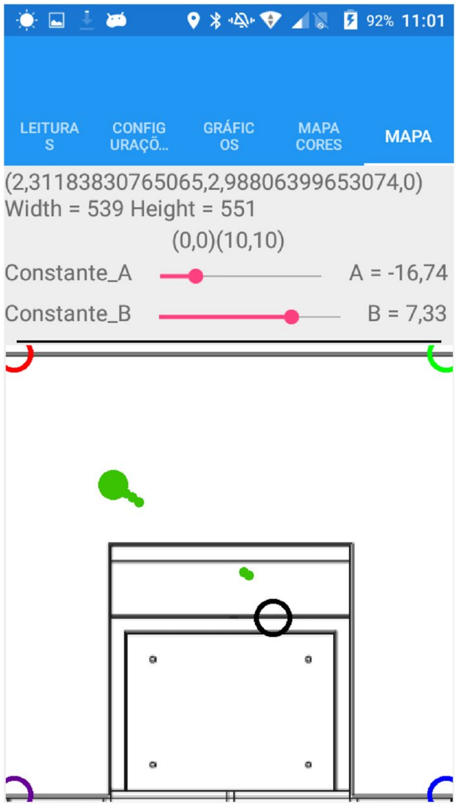


Fig. 14 Position mapping, example

Acknowledgements "This work is financed by national funds through FCT - Fundação para a Ciência e Tecnologia, IP, under the project UID/Multi/04016/2019. Also financed by CityAction and BlueEyes project, respectively, CENTRO-01-0247-FEDER-017711, and 02/SAICT/2016, supported by Centro Portugal Regional Operational Program (CENTRO 2020), under the Portugal 2020 Partnership Agreement, through the European Regional Development Fund (ERDF). Furthermore, we would like to thank the Instituto Politécnico de Viseu and CI&DETS for their support".

References

Al Nuaimi K, Kamel H (2011) A survey of indoor positioning systems and algorithms. In: 2011 international conference on innovations in information technology (IIT). IEEE, pp 185–190

Bahl P, Padmanabhan VN, Balachandran A (2000) Enhancements to the radar user location and tracking system. Microsoft Res 2(MSR-TR-2000-12):775–784

Bluetooth S (2010) Bluetooth core specification version 4.0. Specification of the Bluetooth System

Cecílio J, Duarte K, Furtado P (2015) Blindedroid: an information tracking system for real-time guiding of blind people. Procedia Comput Sci 52:113–120

Cecílio J, Duarte K, Martins P, Furtado P (2018) Robustpathfinder: handling uncertainty in indoor positioning techniques. Procedia Comput Sci 130:408–415

Chawathe SS (2008) Beacon placement for indoor localization using bluetooth. In: 2008 11th international IEEE conference on intelligent transportation systems. ITSC 2008. Citeseer, pp 980–985

Chen L, Pei L, Kuusniemi H, Chen Y, Kröger T, Chen R (2013) Bayesian fusion for indoor positioning using bluetooth fingerprints. Wirel Pers Commun 70(4):1735–1745

Chen Z, Zou H, Jiang H, Zhu Q, Soh YC, Xie L (2015) Fusion of WiFi, smartphone sensors and landmarks using the Kalman filter for indoor localization. Sensors 15(1):715–732

Ciabattoni L, Foresi G, Monteriù A, Pepa L, Pagnotta DP, Spalazzi L, Verdini F (2019) Real time indoor localization integrating a model based pedestrian dead reckoning on smartphone and BLE beacons. J. Ambient Intell Humaniz Comput 10(1):1–12

Decker C, Wattenhofer R (2013) Information propagation in the bitcoin network. In: 2013 IEEE thirteenth international conference on peer-to-peer computing (P2P). IEEE, pp 1–10

Dong Q, Dargie W (2012) Evaluation of the reliability of rssi for indoor localization. In: 2012 international conference on wireless communications in unusual and confined areas (ICWCUCA). IEEE, pp 1–6

Duarte K (2014) Smart-guia: a shopping assistant for blind people. Master's thesis

Faragher R, Sarno C, Newman M (2012) Opportunistic radio slam for indoor navigation using smartphone sensors. In: Position location and navigation symposium (PLANS), 2012 IEEE/ION. IEEE, pp 120–128

Ferris BD, Fox D, Lawrence N (2007) Wifi-slam using gaussian process latent variable models

Forno F, Malnati G, Portelli G (2005) Design and implementation of a bluetooth ad hoc network for indoor positioning. IEE Proc-Softw 152(5):223–228

Fu B, Kirchbuchner F, von Wilmsdorff J, Grosse-Puppendahl T, Braun A, Kuijper A (2019) Performing indoor localization with electric potential sensing. J Ambient Intell Humaniz Comput 10(2):731–746

Harle R (2013) A survey of indoor inertial positioning systems for pedestrians. IEEE Commun Surv Tutor 15(3):1281–1293

Heydon R (2013) Bluetooth low energy: the developer's handbook, vol 1. Prentice Hall, Upper Saddle River

Honkavirta V, Perala T, Ali-Loytty S, Piché R (2009) A comparative survey of wlan location fingerprinting methods. In: 2009 6th workshop on positioning, navigation and communication. WPNC 2009. IEEE, pp 243–251

Huang J, Millman D, Quigley M, Stavens D, Thrun S, Aggarwal A (2011) Efficient, generalized indoor wifi graphslam. In: 2011 IEEE international conference on robotics and automation (ICRA). IEEE, pp 1038–1043

Instruments T (2006) CC2420: 2.4 GHz IEEE 802.15. 4/ZigBee-ready RF Transceiver

King T, Kopf S, Haenselmann T, Lubberger C, Effelsberg W (2006) Compass: a probabilistic indoor positioning system based on 802.11 and digital compasses. In: Proceedings of the 1st international workshop on Wireless network testbeds, experimental evaluation & characterization. ACM, pp 34–40

Koyuncu H, Yang SH (2010) A survey of indoor positioning and object locating systems. IJCSNS Int J Comput Sci Netw Secur 10(5):121–128

Liu H, Darabi H, Banerjee P, Liu J (2007) Survey of wireless indoor positioning techniques and systems. IEEE Trans Syst Man Cybern C (Appl Rev) 37(6):1067–1080

Palumbo F, Barsocchi P, Chessa S, Augusto JC (2015) A stigmergic approach to indoor localization using bluetooth low energy beacons. In: 2015 12th IEEE international conference on advanced video and signal based surveillance (AVSS). IEEE, pp 1–6

Subhan F, Hasbullah H, Rozyyev A, Bakhsh ST (2011) Indoor positioning in bluetooth networks using fingerprinting and lateration approach. In: 2011 international conference on information science and applications (ICISA). IEEE, pp 1–9

Youssef M, Agrawala A (2005) The horus wlan location determination system. In: Proceedings of the 3rd international conference on mobile systems, applications, and services. ACM, pp 205–218

Zhuang Y, Yang J, Li Y, Qi L, El-Sheimy N (2016) Smartphone-based indoor localization with bluetooth low energy beacons. Sensors 16(5):596

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.