International Journal of Sensor Networks and Data Communications

Bae and Choi., Int J Sens Netw Data Commun 2018, 7:4
DOI: 10.4172/2090-4886.1000159

Research Article Open Access

# Indoor Positioning System with Pedestrian Dead Reckoning and BLE Inverse Fingerprinting

**Han Jun Bae and Lynn Choi***

*Division of Electrical Engineering, Korea University, Seoul, 02841, Korea*

## Abstract

Since the adoption of Bluetooth Low Energy (BLE) in the Bluetooth standard in 2010, BLE beacons are emerging as one of the most viable solutions for indoor localization due to its power efficient architecture, short scan duration, low cost chipset, and wide adoption in the devices. The existing indoor positioning systems based on BLE beacons employ the classical fingerprinting (FP) technique where user terminals collect signals from the beacons and do most of localization computations, requiring significant power consumption on user devices. However, constant power consumption on limited battery life of a mobile device can be problematic when it comes to supporting server-oriented tracking applications. To address this issue, we have proposed a new fingerprinting technique called inverse fingerprinting (Inv-FP), which is a server side BLE fingerprint system where most of the positioning computations are done by BLE sniffers and servers, thus minimizing the computation overhead of user devices. However, the absolute positioning schemes such as FP and Inv-FP do not use the current position estimate to determine the next position. This leads to discontiguous, irregular route prediction especially when the positioning accuracy is low, since it does not reflect the continuity of the position change according to the movement of the user. In contrast, a relative positioning scheme such as Pedestrian Dead Reckoning (PDR) determines the current position based on the previous position, reflecting the continuity of the position change but it cannot estimate the current position without the initial position. In this paper, we implement both FP and Inv-FP and evaluate their performance in small and large-scale testbeds. We analyze various characteristics of Inv-FP in comparison with the classical beacon based FP, and demonstrate that Inv-FP can match the performance of FP but with minimal power consumption on user devices. In addition, we propose a new localization algorithm that can combine Inv-FP with PDR. By integrating PDR with Inv-FP, we show that localization error can be reduced by reflecting the advantages of each method.

**Keywords:** Indoor localization; Fingerprinting; Inverse-fingerprinting; Bluetooth low energy; Beacons; Sniffers; PDR

## Introduction

Due to the potential of indoor location-aware services, various approaches to indoor positioning system have been proposed by both academia and industry in the last few decades. While Global Navigation Satellite Systems (GNSS) became de facto standard for outdoor localization, there is no such representative solution for indoor localization to this day. Since environmental hurdles such as construction materials, furniture, and people inside buildings make signal susceptible to attenuation, diffraction and reflection, indoor localization is more challenging than outdoor localization. In addition, most location-based services (LBS) like asset tracking and indoor navigation service often require more fine-grained positioning accuracy in indoor environment than in outdoor environment. To achieve sub-meter level accuracy and to overcome environmental obstacles, diverse approaches have been investigated. Most of the existing indoor positioning systems can be classified into signal-based, image-based or sensor-based. Amongst them, RF-signal-based systems are the most common since widespread network devices make them easily deployable and the system guarantees reasonable performance with affordable cost. Although real systems can employ various combinations of those three types, this paper focuses on standalone signal-based localization.

Figure 1 shows a more detailed classification of signal-based systems from earlier studies [1,2]. The systems can be differentiated by underlying wireless technology, positioning algorithm, mapping method, location type, and etc. For instance, Horus [3] system adopts fingerprinting to estimate the absolute position of target by using a probabilistic positioning called Bayesian inference with Wi-Fi signal strength. Spot-Fi [4] system is built on top of sniffers that calibrate the angle of arrived signals to use geometric mapping of triangulation to produce location estimates. iBeacon [5] is a beacon device which locates targets in the proximity of symbolic locations such as stores, entrances or counters with BLE signal strength. Other signal-based systems can also be described using some or all of the criteria described in Figure 1.

Indoor positioning with BLE signals has come into the spotlight recently and BLE beacon based fingerprinting system (FP) is regarded as a practical solution for various location based services (LBS) owing to low device cost, power efficiency, and short scan time compared to indoor positioning with Wi-Fi devices. We observe that most location based services except for navigation or routing require long-term tracking of targets. Workforce tracking, location sharing, advertising by location, and game applications are examples of such services and they impose significant power consumption on user devices since the running time of tracking services ranges from several hours to even a few months. That is, trivial power dissipation in user device can even preclude the provision of services with long time operation.

To make long-term tracking services feasible, we have proposed a fingerprinting technique called inverse fingerprinting (Inv-FP) [6], which is a server side BLE fingerprint system where a user device

***Corresponding author:** Lynn Choi, Division of Electrical Engineering, Korea University, 02841, Korea, Tel: +82-2-3290-3249; E-mail: lchoi@korea.ac.kr

**Received** September 01, 2018; **Accepted** October 22, 2018; **Published** November 05, 2018

**Citation:** Bae HJ, Choi L (2018) Indoor Positioning System with Pedestrian Dead Reckoning and BLE Inverse Fingerprinting. Int J Sens Netw Data Commun 7: 159. doi: 10.4172/2090-4886.1000159

| | |
|---|---|
| **a) Wireless technology** | |
| WLAN, Bluetooth, UWB, RFID, IR, GPS, ZigBee, FM, UHF, Ultrasound, Acoustic | |
| **b) Infrastructure** | |
| Beacon-based, Sniffer-based, Infrastructure-free | |
| **c) Mapping method** | |
| Geometric mapping, Fingerprint, Proximity | |
| **d) Physical measurement** | |
| Power, Time, Angle, Phase | |
| **e) Positioning algorithm** | |
| K-NN, Probability methods, Neural network, SVM, ⋯ | |
| **f) Location type** | |
| Physical location, Symbolic location, Absolute location, Relative location | |

**Figure 1:** Classification metrics for signal-based indoor localization systems.

simply broadcasts BLE signals while multiple BLE sniffers collect the signals to estimate the location of the user. Although BLE is designed to target specifically for beacon applications, BLE sniffer devices start to emerge recently [7] and several BLE chipsets [8] began to support the interoperability of advertising/scanning functionalities, enabling the implementation of sniffer based systems. Most of localization computations are at the server side through BLE sniffers and thereby power consumption at the client side can be effectively diminished.

However, the absolute positioning schemes such as FP and Inv-FP do not use the current position estimate to determine the next position. This leads to irregular and discontiguous route prediction, especially when the positioning accuracy is low. In contrast, a relative positioning scheme such as PDR estimates the user movement based on the previous position. Therefore, it can produce a smoother contiguous route for the pedestrian movement. This in general leads to smaller localization error for a short distance, but it often results in huge localization errors for a long distance due to the accumulation of the errors. This is mainly because PDR cannot absolutely determine the current position without the initial position.

In this paper, we investigate the notable changes by altering the system design of beacon based fingerprinting to sniffer based fingerprinting, and evaluate performance of Inv-FP against FP. In addition, in order to produce a smoother route prediction according to user movement, we propose and evaluate a new localization algorithm that combines Inv-FP with PDR. The followings are the main contributions of this paper:

1. We implement sniffer-based BLE localization technique called Inv-FP in small and large testbeds and verify that its localization accuracy can be at par with beacon based BLE fingerprinting system with much less power consumption on user devices.
2. We argue that a server-side Inv-FP system is more practical for long-term tracking services than classical beacon based fingerprinting system since it can provide long-term tracking services without bothering users and it can also minimize the power consumption of user devices.
3. We propose a new localization algorithm that can combine the advantage of both Inv-FP and PDR, and verify that its localization accuracy can be less than Inv-FP only system.

The rest of this paper is organized as follows. Section 2 discusses the background and motivation of our work. Section 3 discusses related works. Section 4 explores the design space of both fingerprinting and inverse fingerprinting systems. Section 5 presents our experimentation methodology and evaluates the performance of our proposed Inv-FP system in comparison with classical fingerprint system. Finally, Section 6 concludes the paper.

## Fingerprinting Methods and Energy Issues

In general, indoor localization systems target two kinds of location based services. One is client-oriented service where users need their location individually, and the other is server-oriented service where the location information of the individuals should be collected and used by a server. Shopping list routing and navigation inside airports belong to the former case while real-time tracking for doctors, location sharing of teammates, and augmented reality based game applications belong to the latter case. Figure 2a illustrates what user devices typically do for each kind of service in beacon based systems. In beacon based systems, most of localization operations are done at the client side. Each user device scans signals from beacons and performs localization computation such 2s fingerprinting and PDR. For server-oriented service, the user device needs additional operation of wireless transmission to send their location information to the server. Assuming that people usually move at most 1.5 meters per second, location update interval of 1 second is reasonable for real-time tracking. Thus, wireless transmission to a server must be repeated every second during the whole service time. Figure 3 shows how wireless operation affects battery life of a smartphone. 1Hz WiFi transmission requires as much power consumption as continuous BLE scanning and 1Hz LTE transmission demands even more power. Considering that many of the server-oriented services target organizations such as companies or schools rather than each individual, the beacon based system that imposes most of work on each individual is counter-intuitive and quite detrimental to the battery life of user devices. The examples of these applications include intrusion detection and most of tracking services such as employee tracking and object tracking. Furthermore, most tracking services often run much longer compared to other localization services, demanding frequent location updates and more power consumption.

As shown in Figure 2b, sniffer based system can remove most of these power burden from each individual device since simple BLE broadcasting is required at the client side. In sniffer based systems, all the signal gathering and localization operations are performed by sniffers and servers. However, note that all the existing BLE indoor localization systems assume beacon based systems. To make long-term tracking services practical, we propose a new fingerprinting technique called Inv-FP, which is an indoor positioning system at the server side with sniffer devices.

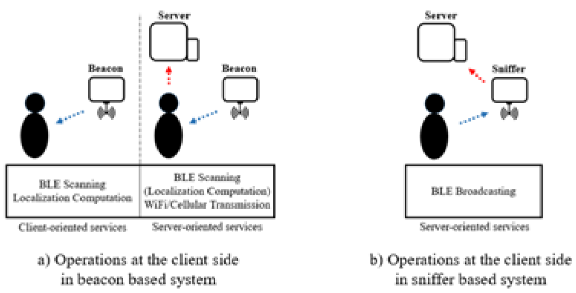



**Figure 2:** Beacon based system *vs*. sniffer based system.

## Related Works

In RADAR [9], the concept of fingerprinting is introduced for the first time. It employs K-NN (K-Nearest Neighbor) as positioning algorithm and proves that empirical method based fingerprinting outperforms signal propagation model based fingerprinting. Interestingly, the first fingerprint system is built on sniffer devices even though it isn't considered as a productive approach in the paper. Since [9], numerous fingerprinting studies aim to improve the localization accuracy with different positioning algorithms. Amongst all, Horus [3] is the highest performance fingerprinting system where localization accuracy is further enhanced by employing Bayesian inference algorithm. The location of a device is estimated with the highest probability given a probability distribution of RSSI measurements on the target area. We adopt K-NN in our experiment for simplicity since performance differences among various positioning algorithms are not our main focus. While most of signal based studies implement systems on beacon devices, sniffer based systems [10-13] are built only for specific motivations. Wigem [10] collects signals from different user devices at the server side where expectation-maximization algorithm is employed to resolve hardware variance problem. In [11,12], wireless sniffers are used to build signal propagation model in real-time to eliminate labor-intensive site survey. In [13], beacon devices exchange signals with sniffers to maintain signal propagation model up to date without manual labor. To the best of our knowledge, this paper is the first trial to implement the localization system on sniffer devices in order to reduce power consumption of user device considering specific LBS. The power consumption issue of localization is also studied in [14] where clustering of user devices reduces power consumption by sending single location update for the entire group although it sacrifices the positioning accuracy of individuals. In [15,16], the performance and characteristics of BLE fingerprinting system on beacon devices are well studied.

## System Design

### Beacon based fingerprint system (FP)

Fingerprinting assumes that each location has its distinctive characteristic against other locations in an area. Target at a specific location can obtain that unique characteristic, also called fingerprint, and use it to locate itself by matching it up with pre-collected fingerprints. With the advent of widespread network infrastructure, there are lots of inherent signals around in indoor environment and fingerprint localization makes the best use of them. To obtain signal characteristic of a given location, fingerprint system has both senders and receivers of signals. The sender of a signal is called a beacon while the receiver of a signal is called a sniffer. The system is beacon-based if a target device is a receiver, and it is sniffer-based if a target device is a sender. The procedure of FP generally consists of two main phases.

**Offline phase:** This step is also called training phase or site-survey. As illustrated in Figure 4, reference points are determined at a target area and fingerprints are collected at each reference point to construct a fingerprint database, a.k.a., a radio map. Fingerprint is a vector of received signal strength indicator (RSSI) from each beacon, and sometimes denotes the average or deviation of RSSIs. There are two methods to record fingerprint at each reference point. In empirical method, fingerprints are literally collected manually at each physical location of reference points. In radio propagation model method, fingerprints are estimated based on the site-specific signal propagation model rather than actual measurements. A radio map can be stored either at a central server or at user devices depending on the implementation. Generally, each user device stores the radio map individually for its localization computation.

**Online phase:** A user device starts to sample signals from beacons as soon as the position information is required by an application. The device produces the fingerprint of a current location from the received signals and compares it with those of reference points in the radio map. In case of RSSI vector fingerprint, Euclidian distances between RSSI vectors are calculated to find a reference point of a closest RSSI vector, so-called nearest neighbor (NN). The famous K-NN algorithm

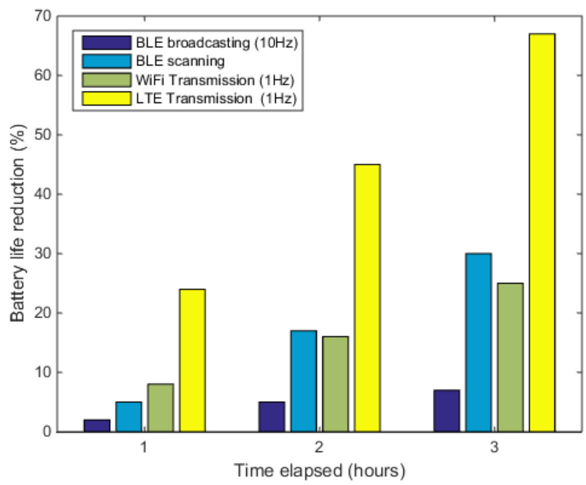



**Figure 3:** Battery life change in iPhone6.

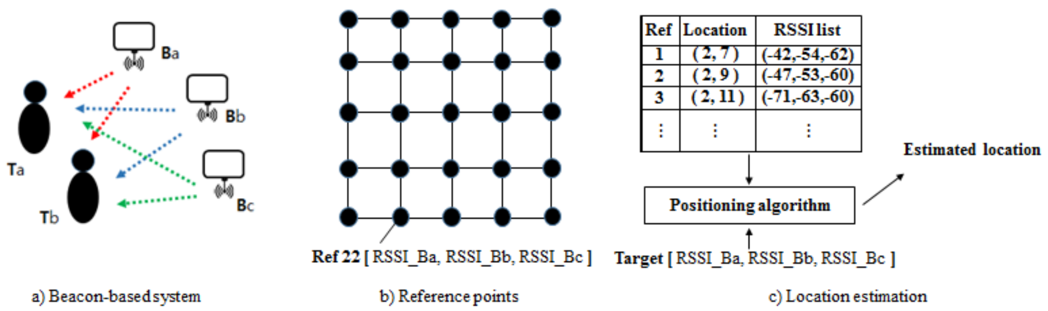



**Figure 4:** Beacon based FP.

**Citation:** Bae HJ, Choi L (2018) Indoor Positioning System with Pedestrian Dead Reckoning and BLE Inverse Fingerprinting. Int J Sens Netw Data Commun 7: 159. doi: 10.4172/2090-4886.1000159



[9] produces K nearest neighbours and estimates the final location as a weighted sum of their locations. While K-NN algorithm is a deterministic approach, the maximum likelihood location estimate using Bayesian inference is a probabilistic approach. The algorithm for such location estimation is generally called positioning algorithm. Other than the two cases, numerous other algorithms have been proposed so far. The estimation of a single location is called one-shot localization while continuous localization of successive locations is called tracking. To provide server-oriented tracking services described in Section 2, the device needs to periodically communicate with the central server, resulting in increased communication traffic and more power consumption.

Spacing of reference points, the number of collected RSSI samples, indoor environmental change between offline phase and online phase, the number of beacons per unit area, beacon transmission power and deployment, the size of target area, fingerprint resource, signal kind, location update interval, and hardware variance are factors which can affect the positioning performance of fingerprint system.

## Sniffer based inverse fingerprint system (Inv-FP)

Inv-FP is a sniffer-based fingerprint system. Target device becomes a sender of signals while the sniffer device becomes a receiver. Thus, the signal flows in the reverse direction as compared to beacon-based fingerprint system. This is illustrated in Figure 5. Like FP, the procedure of Inv-FP also consists of two main phases.

**Offline phase:** In Inv-FP, target sends signals at a reference point and fingerprint is a vector of RSSIs received by sniffers. Since each sniffer device produces a singleton data item of sampled RSSIs, a central server needs to collect them from multiple sniffers to produce a fingerprint vector. Thus, the central server is not optional but mandatory for Inv-FP system, and the radio map is only stored at the server. Since most of fingerprint operations are performed by the server and sniffers, Inv-FP is classified as a server-side fingerprint system.

**Online phase:** Sniffer devices sample signals from user devices and relays them to the server which collects and aggregates them to produce fingerprints for each target. Since the radio map constructed in Inv-FP has the same formation as in FP, the same positioning algorithms can be applied as well. The estimated location information can be sent from the server to a target device if it is required by localization application. Since most of localization operation is done by sniffers and servers, location services can be provided with minimal involvement of users and much less power consumption on user devices. This characteristic makes the Inv-FP more appropriate for long-term tracking services.

## Pedestrian Dead Reckoning system (PDR)

The Pedestrian Dead Reckoning (PDR) is the process of calculating the current position from the initial given position by estimating the movement of a pedestrian. More specifically, PDR estimates the step count, the step length and the orientation of the movement by using the IMU sensor with a smart device such as smartphone. It usually determines the step by analysing the pattern of the accelerometer sensor data and estimates the direction of the user movement by analysing the IMU sensor data, i.e. gyroscope, magnetometer, and accelerometer sensor signals of the device. Compared to RF fingerprinting schemes it is a relative positioning scheme since it calculates the next position relative to the current position by estimating the relative user movement. This leads to contiguous location tracking which is not possible with the current RF signal-based localization schemes. However, it can only provide a relative positioning result. Without knowing the current absolute location, its positioning result can be expressed only relative to the unknown starting point. Furthermore, the localization error of PDR increases over time due to the accumulating error caused by the inaccuracy of the IMU sensor data.

## Inv-FP system with integrated PDR

In PDR, the shorter the distance, the localization errors of PDR are in general less than those of Inv-FP. However, as the travel distance of a pedestrian becomes longer, the localization errors are accumulated, which leads to a substantially larger localization error for PDR compared with RF fingerprinting. In addition, PDR alone cannot estimate the current position without initial position information. In contrast, both FP and Inv-FP can estimate the current position anytime with a single point of signal data. To take advantages of both schemes, in this paper we propose a new localization algorithm that combines Inv-FP or FP with PDR.

Figures 6 and 7 shows the flow chart of the proposed localization algorithm. The initial position is estimated by using the absolute positioning scheme such as FP or Inv-FP. Then, the next position of the user is estimated by using PDR every step while the absolute position is updated by the absolute positioning scheme, i.e. FP or Inv-FP every k constant steps, thereby limiting the cumulative errors caused by PDR. The absolute position estimation data (P_abs) is not directly applied for every step to prevent the position data from sudden fluctuation caused by the localization inaccuracy. Instead, the difference (e) between the current position data and the position data estimated through the absolute positioning scheme is applied to every k steps. In our evaluation, we experimentally chose the value of 10 for k.

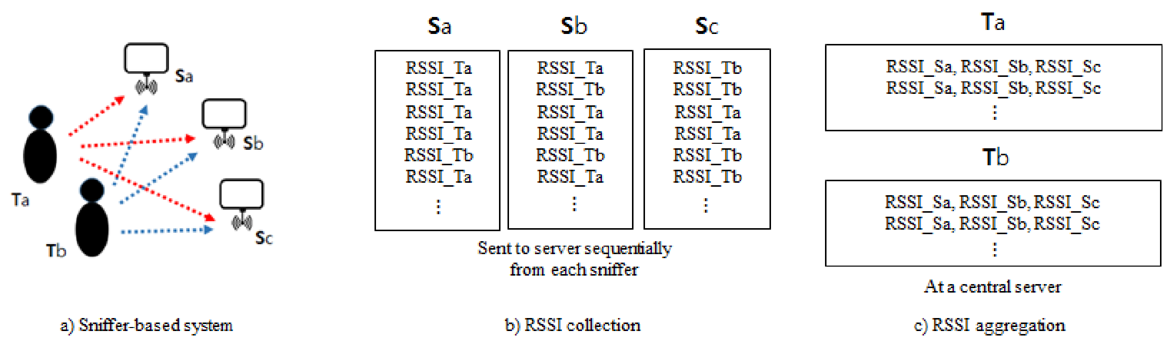



**Figure 5:** Sniffer based Inv-FP.

**Citation:** Bae HJ, Choi L (2018) Indoor Positioning System with Pedestrian Dead Reckoning and BLE Inverse Fingerprinting. Int J Sens Netw Data Commun 7: 159. doi: 10.4172/2090-4886.1000159



# Evaluation

## Implementation

**Infrastructure**: We have implemented both sniffers and beacons using Raspberry Pi 2 Model B with Raspbian Jessie pre-installed. We integrate CSR4.0 [17] compatible BLE dongles into both devices to support Bluetooth Low Energy. We have developed Bluetooth applications to support both sniffers and beacons on top of BlueZ stack version 5.17 [18-20]. WiFi dongles are equipped only with sniffers to deliver RSSI samples wirelessly to a central server with each sniffer MAC address. The server is a t2.micro instance deployed on Amazon Web Service (AWS) platform.

**User device:** A tester carries iPhone 6 as a user device. During the experimentation, it either scans or advertises signals with transmission interval of 33ms (30Hz) on our custom application.

## Experimentation methodology

We use two campus testbeds, College of Engineering Building Lobby and Hana Square Basement Level 1 Floor. We place 7 sniffers in a 25 x 10 square meter area in the Engineering Building testbed as shown in Figure 8a. The figure also shows the position of sniffers as orange circles. 52 reference points are placed at the vertices of grid cells. A side of the grid cell is 2.24 meters and 25 test points are randomly generated in the target area.

Hana Square testbed is approximately 11 times larger than Engineering Building testbed. We place 30 sniffers in a 94.4 x 24.8 square meter area in the Basement Level 1 Floor of Hana Square as illustrated in Figure 8b. The figure also shows the position of sniffers as orange circles. 228 reference points are placed in the gray space. A side of the grid cell is 2.33 meters and 100 test points are randomly generated in the target area.

We fix the orientation of our target device both in offline phase and online phase to simplify the radio map construction and footprint generation. RSSI samples from each sniffer are median-filtered to produce a RSSI vector for reference points and test points. The same methodology is applied to beacon-based fingerprinting set-up.

## Evaluation

**Localization of a stationary target:** Figures 9 and 10 show the localization errors and location estimates of a single target at a fixed position. Although the test user is stationary during the sampling period, localization error is fluctuating and location estimates are unsettled. The deviation of localization error at a fixed location must be small to determine whether a target is moving or not and to improve the overall positioning accuracy. Since target devices can increase their advertising frequency in Inv-FP, more location estimates can

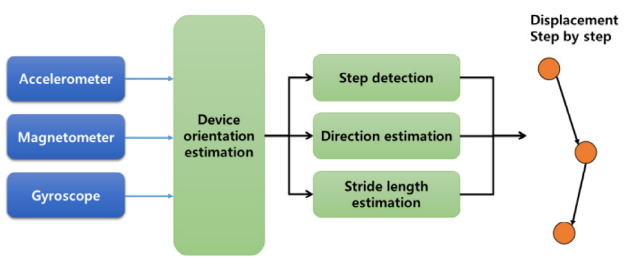



**Figure 6:** The overview of a PDR system.

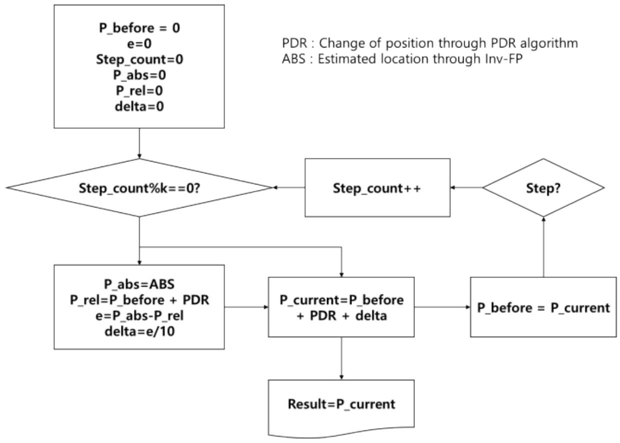
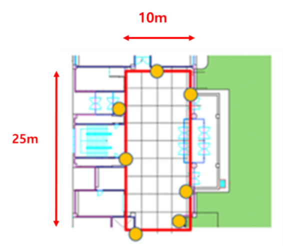
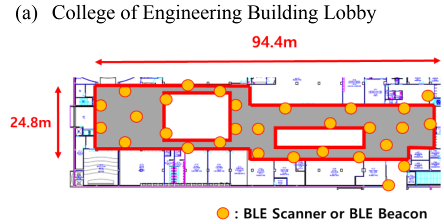



**Figure 7:** The flow chart of the algorithm combining PDR and Inv-FP.




(a) College of Engineering Building Lobby




(b) Hana Square Basement Level 1 Floor

**Figure 8:** Floor plan of the test beds.

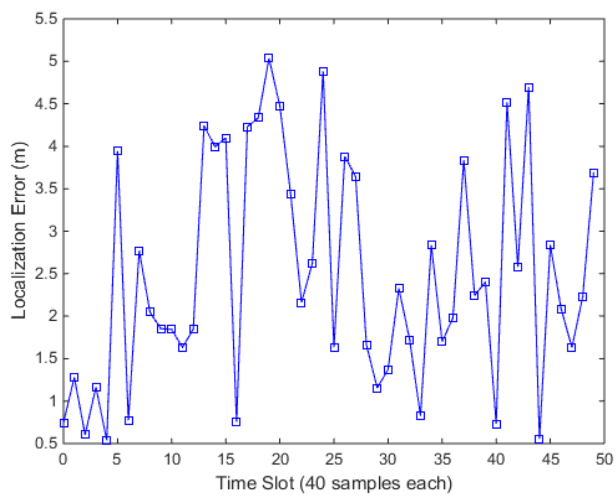



**Figure 9:** Localization error at a fixed position.

be obtained per fixed time interval. By averaging multiple location estimates, localization errors are expected to be stabilized. We average out 10 location estimates in which 10 samples are median-filtered for one estimate. Figure 11 shows the averaged-out location estimates with increased advertising frequency. The results show that the standard deviation of location estimates is reduced from 1.62 meters to 1.07 meters. This means that localization errors of a stationary person can be stabilized by increasing the advertising frequency. The accuracy of tracking can also benefit from the stabilization of localization accuracy. However, power consumption on a user device is proportional to the advertising frequency. So, in this paper, for calculating localization error, we use 10 samples in which the location error is saturated.

**Localization accuracy of Inv-FP with k-NN algorithm in the small engineering testbed:** To evaluate the localization accuracy of Inv-FP, we use k-NN algorithm for the position estimation. Figure 12 shows the localization error by varying the value of k from 1 to 7. As shown in the figure, Inv-FP shows the smallest localization error in both the minimum and the average location errors amongst all the values of k. The minimum, maximum, and the average localization errors of Inv-FP are 0.11 meters, 5.89 meters and 2.16 meters respectively when k is 4. This is because when the value of k is too small, there is not enough data to correctly estimate the position. In contrast, when the value of k is too large, the collected data may include samples with low correlation.

**Comparison of Inv-FP with FP in the engineering testbed:** Figure 13 compares the localization accuracy of Inv-FP with that of FP. Devices in both FP and Inv-FP are placed in the same way, and have the same transmission (Tx) power with the same number of samples, 10, per each collection. To eliminate hardware variance between iPhone 6 and Raspberry Pi with CSR 4.0 BLE dongle, we also set up Raspberry Pi as a user device for this experiment. The median and average errors of Inv-FP are 1.90 meters and 2.16 meters while 2.14 meters and 2.18 meters for FP. As shown in Figure 13, it can be inferred that the performance of Inv-FP is comparable to that of FP with the same experimental set up.

**Localization accuracy of Inv-FP with K-NN algorithm in the larger Hana Square testbed:** Unlike the small Engineering testbed, in the much larger Hana Square testbed the number of beacon signals captured by sniffers at the same position may vary depending on the strengths of beacon signals. Therefore, the transmission power of beacons may affect the localization error. Figure 14a-c show the localization performance of Inv-FP when we vary the transmission power of beacons from the default 0 dBm to -12 dBm and -20 dBm. As shown in the figures, considering only the best cases, the average, the minimum, and the maximum localization errors are 1.11 meters, 15.6 meters and 9.09 meters with 0 dBm Tx power, 0.01 meters, 6.64 meters and 3.43 meters with -12 dBm Tx power, 0.71 meters, 6.81 meters and 3.66 meters with -20 dBm Tx power respectively. With -12dBm, Inv-FP shows the best performance. On one hand, if the transmission power of a beacon is too strong as in the case of 0 dBm in the Hana Square testbed, the received signal strength is similarly large anywhere in the space, and thus the signal strengths among the reference points do not greatly differ, resulting in a large localization error. On the other hand, if the transmission power of a beacon is too weak as in the case of -20 dBm, the received signal strength is too weak in most of the area in the space, which resulting in too few beacon signals per reference points, also resulting in a large localization error.

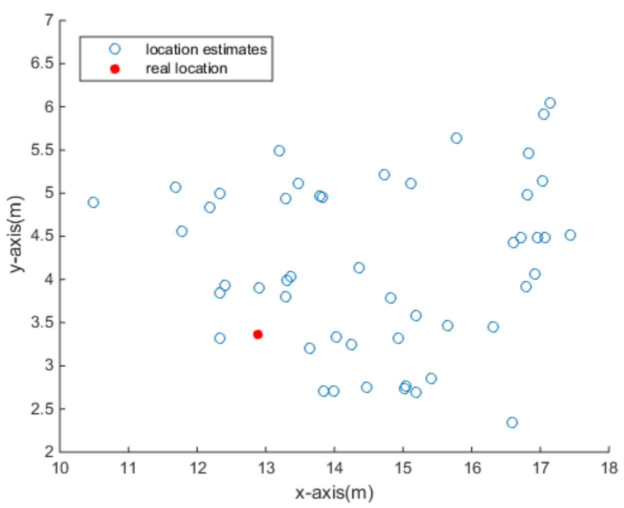



**Figure 10:** Location estimates in comparison with real location.

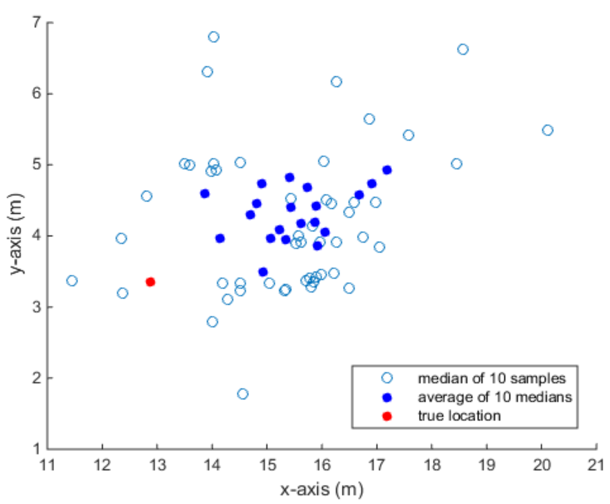



**Figure 11:** Stabilized location estimates for a fixed position.

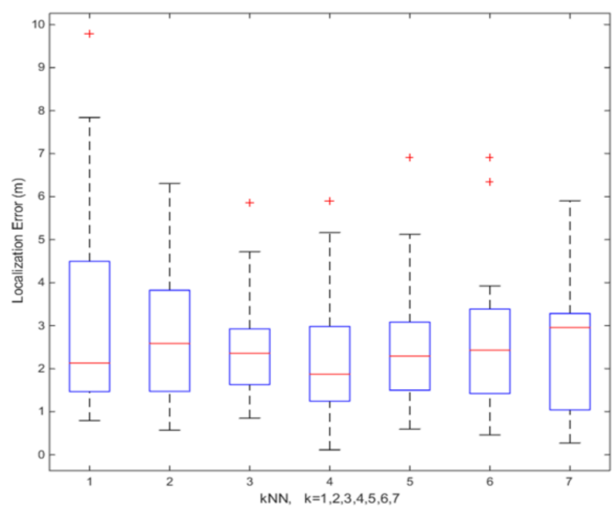



**Figure 12:** Localization error of Inv-FP by varying k in the Engineering test bed.

**Comparison of Inv-FP with FP in Hana Square:** Figure 15 compares the localization accuracy of Inv-FP with that of FP in the Hana Square testbed. The average localization error of Inv-FP is 3.43 meters while 3.56 meters for FP. The localization errors in the Hana Square testbed are more than 50% larger than the localization errors in the Engineering testbed. It can be inferred that the larger the area, the larger the localization error in general as expected. Overall, as shown in the figure, the localization performance of Inv-FP is comparable to that of FP assuming the same experimental set up.

**PDR:** RF signal based fingerprinting alone does not generally deliver high localization performance. There are two main reasons. First, it is due to the unstable signal strength caused by the electromagnetic characteristics of the RF signal in indoor environment such as reflection and diffraction. Second, RF fingerprinting often produces irregular and discontiguous route prediction since its position estimate is independent of the previous estimate. That is the reason why we consider PDR as a peer-assisted method to improve the positioning accuracy.

The PDR system predicts the relative movement of a user by estimating the step count, step length and the direction of the user movement. All of these are computed by using the motion (IMU) sensor data of the smartphone that the user is holding. Thus, the localization error in PDR is not affected by the size of the indoor environment which affects localization performance of FP and Inv-FP, as discussed previously in this section. Table 1 shows the step count accuracy of our PDR implementation, which is about 95%.

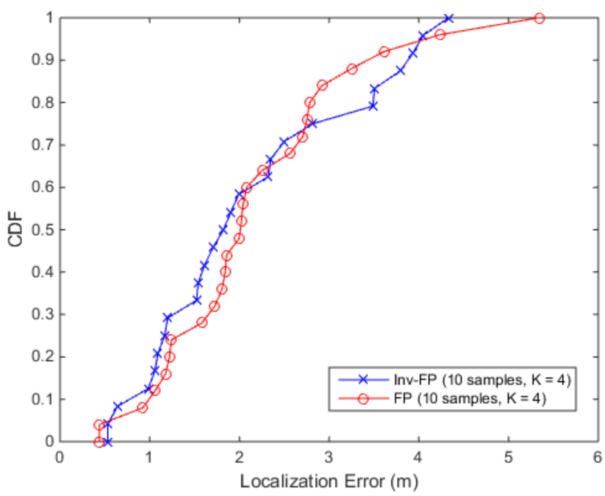



**Figure 13:** Localization accuracy in the Engineering test bed: Inv-FP vs. FP.

Also, unlike FP and Inv-FP, PDR cannot estimate the current position without the initial position. This relative positioning method generally leads to small localization errors in short distance while it results in huge localization errors in long distance due to the accumulated errors as we have discussed in Section IV. Figure shows the localization error of PDR by varying the number of steps when we repeat a specific route in the Engineering testbed as shown in Figures 16 and 17. Figure 18 shows the estimated position with PDR from 0 to 40 steps and from 200 to 240 steps.

As shown in Figure 17 the localization error is quite small, about 1.8 meters on average until the first 10 steps, compared to the FP and inv-FP. However, the localization error increases as the number of steps increases. With 240 steps, the localization error reaches 25.99 meters. As shown in Figure 18 the route generated by PDR after 200 steps seems to follow the direction and the distance of the actual route, but the estimated path is far from the actual path.

Overall, PDR is good in producing contiguous smooth route prediction and also good in high localization performance in short distance while it is bad in localization performance in long distance. By integrating PDR with fingerprinting, we may achieve good tracking and localization performance in both short and long distance since we can avoid accumulated errors in long distance with an absolute positioning method such as finger printing.

**Inv-FP integrated with PDR:** As we have discussed, the localization error of PDR exceeds 1.8 meters after the first 10 steps. Therefore, we reset the starting position every 10 steps by using FP or Inv-FP. Figure 19 shows the position estimation of the algorithm combining PDR and Inv-FP from 0 to 40 steps and from 200 to 240 steps with the same experimental setup. As compared to Figure 18, the estimated route path after 200 steps does not deviate from the actual path even with the increased number of steps. Figure 20 shows the localization errors of PDR, Inv-FP and Inv-FP with PDR for 100 steps in Hana Square testbed. As shown in the figure, localization error of PDR increases constantly as the number of steps increases, whereas the localization error of the Inv-FP is fluctuated largely regardless of the distance. On

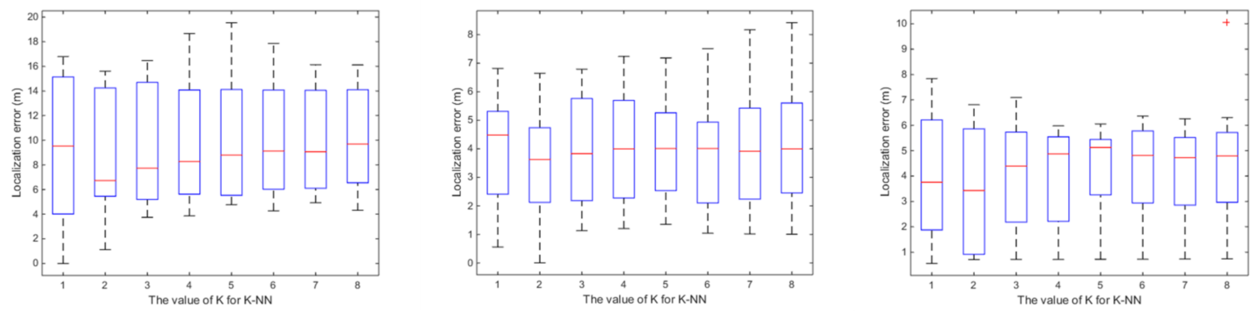



**Figure 14:** Localization error of Inv-FP with 0, -12, -20 dBm Tx power by varying k in the Hana Square test bed.

**Citation:** Bae HJ, Choi L (2018) Indoor Positioning System with Pedestrian Dead Reckoning and BLE Inverse Fingerprinting. Int J Sens Netw Data Commun 7: 159. doi: 10.4172/2090-4886.1000159



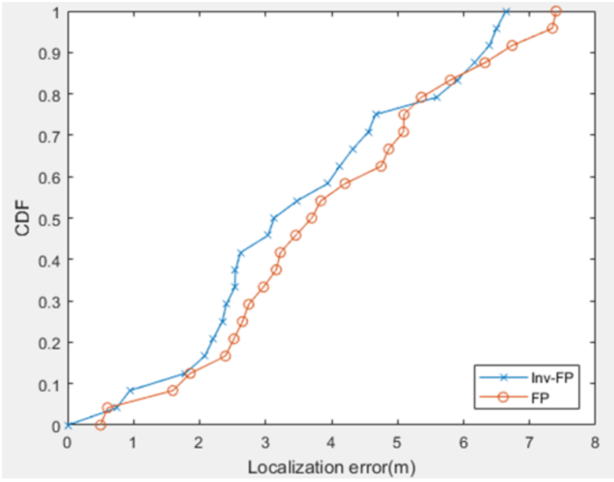



**Figure 15:** Localization accuracy in the Hana Square test bed : Inv-FP vs. FP.

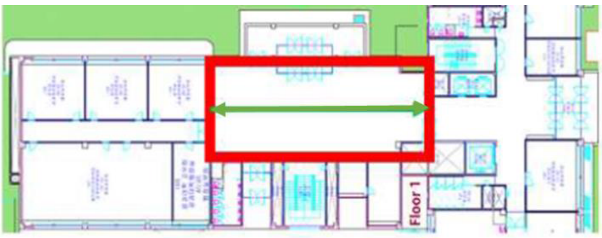



**Figure 16:** Test path of PDR shown in green arrow in the Engineering test bed.

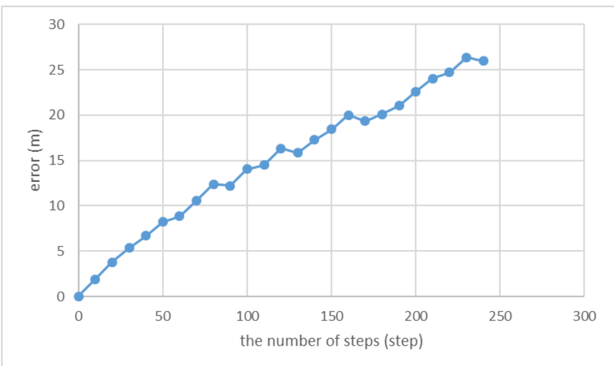



**Figure 17:** The localization error of PDR by varying the number of steps in the Engineering test bed.

the other hand, unlike PDR, the combined algorithm does neither increase the localization error as we increase the number of steps nor it does have the fluctuation in the localization error unlike Inv-FP.

Table 2 shows the localization errors of PDR, Inv-FP and Inv-FP with PDR in two testbeds. PDR, Inv-FP and the combined algorithm have the errors of 0.11 meters/step, 2.16 meters and 1.45 meters in the Engineering building and the errors of 0.11 meters/step, 3.43 meters and 2.12 meters in Hana Square. By integrating with PDR, In-FP can reduce the localization error by 1.31 meters in the Hana Square testbed, which is about 38.2% improvement in the localization performance.

## Conclusion

We classify location based services into two kinds, client-oriented services and server-oriented services. Client-oriented services target each individual who needs his or her location information individually. These applications are best suited by the existing beacon based localization systems where most of localization computation is done by each user device. In contrast, server-oriented services target organizations rather than individuals. However, the existing BLE beacon based systems impose too much work on each user, which is counter-intuitive and detrimental to the battery life of user device. This makes long-term tracking services impractical for the existing beacon based indoor localization systems.

In this paper, we implement a BLE fingerprinting technique called Inv-FP, which can remove most of operational burden from user devices for location based services. Each user device simply broadcasts its BLE signal while signal collection and radio map computations are done at the server side by sniffer devices and servers. Despite the architectural difference compared to classical beacon based fingerprinting system, the Inv-FP shows comparable positioning accuracy compared to beacon based BLE fingerprinting system with minimal power

**Figure 18:** Test result of PDR from 0 to 40 steps (colored in red circles) and from 200 to 240 steps (colored in yellow circles) in the Engineering test bed.

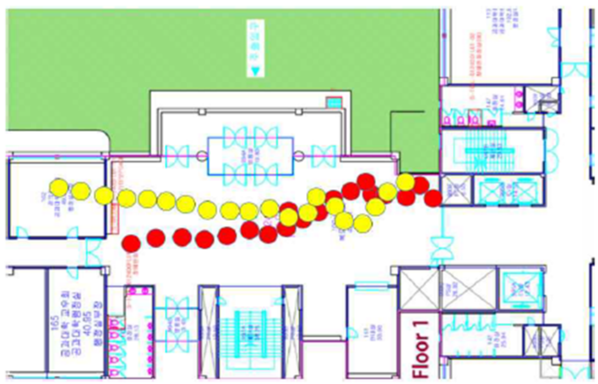



**Figure 19:** Test result of Inv-FP with PDR in the Engineering test bed from 0 to 40 steps (colored in red circles) and from 200 to 240 steps (colored in yellow circles) in the Engineering test bed.

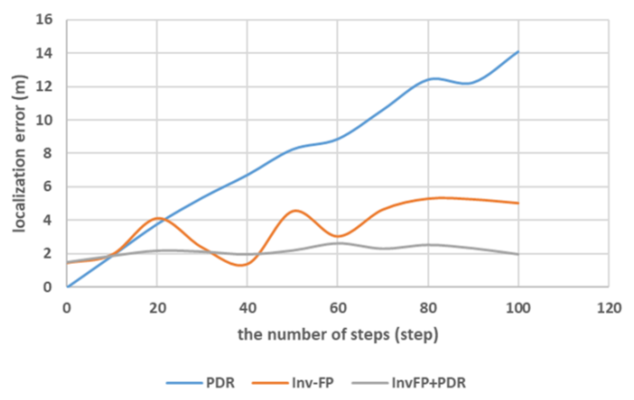



**Figure 20:** The localization error of PDR by varying the number of steps in the Hana Square test bed.

| | Step count |
|---|---|
| Step in reality | 2401 |
| Step in application | 227 |
| Error (%) | 5.42 |

**Table 1:** Accuracy of the step count.

| | PDR | Inv-FP | Inv-FP+PDR |
|---|---|---|---|
| Engineering building | 0.11 m/step | 2.16 m | 1.45 m |
| Hana Square | 0.11 m/step | 3.43 m | 2.12 m |

**Table 2:** Average localization error in the Engineering and Hana Square test beds.

consumption on user devices in both small and large testbeds. We also show that the localization performance of BLE inverse fingerprinting can be substantially improved by integrating with PDR, by taking the advantages of both PDR and inverse fingerprinting.

## Acknowledgement

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (NRF- 2017R1A2B2009641) and by the MSIT (Ministry of Science and ICT), Korea, under the ITRC(Information Technology Research Center) support program (IITP-2018-2015-0-00363) supervised by the IITP (Institute for Information & communications Technology Promotion). This research was supported by Korea University.

## References

1. Liu H, Darabi H, Banerjee P, Liu J (2007) Survey of wireless indoor positioning techniques and systems. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews 37: 1067-1080.
2. Liu J, Jain R (2014) Survey of wireless based indoor localization technologies, pp. 1-17.
3. Youssef M, Agrawala A (2005)The horus WLAN location determination system, In Proceedings of the 3rd ACM Mobi Sys pp. 205-218.
4. Kotaru M, Joshi K, Bharadia D, Katti S (2015) Spotfi: Decimeter level localization using WiFi. ACM SIGCOMM Computer Communication Review pp. 269-282.
5. https://en.wikipedia.org/wiki/IBeacon.
6. An JH,Choi L (2016) Inverse fingerprinting: Server side indoor localization with Bluetooth low energy. In Proceedings of the IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), pp. 1-6.
7. https://www.nordicsemi.com/eng/Products/Bluetooth-Smart-Bluetooth-low-energy/nRF-Sniffer
8. http://www.100y.com.tw/pdf_file/39-Nordic-NRF51822.pdf.
9. Bahl P, Padmanabhan VN (2000) Radar: An in-building RF-based user location and tracking system. Proceedings IEEE INFOCOM 2000. Conference on Computer Communications. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies (Cat. No.00CH37064) pp. 775-784.
10. Goswami L, Ortiz E, Das SR (2011) Wigem: A learning-based approach for indoor localization," Conference Paper published 2011 in Proceedings of the Seventh Conference on emerging Networking Experiments and Technologies on - CoNEXT '11 pp. 3.
11. Luís Felipe M. de Moraes, Bruno Astuto A. Nunes (2006) Calibration-free WLAN location system based on dynamic mapping of signal strength. In Proceedings of the international workshop on Mobility management and wireless access - MobiWac '06 pp: 92-99.
12. Krishnan P, KrishnakumarAS, Ju WH, Mallows C, Gamt SN, et al. (2004) A system for LEASE: location estimation assisted by stationary emitters for indoor RF wireless networks. In Proceedings of the 23rd IEEE INFOCOM 2: 1001-11.
13. Lim H, Kung LC, Hou JC, Luo H (2006) Zero-configuration, robust indoor localization: theory and experimentation. In Proceedings of the 25th IEEE INFOCOM 2: 1-12.
14. Neishaboori A, Harras K (2013) Energy saving strategies in WiFi indoor localization. Proceedings of the 16th ACM international conference on Modeling, analysis & simulation of wireless and mobile systems pp. 399-404.
15. Kriz P, Maly F, Kozel T (2016) Improving indoor localization using Bluetooth Low Energy beacons. In Mobile Information Systems 2016: 1-11.
16. Faragher R, Harle R (2014) An analysis of the accuracy of Bluetooth Low Energy for indoor positioning applications. In Proceedings of the 27th International Technical Meeting of The Satellite Division of the Institute of Navigation pp. 201-210.
17. http://www.csr.com/sites/default/files/csr8510.pdf
18. http://www.bluez.org/
19. Bluetooth SIG. Bluetooth Specification Version 4.0.
20. Paterna VC, Auge AC, Aspas JP, Bullones MP (2017) A Bluetooth low energy indoor positioning system with channel diversity, weighted trilateration and Kalman filtering. Sensors 17: 2927.