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doi:10.15199/48.2022.09.17

Research of Accuracy of RSSI Fingerprint-Based Indoor Positioning BLE System

Abstract *Radio localization in indoor environment is still a challenging task due to environment volatility. In the paper are compared achieved localization accuracies for RSSI-Fingerprinting method utilizing Bluetooth Low Energy (BLE) for two different environments: large empty hall and narrow corridor. Measurements were done by 6 different smartphones of 3 different producers, which makes those measurements unique as accuracies achieved by different devices can be compared.*

Streszczenie. Lokalizacja radiowa w środowisku wewnętrznym jest nadal trudnym zadaniem ze względu na zmienność środowiska. W artykule porównano uzyskane dokładności lokalizacji dla metody RSSI-Fingerprinting z wykorzystaniem technologii Bluetooth Low Energy (BLE) dla dwóch różnych środowisk: dużego pustego holu i wąskiego korytarza. Pomiary zostały wykonane przez 6 różnych smartfonów 3 różnych producentów, co czyni te pomiary wyjątkowymi, ponieważ można porównywać dokładności uzyskiwane przez różne urządzenia.. ***(Badanie dokładności lokalizowania w środowisku wewnątrzbudynkowym z wykorzystaniem technologii BLE i metody RSSI-fingerprinting****).*

Keywords: Radiolocalization; Bluetooth Low Energy (BLE); Fingerprinting; Indoor Positioning System (IPS).
Słowa kluczowe: radiolokalizacja, Bluetooth, IPS

Introduction

In recent years, the rapid increase of interest in the Internet of Things (IoT) concept has been observed, including smart buildings or smart cities and the benefits they give to their citizens and governments [1]. Those benefits include improved garbage and energy management, effective pedestrian and traffic flow control or better healthcare [2]. There's also an increase in awareness among societies and smart technologies developers of the life quality of frail people. Particular attention is paid to the blind and visually impaired [3, 4]. Hence, the positioning and navigation systems with features corresponding to their needs are proposed and implemented to enhance their autonomy and mobility in unfamiliar environments.

Most outdoor location-based services (LBS) are provided with the use of Global Positioning System (GPS). However, localization accuracy is not satisfactory when it comes to determining the position of the user located inside the building or within the high-density urban area. Furthermore, half of the world's population lives in urban areas and it is projected to grow to 68% by 2050 in general [5] and approximately to 13% in 101 world's largest cities [6]. Thus, Indoor Positioning Systems (IPS) have to be developed. In general, an Indoor Positioning System is composed of user devices and infrastructure installed in the building or in its vicinity. Possible applications of particular IPS depend on its technology (e.g. radio signal, ultrasound, magnetic field), complexity, localization accuracy and response time. In [7] is proposed a system using inertial sensors and computer vision techniques that allows finding a way to the desired place and return route after reaching the destination. An indoor navigation system utilizing deep neural network and smartphone capabilities, i.e. the accelerometer, gyroscope, and magnetometer has been presented in [8]. Other hybrid localization system is presented in [9]. Indoor positioning system using RSS-based lateration with Radio Frequency (RF) propagation and RF Fingerprinting of Wi-Fi signal was proposed in [10]. Bluetooth Low Energy technology utilization in Indoor Positioning was proposed in [11, 12]. Findings of research about the number of Bluetooth Low Energy (BLE) beacons influence on positioning accuracy in Indoor Positioning System are given in [13], where authors determined the BLE path loss model using 4 actual BLE beacons. Two different smartphones were employed for signal collection to consider device heterogeneity. Localization was done with kNN fingerprinting method.

In this paper the influence of the number of BLE beacons' on positioning accuracy in the indoor environment as well as reference points number and signal collection devices diversity during offline phase of fingerprinting localization method is analyzed.

System model

The system's infrastructure consists of 6 Bluetooth Low Energy iNode Beacons. The BLE technology allows Indoor Positioning System to meet the cheapness requirement due to easy deployment, low hardware cost and low energy consumption [14]. It's also one of the most suitable technologies for indoor navigation and tracking [15]. For measurements 6 smartphones were chosen (Huawei RNE-L21, Samsung SM-A320FL, Samsung SM-A520F, Samsung SM-G965F, Samsung SM-G991B, Xiaomi Mi 9 Lite) with Android version from 8 to 11. Measurements were done via proprietary application and stored in MySQL database. Measurements were divided into offline and online phase as is required in fingerprinting method. In each measurement Received Signal Strength Indicator was read from device and stored in database. Smartphones were distinguished by their model names. To estimate position of user device in online phase the RSSI fingerprinting method with weighted k-nearest neighbor (WkNN) algorithm was utilized.

Fingerprinting consists of an offline and online phase. During offline phase data is collected in locations with known coordinates, called Reference Points (RP). In general, this data type depends on chosen technology and IPS target application. The data collected in presented system is RSSI of signals received from Bluetooth Low Energy beacons. Datasets of averaged RSSI values from beacons for each RP constitute the neighbors in WkNN algorithm. Next, the radiomap of the environment is created based on collected data. In case of RSSI, the radiomap is a set of averaged RSSI values in Reference Points. Due to high fluctuations of RSSI values [16] collected offline data is filtered using Gaussian Filter as described in [17] before radiomap creation. During the online phase RSSI collected at unknown location is averaged and compared with values in radiomap. The position is estimated using a matching algorithm, which is WkNN with $k = 3$ for presented study.

The algorithm determines similarity between the incoming RSSI average data set and its neighbors by calculating the distance between these sets. The neighbors are data points in the radiomap. In this research we use Euclidean distance

$$d = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2}, \quad (1)$$

where d is Euclidean distance between data sets, q_i is the RSSI measured on the RP from i-th BLE beacon during offline phase and p_i is the RSSI measured from i-th BLE beacon during online phase. Next, the weights for k neighbors with smallest distances are calculated. The bigger the distance, the smaller the weight is. In this research the weights are calculated as defined in [18]

$$w_i = \frac{1/d_i}{\sum_{j=1}^{k} 1/d_j}, \quad (2)$$

where d_i and w_i are the distance and weight for i-th neighbor respectively. Then, the position of the user device is estimated using weights and RP coordinates using

$$(x, y) = \sum_{i=1}^{k} w_i (x_i, y_i), \quad (3)$$

where (x, y) and (x_i, y_i) are coordinates of the user device and i-th neighbor respectively and w_i represents the weight for i-th neighbor.

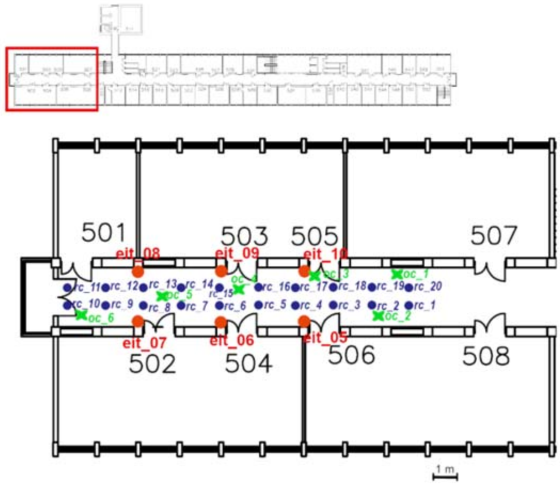

Fig.1. The deployment of devices in corridor

Measurements

Measurements were carried out in Gdańsk University of Technology, in the Faculty of Electronics, Telecommunications and Informatics (ETI) buildings A and B. Beacons were mounted to the walls or columns (depending on the environment) at a height of 2.1 m. Their settings were as follows: power +8 dBm; broadcasting frame time: 0.32 s; broadcasting channels: 37, 38, 39. Each of 6 smartphones were mounted to 1.1 m high tripods. Each smartphone carried measurements in each point for 5 minutes. All of the measurements were carried out in two different environments: narrow corridor on the 5th floor of the ETI A and main hall in ETI B. The deployment of devices in corridor is shown in Figure 1 and in the hall is in Figure 2. In those figures' beacons are marked as red dots, measurement reference points in offline phase (later called reference points) as dark blue dots and measurement points in online phase (later called online points) as green 'x' symbols.

Measurements in corridor were carried out on the 5th floor of the ETI A building. All of the measurement points were located in an even way to cover the same surface area. The whole area was 18.14 m × 2.6 m. Distance between the next measurement points was 1.5 m and between two rows of these points 0.6 m. Distance between the next beacons was 3.58 m and between two rows of beacons was 2.6 m. Those measurements were analyzed in 4 scenarios:

- in first scenario measurements from all points were taken;
- in second scenario all beacons and measurements from one line of offline points (rc_1 – rc_10) were used;
- in third scenario all reference points were used, but measurements only from beacons eti_05, eti_06 and eti_07 were analyzed;
- in fourth scenario were used measurements from beacons eti_05, eti_06 and eti_07 in points rc_1 – rc_10.

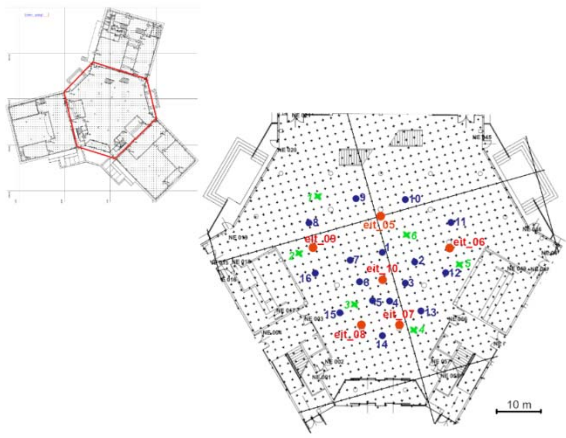

Fig.2. The deployment of devices in the hall

Results

There were 84773 measurements taken in the corridor of the fifth floor of building A in the offline phase and 7454 measurements in the online phase. Regarding hall in building B - 70221 RSSI values were collected in the offline phase and 4342 in the online phase. There was a noticeable difference in number of measurements taken by different phones. Some of them could collect up to 250 results, whereas particular two phones collected only around 10-15 RSSI values in the same reference points. Moreover, the range of measured RSSI values differs for different devices, e. g. Samsung SM-A320FL in reference point 113 measured RSSI range was <-71 dBm, -67 dBm>, whereas Samsung SM-G965F in the same point measured <-95 dBm, -71 dBm>.

To compare radio localization accuracy cumulative distribution functions were plotted in figures 4 to 10. In Fig. 4 to Fig. 7 are presented results for different scenarios in the corridor. For each smartphone separate distribution cumulative function was plotted. A similar graph but for the main hall is presented in Fig. 8. Fig 9 and 10 presents results distinguish with measurement points in online phase accordingly for main hall and for scenario 3 in the corridor.

From analysis of results presented in Fig. 4 – 8 it can be concluded that despite different values of measured RSSI by each device the achieved localization accuracy is similar between each device. However, comparing results for the corridor and the main hall it is clearly seen that system deployment and the hall environment is unfavorable for the localization purposes as RMSE values for the hall are higher than for the corridor. In such area there should be planned much denser arrangement of reference points and beacons. Comparing different scenarios in corridor it is worth mentioning that slightly better results are achieved for scenario 3 where there were utilized only 3 beacons but all 20 reference points.

Accuracy is also influenced by the position of the localized device what can be seen in Fig. 9 and 10. For both environments, points in online phase were distributed in such a way that it would be noticeable how important is their location relative to reference points. For those online points which were out of area delimited by reference points or close to the border the RMSE values are the greatest.

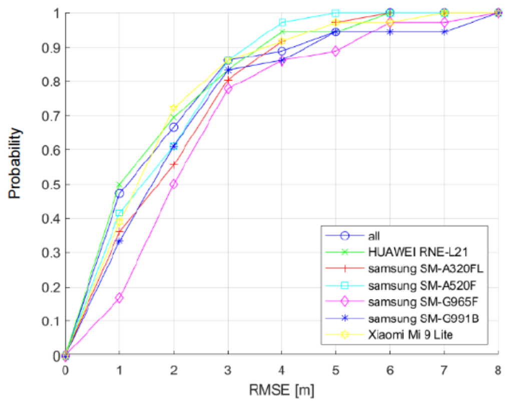

Fig.4. Distribution function of RMSE for the first scenario in the corridor

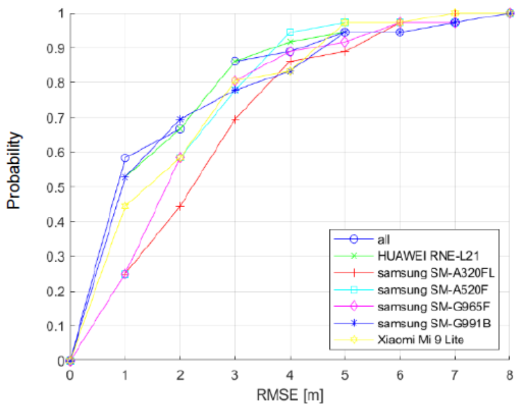

Fig.5. Distribution function of RMSE for the second scenario in the corridor

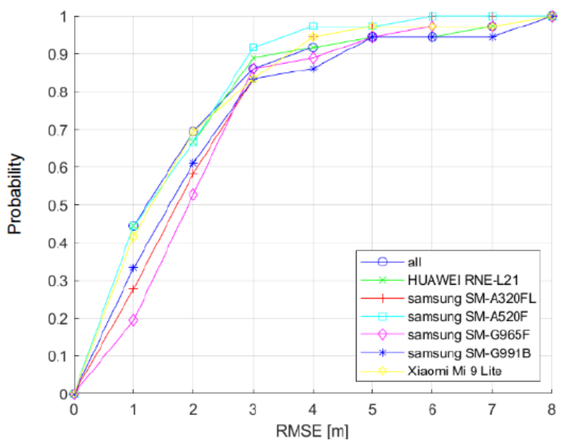

Fig.6. Distribution function of RMSE for the third scenario in the corridor

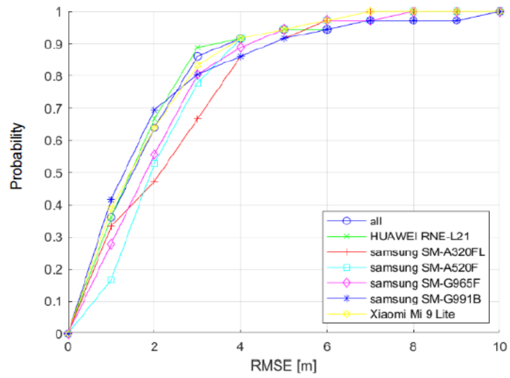

Fig.7. Distribution function of RMSE for the fourth scenario in the corridor

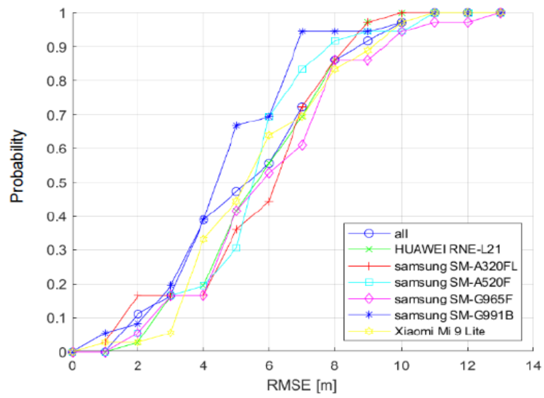

Fig.8. Distribution function of RMSE in the main hall

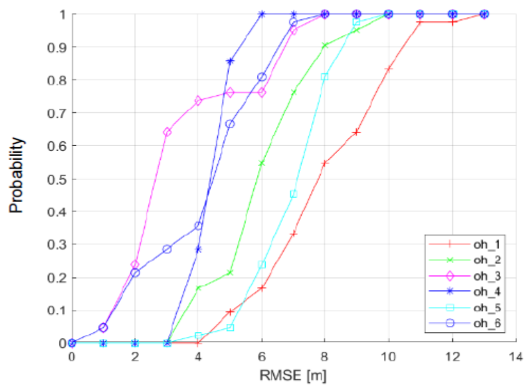

Fig.9. Distribution function of RMSE in the main hall distinguished for each measurement point from online phase

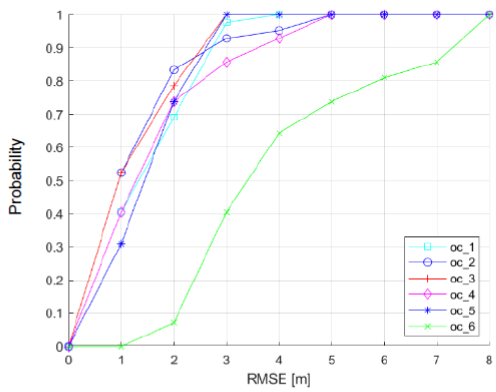

Fig.10. Distribution function of RMSE in the corridor and scenario 3 distinguished for each measurement point from online phase

For the main hall scenario points with the worst results were oh_1 and oh_5. First one was out of the designated area and even though the second one was quite close to the border it only had one reference point in its proximity. Similar situations occurred for points oh_2 and oh_4. However even though they were also placed quite close to the border of the area, oh_2 and oh_4 were both nearby 3 reference points and thanks to that they got better results than oh_5 (oh_4 was slightly closer to its closest reference points and due to that fact, it got the best results out of all points placed in difficult conditions). The best results were achieved for point oh_3, which was placed in the middle of the designated area and it was surrounded by a few reference points.

In the case of the narrow corridor scenario the greatest accuracy errors are for point oc_6. Errors for the rest online points in corridor are similar. The reason for such results might be due to localization of this particular oc_6 point which was in the end of the corridor, near big window where propagation conditions were different comparing to the rest of the corridor.

Conclusions

Radio localization in indoor environment is still a challenging task due to the difference between propagation conditions in each building, even in each place inside one building. In this paper authors proved that for different indoor spaces (a corridor and a hall) radio localization system achieves different accuracies. There are also shown results for 6 different measuring devices. Those results are promising as far as crowdsourcing in offline phase is considered. In the paper is also presented an interesting analysis for different online points which proves that the area of applicability of the system must lie inside area restricted by the beacons. Moreover, the number of reference points measured in offline phase also has an impact on the localization accuracy.

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