MOBILE APPLICATION FOR BLE INDOOR POSITIONING

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Abstract: Distance estimation in indoor localization is mainly solved by Received Signal Strength Indicator (RSSI). In our approach, the RSSI is determined empirically, and it's used to estimate the distance between the user and beacons in a mobile app solution. Trilateration and Kalman filter help obtain better accuracy. The paper proposes a classical solution for indoor localization, but with features like blueprint implementation, Google Maps integration, and manual beacon positioning.
Keywords: localization, Bluetooth low energy, trilateration, beacon

I. INTRODUCTION

Outdoor localization systems can be set up using Internet of Things (IoT) systems. Satellites, Cellular networks, Radiofrequency, or Optical technologies are the main approaches for implementing a functional outdoor localization scenario.

Indoor positioning systems are used to localize persons and objects which are inside a building. Due to their characteristics, some of the technologies mentioned above cannot perform this action, meaning that the solution is solved by the following technologies: WI-FI, Bluetooth Low Energy (BLE), Radio-Frequency Identification (RFID), and Ultra-wideband (UWB)

In this paper, we propose a mobile application that can be used for indoor localization. The mobile app works with three beacons systems in a two-floor house and uses them to locate the user by RSSI index.

The necessity of indoor positioning systems is related to the continuous development of the smart city concept. The applicability of the indoor location system can be found in environments such as healthcare, education, corporate offices, transportation hubs, and malls. In [1] *Bai L. et. al* uses a BLE-based indoor positioning system for monitoring old people living with dementia or individuals with disabilities. Trilateration-based methods and fingerprinting-based methods are used for location and tracking in this paper. The Bluetooth beacons are replaced with ESP-32 modules in the paper of *S. Sophia et. al* [2] for transmitting and receiving the code for indoor localization.

A more complex implementation of the indoor positioning system was proposed by *Apiruk Puckdeevongs et al* [3]. The authors applied the fingerprint techniques in a classroom environment to detect classroom attendance. Localization in environments like malls and museums is possible if visitors are equipped with a BLE device. Once this is set a museum indoor localization can be implemented as in the article [4]. The authors collect the information from the visitors and later locate the user by using a non-linear least square algorithm. As can be seen, the implementations of this system are multiple, and the technologies used allow for locating users with a very low precision. *G.S de Blasio et. al* describes in their paper [5] a part of the technologies used in indoor positioning.

Modifying the filtering technique for BLE indoor localization can also be a solution in some cases. *F. S. Daníş et al* [6]. propose in their work an Adaptive Sequential Monte Carlo Filter.

The new approaches in indoor localization are Convolutional Neural Networks (CNN) or Deep learning methods. In the work of [7] the indoor localization problem is formulated as 3D radio image-based region recognition. The 3D radio images are constructed based on RSSI fingerprints. The authors state that this solution outperforms other popular approaches.

The paper is divided into four sections: introduction, methods and algorithms, results, and conclusions. The first section presents the idea of the article and state of the art. The next section, Methods and algorithms, describes all the algorithms used in implementation. Among them, you can find the trilateration, RSSI, and Kalman filter. The section Results shows the obtained parameters. Finally, the Conclusion section indicates the ideas of the work and proposes new approaches.

II. METHODS AND ALGORITHMS

The well-known Bluetooth technology offers users an end-to-end solution capable of resolving the connection problem. The solution derived from Bluetooth, BLE was designed for low-power transmission. One of the features of BLE is that devices using BLE can determine the location of other devices.

The process proposed is shown in the following diagram (Figure 1). The diagram indicates the steps the

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must be followed: computation of RSSI with two proposed methods. The chosen solution will be the one based on Friis equation [8], the next step is to improve RSSI, by Kalman filtering and to determine the position of BLE. Finally, in the last step the estimated distance is computed.

Beacons are devices operating on BLE protocol and broadcasting at fixed time intervals small data packets. Beacons have only one purpose, namely, to emit a signal by which they warn that they are there. Using the strength of the received signal, a beacon determines the distance that separates it from the Bluetooth antenna of a mobile device. This technology is developing further, offering more precise positioning by utilizing the use of magnetic field detection, gyroscope, accelerator meter, and Near Field Communication (NFC) chips.

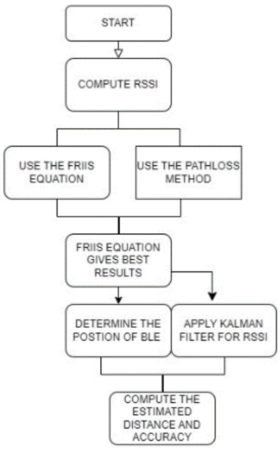

Figure 1. The process diagram

The RSSI computing is needed for determining the corresponding distance from the sender to the receiver. There are multiple solutions to compute it. Most of them use the Path loss [9] approach as defined in equation (1)

$$\overline{PL} = \overline{PL}(d_0) + 10n\log\left(\frac{d}{d_0}\right) \tag{1}$$

where n is the path loss exponent which indicates the rate at which the loss increases with distance d_0, d_0 is the close-in reference distance which is determined from measurements close to the transmitter, and d is the Transmitter – Receiver (T-R) separation distance.

Some of them include Friis equation [8]. According to Ivanić M. and Mezei I. in their work [10] the RSSI index can be determined as follows, based on Friis equation:

$$RSSI \sim 10 * \log\left(1/d \right)^{n} \tag{2}$$

$$RSSI = -10 * n * \log(d) + S \tag{3}$$

$$RSSI = -m * D + S \tag{4}$$

where d – distance, S – constant, m = 10*n, n – the signal propagation exponent, and D = log(d).

Once we have the estimated distance from the sender and each receiver, we must next estimate the position of the BLE device. For this, we may use trilateration.. Trilateration uses the known distance from at least three fixed points in 2D space to calculate the position of an object. Trilateration works by finding the intersection of a series of circles distance measurement. So, the detection of the unknown location can be obtained by the intersection of 3 circles, corresponding to beacons in several cases: the circles intersect in one point, the circles intersect in an area of points, and two circles intersect in an area, the other does not intersect. In our work, the beacons represent the 3 points, and the distance measurement is done by RSSI. For each beacon, the range of BLE values is represented by a circle. For each beacon, the range of BLE values is represented by a circle.

In our approach we consider the case where the circles intersect at one point, the user position (Figure 2). The user position has coordinates C(x,y). The position of this can be found if the coordinates of the three beacons C_1, C_2, and C_3, and the corresponding RSSI values are known.

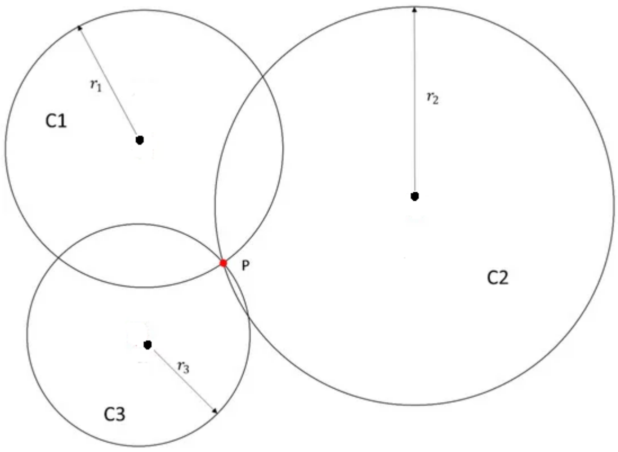

Figure 2. The triangulation process with a point intersection

The RSSI value can be translated into the distance, but in practice, a discrepancy appears. In an ideal world, the RSSI value is only dependent on the distance between the two devices. However, RSSI values are heavily influenced by the environment and have, consequently, high levels of noise. This noise is, for example, caused by multi-path reflections: signals bounce against objects in the environment such as walls and furniture. A proposal for noise filtering can be the Kalman filter. As stated in the literature [11] the Kalman filter can remove noise from a very noisy signal. The proposed implementation is described below.

Table 1. Kalman filter explained

Initial estimates for $\hat{x}_{k-1}$ and P_{k-1}
TIME UPDATE ("PREDICT")
1. Project the state ahead $\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k$ 2. Project the error covariance ahead $P_k^- = AP_{k-1}A^T + Q$
↓
MEASUREMENT UPDATE ("CORRECT")

1. Compute the Kalman gain
$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$$
2. Update estimate with measurement z_k
$$\hat{x}_k = x_k^- + K_k (z_k - H x_k^-)$$
3. Update the error covariance
$$P_k = (I - K_k H) P_k^-$$

The mobile app was developed on Android and was designed in a way that a user can easily update a blueprint of the building in which the indoor location will work. The application must be tested on a mobile phone and not an emulator, due to the usage of Bluetooth. The device should have a minimum Bluetooth version of 4.0 so that the beacons will function correctly. In the manifest file, we set up the permission for bluetooth, to access external hardware. The implementation was done with the use of several libraries, like Picasso library, AltBeacon library, and Google Maps for positioning the house on the map. For using the Google maps features, an API key must be provided by the Google maps cloud site. This was added in the AndroidManifest.xml as a <meta-data> attribute.

We designed five views for the app, one for the user interface, and one each for the functions of the app: Nearby beacons, Floor plan, Information about location and Where am I. The last one was designed for integration with Google maps.

For the NearbyBeacons activity, the Monitoring and Ranging Activity from the AltBeacon library was used.
For the positioning to be done, the program must extract from the beacon, the RSSI value, the Tx power, and the Universally Unique Identifier (UUID). The purpose of the UUID is to distinguish beacons in your network from all other beacons in networks outside your control.

The „FloorPlan” option on the UI menu opens a new view with an activity that contains the blueprint of the floor where the user is. The floor plan saved in the storage memory is automatically downloaded and then fetched using Picasso library. On the floor plan, a blue dot is positioned at the location where is the user.

The main view is Where am I, which not only integrates the blueprint in Google maps, but also detects the position of the user to beacons. Google maps integration depends on detection of beacons. Then, the RSSI value must be filtered. As proposed the Kalman filter was used. The Kalman filter uses process and measurement noise which can be calculated for each beacon, particularly for better precision. Measuring these values is done by running this filter with a unit test and picking up the most suitable value. After the filtering finishes the trilateration technique must be applied. To implement this, we need to know the exact locations of the beacons in terms of latitude and longitude. The distance between each beacon and the user is calculated using the Friis model from (4).

III. RESULTS

The proposed work was the design of a mobile application for indoor localization using BLE. The app creates a scenario for locating a user in a two-floor house. The location is determined by three beacons positioned in different locations on the first floor.

The implementation was done with the use of Android software and some libraries, like Picasso library, AltBeacon library, and Google Maps, the last one being for positioning the house on the map.

Figure 3 shows the blueprint of the ground floor, in which we can observe that is a place where obstacles may appear. Also, in this figure, we notice a blue dot which represents the position of the user.

Once the beacons are positioned, the application implements the above-mentioned technologies for estimating the distances from the user to the beacons. These distances will vary from the real distances that were measured beforehand.

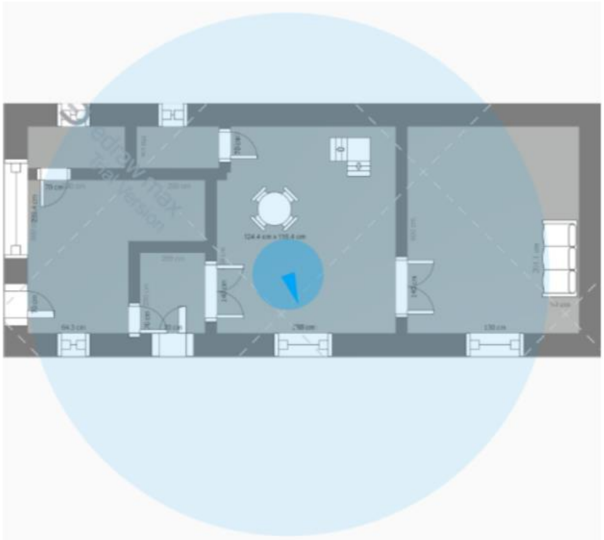

Figure 3. Floor map and user position

One important function of the mobile app is to find and display information about the nearby beacons. The information displayed includes the UUID of the beacon found, the Tx power, and RSSI. Figure 4 shows the above parameters.

TxPower of
4cc54d62-2403-443b-89b6-2282490ab3c0i
s -69.0 and RSSI is : -73.0 and is at
1.5003357378151896 330d6309-
e7b1-42f0-a7d5-0306c1ea1d69
TxPower of f159a8d4-2a61-4a66-b61a-
da84353ad9d6is -69.0 and RSSI is : -100.0
and is at 15.833428091120975
f159a8d4-2a61-4a66-b61a-da84353ad9d6
TxPower of 330d6309-e7b1-42f0-
a7d5-0306c1ea1d69is -69.0 and RSSI is :
-79.0 and is at 2.6653221969634
4cc54d62-2403-443b-89b6-2282490ab3c0

Figure 5. Values of UUID, Tx power, and RSSI for the three beacons

The experiments made took into consideration the distance between the user and beacons. The position was chosen in the way that between them we should have no obstacles, some obstacles, and a lot of obstacles. In each case, the estimated distance and relative accuracy are determined. The cases could be labeled as “best”, “good” and “worst”.

A comparison with [10] is made. The authors propose an improvement of RSSI ranging based on RSSI computing they used the same method, but the parameter values were m = -36, S = -55. We compared our results for all three beacons with indoor results from above mentioned paper. The following tables present the estimated distance and relative accuracy for each case.

Table 2 Distance estimation accuracy for "worst" position

RSSI (dBm)	Real distance (m)	Estimated distance (m)	Relative accuracy
-87.0	5.1	6.51	78%
-90.0	1	3.51	28%
-73.0	2.5	3.2	78%

Table 3 Distance estimation accuracy for the "good" position

RSSI (dBm)	Real distance (m)	Estimated distance (m)	Relative accuracy
-86.0	5.6	7	80%
-90.0	1.6	2.5	64%
-85.0	2.8	3.8	73%

Table 4 Distance estimation accuracy for the "best" position

RSSI (dBm)	Real distance (m)	Estimated distance (m)	Relative accuracy
-85.0	2.4	2.66	90%
-84.0	5.2	5.60	93%
-83.0	1	0.94	94%

As can be observed from the results when we have fewer obstacles the accuracy is higher. Another conclusion is that when the distance from the user to the beacon is low, the accuracy is high. A similar result was obtained in the work of Ivanić M. and Mezei I. when, for indoor measurements, the accuracy is like the ones from Table 3. Their results can be seen in Table 5.

Table 5 Distance estimation accuracy in [10]

RSSI (dBm)	Real distance (m)	Estimated distance (m)	Relative accuracy
-44	0.5	0.4948	99%
-54	1	0.938	94%
-67	2	2.1544	92%
-73	3	3.1623	95%
-78	4	4.3540	91%
-80	5	4.9482	99%
-82	6	5.6234	94%

Comparing our data with Table 5 we can notice that for distances around 1 m, the accuracy is similar. So, we can conclude that the RSSI-based distance estimation features good distance estimation accuracy, particularly for the low-distance measurement scenarios.

IV. CONCLUSIONS

In this paper, the RSSI index was implemented for estimating the distance between a user and a beacon for indoor localization. The RSSI index was filtered by Kalman filter to remove the noise that is due to the environment. The final solution was incorporated into a mobile app that allows the user to set up some parameters and the location of the beacons in the house. Once the beacons and obstacles are established the measurement can be done. The work proposes three scenarios for user-beacon communication: with a lot of obstacles, with some obstacles, and with no obstacles. The accuracy was higher in the case with no obstacle and with a small real distance, around 1 m. The same result was obtained when compared with another work.

Future directions for the research could be experiments with CNN or deep neural networks for determining RSSI from WI-FI fingerprint or RSSI images.

REFERENCES

[1] L. Bai, F. Ciravegna, R. Bond and M. Mulvenna, "A Low Cost Indoor Positioning System Using Bluetooth Low Energy," in IEEE Access, vol. 8, pp. 136858-136871, 2020, doi: 10.1109/ACCESS.2020.3012342

[2] S. Sophia, B. M. Shankar, K. Akshya, A. C. Arunachalam, V. T. Y. Avanthika and S. Deepak, "Bluetooth Low Energy based Indoor Positioning System using ESP32," 2021 Third International Conference on Inventive Research in Computing Applications 2021, pp. 1698-1702, doi: 10.1109/ICIRCA51532.2021.9544975

[3] A. Puckdeevongs; N.K. Tripathi; A. Witayangkurn; P. Saengudomlert "Classroom Attendance Systems Based on Bluetooth Low Energy Indoor Positioning Technology for Smart Campus". Information 2020, 11, 329. https://doi.org/ 10.3390/info11060329.

[4] R. Giuliano; G.C. Cardarilli; C. Cesarini; L. Di Nunzio; F. Fallucchi; R. Fazzolari; F. Mazzenga; M. Re; A. Vizzarri "Indoor Localization System Based on Bluetooth Low Energy for Museum Applications". Electronics 2020, 9, 1055. https://doi.org/10.3390/electronics9061055.

[5] G.S. de Blasio, A. Quesada-Arencibia, C.R. García, J.C. Rodríguez-Rodríguez "Bluetooth Low Energy Technology Applied to Indoor Positioning Systems: An Overview" In: Moreno-Díaz, R., Pichler, F., Quesada-Arencibia, A. (eds) Computer Aided Systems Theory – EUROCAST 2019, vol 12013.doi.org/10.1007/978-3-030-45093-9_11

[6] F. S. Daníş, A. T. Cemgíl and C. Ersoy, "Adaptive Sequential Monte Carlo Filter for Indoor Positioning and Tracking With Bluetooth Low Energy Beacons," in IEEE Access, vol. 9, pp. 37022-37038, 2021, doi: 10.1109/ACCESS.2021.3062818.

[7] R. S. Sinha, S. H. Hwang, "Comparison of CNN applications for RSSI-based fingerprint indoor localization. Electronics, 2019, 8(9), 989.

[8] H.T. Friis, "A Note on a Simple Transmission Formula" Proceedings of the I.R.E. and Waves and Electrons, May, 1946, pp 254–256

[9] T.S. Rappaport, Wireless Communications—Principles and Practice. Upper Saddle River, NJ: Prentice-Hall, 1996.

[10] M. Ivanić and I. Mezei, "Distance Estimation Based on RSSI Improvements of Orientation Aware Nodes," 2018 Zooming Innovation in Consumer Technologies Conference (ZINC) 2018, pp. 140-143, doi: 10.1109/ZINC.2018.8448660.

[11] W. Bulten, A. C. V. Rossum and W. F. G. Haselager, "Human SLAM, Indoor Localisation of Devices and Users," 2016 IEEE First International Conference on Internet-of-Things Design and Implementation (IoTDI), Berlin, 2016, pp. 211-222. doi: 10.1109/IoTDI.2015.19