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Intelligent beacon location and fingerprinting

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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. Indoor location identification plays a fundamental role as a business and personal level. At a business level, indoor location pinpointing where GPS signal is nonexistent is used to advise users and send push notifications (e.g., stores publicity, guide persons with special needs, or even for emergency evacuation).
In this work is studied how BLE beacons radio signals can be used for indoor location scenarios, as well as their precision. The proposed study is performed inside the campus of Viseu Polytechnic Institute, using hundreds of students, each with his smart-phone, as proof of concept. Experimental results show that BLE allows having less than 1.5 meters error approximately 90% of the times.

Keywords: beacons; wireless; GPS; indoor location; blockchain; 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

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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. As future discussion topic, these data are then shared across users and storage servers using a blockchain p2p concept, for data mining, dissemination, and validation.
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 locations, to pinpoint users location. Other nearby locations are then estimated [8] [6]. Collected information is shared using a blockchain strategy [7] 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.
Results using a prototype implemented in Java (J2SE and Android), show that indoor location, within 3 meters distance estimation is precise with low error margins (1.5 meters or less). Above, 3 meters range, distance estimation have high error margins, sometimes reaching 5 meters or more.
The paper is organized as follows. In Section 2 is discussed the main motivation that led to this work. Section 3, states the main contributions. Section 4 related-work on location dissemination. Section 5 describes how the experimental method was implemented. Section 6 describes the used testbed. Section 7, describes the obtained results. Finally, Section 8, 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. However, as can be seen in Figure 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 used to reduce battery consumption relies on using concise messages [13], 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.

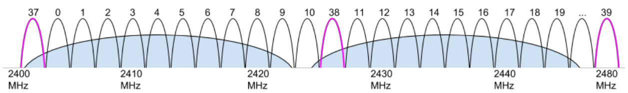

Fig. 1: 40 BLE channels and two commonly populated WiFi channels (channel 1 and 6)

In Figure 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.

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 [1] [18] [19]. 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 [2] [14] [17] [21]. Nevertheless, these techniques have been initially developed for WiFi technology and later adapted to BLE.
Classic Bluetooth (before version 4.0) has many proposed proximity techniques [4] [11] oriented to triangulation [4] [20], and, fingerprinting [5] [20]. 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 seconds, while during that time the user can travel more than 15 meters. 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 [3].
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 [9] [15] [12]. 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. [10].

5. Experimental method

In Figure 2 is shown the diagram for the proposed position detection 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 (Figure 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,

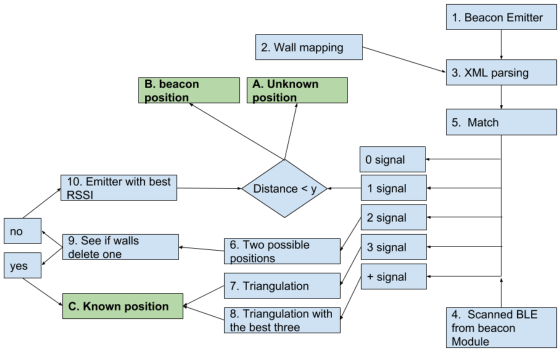

Fig. 2: Location flowchart

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 meters) 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 there are two signals match, the proposed approach first calculates the two possible positions (Figure 2, step 6), which correspond to the intersection of the two circumferences, centered on the beacon, with a radius equal to the distance.
The wall conditions are checked (Figure 2, step 9), and if only one position is possible it is returned "Known position", else, the algorithm chooses the beacon with strongest RSSI (Figure 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 (Figure 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 meter, 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:

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

In Equation 1, fingerprint *fm*, includes beacons ID measures $becon = \{be_1, ..., be_n\}$ 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 Equation 2, σ, represents the standard deviation associated to the fingerprint measurement noise.
Other used method to estimate the distance was and validate results was the same as used on sensors from Sun Microsystems, integration 802.15.4 radio (cc2420) with 2.4GHz antenna. Each RSSI value was obtained by averaging over 8 symbol periods (128μs) in the register [16]. The distance estimation model radio is given as:

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

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

6. Experimental testbed

Figure 3, shows the testbed floor plan, covering in total 8000 m^2 (200 meters by 40 meters). 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 meters 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.

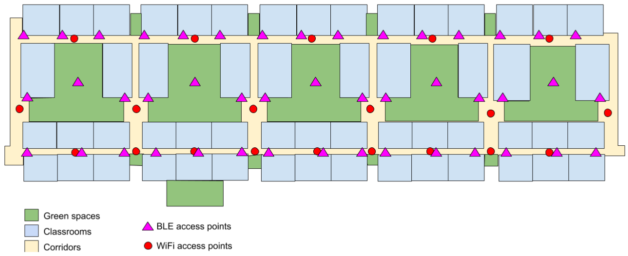

Fig. 3: Plan of a building floor

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

7. Results analysis

The presented results were obtained during a set of walking experiments. Each walk had a duration of 5 to 20 minutes, and the entire testbed area 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 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 4 shows BLE RSSI values, measured in a static position, 3 meters 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 2.4GHz band. The variation that occurs on these results has two main reasons: the channel strength variations, and multipath interference due to wall reflections. Note that, with WiFi working on 20 MHz, this issue is not a problem. Regarding the multipath, this raises an additional problem related to signal to fade in environments with several obstacles (e.g., walls).

Figure 5 shows how BLE signal variate when walking in a circular shape with 3 meters 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 centimeters. 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 Figure 6 is shown RSSI signal strength measures to create a heat-map relative to a specific position in the testbed map. These measures were performed using a Gaussian Process regression. With this results, it is possible to better

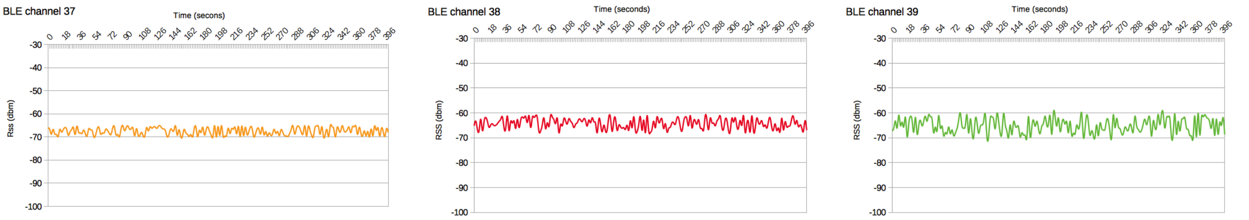

Fig. 4: Broadcast channel 37, 38 and 39, signal measure, static position

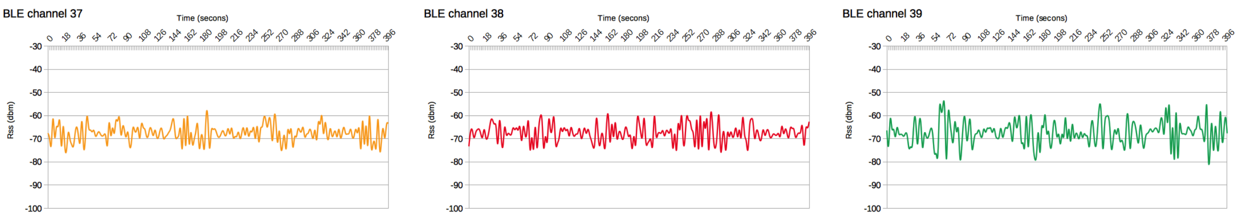

Fig. 5: Broadcast channel 37, 38 and 39, signal measure, moving position

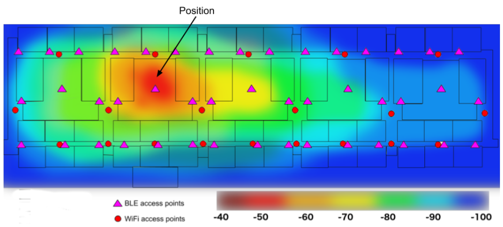

Fig. 6: BLE signal strength heatmap (200 meters by 40 meters)

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 7, shows how the measured error distance (in meters) increases as the measuring device (smartphone) moves further away from the BLE beacon. Only by observing Figure 7, it is possible to conclude that until 3.5 4.0 meters distance the measured error margin is shallow, around 0.5 meters. 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 meters error within a real length of 20 meters from the beacon.

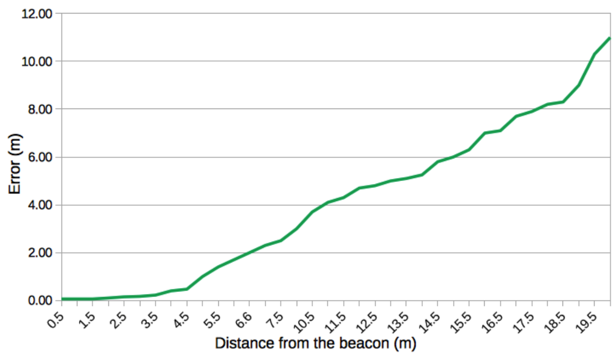

Fig. 7: Real error vs. distance from the beacon

In the results from Figure 8, 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 potent signals at a given location.

Using the presented testbed, beacons were deployed, with 100% of the testbed coverage, using transmission power between -10 and -20 dBm. This range of values was selected since they do not have an impact on accuracy.

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.

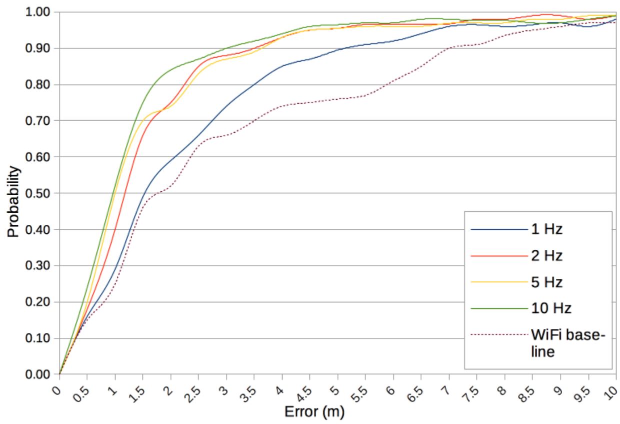

Fig. 8: Cumulative probability of Error distance measuring (m)

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)

Results from Figure 8 were obtained from 8 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. A significant improvement is achieved when using BLE beacons with frequencies of 10 Hz, < 3 m, 94% probability.

8. 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 accuracies of < 3 m 94% of the times. 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.

As future work, this study opened several doors and new ideas. 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), 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. When more users join, to 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.

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References

[1] K. Al Nuaimi and H. Kamel. A survey of indoor positioning systems and algorithms. In *Innovations in information technology (IIT), 2011 international conference on*, pages 185–190. IEEE, 2011.

[2] P. Bahl, V. N. Padmanabhan, and A. Balachandran. Enhancements to the radar user location and tracking system. *Microsoft Research*, 2(MSR-TR-2000-12):775–784, 2000.

[3] S. Bluetooth. Bluetooth core specification version 4.0. *Specification of the Bluetooth System*, 2010.

[4] S. S. Chawathe. Beacon placement for indoor localization using bluetooth. In *Intelligent Transportation Systems, 2008. ITSC 2008. 11th International IEEE Conference on*, pages 980–985. Citeseer, 2008.

[5] L. Chen, L. Pei, H. Kuusniemi, Y. Chen, T. Kröger, and R. Chen. Bayesian fusion for indoor positioning using bluetooth fingerprints. *Wireless personal communications*, 70(4):1735–1745, 2013.

[6] Z. Chen, H. Zou, H. Jiang, Q. Zhu, Y. C. Soh, and L. Xie. Fusion of wifi, smartphone sensors and landmarks using the kalman filter for indoor localization. *Sensors*, 15(1):715–732, 2015.

[7] C. Decker and R. Wattenhofer. Information propagation in the bitcoin network. In *Peer-to-Peer Computing (P2P), 2013 IEEE Thirteenth International Conference on*, pages 1–10. IEEE, 2013.

[8] Q. Dong and W. Dargie. Evaluation of the reliability of rssi for indoor localization. In *Wireless Communications in Unusual and Confined Areas (ICWCUCA), 2012 International Conference on*, pages 1–6. IEEE, 2012.

[9] R. Faragher, C. Sarno, and M. Newman. Opportunistic radio slam for indoor navigation using smartphone sensors. In *Position Location and Navigation Symposium (PLANS), 2012 IEEE/ION*, pages 120–128. IEEE, 2012.

[10] B. D. Ferris, D. Fox, and N. Lawrence. Wifi-slam using gaussian process latent variable models. 2007.

[11] F. Forno, G. Malnati, and G. Portelli. Design and implementation of a bluetooth ad hoc network for indoor positioning. *IEE proceedings-Software*, 152(5):223–228, 2005.

[12] R. Harle. A survey of indoor inertial positioning systems for pedestrians. *IEEE Communications Surveys and Tutorials*, 15(3):1281–1293, 2013.

[13] R. Heydon. *Bluetooth low energy: the developer's handbook*, volume 1. Prentice Hall Upper Saddle River, 2013.

[14] V. Honkavirta, T. Perala, S. Ali-Loytty, and R. Piché. A comparative survey of wlan location fingerprinting methods. In *Positioning, Navigation and Communication, 2009. WPNC 2009. 6th Workshop on*, pages 243–251. IEEE, 2009.

[15] J. Huang, D. Millman, M. Quigley, D. Stavens, S. Thrun, and A. Aggarwal. Efficient, generalized indoor wifi graphslam. In *Robotics and Automation (ICRA), 2011 IEEE International Conference on*, pages 1038–1043. IEEE, 2011.

[16] T. Instruments. Cc2420: 2.4 ghz ieee 802.15. 4/zigbee-ready rf transceiver, 2006.

[17] T. King, S. Kopf, T. Haenselmann, C. Lubberger, and W. Effelsberg. 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*, pages 34–40. ACM, 2006.

[18] H. Koyuncu and S. H. Yang. A survey of indoor positioning and object locating systems. *IJCSNS International Journal of Computer Science and Network Security*, 10(5):121–128, 2010.

[19] H. Liu, H. Darabi, P. Banerjee, and J. Liu. Survey of wireless indoor positioning techniques and systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37(6):1067–1080, 2007.

[20] F. Subhan, H. Hasbullah, A. Rozyyev, and S. T. Bakhsh. Indoor positioning in bluetooth networks using fingerprinting and lateration approach. In *Information Science and Applications (ICISA), 2011 International Conference on*, pages 1–9. IEEE, 2011.

[21] M. Youssef and A. Agrawala. The horus wlan location determination system. In *Proceedings of the 3rd international conference on Mobile systems, applications, and services*, pages 205–218. ACM, 2005.