BLE Indoor Positioning System Using RSSI-based Trilateration

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Abstract

Systems for outdoor positioning such as Global Positioning System (GPS), Global Navigation Satellite System (GLONASS) or Galileo are commonly used in our everyday lives through smartphones or in-car devices to establish our current position outdoors and/or to navigate to a specified destination. There is, however, no standard solution to establish our position indoors, where satellite signals do not reach. In this paper we present a system for indoor positioning that uses Bluetooth Low Energy (BLE) beacons as transmitting nodes with known positions and the Received Signal Strength Indicator (RSSI) designating the strength of the signal emitted by the nodes with the help of trilateration to establish user's position in a building with a mobile application. Due to the signal's instability we propose enhancements that improve positioning precision. We report results of the conducted tests performed in both static and dynamic scenarios, whose precision is acceptable in most of the typical indoor positioning schemes.

Keywords: indoor positioning system, Bluetooth Low Energy, BLE, beacon, trilateration

1 Introduction

Location information is very important in modern information systems. Thanks to location information it is possible to determine the position of people and objects in space, and thus also to: realize navigation to the destination, perform monitoring and tracking, do traffic and behavior analysis, as well as deliver context-aware services.

Indoor Positioning Systems (IPS) allow for enriching the software with localization information in places where location information has not been available so far. Very intensive development of technology, miniaturization of electronic systems and the resulting increase in computational and energetic efficiency resulted in the proliferation of mobile devices equipped with efficient processors, multiple sensors and receivers, as well as the development of mobile operating systems and wireless technologies (including the creation of the Bluetooth Low Energy standard (BLE)). The advances of these technologies provide new perspectives for indoor positioning solutions.

Indoor positioning systems primarily allow to determine the location inside a building and are a basis for related, more complex systems using location information, such as: (i) personal navigation systems inside: airports (e.g. to the gate), shopping centers (e.g. to a selected store), stores (e.g. along an optimal path to buy all items on the shopping list), museums (e.g. following a designated tour route or to an exhibit of choice), stadiums (e.g. to a place or sector), as well as car navigation in underground car parking lots (e.g. to the nearest free parking place); (ii) systems for personnel monitoring inside the buildings (e.g. security services or security staff, doctors in a hospital) or underground constructions

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(e.g. miners in a mine); (iii) systems for analyzing how people move and behave, for example inside exhibition halls or shopping centers for the purpose of evaluation of stands, premises or advertising spaces; (iv) utilititarian and social applications, e.g. allowing to find friends at the concert, or save car parking place in the underground parking lot; (v) integration with intelligent buildings and the Internet of Things systems. A variety of possible applications for indoor positioning systems and the fact that reliable and commonly used implementations of such solutions do not exist in buildings in which we often stay indicate a huge potential for the development of such technology.

In recent years, both in the academic and commercial environments, intensive research is conducted on technologies and solutions in the field of IPS systems. One can observe new developments in the form of new protocols, such as iBeacon [1] or Eddystone [2, 3], the emergence of a new class of devices on the market, such as beacons (e.g. Estimote beacons [4]), as well as first commercial systems focused on indoor localization (e.g. Indoorway [5]). Solutions in the field of IPS systems are also increasingly frequently the subject of research and scientific work.

There exist many methods and algorithms for indoor positioning [6, 7, 8, 9]. Depending on their general characteristics one can distinguish several classes thereof: trilateration-based techniques, scene analysis techniques (also known as fingerprinting), proximity detection techniques, and dead reckoning techniques.

Trilateration consists in determining the position based on distance measurements from at least three reference points (beacon nodes or WiFi access points) and solving a system of equations of circles or spheres. There exist mathematical tools for solving the equations. Direct distance measurement is not possible, therefore other characteristics, like radio frequency signal propagation, are measured, based on which the distance is then computed. The most important methods used to measure the distance in trilateration are received signal strength (RSS or RSSI, the designations are interchangeable), time of arrival (TOA), time difference of arrival (TDOA) and roundtrip time of flight (RTOF).

RSSI represents the relationship between a transmission and received powers; thus it can be used to compute distance between a transmitter and a receiver when electromagnetic wave propagates in a line of sight link [10].

TOA measures propagation time. On the basis of the time of sending the signal and the time of its receipt, knowing the speed of wave propagation, one can calculate the distance that the signal has covered. Trilateration using the TOA method is used in the GPS system.

TDOA measures the difference in time of the signal receipt between different receivers. Knowing the time difference while receiving the signal in two receivers it is possible to determine the relative distance from each of them.

RTOF measures time of flight of the signal travelling from the transmitter to the measuring unit and back. It is an extension of the TOA method.

In the scene analysis (fingerprinting) techniques the positioning process consists of two phases: offline and online. During the offline phase, the signals (fingerprints) reaching the receiver are measured repeatedly throughout the positioning area (measurements are made with a certain resolution, e.g. 1 meter). Then, during the online phase, a comparison of the current signal reading with the values saved in the previous phase is performed, and the process of matching to the locations where the measurements took place is done. In this class of solutions to match the current readings to the known signal samples machine learning methods are utilized, reducing the problem of positioning to the classification problem. The techniques of proximity detection are based on locating a large number of receivers or transmitters in the positioning area. The exact position of the device is not returned here, but rather relative location information. This positioning technique is used e.g. in cellular networks to assign user's device to the antenna with the strongest signal and to register user's position to be in the proximity (cell) of that antenna.

In the methods of dead reckoning, the position is determined by calculating the distance (e.g. number of steps) travelled from the last known position. Dead reckoning can be used as a complement to other methods in situations where the signal required for their correct operation is fading or is too weak.

In this paper, we demonstrate a system for indoor positioning using signal from BLE beacons, RSSI distance estimation and the trilateration approach. We argue that with proper beacons placement and the proper techniques of signal processing it is possible to create an indoor positioning system that is relatively easy and inexpensive to deploy and returns sufficient accuracy for static and dynamic use cases where indoor location is needed. The proposed IPS system is highly practical and accessible for end users. The employed approach to indoor positioning is advantageous in comparison to other solutions.

The rest of the paper is organized in the following way. In Section 2 we review approaches to indoor localization, particularly these using BLE devices and trilateration. In Section 3 we present the assumptions of the realized indoor positioning system. Section 4 discusses evaluation results of the system for static and dynamic scenarios. Section 5 concludes the paper. Section 6 discusses advantages of the presented system over some other IPS implementations.

2 Related Work

Devices most frequently used for indoor positioning are smartphones. Currently smartphones can natively receive WiFi and BLE signals usable in indoor positioning. BLE standard is supported in consumer devices since 2011 [11], so all previous attempts at indoor positioning were done using WiFi due to its wide availability in office environments and at universities where a lot of experimentation on the quality of indoor positioning is done. [12] compared the properties of WiFi and BLE for the purpose of trilateration-based indoor localization. The authors pointed out disadvantages of WiFi access points (APs) for localization compared to BLE devices: WiFi APs are typically placed in locations optimized for communication purposes rather than localization; additionally their placement is constrained by the availability of mains power (which lowers their usefulness for localization), low scan rate and higher energy consumption on mobile devices (five times higher, as BLE requires lower transmission power and provides a mechanism for power control [13]). The conducted tests showed that BLE is a more accurate location technology than WiFi. [14] experimented with indoor localization based on the WiFi signal using fingerprinting and trilateration and was not satisfied with the positioning accuracy, which is generally in the range of 3-5 meters.

RSSI signal (Radio Signal Strength Indication, measured in dBm) in BLE devices also poses challenges when it comes to indoor localization. In [10] the authors performed some experiments to test its reliability. The tests were done in a long empty corridor with two nodes: one node being a base station using Texas Instruments CC2420 directly connected to a computer via a cable, the other node was mounted on an ankle of a user. The authors note that since RSSI cannot be decimal or fractions, it can distinguish between distances large enough to cause at least a unit change in signal power at the receiver. Therefore it is not sensitive to small distance changes. The reference curve showing the dependence of the measured distance and RSSI value deviates between the model (for the static setup, where the user node is not moving during measurements) that can be computed using mathematical formulas and the measurements the authors performed in the course of experiments. RSSI becomes more and more sensitive as the distance decreases. For the dynamic setup, i.e. where the user moved during the measurements, the RSSI values turned out to be very unreliable. For example, the value of -90 dBm was measured for both 7 m and 26 m distances. Due to the signal instability the authors used multiple measurements and computed a moving average in one experiment and a weighted average in another experiment to reduce the fluctuations. Despite these measures the signal fluctuated considerably, so the conclusion drawn by the authors was that RSSI was unsuitable for determining the location.

Even though both WiFi and BLE signals have their drawbacks, their availability in smartphones makes them worthwhile of indoor positioning trials. Because BLE is a more accurate technology for location than WiFi, many approaches to indoor localization systems are based on BLE beacons.

A widely studied approach to indoor positioning is the approach basing on fingerprinting. Details related to some implementations of this approach using WiFi as well as BLE beacons can be found in the literature [14, 15, 16, 17, 18, 19]. Some commonly known limitations of this method of positioning are [6], e.g.: the construction of the radio map needs to be realized in advance and updated every time some changes in the mapped room/area take place (e.g. furniture reallocation, reallocation or installation of the access points); in case of the WiFi realization of the method, heterogenous mobile devices differently measuring signal strength need to be calibrated to return dependable results. A commercial system based on this approach, Indoorway [5], claims to achieve the accuracy of 1-2 meters.

An approach to indoor positioning that uses trilateration and BLE beacons is an alternative to fingerprinting. In contrast to the fingerprinting, whose results can easily change along with the changes in the configuration of the underlying space, trilateration does not require dedicated radio maps of the considered space, just proper beacon placement. It is thus more robust and gives satisfactory precision for most applications. [20] provides theoretical analysis of optimum node placement for indoor localization using trilateration. In particular, three theorems regarding accurate positioning are given, proved, and implemented in the test system. They say that the localization error is minimized when three reference nodes used for positioning form an equilateral triangle, in large sensor networks the reference nodes should be placed symmetrically and in such a way that the position of a new reference node can be calculated based on the position of the three original nodes. The main goal for these considerations is the development of a new localization algorithm which the authors simulate and test on Zigbee platform. [21] considers the problem of indoor localization but rather than estimating an exact position of a user the author wants to get to know the room in which the user is located. As a consequence the problem is brought to the problem of finding a maximum resolution sub-hypergraph. The author prosposes an algorithm to generate such a sub-hypergraph and reports the results of experimenting with the approach. The ideas presented in the paper are advantageaus in that the author proves that it is possible to successfully use Bluetooth beacons for indoor localization. The limitation of the proposed approach is the resolution of the method: it is unable to precisely tell the location of the user in terms of their coordinates in the building but limits the localization information to a room, which makes it practically useless in large spaces such as e.g. airport terminals or sports halls. [22] analyses influence of different factors on the accuracy of indoor positioning using radio beacons. The factors noted by the authors are: lack of signals from minimum three radio stations, adverse geometry of reference nodes increasing localization error, negative effects of radio signals multipath propagation on localization accuracy, signal reflections, signal propagation model. The authors propose simulation software allowing for evaluation of localization accuracy depending on the placement of reference stations.

In the literature one can find indoor localization results basing on experimental systems using BLE devices and the trilateration approach. [13] discusses an indoor positioning system using trilateration. The system is basing on RSSI coming from Bluetooth 2.1 available in Android mobile phones. Five such devices were used in the reported experiments that were performed in a 6 m by 8 m classroom. Four devices (referred to as reference nodes) were located in the corners of the room, while the fifth phone was used as a mobile node and its position was computed. The authors observed that if all four distances between the mobile and reference nodes were measured they would not intersect in one point, but rather return a plane. To get the precise location of the mobile node three approaches were used: least square estimation (LSE), three border positioning and centroid positioning. The best results, and thus acceptable positioning, were achieved for LSE. The authors also report on experiments showing how covering the signal with human body affects the positioning. The value of the article is in the presented exploration of the possibility of using Bluetooth 2.1 signal for indoor positioning. However, the authors present positioning results made in just one, regularly shaped room with a single, specific setup of reference nodes. Therefore it is not known how their approach would work for multiple, potentially irregularly shaped rooms and whether the proposed nodes placement would work properly in a more complex environment.

[23] argues that due to the specifics of trilateration (the intersection of three circles of signal coming from three transmitters indicate the position of the mobile receiving device) such scenarios are possible in which the circles do not intersect or they intersect in multiple points and not just one. Because of that they use iRingLA algorithm to compute the position indoors. iRingLA is an alternative to trilateration in which rings are drawn around the beacons instead of circles. Inner and outer radiuses of the rings are computed based on RSSI measurements. Next, a matrix containing all the intersection points of the rings is constructed with the most likely containing the receiver. Based on the positions of the selected candidates an estimation of the position is performed. The authors did localization experiments in an empty 4 m by 4 m room with three EALOGIC iBeacon transmitters. The device used for positioning was iPhone 5S. The average positioning error for a series of measurements was 0.4 m. The advantage of the presented experiments is the use of iRingLA algorithm. The authors, however, realized all experiments in just one, small, regularly shaped, empty room, which leaves the reader with uncertainty as to how the approach would perform in closer to real-life scenarios, where oftentimes we have to deal with large, irregularly shaped spaces.

[24] reports on an indoor positioning system based on Texas Instruments CC2540 BLE beacons, where position is established using trilateration. The authors conducted the experiments at the university lab consisting of seven rooms using nine nodes and an Android-based smartphone for beacons signal reception. The beacons were installed on the ceiling; each measurement was repeated 50 times. The noisy measurements were filtered out. Average RSSI values were recorded and matched to an identified curve fitting the data. The achieved localization accuracy was between 0.5 and 1 meters. The system implemented by the authors and reported in the paper returns very good positioning results. However, the authors did not test the system in the dynamic scenarios, so it is not clear whether the good static result would also be reflected in the case of locating a user being on the move.

[25] describes an indoor positioning system based on BLE easiBeacon devices placed in the distance of 7 m from each other on the area of $110\,m^2$, where position of a Nexus 5 smartphone is derived using trilateration with an accuracy function and a corrective function. As at each point the measurements are repeated 5 times, the accuracy function iteratively computes the position of the user by finding middle points between estimated positions. The corrective function is used to display the position of the user correctly on the building map, i.e. whenever the computed position is outside the building the system should draw it properly inside. The implemented system returns satisfactory results. In the experiments the authors used two different smartphones to verify the positioning results with no significant difference in the location readouts. The reported experiments, however, were done for static cases only.

Yet another system using the BLE signal and beacons is the PDR system (pedestrian dead reckoning) proposed in [26]. The system, using a magnetometer and a step counter, counts the steps taken together with their direction vector. Then, based on the steps, it calculates the current position, relative to the last known exact position, which in turn is determined at the time of a strong Bluetooth signal detection from a beacon with a defined position. In addition, the system can detect new unknown beacons and save them as new reference points with positions resulting from the current steps, thanks to which it updates itself with new beacons and performs calibration. The author of the work proposed 6 variants of the positioning algorithm, the most accurate of which has an average accuracy of 3.4 m. The advantage of this system is that it does not require placing beacons in every room, because they are only used for reference. The disadvantage of the system is that it requires prior calibration of the steps model for each user and the fact that it also requires the phone to be in stable orientation relative to the user - pocketing or removing the phone from the pocket or purse negatively affects the accuracy.

The classification of the topics of the works covered in this section is visually presented in Figure 1.

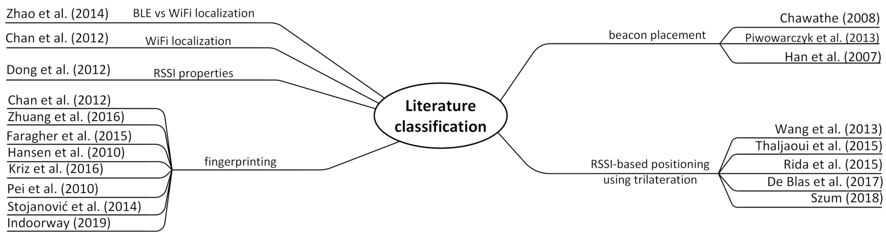

Figure 1: Literature classification with contributions from different authors.

Here we would like to briefly sum up in particular the experimental systems for indoor localization based on BLE beacons that use trilateration which we discussed in this section. The realization of such systems offering acceptable accuracy is possible even though the RSSI signal used to establish the position is not particularly dependable. Better location precision is achieved by systems doing multiple measurements and using techniques to compute the best position out of the measured values. Not all the presented systems were tested in the dynamic setup and most of them were tested in small, regularly shaped rooms.

3 The Positioning System

The system presented herein utilizes Bluetooth Low Energy beacons as signal transmitters, and a standard smartphone for signal receiving and processing. For position determination we used an RSSI-based trilateration algorithm. The positioning algorithm was implemented as part of an Android mobile application. This section gives technical details related to beacons that were used in the system, as well as system design and explains the trilateration technique.

3.1 Communication Between System Nodes

Communication between system nodes, that is between beacons and a user smartphone, is realized with the use of Bluetooth Low Energy (BLE). BLE is low power technology operating in the 2.4 GHz ISM radio band. The technology is driven by the need for consumer devices like smartphones to be able to connect to low power sensors (e.g. smart watches) without requiring long handshake period of Bluetooth 2.2 [12]. Bluetooth beacons are small Bluetooth Low Energy devices that broadcast their unique identifier and other telemetry data. They usually implement two most popular advertising protocols: Apple iBeacon (2013) and Google Eddystone (2015).

For the implementation of the IPS system we chose Estimote Location Beacons. The devices transmit BLE v. 4.2 signal at 2.4 GHz and implement both of the mentioned protocols, as well as an additional Estimote protocol. Broadcasting power can be adjusted within the range from -40 dBm to 10 dBm (0.0001 mW to 10 mW respectively). The Estimote Location Beacons are also equipped with additional sensors such as: barometer, thermometer, motion and light sensors, as well as light-emitting diode (LED), near field communication (NFC) module and 4 general-purpose input/output (GPIO) connectors. The beacons are powered by a CR2477 button cell battery of 1000 mAh capacity. Depending on the operation mode and configuration the beacon is capable to work up to 5 years on one battery. To optimize power consumption beacons do not broadcast their signal constantly; it is emitted in time intervals, which can be adjusted within the range from 100 ms to 2 s. Both the broadcasting power and the broadcasting interval have direct impact on the remaining battery life. With the configuration set to 4 dBm broadcasting power and 100 ms broadcasting interval, which were used in the implemented system, the devices report 2 years of remaining battery life.

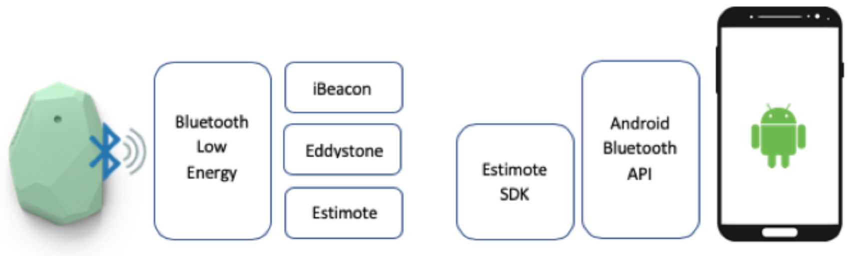

Figure 2: Estimote beacon communication schema.

Estimote Inc. provides a software development kit (Estimote SDK) for Android and iOS platforms. The SDK enables developers to interact with beacons programmatically, independently of platform specific BLE interface details. The SDK can be used free-of-charge to interact with up to 20 beacons; in order to interact with more beacons, a paid subscription is required. The communication schema for Estimote beacons for an Android device that we used is given in Figure 2.

3.2 Trilateration

Trilateration is a mathematical technique for determining the position basing on the distances from three reference points. In two-dimensional space the distance from one reference point sets a circle on which the positioned object is located. The distance from the second reference point sets second circle whose intersection with the previous one defines two hypothetical object positions. The distance from the third reference point allows for the exact calculation of the object location. Trilateration may be carried out similarly in three-dimensional space. In such a case spheres are considered instead of circles. (The calculations can also be carried out with more than three reference points; the process is then called multilateration.)

Mathematically trilateration in two-dimensional space means finding a point that satisfies three circle equations which is the equivalent to solving a set of three equations with two unknowns, as given in Equations 1-3.

$$r_a{}^2 = (x - x_a)^2 + (y - y_a)^2 \tag{1}$$
$$r_b{}^2 = (x - x_b)^2 + (y - y_b)^2 \tag{2}$$
$$r_c{}^2 = (x - x_c)^2 + (y - y_c)^2 \tag{3}$$

The x and y unknowns are coordinates of a point which represents the position of an object that we would like to determine. The r_a, r_b, r_c represent the measured distances from reference points. The $x_a, y_a, x_b, y_b, x_c, y_c$ are the known coordinates of reference points. It must be noticed that the reference points are usually defined in a local coordinate system of the building floor; the distances are usually measured in commonly used units (e.g. meters). Before applying distances to trilateration equations they must be first scaled to the same coordinate system as the reference points. The coordinate system for a sample trilateration problem has been shown in Figure 3.

It is important to notice that the situation in which all circles intersect in exactly one point is rather theoretical and hardly probable in real conditions. Due to the fact that signals get disturbed the circles may not intersect at all or the intersection may designate an area instead of a point. The set of trilateration equations may not have a proper solution then, which is a serious difficulty as far as implementation is concerned. In such a case the solution cannot be calculated directly and approximation techniques must

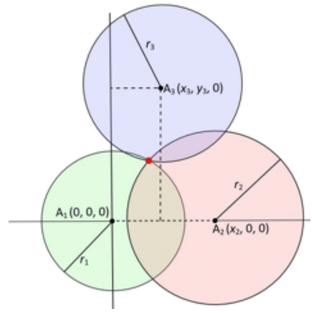

Figure 3: Local coordinate system for a sample trilateration problem [27].

be used. One of the frequently used approximation techniques employs Lavenberg-Marquard nonlinear optimization algorithm [28].

For the implementation of the system an open-source trilateration library was used that employed the Lavenberg-Marquard nonlinear optimization algorithm for solving the trilateration problem [29].

3.3 Signal Propagation Model and Distance Estimation

In order to perform trilateration it is essential to estimate the distances from reference points. Due to the free-space path loss phenomenon (FSPL) the received signal strength may be utilized to estimate the distance from the signal transmitter. The relationship between free-space path signal loss and the distance between the transmitter and the receiver is expressed with Equation 4 derived from Friis transmission formula given in [30].

$$FSPL = (\frac{4\pi d}{\lambda})^2 = (\frac{4\pi d f}{c})^2 \tag{4}$$

The d symbol represents the estimated distance in meters between the transmitter and the receiver, λ represents the wave length in meters, which can be substituted with quotient of c and f, where c is the speed of light in vacuum (in m/s), and f is frequency in Hz. The square is implied from the inverse square law, which describes theoretical relationship between signal strength and distance. In real life conditions though, due to reflections, interferences, refractions and diffractions, the real relationship may be stronger or weaker. As a result, the power of 2 is substituted with a constant γ, called propagation constant or path-loss exponent, which describes the intensity of signal strength loss on the propagation path in a particular environment (signal strength loss is typically stronger in open spaces with obstacles suppressing the signal and weaker in closed spaces where the signal reflects and strengthens). In consequence, the equation can be transformed to the form given in Equation 5.

$$FSPL = (\frac{4\pi d f}{c})^\gamma \tag{5}$$

FSPL can also be expressed in dB (Equation 6) and separated into a sum of two factors, as shown in Equation 7.

$$FSPL(dB) = 10\log_{10}((\frac{4\pi d f}{c})^\gamma) \tag{6}$$

$$FSPL(dB) = 10\gamma\log_{10}(d) + 10\gamma\log_{10}(\frac{4\pi f}{c}) \tag{7}$$

Both the speed of light in vacuum and π have known, constant values. However, the frequency of Bluetooth signal is variable and fits between 2.4 and 2.4835 GHz. The propagation constant depends on the environment where the signal is transmitted, as mentioned above. Therefore, the second part of the sum in Equation 7 can be substituted with one constant called Measured Power (or TxPower), which is usually denoted with A. The A constant is evaluated precisely by the manufacturer at the distance of 1 meter (then the first part of the sum equals zero) and it is hardcoded into each device. Each beacon transmits the value of the A constant which enables the distance estimation based on the received signal strength. The method is called RSSI (Received Signal Strength Indicator) and is described by Equation 8.

$$RSSI = -10\gamma \log_{10} d + A \tag{8}$$

Simple transformation of the Equation 8 leads to the desirable (from our perspective) form useful for distance estimation (Equation 9).

$$d = 10^{\left(\frac{A-RSSI}{10\gamma}\right)} \tag{9}$$

Value of the propagation constant depends on the particular environment. According to the inverse square law it is equal to 2 in free space. In environments with a lot of obstacles the relationship may be stronger, while in indoor environments it may be weaker due to signal reflections and reinforcements. Although the general empirical value ranges are known (outdoors: 2.7-3.5; indoors: 1.6-1.8) [31], the exact value can be different for every building and should be determined for the particular environment.

The impact of the accuracy of the propagation constant is higher at further distances. A -70 dBm signal received at the distance of 3 meters would be estimated at 3.1623 m for $\gamma = 1.6$ while for $\gamma = 1.8$ the estimation would result in 2.7826 m which means inaccuracy of 0.3797 m. However, a -76 dBm signal received at 8 meters would be estimated at 7.4989 m for $\gamma = 1.6$ and 5.9948 m for $\gamma = 1.8$ which means inaccuracy of 1.5041 m, depending on the value of the propagation constant.

In order to determine the value of signal propagation constant we conducted an experiment. The signal was repeatedly measured at known distances and the propagation constant was calculated with the formula given in Equation 10.

$$\gamma = \frac{A - RSSI}{10 \log_{10} d} \tag{10}$$

The measurements were carried out in a large, empty office room (around $100\,\mathrm{m}^2$ and $3\,\mathrm{m}$ high) every one meter (with one exception) on a straight line. The beacon was placed on the wall at the height of 1.2 m. The measurements were taken with Samsung S7 smartphone in a protective case. The phone was held in hand in a natural way at approximately 1.2 m above the floor.

600 measures were carried out at 12 different distances (50 measures for each distance) and the total average value of the propagation constant was evaluated at 1.735925. The collected signal data was then used to verify the accuracy of the signal propagation model and the distance estimation. The results are gathered in Table 1.

It can be observed that up to the distance of 4 meters from the signal transmitter the distance estimation is very precise (average error is about 37 cm). For the distances from 4 to 8 meters the average error is slightly higher, yet still acceptable (avg. error below 2 m). Above the distance of 8 meters the estimation can be considered useless in terms of the positioning. The total error average for distances from 0.5 to 8 meters is 0.83 m. The maximal error observed for this distance range was 3 m. The 90^{th} percentile for 0.5-8 m range was estimated at 2.3 m. Such values are promising in terms of further positioning as far as human perception of indoor localization is considered.

Distance [m]	Estimated distance [m]	Average error module [m]	Error module 90^{th} percentile [m]
0.5	0.5793	0.0793	0.1717
2	2.1788	0.1788	0.8897
3	3.2426	0.2426	1.3020
4	4.3713	0.3713	1.6089
5	4.0626	0.9374	2.1103
6	4.5138	1.4862	2.2324
7	5.6494	1.3506	2.6980
8	6.0057	1.9943	2.4607
9	12.8308	3.8308	7.2080
10	10.8977	0.8977	4.1946
11	15.4477	4.4477	7.5070
12	22.7653	10.7653	12.1295

Table 1: Mean values of distance and average errors for 12 distances.

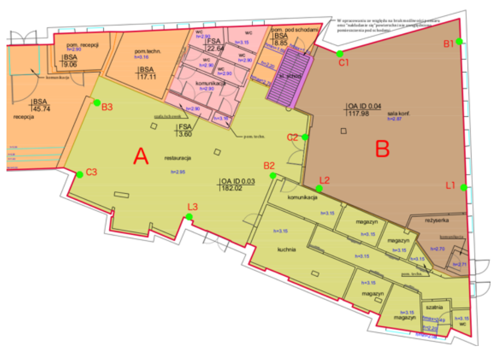

Figure 4: t in the office rooms (beacons are marked as green circles).

4 Evaluation of the IPS System

In order to evaluate the quality and precision of the designed system, the system was implemented and tested in an office building. In this section, we discuss beacons deployment in the tested office rooms and present results of the positioning in static and dynamic scenarios.

4.1 Beacons deployment

The system was implemented and tested in two large office rooms of irregular shapes. As already mentioned, the way of beacons deployment in the building has direct impact on the overall system quality. The beacons should be placed in such a way that everywhere in the rooms there is a line-of-sight propagation available from at least three transmitters; it is then possible to perform trilateration based on strong and direct signals.

According to manufacturer's recommendations [32] the beacons should be placed around 2 m above the floor level in order to reduce line-of-sight shadowing and should not be installed on metal surfaces, as these may cause signal interferences. It is advised to deploy beacons on wooden, brick, plastic or glass surfaces. The beacons were installed according to these recommendations, as shown in Figure 4.

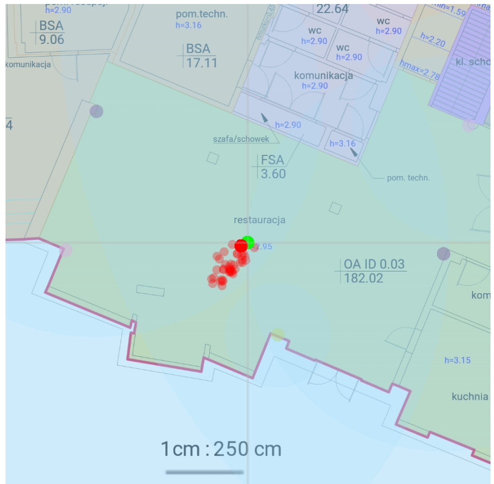

Figure 5: Floorplan with the real position marked green and 40 taken measurements marked red.

4.2 Static Analysis

In order to evaluate the accuracy of the output position of the implemented system a set of measurements was carried out in static positions defined a priori. Before each series of measurements, a real position was manually defined, so it was possible to use it as a reference in the experiments.

At each position 40 measurements were carried out. Figure 5 depicts the floorplan with red points being the taken measurements while the real position is marked with the green point. For each series of measurements, the accuracy error was calculated as a Euclidean distance between real and system-output positions. Then the minimal, maximal and average error values were calculated, as well as 90^{th} percentile value.

4.2.1 Raw Signal

At the beginning raw signals were used to determine the position. The first series of measurements at the first location was shown in Figure 5. For the first series of measurements we achieved the following errors: the minimal error was 0.28 m, the maximal error was 1.75 m, the average error was 1.00 m and the 90^{th} percentile was 1.55 m. Such values would be satisfying for the system, but further measurements revealed a negative effect shown in Figure 6.

The minimal error for the second series has degraded to 5.40 m, the maximal error grew to 8.82 m, the average error to 6.49 m and the 90^{th} percentile to 7.87 m. For the third series the values were: minimal 2.81 m, maximal 7.33 m, average 5.45 m, the 90^{th} percentile 6.52 m. So, in those two locations the results were significantly worse compared to the first one.

The reason behind such large error values was that all the received signals were taken into account during trilateration, including those very weak or received from remote beacons located in other rooms, behind the walls. Those weak signals had negative effect on the output position. In order to avoid such situation the weak signals should be ignored.

4.2.2 Minimal Signal Strength Threshold

In the next series of measurements, a minimal signal strength threshold was set for -78 dBm, which was the value of the weakest signal received at 8 meters. All the signals below the threshold value were ignored. The measurements were made in the same positions as the previous ones. The example results

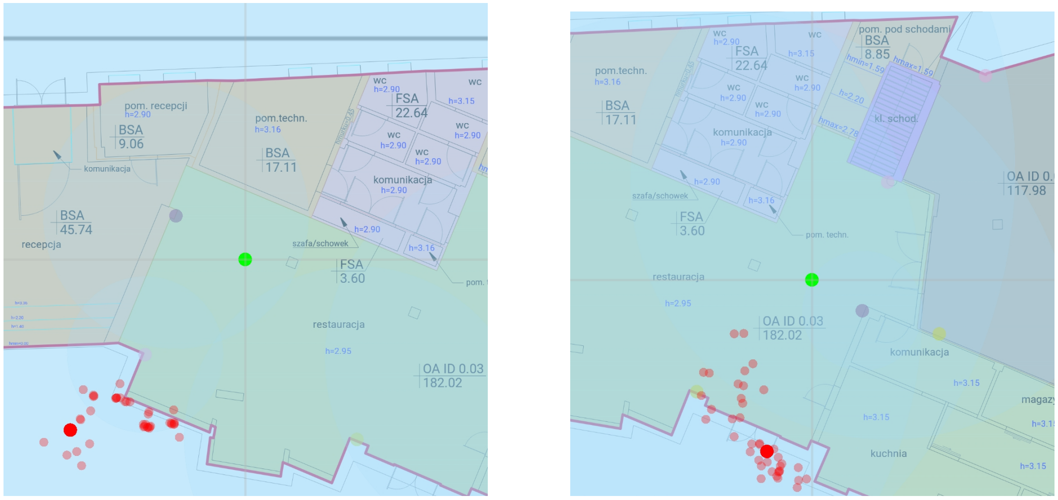

Figure 6: Negative effect on the measurements resulting from including weak signals from beacons located in other rooms.

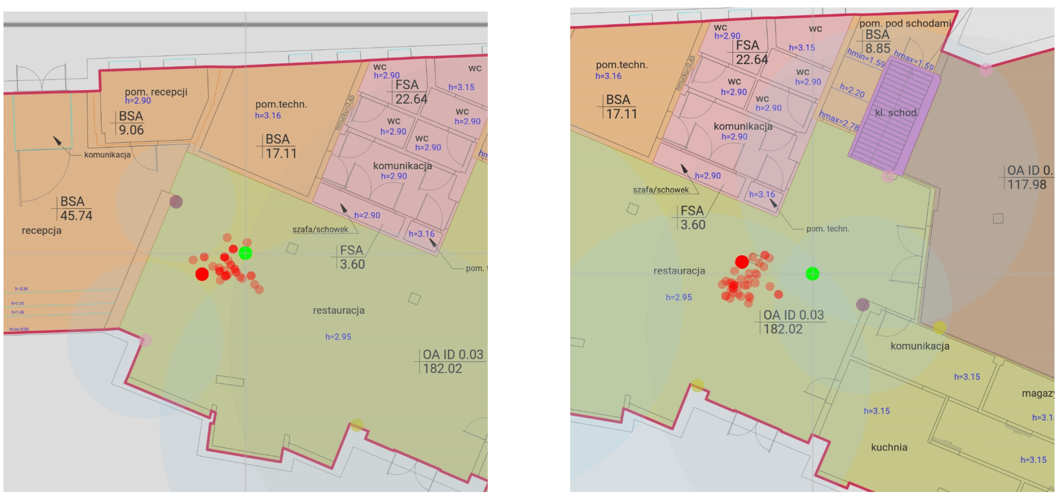

Figure 7: Computed positions (red dots, green dots represent the real positions) after filtering out weak beacon signals.

of positioning with the filtered out signals are presented in Figure 7. It can be clearly observed that the accuracy significantly improved. A comparison of 8 series of measurements is presented in Table 2.

Improved values were marked green, worsened values were marked red. Despite the fact that in one position the accuracy degraded, in the majority of positions signal filtering enhanced the accuracy of the positioning. The minimal error was 0.04 m, the maximal error was 8.72 m, the average error was 2.18 m. The 90^{th} percentile was 3.07 m.

While conducting the measurements, we observed that the received signals fluctuate even though the receiver is in a constant position. This is due to phenomena such as signal reflections, multipath propagation or electromagnetic field changes. The signal strength may significantly weaken for a few seconds. Those fluctuations cause the output position to be less stable and affect the accuracy of positioning.

Position	Filtering threshold	Minimal error [m]	Maximal error [m]	Average error [m]	90^{th} percentile [m]
A	none	0.2781	1.7465	1.0069	1.5450
B	none	5.4041	8.8239	6.4933	7.8728
C	none	2.8135	7.3378	5.4598	6.5222
D	none	3.8631	9.1200	5.5188	6.5606
			Total 160 measurements:	4.6197	6.6421
A	-78 dBm	1.6913	4.6920	2.4300	2.7647
B	-78 dBm	0.0346	1.7099	0.8176	1.2076
C	-78 dBm	1.2940	2.9579	2.2559	2.7986
D	-78 dBm	1.3121	8.7208	3.2005	6.6799
			Total 160 measurements:	2.1760	3.0685

Table 2: Comparison of error values before and after applying signal filtering for four selected measurement positions, referred to as A, B, C, and D.

4.2.3 Signal Smoothing

Signal fluctuations can be reduced with the use of signal smoothing techniques. Moving average is one of the possible smoothing approaches. In our experiments we compared two moving average variants: simple (SMA) and weighted (WMA). The simple moving average is just an average of n last data points, while the weighted moving average assigns different weights to data points from different periods, usually according to an arithmetic progression. The SMA and WMA variants are expressed with the formulas given in Equations 11 and 12.

$$SMA = \frac{p_0 + p_1 + ... + p_{n-1}}{n} \tag{11}$$

$$WMA = \frac{np_0 + (n-1)p_1 + ... + p_{n-1}}{n + (n-1) + ... + 2 + 1} \tag{12}$$

In the formulas for SMA and WMA p_0 represents the most recent value, while n represents the size of the history window. The size of the history window represents the number of last observations that the current signal should be referred to. The bigger the window, the stronger the smoothing that is applied, which causes the signal to be more stable and less susceptible to signal changes resulting from relocating. The size of the history window was set to 5 in the implemented system.

Different definitions of the two presented moving average variants imply their slightly different characteristics. SMA applies stronger smoothing in comparison to WMA, as it treats equally all observations in the history window. WMA favours the most recent observations, gradually lowering the weights of older data points, which makes it more sensitive to signal changes when the object is relocating.

In order to evaluate the impact of signal smoothing, further measurements were carried out. In some locations higher concentration of output positions have been observed, as presented in Figure 8. In most of the tested locations signal smoothing slightly improved accuracy of the positioning. The WMA method lowered the average error from 2.17 m to 1.8 m (improvement by 0.37 m), while SMA lowered average error from 2.17 m to 1.89 m (improvement by 0.28 m).

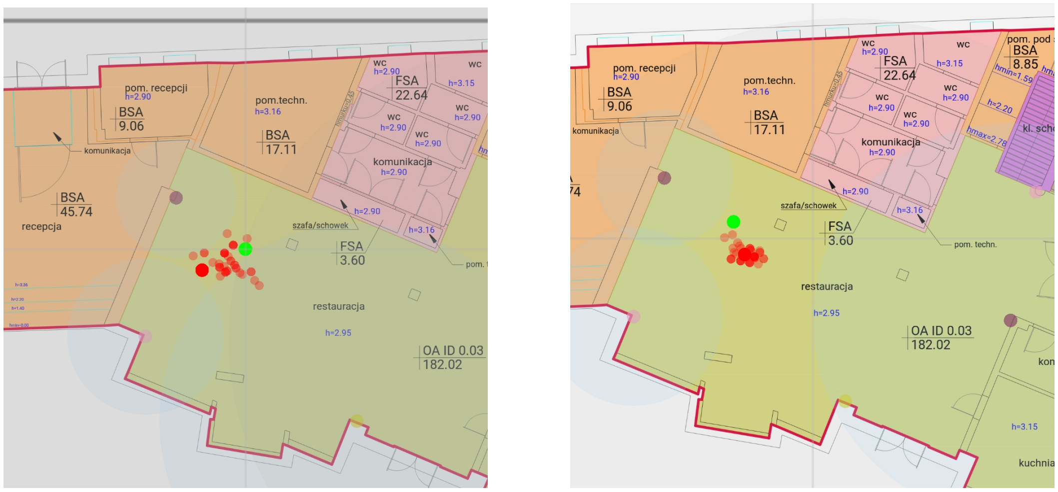

Figure 8: Computed positions (red dots, green dots represent the real positions) before and after signal smoothing.

4.2.4 Centroid Calculation

Methods presented in the previous section refer directly to the received signals. They were introduced in order to stabilize the signal and eliminate fluctuations stemming from temporary signal disruptions. Those methods slightly improved the accuracy of positioning. For further improvement we considered another averaging method, namely centroid calculation.

Centroid of a plane figure is the arithmetic mean position of all the points in the figure. The definition extends to any object in an n-dimensional space: its centroid is the mean position of all the points for all coordinates. For a set of points, it is the point which minimizes the sum of squared Euclidean distances between itself and each point in the set.

In the implemented system the final position of the user's smartphone (and thus the user) was calculated as a centroid of the last 5 trilateration output positions. Further measurements were carried out, however any significant improvement in the overall system accuracy could not have been observed, yet in some locations the output positions were slightly more concentrated.

4.2.5 Summary of the Static Analysis

With all the enhancements presented in the previous sections that were applied, i.e. the minimal signal strength threshold, the SMA signal smoothing and the centroid calculation, we carried out 320 measurements at 8 specified positions. The measurements from 6 sample locations are presented in Figure 9. A comparison of methods employed to enhance the quality of positioning is presented in Table 3.

The accuracy for all the measurements ranged from 0.11 m (minimal error) to 4.43 m (maximal error), the average error was estimated at 1.75 m. For 90% of the measurements the accuracy ranged from 0.11 m to 2.53 m (90^{th} percentile). Such results are satisfying in terms of human perception of indoor localisation.

4.3 Dynamic Analysis

Static analysis proved that our system is capable of determining the position with sufficient accuracy when object remains still. The next phase of the system analysis was to see whether the output position accuracy was still satisfying for moving objects.

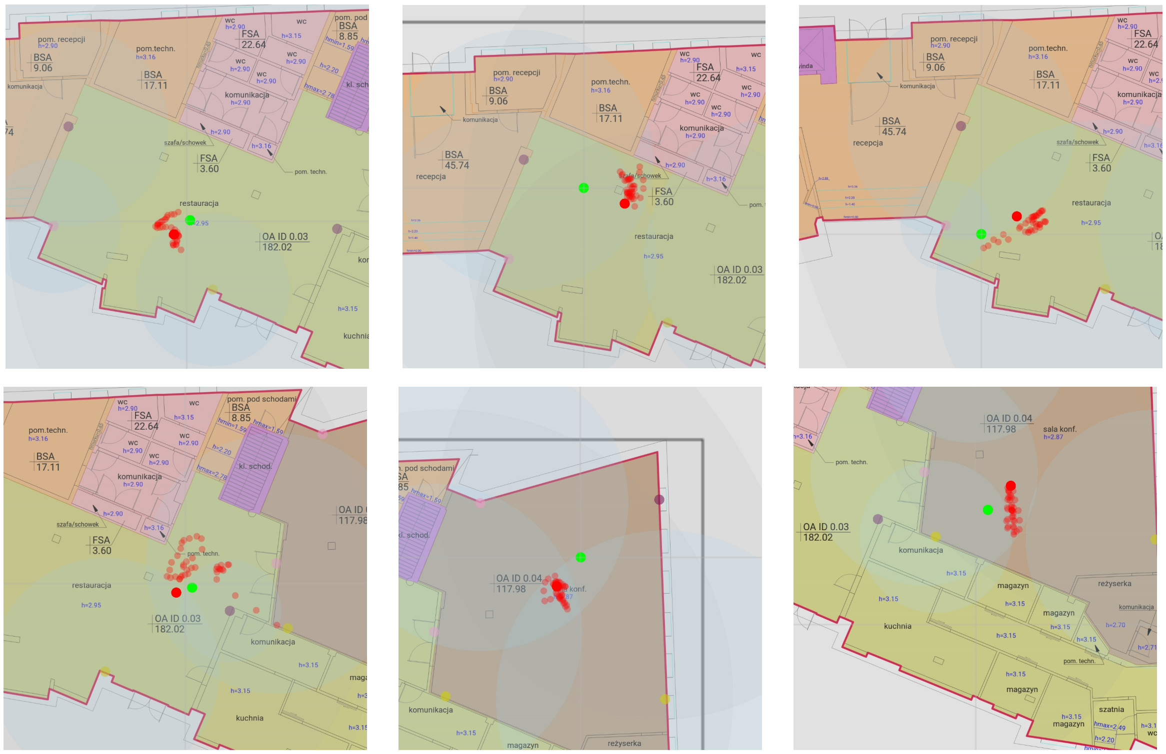

Figure 9: Measurements for 6 sample locations with filtering, smoothing and centroid calculations (large red dots, green dots represent real positions).

Method	Raw signal	Minimal signal strength threshold	Signal smoothing	Centroid calculation
Signal strength threshold [dBm]	-	-78	-78	-78
Smoothing method	-	-	SMA	SMA
Centroid	no	no	no	yes
Tested locations	4	4	4	8
Total number of measurements	160	160	160	320
Results:				
Maximal error [m]	9.12	8.72	5.25	4.43
Average error [m]	4.62	2.18	1.89	1.75
Median [m]	5.49	2.17	1.72	1.75
90^{th} percentile [m]	6.64	3.07	2.73	2.53

Table 3: Comparison of methods employed to enhance the quality of positioning.

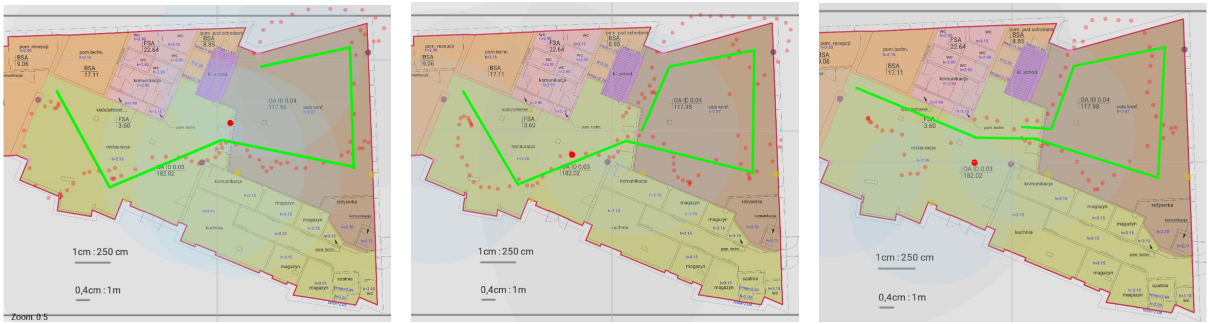

Figure 10: Computed positions of a moving object (red dots) vs. real movement trajectories (green polylines).

In contrast to the static analysis, in this scenario it is impossible to define the real position in order to refer the system output positions to it, as the real position is changing during relocation. Nevertheless, the track of output positions may be saved in order to evaluate it later. In Figure 10, the measurements for the three covered paths were presented. System output positions were marked with red points, while the real paths were marked using green polylines.

One can see that on some sections of the traversed paths the accuracy is acceptable, while on few sections it is burdened with significant error, especially on the first section which is starting at the west area of the building and also on the section located alongside north wall of the building, where output positions are even located beyond the building.

The sections where inaccuracy may be observed are areas where received signals were too weak and unstable to provide accurate positions. In such areas additional beacons should be placed in order to improve the accuracy.

For the next experiment all beacons were placed in one room to decrease the distances between them, which should result in stronger and more stable signal available in the whole positioning area. The results were presented in Figure 11. It can be observed that with the increasing number of beacons in the room the accuracy of positioning improved. This is due to the fact that in every place of the room strong enough signal was available.

5 Conclusions and Recommendations

The implemented system showed satisfying positioning accuracy during the static analysis. With the minimal signal strength threshold, signal smoothing and centroid calculation applied the accuracy ranged from 0.11 m to 4.43 m (with the average accuracy of 1.75 m), while for 90% of the measurements the accuracy was better than 2.53 m.

During the dynamic analyses at some sections of the traversed paths a drop in accuracy was observed. We linked that to the areas where received signals were too weak and unstable to determine accurate positions. The increase in the number of beacons in one room, and consequently decrease in the distances between the beacons, significantly improved the positioning accuracy in the dynamic scenarios.

There are some possible enhancements that can be applied to the system for further improvement of the positioning accuracy. Firstly, at the hardware layer, beacons emitting stronger signal can be used. The Estimote Location Beacons that we used transmit BLE signal with the maximum power of 4 dBm, while newer hardware version of these devices are capable of transmitting the signal with 10 dBm power. Stronger signal can improve the quality of positioning. Also, as the last experiments showed, the increase in density of beacons placement improves the quality of positioning.

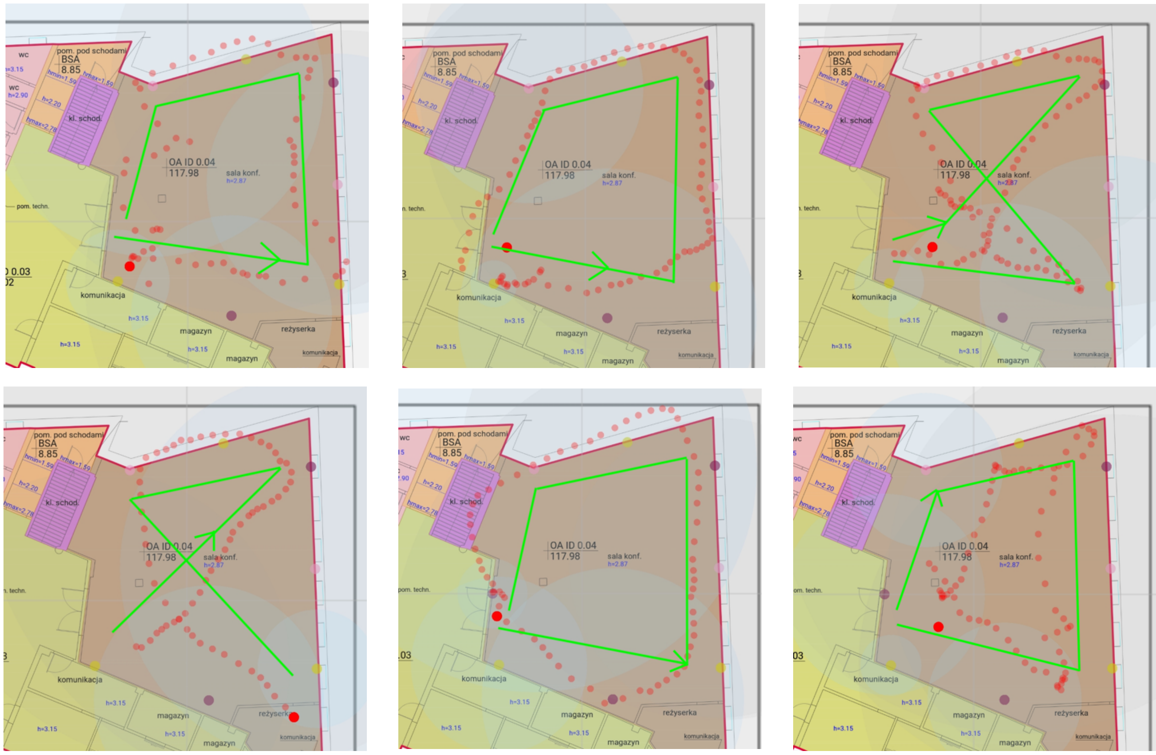

Figure 11: Computed positions of a moving object (red dots) vs. real movement trajectories (green polylines) with increased number of beacons.

Enhancements can also be introduced at the floor plan layer. Not only beacons locations could be defined but also the building outlines as well as forbidden areas like walls, closed rooms and closed spaces. Then, the positioning algorithm could exclude those results of trilateration that do not fit within the allowed areas and adjust the final position accordingly. Analogously, a graph of allowed paths could be defined, and all trilateration output positions could be pulled towards the allowed paths. What is more, if rooms were also defined at the floor plan layer, the minimal signal strength threshold proposed in subchapter 4.2.2. could be enhanced with room-aware logical approach where signals from rooms other than the current one are filtered out.

The designation of signal propagation constant is another field where improvements could be used. Once manually calibrated constant may be different for rooms of different types within the same positioning area. Calibration could be held on room level (or custom user-defined area level) so as to reflect signal propagation more precisely in each room. In situations where system deployment ease is crucial a set of typical propagation constant values for different room types could be prepared. The presentation layer could also be enhanced. The point which represents the current position could be animated between subsequent results of trilateration with the use of interpolation, which would eliminate the "hopping" effect and could make the final position move smoothly in a continuous way.

6 Discussion

In this chapter we discuss advantages of our system over selected systems (Indoorway and PDR) presented in the first part of the paper.

As far as the deployment of the system is concerned it only requires to install beacons in the building and prepare floor plan with defined positions of the deployed devices. The beacons are small, easy to install and relatively cheap. System maintenance is limited only to changing beacon batteries once every two years.

Compared to the Indoorway system, the proposed BLE trilateration-based system is easier to extend. In order to cover subsequent rooms or floors it is only necessary to place additional beacons there. In the proposed solution it is also easier to eliminate the areas in which poor accuracy was observed during system usage. In both cases the Indoorway system would require building signal heatmap from scratch.

In comparison to the PDR system there is no need to perform step length calibration for each user. The BLE trilateration-based system is also less susceptible to the changes of smartphone orientation than the PDR system. Moreover, PDR requires that the phone is equipped with magnetic field sensor, gravity sensor and steps sensor [26], which are not standard features of every smartphone.

The manufacturer of Indoorway system states that its accuracy is in the range of 1-2 m [33]. The author of the PDR system proved that its average accuracy is 3.4 m [26]. The results of measurements documented in this paper proved that the proposed BLE trilateration based IPS system provides information about indoor position with an average accuracy of 1.75 m and the accuracy better than 2.53 m in 90% of the cases, what situates it between the two compared solutions accuracy-wise.

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