Accuracy Enhancements in Indoor Localization with the Weighted Average Technique

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***Abstract*—Indoor localization is a topic that has drawn great attention over the last decade. One of the main goals of the research in the field is to improve the achieved accuracy. Along with the accuracy, factors like the easiness of deployment and reconfiguration, the cost, the computational complexity, and the ability to tune the desired accuracy in specific areas are also important. In this study, we used Bluetooth Low Energy (BLE) technology, that offers a low cost and is easily deployed and reconfigured. The weighed average method, combined with the selection of the closest beacons and the averaging of the received signal strength indication (RSSI) at the distance domain proposed in this paper, offers an accuracy down to 0.97 meters, depending on the deployment configuration. This method was tested in our lab and was following installed at the hospital in Perugia, Italy, in the context of the Ambient Assisted Living (AAL) Virgilius project, where users can navigate with a smartphone.**

***Keywords*—Indoor Localization; Received Signal Strength; Positioning; Bluetooth**

I. Introduction

During the last years, the field of indoor positioning has drawn an increasing attention of researchers. Outdoor positioning has been ahead, having reached many users through commercial applications. Nowadays, almost all new mobile devices are equipped with global positioning system (GPS) technology, which has familiarized most users with the concept of positioning. On the other hand, no indoor positioning method has been broadly recognized as a standard one, and the research in this domain has led to having multiple alternatives.

A technology commonly used for positioning in indoor environments is the Wi-Fi signal [1][2]. One advantage of using Wi-Fi is that most buildings have several Wi-Fi access points, in order to provide internet access, so the hardware required is already installed. On the other hand, usually the access point network is not dense enough to facilitate a satisfactory precision of localization. Moreover, the transmission of the Wi-Fi access points is unstable, as well as the reception in big distances due to multipath effects, and therefore using the RSSI of them can be problematic.

In this study, we work with BLE technology. BLE is a wireless technology used for transmitting data over short distances. It has a low energy consumption and cost, while maintaining a communication range similar to that of its predecessor, Classic Bluetooth. As transmitters, we used iBeacons, an Apple technology standard, and more precisely the Tod iBeacons [3]. The iBeacon technology allows mobile applications (running on both iOS and Android devices) to listen periodically for signals from beacons and react accordingly. Each beacon broadcasts a self-contained packet of data periodically. The packets contain the mac address of each beacon, so that the receiver can distinguish among them. The RSSI can be used to estimate the distance between the mobile device and the transmitting beacon [1][4][5][6]. Due to their low cost and low consumption, a dense network can be deployed. Having a dense deployment can lead to a reliable distance estimation, at least from the closest beacons.

This distance estimation is used to derive the actual position, usually by using lateration methods [7][8]. These methods can have some drawbacks, as for example, when the estimated distances are wrong, or when the beacons used are aligned, an estimated position that is far from the real one may be returned. Furthermore, using different mobile devices with different receiving capabilities can add a systematic error to each distance estimation that will dramatically affect the lateration outcome.

In our method, we proceeded with another approach. We propose a placement of beacons such that the beacons surround all the area that we want to cover. The position prediction is limited to the area that is defined by the polygon that the beacons' positions define. We get a distance estimation from each beacon, by averaging the estimated distances that correspond to the latest RSSI measurements from this beacon. In this way, we cope with the instability of the RSSI.

Having this filtered distance estimation, we focus only on the B closest beacons. In this work, we propose $B = 4$, as will be discussed later. We use the inverse value of the distance estimation as weight, in order to perform a weighted average of the positions of the 4 closest beacons. This weighted method, is also met in [9]. That work, to our knowledge, does not have RSSI filtering, nor does it focus on the closest beacons. The weighted method in [9] is used with radio frequency identification (RFID) technology, as an area/room selection first step, before performing a server side supervised machine learning positioning method.

The lateration approach uses the assumption that distance estimations are close to accurate, which is unlikely. Our proposed method anticipates the uncertainty of this estimation as an absolute value. It firstly utilizes that the expected error is smaller in small distances, and secondly, the main conceptual idea of RSSI methods, that a stronger RSSI reception from beacon a as compared to beacon b is interpreted as being closer to beacon a, especially after averaging distance estimations.

The advantages of the proposed technique are numerous. The Bluetooth beacons are easily deployed and rearranged in order to cover new areas of a building or to improve accuracy with a more dense placement. For example, the deployment could be more dense in a corridor with many doors, where accuracy is critical, compared to a long corridor with few doors, that may simply link two buildings. Another advantage is that this method does not require the creation of a radio map [10], where measurements of RSSI from all access points should be stored for many points of the area where it will be used. One can reconfigure the deployment, by adding for example one beacon, with no need to retake any measurements for a radio map, but simply by storing the position of the new beacon. Our method also offers low computational and implementation complexity. Finally, as all RSSI techniques, it has the advantage that most modern mobile phones can offer the RSSI of a Bluetooth reception, and thus no extra hardware or modification of the devices is required.

The rest of this paper is organized as follows. In Section 2, we present the propagation model and how it is used to derive distance estimations form the RSSI values. In Section 3, we present the idea of performing a weighted average of the known beacon positions. Measurements and both theoretical and experimental results are reported and discussed in Section 4. Finally, future work directions along with conclusions drawn are presented in Section 5.

II. Propagation model and RSSI methods

In RSSI methods used in localization, the received signal strength is used as a measure from which the distance between the transmitter and the receiver can be inferred. Nevertheless, the RSSI received at a given time and space depends on many other factors other than the relative distance of the two devices. Even the slightest changes in position and orientation can provoke dramatic variations to the RSSI values [11]. Moreover, the movement of people and objects in the environment often has great effect on the signal. In general, RSSI is vulnerable to strong multipath effects, especially indoors [11]. Furthermore, factors like temperature and humid conditions can affect the propagation of the signal [11]. Using a set of RSSI measurements instead of a single instantaneous measurement can improve the accuracy of the distance estimation [5].

The RSSI, apart from the propagation channel, depends on the transmitter and the receiver. For a given installed system the transmitters are the same, but it would be desirable that each user could use the system by using her personal mobile device (smart phone, tablet, etc.). Taking under consideration all these factors, we propose the propagation model and its parameters that will be used in our system.

The propagation model commonly used for the RSSI to distance correspondence, where the expected RSSI r_i in distance d_i is calculated, is the following:

$$r_i = r_0 - 10\; n\; log_{10}(d_i/d_0) \tag{1}$$

In this formula, r_0 is the received RSSI at a reference distance d_0, and n is the path loss exponent which depends on the transmission channel, the transmitter and the receiver. Using 1 meter as reference distance, and solving for d_i, the formula is simplified to:

$$d_i = 10^{\frac{r_0 - r_i}{10\; n}} \tag{2}$$

A Tod Bluetooth iBeacon was placed at the center of the corridor of Figure 3, and RSSI measurements were performed at several points at a known distance from the iBeacon. We performed these measurements using a Samsung Galaxy S4, and then ran a regression to find the parameters of the best fitting curve described by (2). In Figure 1, we see the measured RSSI values (black dots) in several distances (at 0.25,0.5,1,2,3,4,5 and 6 meters), and with blue color the resulted propagation model as the best fitting curve. The estimated values of these parameters are $r_0 = -62.72$ and $n = 2.2853$. Substituting in (2), we get:

$$d_i = 10^{\frac{-62.72 - r_i}{2.2853}} \tag{3}$$

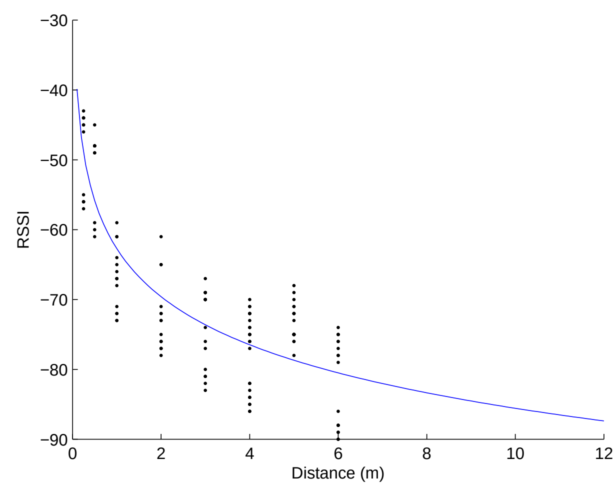

Fig. 1. RSSI measurments at several disances (in black) and the resulting propagetion model (in blue) as the best fitting curve described by (2).

In order to have a more reliable distance estimation we do not use just the latest RSSI reception but a set of the latest ones. Due to the non linear relation of distance with RSSI, it is important to decide if we will average the RSSI values and then get the distance estimation as their average, or if we should calculate the corresponding distance of each RSSI reception and then use the average of these distances. In Figure 1, we see that for distances from 0 to 5 meters, the RSSI differs significantly. On the other hand, for distances greater than 15 meters, RSSI differences are minor. Since we target to utilise the reliability and distinguishability of the small distance measurements, we direct our method to this part of the propagation model. Given that the derivative of the RSSI curve changes with the distance, averaging the RSSI values inserts an intrinsic error to the estimation.

To state this argument we explain a simple example. Assume that users are moving and the RSSI measurements they receive from each beacon correspond exactly to the real distance from it at each moment. Averaging in the distance domain, provides the users' average distance. On the other hand, due to the non linear relation of distance and RSSI, averaging RSSI values first, will give a distance estimation different than the average distance.

Furthermore, in case where the measurements of the RSSI values are biased, in short distances, small RSSI errors have small consequences to the distance estimations. On the other hand, for big distances, a small fluctuation of the RSSI values can have a dramatic consequence to the estimated distance. In the proposed method, only the RSSI values of the closest beacons are used, so averaging in the RSSI domain would introduce a bias. For these reason, averaging in the distance domain was selected.

III. Weighted average of beacon position

Initially, it is worth noting that the method proposed can give estimations of positions only inside the polygon area that is defined by the positions where the beacons are placed. For an indoor localization system and its applications, it may be desirable to constrain the prediction inside a specific area, i.e., inside the building. In case where map matching is used to provide navigation, a jump of the estimation outside a building could lead to problematic navigation. Thus, in practice, to provide coverage in a rectangular room or a corridor with the proposed method, $B = 4$ is the minimum number of beacons to cover this area. Later in this work, we discuss proposed configurations.

Having obtained an estimation about the distance of the mobile device from each beacon, we proceed to the position estimation. Due to the phenomenon of multipath effects, it is unrealistic to claim that at every moment the distance estimation will be precise. Especially in big distances, just a small difference in the RSSI values is translated to big distance differences. On the other hand in small distances the RSSI values are quite distinguishable. We utilize this fact, in the following way. From the list of beacons that are detected, we keep the 4 closest beacons. Assuming that the mobile device is inside the coverage area (beacon defined polygon), the estimated position will also be inside the quadrilateral defined by these four beacons. Let $[e_1, e_2, e_3, e_4]$ be the estimated distances from the 4 closest beacons, while $[lat_1, lat_2, lat_3, lat_4]$ and $[lon_1, lon_2, lon_3, lon_4]$, the corresponding latitude and longitude of their positions. We calculate the latitude Lat_{est} and longitude Log_{est} of the estimated position as follows:

$$Lat_{est} = \frac{\sum_{i=1}^{4} \frac{lat_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}}\ ,\ Lon_{est} = \frac{\sum_{i=1}^{4} \frac{lon_i}{e_i}}{\sum_{i=1}^{4} \frac{1}{e_i}} \tag{4}$$

In (4), we calculate the weighted average of the four closest beacons' positions, using as weight $1/e_i$, that is the inverse of the estimated distance from beacon i. By using this weighted average the prediction is limited inside the quadrilateral of the closest beacons, and with the specific weight that is proposed, the prediction is pulled towards the closest beacon, although allowing the rest of the beacons to contribute inversely proportionately to their distance.

The minimum number of closest beacons that could be used is 3, since 3 points define a plane. In the case where the 3 closest beacons were used, the defined area would be a triangle. In the middle area of this triangle, the estimation is slightly better comparing to the case where 4 beacons are used. The drawback with the usage of only 3 closest beacons is that when the user is moving and passes from one triangle to the other, the accuracy of estimation near the common edge of the two triangles is significantly degraded. Using the 4 closest beacons offers a smooth transition from one triangle to another. In the following section, along with the system's accuracy measurements, an error analysis of these two cases is presented.

IV. Measurements, results and discussion

The weighted average method proposed may have an error in the location estimation even when the distance estimations are precise. We model this error in Figure 2, for the cases where 4 and 3 closest beacons are used. We simulate the deployment at the corridor where our system was tested. The beacons are placed at a hight of 2.40 meters, following a zigzag pattern (alternatively at the left and right wall of the corridor), every four meters along the direction of the corridor. The orientation of the beacons is towards their opposite wall. We observe that, for the first scenario (4 closest beacons), the error is lower at the center of the corridor, and changes smoothly as we move along the length of the corridor. On the other hand, using just 3 beacons degrades significantly the accuracy estimation at a broader area. The error increases rapidly when approaching at the edges of the triangles that the 3 closest beacons define.

Our method was tested in the corridors of the Centre Universitaire d'Informatique (CUI), of the University of Geneva. Measurements were taken with two ways. First, by letting the mobile device at a specific place and receiving the estimated positions it calculated. A second approach was to test the localization while having the mobile device moving, which better corresponds to real life scenarios.

In order to get a broad estimation of the positioning accuracy, we took 1000 measurements at three points in the corridor. Two mobile devices were used for these measurements,

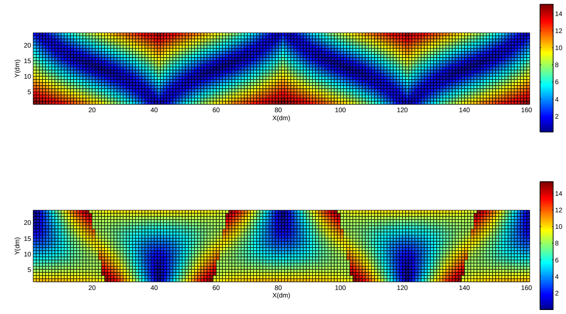

Fig. 2. Error in decimeters (color scale) of position estimation in a corridor at the position x,y, when using 4 (upper plot) and 3 (lower plot) closest beacons method.

a Samsung Galaxy S4, which was used for the creation of the propagation model (3), and a Samsung Galaxy Note 3. The goal was to test the adaptability of the system to different devices, with different reception characteristics.

The results are represented in the following table. In Figure 3, the beacon positions are highlighted with black color, and the places that the measurements were taken with red. We placed point A to be at the center of the corridor, that better represents the usual usage area. In order to test the accuracy of the system at its limits, we place point B exactly at the wall on the side of the corridor, and point C at the end of the corridor. Both points B and C lay exactly at the limit of the beacon's polygon.

TABLE I. ACCURACY

		Mean error (m)	*σ of error (m)*
Point A	S4	1.22	0.82
	Note 3	0.97	0.48
Point B	S4	3.08	0.76
	Note 3	3.18	1.09
Point C	S4	3.82	2.20
	Note 3	3.50	1.78

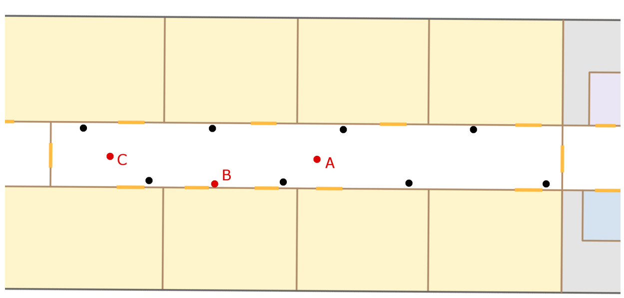

Fig. 3. Test environment. Beacon positions are highlighted with black color, and the places that the measurements were made with red color.

The position estimation is very reliable throughout the corridor, with an average accuracy of 1.22 and 0.97 meters for the two devices. The accuracy drops at the limits of the polygon, but remains reliable, with an average error of 3.08 (and 3.18) meters next to the wall. It is worth mentioning that the accuracy with the Note 3 is really similar to the one with the S4, that is the device used for the propagation model calculation.

Apart from the static measurements, we performed also a dynamic test in the same environment. The corridor is 2.5 meters wide and the trajectory of the mobile phone's movement was 25 meters, at a straight line, and in a constant pace of 1 m/s. In Figure 4, the real trajectory is represented by the grey straight line segments, and the corresponding trajectory of the position estimations by the red crooked line segments. The mean value and standard deviation of the distances between the estimated and the true positions are measured to be $\mu = 2$ and $s = 1.28$ respectively.

The error in the dynamic version is higher than the static one, as expected. Nevertheless, a precision of 2 meters for a moving device that drops to 0.97 when the device is static, can be satisfactory for most indoor position applications. The distance measure used for calculating the error was the two dimensional euclidean distance. Of course, in cases where map matching is used, all position estimations would be projected on the axis of the corridor, reducing the error only at its length-wise component, removing the width-wise component.

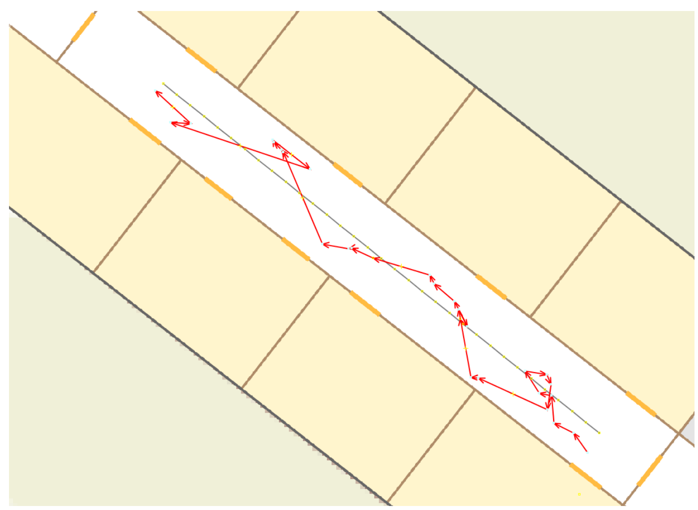

Fig. 4. Real trajectory (grey straight ling segments) and path from postition estimations (red crooked line segments).

V. CONCLUSION AND FUTURE WORK

An innovative indoor positioning system is presented in this paper. The wireless technology used is BLE, which has low cost, and offers ease of deployment. It does not require the creation of a radio map, neither a calibration stage, but simply the awareness of the positions where the beacons were deployed. The scenarios that the technology was tested with were directed towards localization in the corridor area of buildings. Localization in corridors can assist a navigation system to guide a user to a room in a building. The achieved accuracy of localization is 0.97 meters (depending on the device).

Our goal is to further improve this method by testing other beacon configurations [12] (apart from the zigzag pattern) that might optimize the accuracy of estimation by also keeping a low density of beacon deployment. In the context of the the AAL Virgilius Project, beacons were deployed following the zigzag pattern in the corridors of the hospital of Perugia, Italy. The goal was to navigate a user from the entrance of the hospital to the door of the room that the user would choose. Regarding a corridor deployment, the zig-zag pattern is very efficient, but it remains to design a general pattern that works for all room shapes and sizes.

Moreover, the weight used (inverse distance) has been selected after comparison with other possible weights, but remains to be further studied. Lastly, after obtaining a series of position estimations, we intend to apply an extra filtering step, in order to smooth the transition among position estimations.

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References

[1] S. Mazuelas *et al.*, "Robust indoor positioning provided by real-time rssi values in unmodified wlan networks." *J. Sel. Topics Signal Processing*, vol. 3, pp. 821–831, 2009.

[2] M. Lee and D. Han, "Voronoi tessellation based interpolation method for wi-fi radio map construction." *IEEE Communications Letters*, vol. 16, no. 3, pp. 404–407, 2012.

[3] "Tod iBeacons," 2014, URL: https://www.todhq.com/ [accessed: 2014-09-09].

[4] F. Vanheel, J. Verhaevert, E. Laermans, I. Moerman, and P. Demeester, "Automated linear regression tools improve rssi wsn localization in multipath indoor environment." *EURASIP J. Wireless Comm. and Networking*, vol. 2011, p. 38.

[5] C. Papamanthou, F. P. Preparata, and R. Tamassia, "Algorithms for location estimation based on rssi sampling," in *ALGOSENSORS*, 2008, pp. 72–86.

[6] M. Saxena, P. Gupta, and B. N. Jain, "Experimental analysis of rssi-based location estimation in wireless sensor networks," in *In Proc. Int. Conf. Communication System Software and Middleware*, 2008, pp. 503–510.

[7] Z. Yang, Y. Liu, and X.-Y. Li, "Beyond trilateration: On the localizability of wireless ad hoc networks," *IEEE/ACM Trans. Netw.*, vol. 18, no. 6, December 2010, pp. 1806–1814.

[8] K. Lu, X. Xiang, D. Zhang, R. Mao, and Y. Feng, "Localization algorithm based on maximum a posteriori in wireless sensor networks," *IJDSN*, vol. 2012, pp. 1–7.

[9] H. Zou, L. Xie, Q.-S. Jia, and H. Wang, "An integrative weighted path loss and extreme learning machine approach to rfid based indoor positioning," in *Indoor Positioning and Indoor Navigation (IPIN), 2013 International Conference on*, Oct 2013, pp. 1–5.

[10] S. Sorour, Y. Lostanlen, S. Valaee, and K. Majeed, "Joint indoor localization and radio map construction with limited deployment load," *IEEE Transactions on Mobile Computing*, vol. 99, 2014, no. PrePrints, p. 1.

[11] G. Zanca, F. Zorzi, A. Zanella, and M. Zorzi, "Experimental comparison of rssi-based localization algorithms for indoor wireless sensor networks," in *Proceedings of the Workshop on Real-world Wireless Sensor Networks*, ser. REALWSN '08. New York, NY, USA: ACM, 2008, pp. 1–5.

[12] N. Bulusu, D. Estrin, and J. S. Heidemann, "Adaptive beacon placement." in *ICDCS*. IEEE Computer Society, 2001, pp. 489–498.