# Semi-Automatic Self-Calibrating Indoor Localization Using BLE Beacon Multilateration

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*Abstract*—**The indoor localization within public environments remains a complex and challenging task due to a number of issues related to the sensor infrastructure, space geometry and mobile device restrictions. This paper describes a hybrid indoor localization method based on received signal strength multilateration and pedestrian dead reckoning using internal smartphone sensors and relies on Bluetooth Low Energy beacons. Taking into account the beacon's zone of proximity and internal sensor data, the proposed method includes semi-automatic online calibration procedure of log-distance path loss propagation model. The proposed procedure takes into account smartphone heading angle and beacon signal obstructions due to user's body and moving people bodies.**

## I. Introduction

The location-based service development raises significant interest for the researchers and engineers. The provided localization information could be consumed by a number of context-aware applications. Traditionally, certain location-specific scenarios are considered depending on a purpose of the complex buildings like airports, museums [1], a shopping malls or office environments. For example, considering a wireless network security task in an environment, which aims to detect [2] and localize rough Wi-Fi access point. Thus, depending on the task, one can consider as an object to be localized a reference node [3], a mobile device, a robot [4] etc. Moreover, not only buildings are considered as the object but also other forms of construction sites like, for example, mines, sewer etc. also engineering structures [5], [6], [7]. Moreover, an indoor localization area [8] and an object to be localized could be a transport vehicle [9].

The wireless localization methods can be classified into signal propagation models based techniques and scene analysis, also known as fingerprinting, which refers to feature of a scene data collection and online data matching. The outdoor localization techniques based on signal propagation models like received signal strength (RSS), the time of arrival of the radio signals from transmitters (TOA) [10], [11], [12], the time difference of the arrival of several radio signals (TDOA) [13], the time-of-flight of the signal traveling from a transmitter to a receiver (RTOF) [14], [15], the angle of arrival (AOA) [16], [17] and the distance of arrival (DOA) [18] are applicable for indoors too.

However the aforementioned localization techniques suffer from missing line-of-sight channel between the transmitter and the receiver, multipath signal propagation, scattering, shadowing and fading. Such effects are caused by moving people and reflecting surfaces. Thus, the most popular approaches rely on RSS measurements like RSS multilateration and RSS fingerprinting.

Since Wi-Fi networks are prevalent in public indoor environments, their usage is more desirable than Bluetooth, ZigBee etc., because it doesn't require any additional infrastructure. In opposite, in the last few years, Bluetooth Low Energy (BLE) beacons have become very popular sensing infrastructure that can provide user proximity or location. Among the indoor localization wireless technologies the Bluetooth Low Energy a number of advantages like free allocation, low power consumption and widespread support by smartphones. Moreover, BLE signals have high sampling rate, which helps to accomplish outlier filtering [19], [20].

The variations of multilateration and fingerprinting are suitable for BLE beacons but have their own issues. RSS-based location fingerprinting refers to techniques based on signal measurement collection (fingerprints) and object location estimation by matching online measurements with appropriate location-related measurements [21], [22]. The issues related to BLE-based location fingerprinting are the vast number of RSS measurements at training phase, collisions and high variance of RSS measurements, which induces errors during the matching algorithm usage. Therefore, fingerprinting is only able to achieve 2.5-3 m of localization accuracy [23]. As well as for fingerprinting, the problems related to BLE multilateration have the same nature and lead to unreliable distance calculation. Because of that, the raw RSS measurements are unreliable and to be filtered. Thus, to overcome these disadvantages many kinds of hybrid solutions are proposed. The widespread solution is the fusion of wireless multilateration and pedestrian dead reckoning techniques. Pedestrian dead reckoning is the technique based on smartphone sensors that have the appropriate issues like accumulated sensor errors, step detection, length of step and heading direction determination. Furthermore, to facilitate the accurate localization and reduce the impact of the environment one can perform offline calibration phase, which comprises raw RSS measurements and their processing according to several smartphone orientation angles. This phase assists the signal propagation model's parameter adjustment.

The proposed method belongs to a group of techniques, which are used for localization within public environments. This task is very usual and requires commonly available technologies for localization, the target localization object is a human with a mobile device and the localization area should be a public building. Since the localization method requires a map of indoor areas, let's assume that such map is obtained already before any localization process phase. The purpose of the method is to provide the accurate localization within public environments, which allows to avoid manual offline calibration phase of the signal propagation model. To

achieve this purpose, the semi-automatic online calibration procedure for RSSI-based multilateration is considered. This multilateration technique uses log-distance path loss model of BLE signal. Log-distance path loss model has several parameters that consider environment features. These parameters can be determined empirically during the offline calibration phase. The semi-automatic online calibration procedure is used to avoid offline calibration phase of log-distance path loss multilateration. The proximity zone can be used to determine several initial values for the semi-automatic calibration procedure. In addition, we propose to use the internal smartphone sensors for distance detection, which is necessary for semi-automatic calibration.

The BLE beacon based localization technique is considered because of beacon mobility that allows to move beacon within an area to achieve line-of-sight propagation channel. The line-of-sight propagation is affected by smartphone antenna orientation change, a number of obstacles and moving human bodies. It means that localization accuracy depends on mobile device orientation hardly. Unfortunately, moving people damage the received signal strength measurement process including a user who needs to be localized because of his/her own body. The typical situation when a user stands back to the BLE beacon leads to decreasing the RSS. To overcome this drawback the special heuristic is used.

The rest of the paper is structured as follows. Section II presents works related to the subject of the paper. Section III describes the multilateration of Bluetooth Low Energy beacons and reliable signal propagation models. Section IV introduces online semi-automatic calibration procedure of the log-distance path loss model. Section V describes necessary improvements of the procedure. Section VI presents the evaluation results of the presented technique.

## II. Related Work

There is a number of indoor localization techniques providing self-calibration for different purposes and by several ways. However, there are no many techniques taking into account signal propagation model's adjustment.

The proposed trilateration algorithm [24] is based on log-distance path loss model uses self-calibration based on particle swarm optimization (PSO) for determining calibrated parameters of log-distance path loss model. If the system accuracy decreases due to external factors, a system calibration request is initialized. User's location is estimated using the least squares trilateration algorithm. The technique relies on periodic estimation of reference node locations and accuracy computation, and then the model parameters are recalibrated when low accuracy conditions are accomplished.

In [25] the fingerprinting tracking approach based on KNN-method is presented. The algorithm uses Kalman filtering to mitigate the effect of RSS fluctuations, which makes fingerprinting technique inapplicable. Then, certain parameters for the presented fingerprinting transformation model are calibrated using recursive least square estimation or simple mean estimation for the case when the number of access points is small and one of the parameters is reduced.

In [26] several automatic calibration (virtual calibration) procedures are presented. The procedures take into account number of walls crossed by signal and the attenuation factors of walls and floors. There are procedures of global virtual calibration and per-wall virtual calibration. Global virtual calibration procedure considers the number of wall crossed by the signal and a common wall attenuation factor are calculated using manually defined actual distance values. The computations are performed via the least square estimation method. Per-wall virtual calibration considers individual wall attenuation factors and the value of path loss exponent should be determined during global virtual calibration procedure.

The PiLoc indoor localization system [27], [28] exploits measured RSS data and collected by pedestrian dead reckoning information contributed by a number of users. The system derives the map of walking path by merging annotated walking segments related to radio signal strengths. PiLoc uses crowdsourcing to collect user walking trajectories using built-in smartphone sensors and Wi-Fi location fingerprints related to collected steps. Several components of the system are intended to assign measurement sets to appropriate environments and floor plan building. The clustering algorithm is used to combine Wi-Fi signal strength values and walking trajectories into disjoint sets that cover different indoor environments. The generated disjoint sets are used to find similar segments that match based on movement vectors and AP signals. Finally, multiple trajectories are merged to build floor plans. Despite of the calibration procedure is the complex procedure of trajectory matching, this system is a good example of exploiting the combination of walking tracks and Wi-Fi RSS measurments.

The self-calibrating technique described in [29] is intended to calibrate log-distance path loss model. The considered parameters are path loss exponent and reference received signal strength. The position estimates provided by received signal strength processing are used for gradually adjusting the values of the parameters. The model includes several improvements like a Hill-Climbing's local search algorithm.

The calibration procedure described in [30] relies on ZigBee calibration nodes. The calibration procedure starts at mobile node calibration request, which is received by calibration node. The sent pocket has an information about of the fixed node to be calibrated. After receiving the calibration request, the calibration node transmits a packet to the selected node. The selected node receives it and retransmits a packet to the mobile node after a certain delay. The acquired result of this round trip time measurement is exploited to dynamically latency estimation, which is performed for each fixed node.

The proposed method relies on signal multilateration of Bluetooth Low Energy Beacons and pedestrian dead reckoning approach combination. The method includes semi-automatic calibration procedure which uses the real distance to the transmitter. The distance is calculated dynamically by built-in smartphone sensors during user movement through the indoor area.

## III. LOG-DISTANCE PATH LOSS BASED MULTILATERATION

Multilateration is a localization technique, which relies on environment map and geometry relations among the reference nodes, namely information about reference point positions within an environment and distances to them. At least three reference nodes are required and distances between the target node and each reference node should be determined. Each reference node forms a circle around itself and its radius corresponds to the distance to the target node. The intersection of these circles encompasses the localization area of the target node. The target node's (T) localization by four reference nodes ($N_1$, $N_2$, $N_3$, $N_4$) is shown in Fig.1.

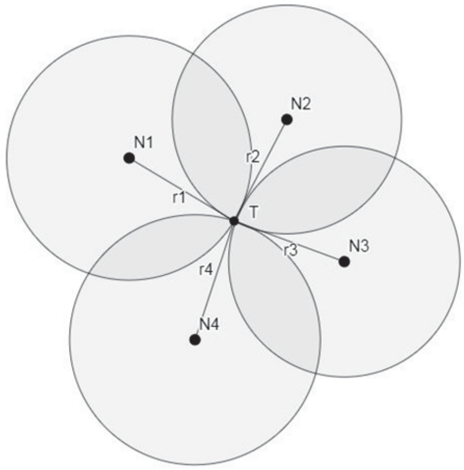


Fig. 1. Target node multilateration by four reference nodes

The distance estimations between target and reference nodes presented in Fig.1 are the radiuses of the appropriate circles. The corresponding task is the distance estimation between the transmitter (reference node) and the receiver (target node) using the signal attenuation model. Radio signal path loss value depends on frequency, antenna orientation, penetration losses through walls and floors, the effect of multipath propagation, the interference with other signals, signal shadowing and scattering among many other factors. Moreover, BLE signal fluctuates a lot, because it is susceptible to the external factors. Thus, the measured signal data are computed by appropriate signal attenuation model and have to be filtered. The widely used approaches for received data processing are Kalman filtering [11], the moving average and Grubb's test used to detect outliers [11].

There are several signal attenuation models like ITU model [31], Hata-Okumara path loss model [32], log-distance path loss. As described in [32] Hata-Okumara path loss model is more reliable than ITU. However, the log-distance path loss model for estimation of distance between receiver and transmitter is more accurate. The model equation is as follows:

$$PL = P_{Tx} - P_{Rx} = PL(d_0) + 10n \times log_{10}\frac{d}{d_0} + X_{\sigma_{RSS}} \quad (1)$$

where $PL$ – is total path loss (dB), $P_{Tx}$ – transmiited power (dBm), $P_{Rx}$ – received power, also RSS (dBm), d – true distance between transmitter and receiver, $n$ – path-loss exponent, $P_t$ – transmitted power of the transmitter (dBm), $PL(d_0)$ – power loss (dBm) at a reference distance $d_0$. The quantity $X\sigma_{RSS}$ in dBm is a random variable representing the noise and is often assumed to be a zero-mean Gaussian random variable with RSS variance σ. The path loss exponent indicates the rate of path loss according to the distance and takes into account multipath effects. $X\sigma_{RSS}$ represents fading effects and without them is set to zero. The path loss model can be expressed also as follows:

$$P_{Rx} = P_{Rx}(d_0) - 10n \times log_{10}\frac{d}{d_0} + X_{\sigma_{RSS}} \quad (2)$$

The $P_{Rx}(d_0)$ indicates received signal strength power at the reference distance $d_0$ and takes into account transmission power, antenna gain and wavelength. This value is affected only by the path loss exponent if $d > d_0$ and can be determined beforehand.

By defining $d_0$= 1m, and $X_{\sigma_{RSS}}$= 0, the appropriate equation for the distance value can be written as:

$$d = 10^{\frac{P_{Rx}(d_0) - RSS}{10 \cdot n}} \quad (3)$$

The parameters $P_{Rx}(d_0)$ and $n$ can be obtained from empirical data and by linear regression. In common case, one can measure the signal power at reference distance only and use the standard value of constant $n$ for indoor environment. However, this approach doesn't take into account smartphone orientation, obstacles and local features of the environment. To make multilateration more location-specific preliminary measurements are used for each reference node to collect signal power values and then estimate the constant $n$. There are several approaches to collect measurements for parameter estimation. The reliable way to do it is to measure signal at different distances and angles of rotation. Thus, the offline calibration phase of multilateration approach is performed.

The purpose of this paper is to investigate how accurate the localization could be when using the automatic calibration of log-distance path loss signal propagation model. The semi-automatic calibration allows to avoid offline calibration and do the same on the fly. The calibration relies on internal smartphone sensors data and process the data for each BLE beacon allocated near to the smartphone.

## IV. SEMI-AUTOMATIC CALIBRATION

The idea of online semi-automatic calibration is that the human with a mobile device can provide the essential data needed for localization by calibration the aforementioned parameters during she/he is walking through the indoor area and using special mobile application to indoor localization. The calibration is performed parallel with multilateration and improves the quality of multilateration. The user's mobile application needs an indoor map, absolute locations of the allocated beacons and technical parameters of beacons like UUID, transmission power etc. The internal readings starts to be collected at the known point corresponding to the nearest location to some beacon with location correction. This correction provides user's location defined as a location near the beacon each time the user enters the appropriate zone of proximity. For this purpose, the internal built-in smartphone sensors like accelerometer and gyroscope has been involved in localization process. Moreover, map-aided information and proximity are used to fix the moment of calibration start. The BLE beacon radiation pattern is important for the whole process, because it influences the measurements, beacon allocation and calibration procedure start/stop, in our case. For this reason, beacons with the omnidirectional pattern are used. Eventually, the proposed semi-automatic calibration procedure is based on an appropriate scenario of human movement through indoors.

Let's consider the important BLE features sufficient for this procedure. First, there are several proximity zones surrounding BLE beacon on certain distances. iBeacon and Eddystone beacons have the nearest zone to provide point of interest tagging. The zones of iBeacon have the preset boundaries confiding the radio signal's power values. There are immediate (closer than 0.5m), near (from 3m down to 0.5m), far (from 3m to 30m) and unknown (when a beacon cannot be detected) zones. In our case, it is sufficient to detect the "immediate" zone, because it indicates the exact user's location. Thus, the signal strength power at reference distance 0.5m is known. The reference signal strength power varies from -50dBm to -40dBm at this distance. This liminal RSS can be equal in each individual case to a different value. Since the reference distance is known too, the path loss exponent *n* can be expressed from equation (3) and calculated.

We assume that if the user appears in the "immediate" proximity zone she/he stays always on the zone's border, because there is no purpose to determine user's location more accurate than 0.5m, and we assume than user with mobile device in a hand actually won't be staying at the beacon closer than 0.3m–0.5m, in this case. The user doesn't need to control the moment she/he meets this zone of proximity, because the mobile application should notify the user about this. The user also has to control the movement pattern to achieve acceptable quality of calibration.

Obviously, the simple measurement of path loss exponent at the nearest distance is not reliable. The measurements at several distances are necessary, because there is a possibility to calibrate path loss exponent using linear least square approximation. For this purpose one need to calculate the distance values. One can see that dependency between logarithm of the distance and received signal power is linear:

$$RSS = P_{Rx}(d_0) - 10n \times log_{10}d \quad (4)$$

Thus, the final equation of the path loss exponent is:

$$n = \frac{P_{Rx}(d_0)\times m - RSS}{10\times log_{10}d} \quad (5)$$

As pointed out above, the distance measurement is necessary for the calibration process. The simplest way to do this is relying on step measurements provided by built-in smartphone sensors. The mentioned idea is shown on Fig. 2.

The straightforward user's movement scenario assumes the straight moving direction regarding the beacon (Fig. 2). Then, during the RSS measurement corresponding to near proximity zone, the user movement on the tangent to the border of the zone are considered. However, this scenario may have several drawbacks like impossibility to move straightly and affecting the signal by user's body. Despite this, a new value of distance can be obtained by internal smartphone sensors. Thus, defined in the immediate zone values of distance $d_1$ and signal power $RSS_1$ and defined after several steps new values of distance and signal power are used to calibrate the path loss exponent. To define the new distance value the velocity calculation of moving user is performed.

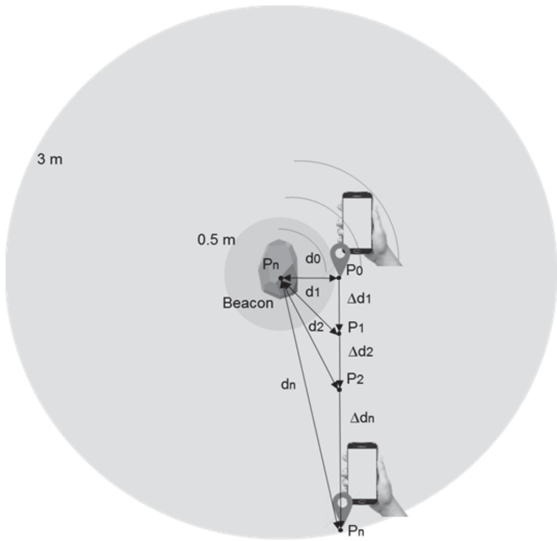


Fig. 2. RSS measurements for BLE beacon semi-automatic calibration

The steps of online semi-automatic calibration of log-distance path loss can be defines as follows:

- *Step 1:* The initialization of parameters $d_0$ and $RSS_0$ related to immediate proximity zone. The initiated distance $d_0$ is 0.5m and $RSS_0$ = -50dBm.
- *Step 2:* BLE beacon immediate proximity zone detection. If the signal power $RSS_1$ is higher than initiated then immediate zone is entered. If the user enters the near proximity zone, her/his position is estimated as located at the border of this zone. From this step the automatic calibration starts.
- *Step 3:* The user starts the move straight through the indoor environment. Calculation of the distance via smartphone sensors is performed. The steps counting is started. The calculated distance is used to obtain the distance to the beacon using step detection and the Pythagorean theorem.
- *Step 4:* If the distance shift is equal to 0.5m then RSS is measured. The given RSS mesurment is used to obtain path loss exponent calibration via equation (5).

- *Step 5:* If the result distance is more than 3m stop the calibration. In another case go to the step 3.

Unfortunately, the aforementioned procedure doesn't take into account several exceptional situations like non-straight movement, another moving people and smartphone orientation.

## V. Semi-automatic Calibration Procedure Improvmnets

### A. Multiple path loss calibrations

The basic scenario described above considers user heading regarding the beacon's immediate proximity zone, but it does not take into account issues related to the dependency of the path loss exponent on smartphone heading regarding the beacon. In the aforementioned case, the angle between user's direction and direction to the beacon is 90°. However, the angle after several steps in straight direction has another value.

If the user turns in this new point the path loss exponent, obviously, will change. This issue is shown in Fig. 3 and Fig. 4. The Fig. 4 shows the user changes the orientation in the new point P1.

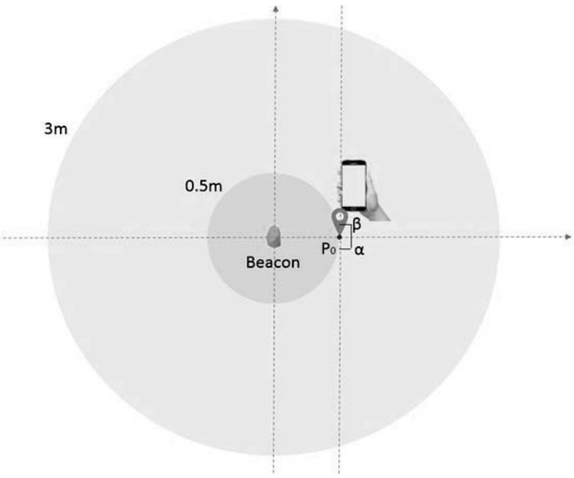


Fig. 3. User heading regarding the beacon at calibration start

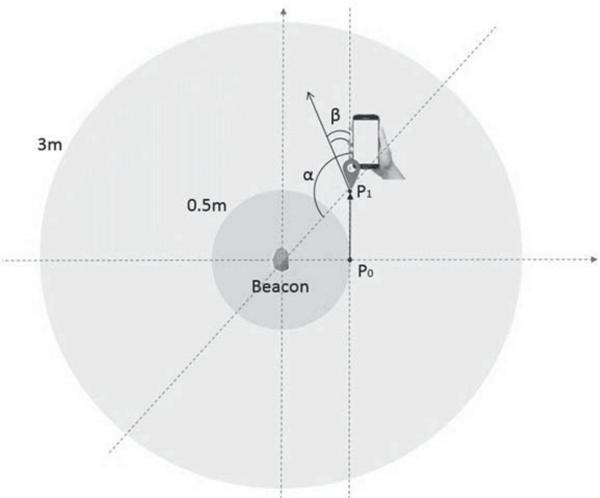


Fig. 4. New user's heading regarding the beacon and general coordinate system after several steps in straight direction

To overcome this drawback we need to calibrate the path loss exponent depending on user's heading regarding to the beacon, user direction and estimated distance to the beacon. Thus, the calibration measurement is a tuple *M*, which can be defined as:

$$M = (B, d, \alpha, \beta, P_r) \quad (6)$$

where $B$ – is a beacon id, $d$ – is a distance between the user and the beacon, $\alpha$ – is an angle of user heading, $\beta$ – is an angle of user's direction regarding general coordinate system, $P_r$ – received signal power.

The measurements with the same values of $B, \alpha, \beta$ only can be taken to path loss exponent calibration process.

### B. Beacon signal obstruction processing

The situation if the user turns her/his back to the beacon leads to significant received signal power decreasing. In this case, the given measurements should not be used for online calibration of path loss exponent. For this purpose, we need to know how to distinguish such user's heading from another moving people. It can be performed, if we detect a rotation without step detection and the received signal power is decreased then there is signal obstruction by user's body. In opposite, if no movement is detected then somebody stands between the user and the beacon. Unfortunately, it is difficult to recognize the obstruction by other people while user moves. Thus, the obstruction by user's body occurs, if no step is detected, the user's heading angle is within the range: [180° - $\theta$ ; 180° + $\theta$], where limit angle $\theta$ depends on beacon allocation and smartphone position regarding the body (position in the user's hand), and received signal power is less than a liminal value $P_{rb}$ which depends on beacon transmitting power and the distance.

This approach helps to distinguish zones where the beacon signals are low while multilateration combined to pedestrian dead reckoning when online calibration is already performed (Fig. 5).

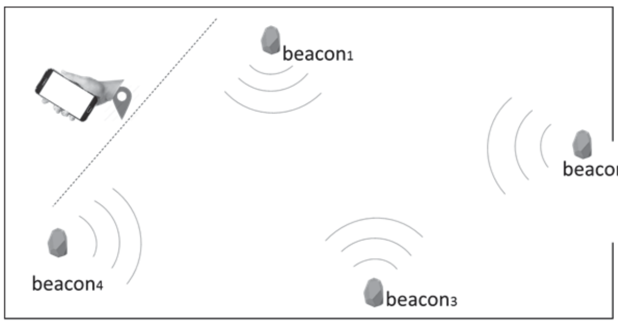


Fig. 5. User heading regarding the beacon after several steps in straight direction

Therefore, we need to keep the measurement history to analyze if the user is going through the zone where signal power is low.

### C. The improved online semi-automatic calibration algorithm

Thus, the algorithm of online semi-automatic calibration of log-distance path loss model is written as follows:

**Algorithm 1** Semi-automatic calibration

Online semi-automatic calibration of the path loss exponent
$d_{border} \leftarrow 0.5$m
$RSS_{immediate} \leftarrow -50$dBm
$RSS_{current} \leftarrow 0$dBm
$\beta \leftarrow 0°$ or another absolute angle
$calibration\_tuples \leftarrow$ empty
$n \leftarrow 2.6$
$B \leftarrow$ empty
$\theta \leftarrow 13°$
**while** $RSS_{current} < RSS_{immediate}$ **do**
  $RSS_{current} \leftarrow$ Measure current RSS
  **if** $RSS_{current} \geq RSS_{immediate}$ **then**
    $B \leftarrow$ Get beacon id
    $\alpha \leftarrow 90°$
    $d_{walked} \leftarrow 0.5$m
    $d_{real} \leftarrow 0.5$m
  **end if**
**end while**
**while** $d_{walked} < 3$m **do**
  **if** step detected **then**
    $RSS_{current} \leftarrow$ Measure current RSS
    $\alpha \leftarrow$ Measure current α
    $\beta \leftarrow$ Measure current β
    **if** $\alpha < 180° - \theta$ and $\alpha > 180° + \theta$
      and $RSS_{current} < P_{rb}$ **then**
      $d_{walked} \leftarrow d_{walked} + step\_lehgth$
      $d_{real} \leftarrow$ Law_of_cosines($d_{walked}$, $d_{border}$, $\alpha - \beta$)
      $n \leftarrow$ Calibrate($B$, $d_{real}$, $\alpha$, $\beta$, $RSS_{current}$, $RSS_{immediate}$)
      $n$ add to $calibration\_tuples$
    **end if**
  **end if**
**end while**

As it is shown by the algorithm, the automatic calibration procedure relies on the aforementioned improvements. We didn't detail how the initial values of path loss exponent, liminal angle and received signal strength, are obtained, because they are pre-set and defined by engineer. The result of the algorithm is a set of tuples are containing calibrated values of path loss exponent according to the user's handing, movement direction and an appropriate beacon. The angle of movement direction $\beta$ should be found by map-aided heuristic or by pedestrian dead reckoning algorithm.

## VI. Evaluation

For testing this technique, a special mobile application was implemented. The application is intended to estimate the distance between transmitter and receiver, and to perform the semi-automatic calibration of pre-set number of BLE beacons. The chosen beacons support iBeacon protocol. This application finds certain beacons by addresses and measures the RSS values of each access point. Presented algorithm 1 has been implemented, and evaluation of semi-automatic calibration provides tuples of calibrated path loss exponents which are ready to be used in multilateration. The mobile operating system is Android 4.4.

The average received signal strength values are measured in several distances from one beacon allocated within one room. These data are measured to distance estimation for multilateration method described above. These measurements are made for each point on one direction at the 0.5 m interval within the near proximity zone. The immediate proximity zone is detected via Android application automatically. The RSS fluctuates a lot at time therefore it is necessary to use its filtered values.

The semi-automatic calibration is performed for the basic scenario with straight user's moving without turns for a scenario with user's heading change and straight movement. Moreover, the case with received signal strength are evaluated. The results are displayed in Table I, Table II Fig. 6.

TABLE I. The evaluation of the real distances and estimated distances after calibration while straight scenario

| Actual distance, m | Estimated distance, m | Direction angle, ° | Heading angle, ° | Path loss exponent | Relative error, % |
|---|---|---|---|---|---|
| 1.12 | 1.44 | 2.71 | 153.23 | 0.866169 | 28.57 |
| 1.58 | 1.91 | 0.75 | 161.69 | 1.400877 | 20.89 |
| 2.06 | 2.73 | 0.22 | 166.14 | 1.788920 | 32.52 |
| 2.55 | 3.83 | 0.28 | 168.63 | 2.543917 | 50.20 |
| 3.04 | 3.99 | -0.04 | 170.70 | 2.551334 | 31.25 |

TABLE II. The evaluation of the real distances and estimated distances after calibration while straight scenario with turns

| Actual distance, m | Estimated distance, m | Direction angle, ° | Heading angle, ° | Path loss exponent | Relative error, % |
|---|---|---|---|---|---|
| 1.12 | 0.85 | 32.71 | 123.23 | 0.866168 | 24.11 |
| 1.12 | 1.35 | 62.71 | 93.23 | 1.154891 | 20.54 |
| 1.12 | 0.5 | 92.71 | 63.23 | 0,288723 | 55.36 |
| 1.12 | 0.23 | 122.71 | 33.23 | -0.28872 | 79.46 |
| 1.12 | 0.10 | 155.94 | 0 | 0.288723 | 91.07 |
| 1.58 | 2.10 | 30.75 | 131.69 | 0.800501 | 32.91 |
| 1.58 | 1.99 | 60.75 | 101.69 | 1.000626 | 25.95 |
| 1.58 | 1.28 | 90.75 | 71.69 | 2.201378 | 18.99 |
| 1.58 | 1.30 | 120.75 | 41.69 | 1.200751 | 17.72 |
| 1.58 | 0.5 | 152.44 | 10 | 0.200125 | 68.35 |
| 2.06 | 2.34 | 30.22 | 136.14 | 1.788917 | 13.59 |
| 2.06 | 2.79 | 60.22 | 106.14 | 2.276803 | 35.44 |
| 2.06 | 2.37 | 90.22 | 76.14 | 3.252576 | 15.05 |
| 2.06 | 3.45 | 120.22 | 46.14 | 1.788917 | 67.48 |
| 2.06 | 1.55 | 150.22 | 16.14 | 0.813144 | 24.76 |
| 2.55 | 1.84 | 30.28 | 138.63 | 2.119931 | 27.84 |
| 2.55 | 2.30 | 60.28 | 108.63 | 2.261260 | 9.80 |
| 2.55 | 3,22 | 90.28 | 78.63 | 1.978602 | 26.27 |
| 2.55 | 2.96 | 120.28 | 48.63 | 1.554616 | 16.08 |
| 2.55 | 1.84 | 150.28 | 18.63 | 0.706644 | 27.84 |
| 3.04 | 2.55 | 29.96 | 140.70 | 2.542099 | 16.12 |
| 3.04 | 2.75 | 59.96 | 110.70 | 2.160784 | 9.54 |
| 3.04 | 2.44 | 89.96 | 80.70 | 2.033679 | 19.74 |
| 3.04 | 1.82 | 119.96 | 50.70 | 1.779469 | 40.13 |
| 3.04 | 1.82 | 149.96 | 20.70 | 0,889735 | 40.13 |

Table II shows the results of calibration with turning at the same line of direction. The heading angles are changed every time at 30°. The user consistently turns his/her face to the beacon. As the result, the localization average error is lower than 1.5 meter.

The shown in Table I results are useful to consider the situation of signal obstruction by user's body. Thus, the heading angle is more than 167° at the distances 3 and 2.5 meters and leads to decreasing localization accuracy. Therefore, by such values of heading angle the path loss exponent's calibrations are not reliable and should be excluded from consideration. The threshold angle for heading $\theta$ in our case is 13°. Moreover, at the straight scenario the localization error is lower than 1m.

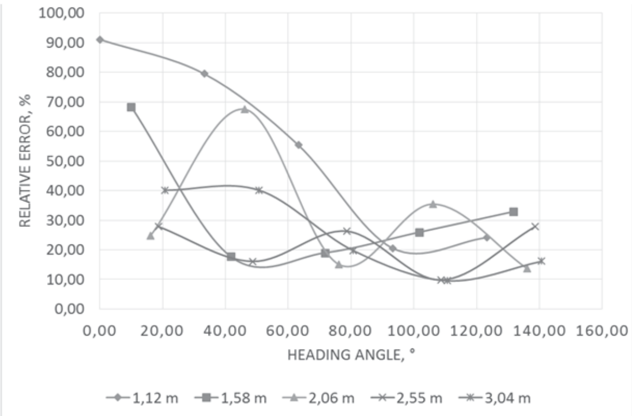


Fig. 6. The dependency between smartphone heading angle and relative error

In Fig. 6 is shown that at the small distances and small heading angles the error is more than at far distances and small heading angles.

## VII. CONCLUSION

The presented online semi-automatic calibration procedure for a log-distance path loss model based multilateration can be used for Bluetooth Low Energy beacon based indoor localization methods. On one hand the procedure is performed parallel with BLE signal multilateration to improve the values of path loss exponents corresponding to a number of distances between user's smartphone and appropriate BLE beacon. On the other hand it can be performed parallel with pedestrian dead reckoning and multilateration hybrid localization to improve the user's location data obtained from internal smartphone sensors using known user's proximity. Thus, its implementation isn't restricted in such localization approaches. Despite the user's application implements multilateration and proposed procedure detects user's proximity and automatically starts the calibration, it requires to control straight direction of movement by the user.

The advantages of proposed procedure are the possibility of online calibration, processing obstacle influences and orientation changes. The procedure is useful to localize a user within a room. The location estimation error is lower than 1.5 meter but only in the case of the straight user's movement. The disadvantages are the facts that the presented method doesn't take into account complex trajectories of user's movements, the user should control her/his movement pattern and big errors at small distances.

To overcome these drawbacks the hybrid method comprising pedestrian dead reckoning technique and multilateration should be realized. The hybrid method should process orientation change more precisely and has to be fully automated. The advancement of this approach could be the construction of complete database of path loss exponent values corresponding to appropriate distances for every beacon in the building. The methods of crowdsourcing are suitable to implement this approach using collaboration of a number of user's.

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