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Comparative Analisis of Digital Filters for Proper Positioning of User Mobile Device Using BLE Transmitters and Multilateration Technique

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Abstract. Nowadays, traveling without systems supporting navigation and guidance to the destination is hard for us to imagine. The outdoor positioning techniques used in these solutions have been mastered mainly by global positioning systems. However, assisting the navigation of users inside large public buildings still needs to be improved. It matters even more for persons with special needs, such as visually impaired, seniors, or people in wheelchairs. Determining the correct position of the user inside the complex space of a multi-floor building is a big challenge for such persons. Several methods can help in this matter. For example, technologies such as RFID, WIFI networks, image recognition, or lidar are used. However, the best solution to this problem is using infrastructures of low energy transmitters (BLE), called beacons. Then, construct an appropriate map to determine the user's position to help guide the user to a destination. Nevertheless, to designate such a position, we need to know each transmitter's signal strength and coordinates. Because of the physical properties of radio waves, the data collected from such transmitters are often inaccurate. This paper compares two methods, the Kalman filter and particle filter, to improve the quality of signal strength data received from BLE transmitters. As a result, the recommendation of the Kalman filter as the best method to improve the quality of these data and use it in the developed applications supporting indoor navigation in large buildings is provided.

Keywords: indoor positioning, BLE transmitters, filtering beacons data, multilateration

1 Introduction

Nowadays, it is easier to imagine our life using various navigation systems that help us reach unknown places while traveling by car, bicycle, or even on foot. Systems such as Google Maps [1] or Open Street Maps [2] are in everyday use. They are widely used to help the user find the destination according to the address or category of the place and then lead him to it. Some solutions of this type also consider the needs of disabled individuals such as blind or visually impaired (BVI) or wheelchair users. These are navigation applications such as GetThere, [3] DotWalker [4], or Seeing Asistant Move [5].

However, the situation is much more difficult when supporting independent navigation of users inside buildings, mainly because the developed solutions cannot use global positioning systems, i.e., GPS [6]. There are several problems to be solved in this case. One of them is appropriately recognizing obstacles and warning the user about them, which is especially important, for example, for the BVI users. It can be solved by using methods such as mapping the environment with lidars [7] or using various types of cameras and then image recognition and its classification [8]. Another critical problem in indoor navigation is the correct positioning of the user's mobile device inside the building, which is crucial to guiding them to their chosen destination. Various methods are used to do this, but the two most effective approaches seem to be the Fingerprint method [9,10] and log-distance path loss model [11]. Solving the positioning problem is crucial because it allows for solutions that support the user's determination of routes or the pedestrians safe drive along the route.

This paper proposes a method of determining the position using beacons located inside the building to improve the methods of user positioning. The log-distance path loss model is used to determine the user's position. However, during the experiments, it turned out that the accuracy of the transmitters' signal strength data often needs to be higher. It occurs when the distance between the user's device and the transmitters is considerably great (namely, exceeds 8m). Therefore, applying several filters to the received data was necessary, which significantly improved the final accuracy of determining the user's coordinates. The Kalman filter and particle filter were compared to check for better results. The comparison led us to conclude that the best results in improving the quality of data obtained from the transmitters are achieved after using the Kalman filter with an average distance from the transmitters of 5m. However, the results obtained after using the particle filter were also sufficient, especially in some situations. It is worth adding that the proposed method is currently implemented as a system to support the navigation and safety of disabled users [12] on our university campus.

In the following sections of this paper, we described an experiment during which we created an appropriate simulation environment, collected data, applied and compared selected filters, and analyzed the results. So, the rest of the paper has the following structure. The following section presents a solution proposed in the literature to support user positioning inside the building. Then, the True-range multilateration method, which gives the best results relatively quickly, is described. In the next section, the preparation and implementation of our method is described. Then, the experiment's results and possible use in real working systems are discussed. The paper ends with a conclusion concerning plans for future research with practical development and implementation of our proposal.

2 Existing solutions for indoor positioning of user's device

As we know, many technologies support user navigation in the outdoor environment. However, the situation is worse regarding navigation inside buildings, which need GPS to determine the user's position. One of the leading technologies that aspired to solve this problem was RFID tags [13]. Although a single RFID transmitter is relatively cheap, due to its modest range of several meters, the system using this technology must be composed of many transmitters, resulting in high costs of its maintenance [14].

The same problem would be met when using optical technologies based on infrared radiation, e.g., IrDA [15]. Moreover, applying the above solutions could have been improved by the need for more generally accepted standards.

Technologies based on Received signal strength indication (RSSI) seem to be a remedy for the above problems [16]. The advantage of these solutions is that the transmitters used in them have a much greater transmission range, which, unfortunately, is often associated with lower signal strength accuracy. This lower accuracy causes the calculated coordinates to be more accurate. Various mathematical mechanisms can be used to correct them. We can divide them into two categories: based on fingerprints [9,10], or log-distance path loss model [11]. In short, the fingerprint method measures the strength of all received signals in a given place and creates a unique fingerprint vector. This vector is then compared with the fingerprints previously stored in the database, resulting in the selection of the best match. On this basis, the user's position is calculated. Even the fingerprint method is more accurate than RSSI. It is time-consuming in development, e.g., it requires two-phase implementations [17] namely the training and developing phases.

RSSI-based technologies are, therefore, a faster solution, although their implementation is associated with other problems. They are based on defining the distance from the transmitter to the receiver using the so-called a propagation model. According to this model, if we have the approximate distance to each transmitter and their positions, we can determine the receiver's position using multilateration techniques [18]. RSSI technologies were initially used with Wi-Fi, but this began to change after the development of the Bluetooth Low Energy (BLE) protocol and the emergence of BLE-based beacons. Beacons appear cheaper, smaller, and less energy-consuming devices [19,20]. Moreover, powering them from batteries allows for installing transmitters without significant problems in various places without frequent replacing or recharging the battery. In addition, smartphones that are usually used as receivers can easily read the signal strength from many Bluetooth devices than from many Wi-Fi networks. For this reason, we decided to use these solutions in our experiment.

3 Method of positioning based on True-range multilateration

To solve the problem of assisting the user's navigation inside buildings, we chose the method of positioning based on True-range multilateration. It uses the infrastructure of BLE transmitters installed in the building and determines the user's position in space based on signals reaching a device from these transmitters

3.1 Determining coordinates of a receiver

The operation of true-range multilateration consists of determining the position of the user device with known coordinates of transmitters and a known radio wave propagation model. It goes as follows: Initially, we have at least three transmitters in a given space. The receiver, a mobile device, is placed inside this area. Then, we use a receiver to measure the strength of the signals received from each transmitter. The situation described above for the three transmitters is shown in figure 1.

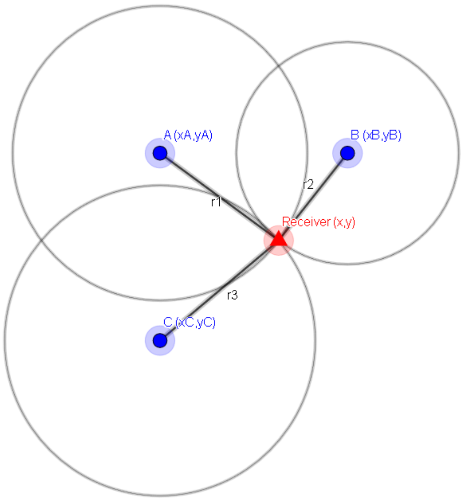

Figure 1. True-range multilateration in the 2-D scenario

To determine a receiver's correct location, we need to calculate the distance from it to each of the transmitters. We can do this using the known strength of the signal sent by the transmitter and received by the receiver. However, this signal strength does not decrease linearly with increasing distance. This change in distance is in line with the radio wave propagation model. It can be expressed using the following formula:

$$RSSI = -10n * log(D/D_0) + C_0 \tag{1}$$

where:

– $RSSI$ is an indicator of signal strength,

- D is the distance between transmitter and receiver,
- $C0$ is the signal strength at a distance of $D0$ (usually equals 1 meter)
- n was an environment variable depending on the wave interference in a given room and determined experimentally. In our experiment, it usually had a value of around 2.

After transforming the above formula, we obtain the following formula that allows us to calculate a distance:

$$D = 10^{\frac{(RSSI+C_0)}{-10n}} \tag{2}$$

By considering the distances from the receiver to each transmitter, we can calculate the coordinates of the above model of signal loss using three simple Pythagoras equations. For example, for one of the three distances shown in figure 1 it can be expressed as follows:

$$(x - xA)^2 + (y - yA)^2 = D^2 \tag{3}$$

Using similar equations for the other two distances, we can calculate the x and y coordinates of the point where the receiver is located.

3.2 Configuration and calibration of the transmitters

The correct hardware configuration and calibration of the transmitters were essential steps in calculating the receiver's coordinates. The configuration process is based on using the Generic Attribute Profile (GATT), which contains sets of parameters and functions that enable the correct configuration of the transmitter. In the case of iNode transmitters used in our solution, their essential parameters were majorID, minorID, transmit interval, and power level.

- MajorID and MinorID are identifiers of a specific transmitter that can be set during their first configuration to be unique in a given building space.
- Transmit interval is the interval at which the transmitter sends its signal. It can also be set during the initial configuration of the transmitter.
- Transmitting power is the signal strength the transmitter sends to the receiver 1m away from it. This parameter can also be set. It should be added here that this parameter is expressed in a logarithmic unit dBm - decibels per meter.

It is obvious that these quantities are interdependent and affect, for example, the lifespan of a transmitter on one battery. When we reduce the transmitting interval or increase transmitting power, the transmitter's operating time on one battery will decrease.

Because beacons are radio transmitters operating in a physical environment, signals received at the same place and time sometimes fluctuate considerably. It adversely affects the calculations we make to determine the receiver's coordinates. For this reason, there is a need to improve the quality of data received from transmitters in time. Various mathematical mechanisms called filters are used for this purpose. In the experiment described in this paper, we compared two filters that give the best results when improving the strength of signals received from BLE transmitters. These are the **particle filter** and **the Kalman filter**.

3.3 Improving the quality of data taken from BLE transmitters

Because signals received from one transmitter at the same place at different times fluctuate quite a lot, the quality of data received from transmitters over time needs to be improved. In the experiment described in this paper, we used two filters that give the best results for improving the strength of signals received from BLE transmitters. These are the particle filter and the Kalman filter. Therefore, the operation of both these filters is based on the conditional probability determined for future values using previously known values. They belong to the Bayesian filter family because they use commonly known Bayes' theorem. So, the Kalman filter can be solved based on the equation 4.

$$P\left(s_t \mid z_t, u_t\right) = \eta P\left(z_t \mid s_{t-1}\right) P\left(s_{t-1} \mid u_t\right) \tag{4}$$

However, the following additional assumptions must be taken into account:

1. The transition between states is linear and may be expressed as follows:

$$s_{t+1} = As_t + Bu_t + w_k \tag{5}$$

   Where:
   - s_t is a state vector,
   - u_t is a state modifying transition,
   - w_k is a Gaussian noise that we should add.
2. The observation is linear and may be expressed as follows:

$$z_{t+1} = Hs_t + v_k \tag{6}$$

   Where:
   - z_t is an observation,
   - v_k is a Gaussian noise we must add.
3. The system is continuous

By meeting the above assumptions, we can divide the operation of the Kalman filter algorithm into two stages: the time update stage and the measurement update stage. In the time update phase, the future state is predicted by using the equation 5 while considering the future state's uncertainty. Because the state conforms to the Gaussian distribution and is fully parameterized by the mean s_t and the covariance of P_t, we can update the covariance as follows:

$$P_{t+1} = AP_tA^T + Q \tag{7}$$

where:

- A is a matrix for the propagation of the mean of the state,
- Q is random Gaussian noise.

The next stage is the measurement update phase. It is a correction step in which the observable variable is measured and combined with the previous distribution to estimate the subsequent distribution. In the first step, the measurement is calculated using the linear model from the equation 6. In the next step, the so-called Kalman gain as follows:

$$K = PH^T \left(HPH^T + Q\right)^{-1} \tag{8}$$

Then, we can calculate the difference between the most recent measurement and the expected value based on the current state estimate. It is called innovation because it brings new data about the process, it is calculated as follows:

$$\hat{z} = (z_t - H_t s_t) \tag{9}$$

At this point, we can calculate the textit a posteriori distribution by combining the following equations ref eq: kalmangain and ref eq: kalmaninnovation.

$$s_t^- = s_t + K\hat{z} \tag{10}$$

$$P_t^- = (I - K_t H_t)\, P_t \tag{11}$$

It completes the second step of the Kalman filter algorithm. The above steps are a single iteration of the Kalman filter, where the output is the input to the next iteration. Single iteration steps are shown in the following listing.

The particle filter differs from the Kalman filter because it is not limited by linear models or Gaussian noise. Its name comes from the representation of the probability function as a set of samples called particles that the following equation can describe:

$$\mathcal{S}_t := s_t^{[1]}, s_t^{[2]}, \ldots, s_t^{[M]} \tag{12}$$

where Each $st^{[M]}$ particle is a specific state instance, that is, a hypothesis that can be true at time t. The basic cycle of a particle filter consists of three steps: sampling, weighting, and resampling. During the first step, each particle from the proposed distribution is verified using the equation:

$$s_t^{[m]} \sim p\left(s_t \mid s_{t-1}^{[m]}, u_t\right) \tag{13}$$

Since the particle filter is a recursive algorithm, the current state is sampled using the previous state. However, because the transition function is noisy, each particle goes through a different transition, which adds variety to the particle set.

In the following - weighing phase, each particle is assigned a weight based on how well it fits in the posterior distribution. After the above steps, the new weighted particle is added to the temporary set of particles.

The final step is a resampling phase. It uses the temporary particles calculated in the previous phase to generate the final posterior distribution. In this step, samples are taken with the particles and replaced with a frequency proportional to their weight. After the resampling step is completed, the obtained set of particles becomes the input data for the next iteration of the particle filter.

4 Positioning method implementation and verification

In order to choose the best method of improving the quality of data received from BLE transmitters, an experiment was carried out in a real environment in the university building.

- In the first stage, applications were implemented that allowed data collection on the signal strengths from the transmitters and applied them to selected mathematical filters.
- In the next stage, a test environment was created consisting of transmitters located in the corridor of the university building, and the tools implemented in the previous stage were installed on the mobile device.
- Then, a data collection phase was carried out, after which the data was transformed and analyzed.
- In the next step, the obtained data were applied to the Kalman and particle filter.
- In the last stage, the obtained data were compared, and a recommendation for the future use of the developed method was developed.

The performed experiment is presented in the following sections.

4.1 Tools implementation

The test environment used during investigations consisted of three software pieces. A client - an Android application written in Java, a server application - implemented with the Express framework in Node.js - and a tool written in Python to test different filtering strategies. The communication in the system takes place on two lines:

- Client-server communication, which was carried out through HTTP requests. The client (the application running on the Android operating system) sends the appropriate HTTP requests to the server, which sends back the response in JSON format.
- Client - beacons, implemented using the Bluetooth 4.0 Low Energy standard protocol. In this case, communication was one-way. It consisted of the client scanning all beacons available within its range at a specified time interval and receiving the necessary information from them.

After starting the client application, the screen shows the logo, a short system description, and four navigation buttons that allow the user to access the bookmarks containing the list of beacons, the map, and the RSSI graph. The following bookmark offers much functionality. It implements a use case where detailed information of all found beacons, such as MAC address, signal strength, MajorID, and MinorID, are displayed. In this case, beacons available in the current space are scanned every 5 seconds. This situation is presented in figure 2.

The following bookmark implements the functionality of locating the receiver (phone) in a given region covered with beacons, the data of which was previously entered into the server application. A ”Locate” button is available when the beacon space scanning operation returns at least three detected transmitters. After sending the request, the server returns the calculated coordinates of the receiver to the client application, They are presented as numbers under the indicator of the number of detected beacons or graphically - as a black circle on the map of the region covered with beacons. his situation is presented in figure 3.

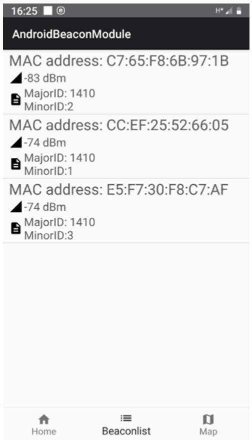

Figure 2. Beaconlist fragment of the client application

The last window of the client application is used to draw a graph with signal strengths for individual beacons. Moreover, a Kalman filter has been implemented directly in the application.

Another part of the implemented environment was the server application. The task was to collect data received by the client application and save it as a report in CSV format. This report was then used to compile the data for the next experiment stage.

The data collected in the client application taken from the server application was imported into a Python script designed to compare the various filtering strategies described in section 3.2. The script returned the filtered data, which was later used to determine the receiver's position (smartphone) and compared with each other.

4.2 BLE transmitters configuration and data acquisition

In order to collect and analyze the data, it was necessary to configure the infrastructure of BLE transmitters. The beacon calibration process consisted of determining the environmental variable using an appropriate radio propagation model and measuring the average signal strength over one meter. The signals transmitted by the Bluetooth transmitters are under the path loss model (see 2 outlined in the previous section:

$$RSSI = -10n * log(D/D_0) + C_0 \tag{14}$$

After transforming the above formula, we will obtain the following formula that allows us to calculate environmental variable n:

$$n = -(RSSI - C_0)/(10 * log(D/D_0) \tag{15}$$

Having this environmental variable, we could proceed to the beacon calibration process.

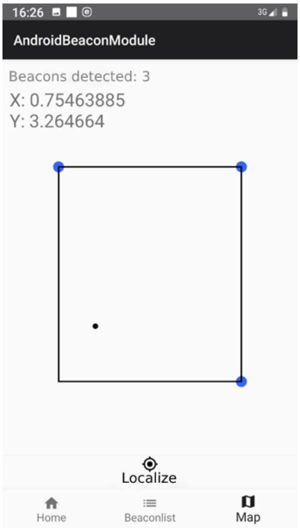

Figure 3. Map screen of the application

The calibrations were performed as follows: The transmitter (beacon) was placed one meter away from the receiver (smartphone) and then moved to a distance of two meters. The devices were held in place for two minutes every 50 centimeters, and the signal strength readings were recorded and averaged. The data was collected into a spreadsheet to determine $C0$, the average signal strength at a distance of one meter as the value -60dBm, while the calculated n was 2.45 in the testing room.

The last step was to mount the beacons in the room where the applications were tested. To obtain the most optimal conditions, we placed the transmitters at a height of 1,6m to avoid attenuating the signal in metals and, above all, in water in the human body, which may appear in the possible signal path. Let us notice that the human body consists mainly of water. The configuration of beacons described above is presented in figure 4. The next step of the

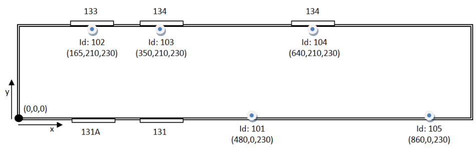

Figure 4. Configuration of beacons

experiment was to collect data from the transmitters, so the receiver (smartphone) was moved every 30 seconds by 50 centimeters along the corridor. Data were collected from 42 positions and stored in JSON files... A database containing records of all carried-out measurements was created using these data. This data was then imported into a Python script and, in this way, applied to the Kalman and particle filters. After collecting and pre-preparing the data, the coordinates of three selected points were calculated using the multilateration technique 4 Measurements were carried out for the following points

- **1** was a point at (150, 160)
- **2** was a point at (650, 160)
- **3** was a point at (850, 160)

In the next stage, the coordinates calculated in this way were compared with the actual coordinates measured in the place where the receiver (smartphone) was located. The table below presents the signal strength measurements from the measuring point with coordinates $X = 150, Y = 160$ (where the nearest BLE transmitter was at a distance of 0, 5m and the farthest 6.6m) presented in dBm for each beacon. The Z coordinate could be omitted because all the transmitters were always placed at the same height, which is 1,6M from the floor. The minorID column contains identifiers of individual beacons, while the following columns present signal strengths for:

- RSSI unfiltered
- RSSI subjected to Kalman filter
- RSSI particle filtered

Table 1. Source data for X=150, Y=160

MinorID	RSSI Unfiltered	RSSI Kalman	RSSI Particulate
101	-66	-66,97	-68,78
102	-48	-46,85	-48,02
103	-66	-64,34	-65,98
104	-	-	-
105	-74	-73	-78,72

This data was then used to calculate the receiver coordinates using the true-range multilateration technique. The table below shows the calculated receiver coordinates for the data from the table. It compares them with the actual coordinates measured where the receiver was physically located. Note that the X and Y columns contain the coordinates of the measurement points in centimeters. The radius of error is the distance in centimeters between the received coordinates and the actual ones shown in the first line.

Table 2. source data for X=150, Y=160 coordinates

	X	Y	Error radius
Real Coordinates	150	160	-
Multilateration - unfiltered RSSI	338	99	198
Multilateration - Kalman filter	353	115	208
Multilateration - particle filter	241	130	96

The same measurements and calculations as those presented above were also carried out for points with coordinates:

- (650,160), located 2 meters from the nearest transmitter but less than 5 meters from the farthest one,
- (850,160) is 1.6 meters from the nearest transmitter but more than 5 meters from the others.

The third point where the measurements were made was the farthest from the other transmitters - only one beacon was located at a distance of fewer than 5 meters, and the furthest was located at a distance of fewer than 7 meters. Let us note that multilateration of the whole range requires at least three transmitters to determine the user's position.

5 Results and recomendations

After collecting the raw data, it turned out that the signal strengths fluctuated significantly. This problem increases when the receiver is in motion or more than 6 meters from the transmitter. We used the Kalman and Particle filter technique to compensate for these fluctuations. In each case during the experiment, filters reduced the error radius. The Kalman filter was better for points distant by 6.5 m and 8.5 m from the transmitter in two cases. It also turned out that the particle filter brought the most significant error reduction for one of the tested measurement points presented in the table (table 2). Thus, the Kalman filter greatly improved the situation where the distance to the BLE transmitters was relatively large, reducing the error by more than a meter. Another advantage of using this filter is its lower computational complexity[21], which caused a faster locating process than with a particle filter. Therefore, it leads to the recommendation that the best results can be achieved using the Kalman filter. However, the transmitters must be placed at a maximum distance of 10 m from each other so that at any time during the user's movement, he has at least three transmitters at a distance not exceeding 6.5m. However, to finally and fully validate this recommendation, more trials with actual data will be needed.

6 Conclusions

This paper address the problem of improving user positioning methods inside buildings where BLE transmitters are installed. The user is equipped with a mobile device to detect signals from the transmitters. By measuring the strength of these signals with the position of the transmitters known, the user's position can be calculated using the multilateration method. However, since the signal strength decreases with decreasing of distance non-linearly, the signal path loss model should be applied to calculate the user's position. In addition, it turns out that the received signals fluctuate, and their strength values are not stable. Therefore, digital methods must be used to improve the results obtained and better calculate the user's position. Two filters that gave the best results were compared. Namely, they were the Kalman filter and the particle filter. Using these filters improves the calculated coordinates best at about 6m from the transmitter. However, the Kalman filter gives the relatively best results. Therefore, to obtain an optimal environment for determining the user's position, it is recommended that the transmitters be placed no more than 8m from each other at a height of about 2.6 m to avoid interference of signals in the human body. Since the applied research environment consisted of 4 transmitters, the experiments will have to be repeated on an immense amount of data to improve the reliability of these conclusions. Currently (October 2023), many transmitters have been installed on a university campus and will conduct measurements with more data. The method of positioning the user in the building is then implemented as a navigation system that is currently being developed on our university campus.

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