Different Approaches to Indoor Localization Based on Bluetooth Low Energy Beacons and Wi-Fi

Radek Bruha and Pavel Kriz(✉)

Department of Informatics and Quantitative Methods,
Faculty of Informatics and Management, University of Hradec Kralove,
Hradec Kralove, Czech Republic
Pavel.Kriz@uhk.cz

Abstract. Thanks to Global Navigation Satellite Systems, the position of a smartphone equipped with the particular receiver can be determined with an accuracy of a few meters outdoors, having a clear view of the sky. These systems, however, are not usable indoors, because there is no signal from satellites. Therefore, it is necessary to use other localization techniques indoors. This paper focuses on the use of Bluetooth Low Energy and Wi-Fi radio technologies. We have created a special mobile application for the Android operating system in order to evaluate these techniques. This application allows localization testing in a real environment within a building of a university campus. We compare multiple approaches based on K-Nearest Neighbors and Particle Filter algorithms that have been further modified. The combination of Low Energy Bluetooth and Wi-Fi appears to be a promising solution reaching the satisfying accuracy and minimal deployment costs.

Keywords: Indoor localization · Indoor positioning · Bluetooth Low Energy · Internet of Things · iBeacon · K-Nearest Neighbors · Particle Filter

1 Introduction

In today's world, it is hard to imagine our lives without a wide range of various modern technologies, such as smartphones. We often use them instead of conventional maps for navigation. A smartphone is also able to localize itself thanks to the Global Navigation Satellite System (GNSS), enabling mobile applications to navigate the user to the destination.

The localization accuracy is typically several meters for the GNSS. The American GPS and the Russian GLONASS are the two globally available systems. It is also possible to use the Assisted GPS (A-GPS) to speed up the localization. The A-GPS downloads the most recent information regarding the satellites' orbital trajectories using a cellular network instead of downloading it via a slow down-link from the satellites.

N.T. Nguyen et al. (Eds.): ICCCI 2017, Part II, LNAI 10449, pp. 305–314, 2017.
DOI: 10.1007/978-3-319-67077-5_29

But the GNSS has its drawback – it is inapplicable indoors. Without the view of the sky, there is no signal from the satellites. Therefore, it is necessary to use other localization methods indoors. These methods can, for example, utilize existing sources of radio signals such as IEEE 802.11 (Wi-Fi) Access Points (AP). But the density of Wi-Fi transmitters in the building may not be sufficient for the high quality localization. Fortunately, they can be supplemented by additional transmitters such as Bluetooth Low Energy (BLE) transmitters, called *Beacons*. A BLE beacon transmits, similarly to a Wi-Fi AP, a unique ID that can be used for unambiguous identification of the transmitter. Modern BLE beacons can communicate with each other via a BLE mesh network and support remote management from the cloud [1].

This paper focuses on the indoor localization using Bluetooth Low Energy and Wi-Fi wireless technologies. Several approaches based on K-Nearest Neighbors and Particle Filter algorithms will be compared. The solutions will be tested in a real environment within the building of the university campus.

The rest of this paper is organized as follows. Section 2 briefly describes the existing positioning techniques and related work. We formulate the problem in Sect. 3. Section 4 describes the radio localization techniques in detail and the proposed solution. Several details regarding the implementation of the mobile application are shown in Sect. 5. We present the results of the testing in Sect. 6. Section 7 concludes the paper.

2 Related Work

There are many approaches to indoor localization. Their feasibility is largely influenced by the sensors and receivers inside smartphones. Furthermore, the quality and availability of the data from the sensors and receivers provided to the applications via an Application Programming Interface (API) determine the achievable precision of the localization.

The three following sensors belong to the basic equipment of smartphones. Firstly, an *accelerometer*, which uses gravity as a reference axis and provides information about the phone's acceleration in each axis. It is used for tilt and movement detection. A linear accelerometer is a special variant that excludes the force of gravity. Secondly, a *gyroscope* provides information on the rotation of the phone in the space in all three axes, namely, the speed and direction of rotation. Thirdly, a *magnetometer* (an electronic compass) measures the Earth's magnetic field and its direction. The combination of these three sensors is referred to as an Inertial Measurement Unit (IMU). It can be used to determine the absolute position of a smartphone in space using so called Sensor Fusion [2]. In the context of the indoor localization, the IMU is used in approaches known as Pedestrian Dead Reckoning (PDR). The PDR uses the IMU sensors for measuring the number of steps (the distance estimation), and detecting changes in the direction of walking [3].

For the radio-based indoor localization, the built-in receivers of IEEE 802.11 (Wi-Fi), cellular networks and Bluetooth (optimally in the Low Energy variant) are the only feasible sources of data. A smartphone is able to detect nearby transmitters thanks to these built-in receivers. The distance from a particular transmitter can be determined by several methods, such as by measuring the signal strength using the *Received Signal Strength Indicator* (RSSI). This method provides a good estimate in open spaces without obstacles. However, indoors, while signal passes through and reflects off various obstacles it is not accurate. The results of the RSSI-based indoor distance estimation should be treated with caution. *Time of Arrival* (ToA, Time of Flight) is a more accurate method of the distance estimation because it is not affected by the attenuation of the signal [4]. But ToA is not supported by smartphones, except for GNSS receivers.

There are three popular approaches to the radio-base localization: *K-Nearest Neighbors* [5], *Multilateration* [6], and a *Particle Filter* [7]. Each method has its advantages and disadvantages. The methods can also give different results in different environments. The K-nearest Neighbors (KNN) approach is based on fingerprints describing (based on measurements) the environment at a given point in space. The KNN has the advantage that it can be implemented even without knowledge of the exact positions of the transmitters. On the other hand, Multilateration and the Particle Filter usually work with known positions of transmitters.

These methods are elaborated by many authors who are trying to improve them. For example, Kumar et al. apply Gaussian regression in fingerprint-based localization algorithms [8]. Song et al. focus on advanced methods of selecting a subset of all available transmitters from measurement [9]. The RSSI may also be replaced by Channel State Information (CSI) according to Yang et al. [10].

In this paper we focus on the comparison of several approaches based on the KNN and the Particle Filter and their modifications (see Sect. 4). The results of evaluation in a real-world environment are discussed.

3 Problem Formulation

The aim of this work is to implement multiple (variously modified) indoor localization approaches and evaluate their results in real environment. The 3rd floor of the building of the Faculty of Informatics and Management, University of Hradec Kralove, was chosen as the test environment.

There are 4 existing dual-band (2.4 GHz and 5 GHz) Wi-Fi access points on this floor and 17 additional Bluetooth Low Energy beacons (made by Estimote) have been deployed there. The beacons have been firmly attached to the ceiling. Their *Advertising Interval* has been set to 100 ms and *Transmitter Power* to −4 dBm.

Series of measurements will be made in this environment. Several different indoor localization algorithms will then be evaluated at 9 testing positions and their accuracy will be compared. We will consider various modifications of the KNN and Particle Filter algorithms based on Wi-Fi signals, Bluetooth Low Energy signals and the combination of both technologies. Fig. 1 shows the positions of Wi-Fi access points W, Bluetooth Low Energy beacons 01 to 17 and testing points A• to I•.

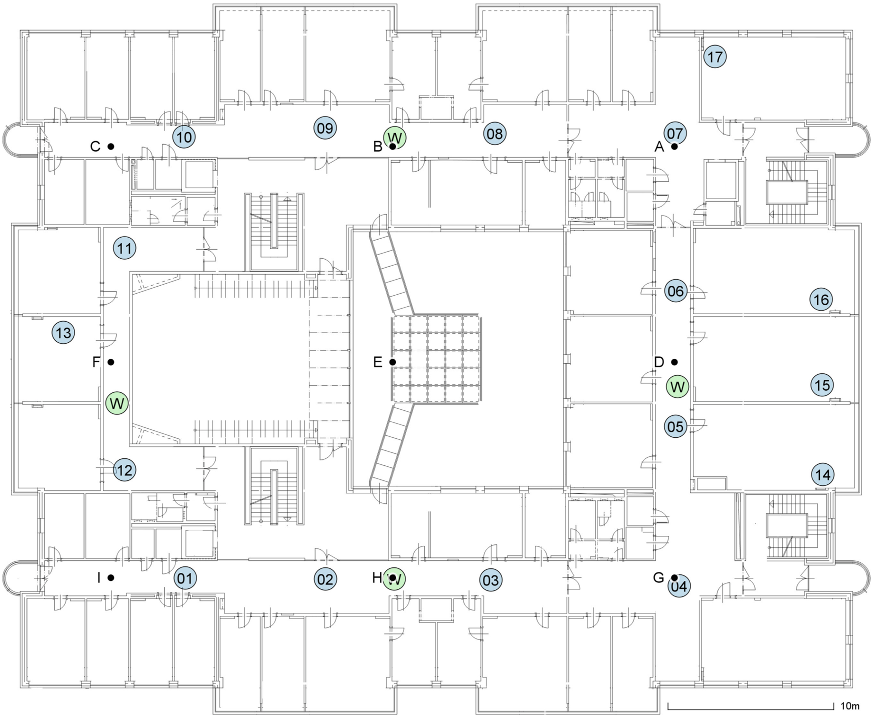

Fig. 1. Floor plan with Wi-Fi access points, BLE beacons and testing points

4 Indoor Localization Techniques and Their Modifications

The following subsections present two basic indoor localization techniques that we evaluate in this work. Various modifications of these techniques (possibly improving the accuracy) will also be described.

4.1 K-Nearest Neighbors

The first technique of radio-based indoor position estimation uses the K-Nearest Neighbors algorithm [5]. This algorithm searches several most similar neighbors – radio fingerprints. In order to be applicable in a new building it is necessary to walk through the whole building first and to measure the strengths of radio signals at reference points with known positions. At each point denoted by B_i an R_i vector of the RSSIs for every transmitter (called the *fingerprint*) is created. The record consisting of B_i and R_i is stored in the database. This process is called a *learning-phase* or an *offline-phase*.

During the *localization-phase* (*online-phase*), the signals from transmitters are received at an unknown position. These signals are compared to the previously measured data (fingerprints) stored in the database. In case the measured signals match an existing R_i fingerprint we will say that the estimated position is the B_i position of the existing R_i fingerprint measured during the learning-phase. Of course, the exact match is very unlikely. Therefore, we sort existing fingerprints by their degree of similarity to the currently measured data. Then we pick the k most similar fingerprints. The degree of similarity among fingerprints is usually calculated using the Euclidean or Manhattan (city-block) distance in Signal Space [11]. We obtain an estimated position by calculating the center (the mean of coordinates) of the similar fingerprints. The choice of the k (number of similar fingerprints to be picked) is an interesting topic. One might think that the higher k would lead to better results, i.e. a higher estimation accuracy. However, it turns out this hypothesis is false and the best results are typically provided by k to be 3 [12]; the same value is used in our experiments. Another interesting topic is the possibility of reducing the number of collected fingerprints while keeping the accuracy to be high [13].

The KNN algorithm has first been modified to be able to select the type of signals from the fingerprint; so it is possible to choose among (1) Wi-Fi signals, (2) Bluetooth Low Energy signals or (3) signals combined from both technologies into a single set. The combined fingerprint is defined as

$$R_i = R_i^W \frown R_i^B \tag{1}$$

where R_i^W is a vector of Wi-Fi RSSIs and R_i^B is a vector of BLE RSSIs. These two vectors are concatenated to a single R_i vector. The k nearest neighbors are then found in a set of fingerprints denoted as R. In our work we call such a modified algorithm the *KNN1*. The KNN1 compares two fingerprints using the Euclidean distance.

Furthermore, we have made a second modification of the KNN algorithm called the *KNN2*. This algorithm can also combine both technologies together but searches for the nearest neighbors independently in two sets by a matching technology. We consider these R_i^W and R_i^B fingerprints to be independent in every place i. The nearest neighbors are found twice; (1) in an R^W set of Wi-Fi fingerprints and (2) in an R^B set of BLE fingerprints. Then the $2 \cdot k$ neighbors are sorted by the distance and the k nearest neighbors are chosen. We can also prioritize individual neighbors based on their technology. For example, we can prioritize Bluetooth Low Energy by setting a higher weight to these neighbors during the calculation of the neighbors' center. The KNN2, in contrast to the KNN1, compares two fingerprints using the Manhattan distance.

4.2 Particle Filter

The second indoor localization technique is based on a Particle Filter (PF) [7]. It gradually refines the estimated position based on continuous measurement. This approach takes into account random perturbations in the RSSI.

In the first iteration of the algorithm, particles with zero weight are generated evenly throughout the space. Some of the particles are identified as possible locations based on the measurement (observation). We increase the weight of such particles. Subsequently, the particles having zero weight are removed. We generate new random particles near the estimated position, i.e. close to the remaining particles. During the next iterations, clusters of highly-probable estimated positions will be formed. The clusters should be reduced gradually into a single position which will be considered the result of the position estimation algorithm.

The Particle Filter typically uses an estimated distance from transmitters based on the RSSI. As it turns out, the estimated distance is very inaccurate indoors. Thus, the algorithm has been modified to take advantage of the data measured during the KNN's learning-phase – the fingerprint database. For each particular signal received from a transmitter a set of fingerprints having similar signal-strength is found. Considering the positions of fingerprints in the set, the area where the observer is found (regarding the particular transmitter) is determined. This process is repeated for each transmitter. It gradually increases the weight of particles in these areas. The positions of particles having high weight corresponds to the estimated position(s) of the observer. Another measurement is then performed and positions are gradually adjusted and refined. In our work we call such a modified algorithm *PF*.

5 Mobile Application

We have created a special mobile application for the Android operating system in order to evaluate indoor radio-based localization techniques in real environment. A person equipped with a smartphone and the application walks through the building and performs measurements in a predefined grid. The measurements (fingerprints) are then stored in the database.

The application is designed for the Android mobile platform version 4.4 (SDK ver. 19) and higher. Due to the lack of Bluetooth Low Energy support in earlier versions than 4.3 [14], it is not feasible to support much older versions of the Android platform. The application also requires a Graphic Processing Unit (GPU) supporting OpenGL ES version 2.0 or higher, which is used for displaying maps of the building with the aid of the *Rajawali* library[1]. We use the *Estimote SDK*[2] for scanning the nearby Bluetooth Low Energy devices (Beacons).

The application stores all data internally within the integrated SQLite database. The simplified database schema is shown in Fig. 2. We have also implemented the synchronization of the collected data among users (their smartphones) using the Couchbase database. It stores individual records in the JSON format and offers advanced synchronization techniques. Synchronization is performed as follows. Internal records from the SQLite database are converted into the local Couchbase Lite database[3]. Couchbase Lite is then synchronized to the server-side Couchbase database. In another device, records in the local

[1] https://github.com/Rajawali/Rajawali.
[2] https://github.com/Estimote/Android-SDK.
[3] https://github.com/couchbase/couchbase-lite-android.

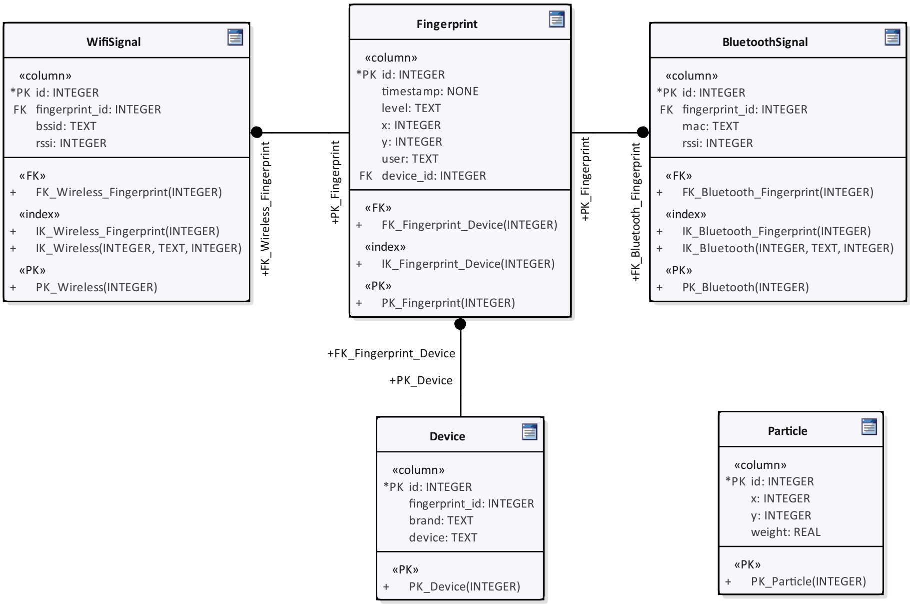

Fig. 2. Simplified SQLite database schema

(already synchronized) CouchBase Lite database are converted back into the local SQLite database. The system architecture is shown in Fig. 3.

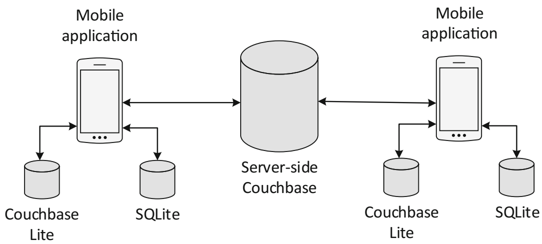

Fig. 3. System architecture overview

During the measurement the application shows how much individual measurements differ from each other. Thus, the person performing the measurement can immediately see whether the measurements are correct or whether something has changed significantly. These changes may indicate errors in measurements or changes in the environment (e.g. removed or new transmitters).

Similarity/difference of measured fingerprints is based on the average values of the RSSI. Differences in RSSIs are shown from two points of view. First, differences among transmitters of a particular technology are considered. For example, we can detect differences in Wi-Fi signals only. Second, signals of a particular individual transmitter are compared. So we can detected that the transmitter has been moved or its transmitting power has been changed. This information is available not only during measurement, but also later when viewing individual fingerprints and it may be displayed on the map.

In the localization phase the application also displays relevant information regarding the selected localization algorithm. For the Particle Filter, an area with our probable position is displayed for each of the transmitter in range. A user can visually check where the highest probability (intersection of signals) is. In the case of the KNN algorithm the closest neighbors are highlighted and the user can manually review the degree of similarity between an existing fingerprint and signals currently measured.

6 Testing and Results

The experiment took place in the corridors of the third floor. Individual measurements were carried out in a grid where each spot was one meter far from another one. It was important to measure the fingerprints precisely and consistently; three measurements were performed in one spot. Measurements were carried out with the aid of the Galaxy S3 Neo smartphone having the Android 4.4.2 (SDK 19) operating system.

The localization accuracy was evaluated in nine locations labeled A to I (see Fig. 1), where the position was estimated three times for each algorithm. The results are shown in Table 1 and Fig. 4. Three algorithms KNN1, KNN2 and PF (see Sect. 4) were tested, each in three variants: using Wi-Fi signals (W), Bluetooth Low Energy signals (B), and the combination of both types of signals (C). The position estimation error (in meters) for each location and each algorithm is presented in Table 1. The error is also shown in the boxplot

Table 1. Localization error (m) for each location and algorithm

	A	B	C	D	E	F	G	H	I	Avg.
KNN1(B)	5.31	18.03	34.53	19.00	17.93	13.03	32.00	5.48	11.76	17.45
KNN1(C)	1.54	1.34	1.44	1.87	3.71	0.01	0.77	2.30	1.24	1.58
KNN1(W)	5.35	1.33	1.88	3.69	3.69	2.01	1.65	1.53	14.71	3.98
KNN2(B)	1.06	1.67	0.20	0.87	5.15	1.99	0.37	1.97	9.02	2.48
KNN2(C)	1.47	3.87	5.21	2.29	6.03	1.94	2.92	2.51	11.67	4.21
KNN2(W)	3.85	7.77	14.89	7.57	21.09	2.00	7.40	3.34	15.45	9.26
PF(B)	8.77	2.07	14.90	7.58	9.36	1.16	14.30	4.97	17.73	8.98
PF(C)	9.97	1.86	13.97	4.99	7.54	0.95	12.67	4.92	15.77	8.07
PF(W)	12.75	1.00	12.80	5.18	9.73	2.50	10.17	0.00	13.55	7.52
Avg.	5.56	4.33	11.09	5.89	9.36	2.84	9.14	3.00	12.32	7.06

(see Fig. 4) where the algorithms are ordered by the average error – the smaller the error is the better the algorithm performs.

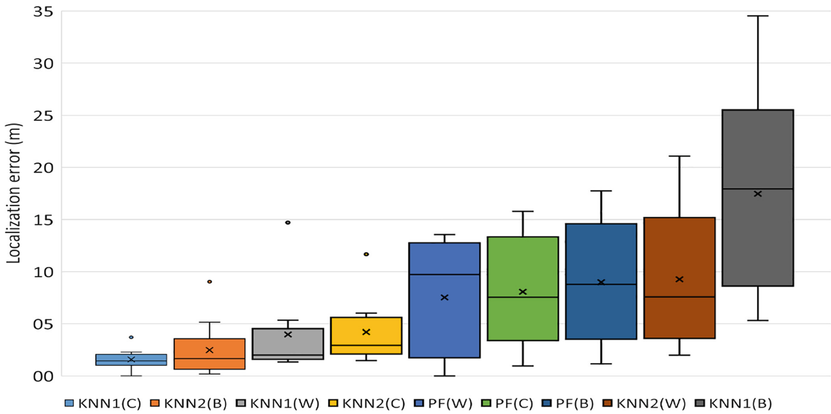

Fig. 4. Localization error chart

The results show that the KNN1(C) – the K-Nearest Neighbors algorithm based on the combination of Wi-Fi and BLE, using one set of signals and Euclidean distance – achieves the highest average accuracy of 1.58 m. The testing point (location) E gives the worst results due to poor signal coverage (both Wi-Fi and BLE) in the center of the building's atrium. The result proves our expectation that an algorithm based on combination of the two technologies will perform very well. Algorithms using the Particle Filter achieved quite a poor accuracy, which may be caused by the bad RSSI-based distance estimation (influenced by reflections and attenuation of the signal) indoors.

7 Conclusion

Aim of the work was to design and implement a mobile application that will be able to estimate the user's position within the building. We used it to further evaluate variously modified indoor localization algorithms and discussed the results. The application is able to effectively synchronize the fingerprint database among multiple mobile devices and provides advanced visualizations of the estimated position with regard to a particular localization algorithm.

The application implements two of the most widely used indoor localization algorithms; the K-Nearest Neighbors and Particle Filter, in 9 variants. The evaluations showed that the Nearest Neighbor algorithm combining Wi-Fi and Bluetooth Low Energy performs the best in the real-world environment (the campus building). The deployment scenario shows a feasible way to deploy additional Bluetooth Low Energy beacons in the building. It should also be noted that the localization error depends on the specific place. The accuracy is worse (sometimes in an order of magnitude) in places with poor coverage than in other places.

The application is robust enough to be further expanded in order to evaluate new indoor localization approaches or current approaches in a new environment.

Acknowledgements. The authors of this paper would like to thank Tereza Krizova for proofreading. This work and the contribution were also supported by a project of Students Grant Agency – FIM, University of Hradec Kralove, Czech Republic (under ID: UHK-FIM-SP-2017). Radek Bruha is a student member of the research team.

References

1. Estimote: Mesh networking - Estimote developer. http://developer.estimote.com/managing-beacons/mesh/
2. Siddharth, S., Ali, A., El-Sheimy, N., Goodall, C., Syed, Z.: A robust sensor fusion algorithm for pedestrian heading improvement. In: Proceedings of 24th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS 2011). p. 1337-0 (2001)
3. Racko, J., Brida, P., Perttula, A., Parviainen, J., Collin, J.: Pedestrian dead reckoning with particle filter for handheld smartphone. In: 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), pp. 1–7. IEEE (2016)
4. Abu-Shaban, Z., Zhou, X., Abhayapala, T.D.: A novel TOA-based mobile localization technique under mixed LOS/NLOS conditions for cellular networks. IEEE Trans. Veh. Technol. **65**(11), 8841–8853 (2016)
5. Yiu, S., Dashti, M., Claussen, H., Perez-Cruz, F.: Wireless RSSI fingerprinting localization. Sig. Process. **131**, 235–244 (2017)
6. Matharu, N.S., Buttar, A.S.: An efficient approach for localization using trilateration algorithm based on received signal strength in wireless sensor network. Int. J. Comput. Sci. Netw. Secur. (IJCSNS) **16**(8), 116 (2016)
7. Sanguino, T.D.J.M., Gómez, F.P.: Toward simple strategy for optimal tracking and localization of robots with adaptive particle filtering. IEEE/ASME Trans. Mechatron. **21**(6), 2793–2804 (2016)
8. Kumar, S., Hegde, R.M., Trigoni, N.: Gaussian process regression for fingerprinting based localization. Ad Hoc Netw. **51**, 1–10 (2016)
9. Song, C., Wang, J., Yuan, G.: Hidden Naive Bayes indoor fingerprinting localization based on best-discriminating AP selection. ISPRS Int. J. Geo-Inf. **5**(10), 189 (2016)
10. Yang, Z., Zhou, Z., Liu, Y.: From RSSI to CSI: indoor localization via channel response. ACM Comput. Surv. (CSUR) **46**(2), 25 (2013)
11. Machaj, J., Brida, P.: Performance comparison of similarity measurements for database correlation localization method. In: Nguyen, N.T., Kim, C.-G., Janiak, A. (eds.) ACIIDS 2011. LNCS, vol. 6592, pp. 452–461. Springer, Heidelberg (2011). doi:10.1007/978-3-642-20042-7_46
12. Honkavirta, V., Perala, T., Ali-Loytty, S., Piché, R.: A comparative survey of WLAN location fingerprinting methods. In: 6th Workshop on Positioning, Navigation and Communication, WPNC 2009, pp. 243–251. IEEE (2009)
13. Gu, Z., Chen, Z., Zhang, Y., Zhu, Y., Lu, M., Chen, A.: Reducing fingerprint collection for indoor localization. Comput. Commun. **83**, 56–63 (2016)
14. Android.com: Bluetooth low energy - Android developers. https://developer.android.com/guide/topics/connectivity/bluetooth-le.html