A BLE-Based Probabilistic Room-Level Localization Method

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***Abstract*—During the last decades, location based services have become very popular and the developed indoor positioning systems have achieved an impressive accuracy. The problem though is that even if the only requirement is room-level localization, those systems are most of the times not cost-efficient and not easy to set-up, since they often require time-consuming calibration procedures. This paper presents a low-cost, threshold-based approach and introduces an algorithm that takes into account both the Received Signal Strength Indication (RSSI) of the Bluetooth Low Energy (BLE) beacons and the geometry of the rooms the beacons are placed in. Performance evaluation was done via measurements in an office environment composed of three rooms and in a house environment composed of six rooms. The experimental results show an improved accuracy in room detection when using the proposed algorithm, compared to when only considering the RSSI readings. This method was developed to provide context awareness to the international research project named SmartHeat. The projects aims to provide a system that efficiently heats a house, room by room, based on the habitants' habits and preferences.**

***Keywords*—Indoor positioning, localization, Bluetooth low energy, RSSI, room-level accuracy**

I. Introduction

In the past two decades, there has been a continuous rise in interest in location-aware applications. After the invention of the Global Positioning System (GPS), more and more devices have included a GPS receiver and have been using this technology. Especially with the rise of the smartphones, Global Navigation Satellite System (GNSS) receivers have become available in the market at low cost, and are nowadays ubiquitous. While the GNSS is an exemplary solution for most outdoor applications, it is not suitable for indoor environments. Therefore, new technologies and systems have been invented that can be used for indoor localization.

One common category of such systems is that of the inertial ones, namely those that use an inertial measurement unit tracking technique, such as the pedestrian dead reckoning [1]. Sound based systems also exist, using for example ultrasound anchor beacons with known position [2]. There are also systems that use other spatially dependent environmental properties such as magnetic fields, visual object recognition and light. Last but not least, there are hybrid systems that are implementing multiple technologies [3] or that are using multinodal sensoring [4].

However, the most widespread indoor localization technique is by using radio transmissions. Methods that use radio include Wi-Fi devices that are popular and widely deployed, and Bluetooth beacons that are of low cost [5]. Those systems either estimate the distance between the transmitter and the receiver by employing path-loss models or employ location fingerprinting to infer a position. The measured radio signal quantities typically include the link quality, the time of arrival (TOA), the angle of arrival, the time difference of arrival, the signal-to-noise ratio (SNR) and the RSSI. The RSSI is the relative received signal strength in a wireless environment, in arbitrary units. RSSI is an indication of the power level being received by the antenna and therefore, the higher the RSSI number, the stronger the signal.

Our approach to indoor localization is based on the use of BLE beacons, using the RSSI value, since it is available in all standard wireless communication devices. The important feature of our approach that distinguishes it from other systems based on Bluetooth is that it does not only rely on radio signal quantities. It also takes into account the geometry of the rooms the beacons are placed in, i.e. the height and the surface area. Since the requirements of the localization system to be developed were minimal cost and setup process for the end user, we used the minimum amount of BLE beacons, that is one BLE beacon per room attached to the ceiling in the center of it, and we opted to develop a more sophisticated algorithm for room detection.

In ubiquitous computing the need for location information is critical and several context aware applications are in need of an indoor positioning system for room localization. Our motivation in developing this indoor localization system with room-level accuracy is to provide contextual information to the international research project named SmartHeat. The project aims to provide a system that efficiently heats a house, room by room, based on the habitants' habits and preferences. It will also be used to provide location information to the F2D fall detection system [6], as a way to provide the system with context awareness in order to improve its accuracy as well as the reaction time of the user's carers. The same solution, though, can be easily deployed and used for any application

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that requires room-level localization.

Ideally, in line of sight conditions the performance of such a system can be accurate. On the other hand, the RF signals indoors are prone to disturbances due to shadowing, fading, the multipath propagation phenomenon and device imperfections. These can lead to major errors when estimating distances based on the radio signal quantities, since the signal can significantly fluctuate. This can be confronted by not using exclusively the newest reading of the signal quantity, but by averaging a set of the latest ones [7].

The rest of this paper is organized as follows. In Section II we present some of the related work on indoor localization using Bluetooth and other technologies. Then, in Section III we present the system we designed, while the experimental evaluation of it in an office and in a house environment is included in Section IV. Finally, our conclusions are drawn in Section V.

II. Related work

Location information is essential for a wide range of ubiquitous and pervasive applications. This is the reason why the topic of determining the position of a device has been the subject of many studies. In this section, we give an overview of some existing systems and implementations that use Bluetooth as well as other technologies as a means to achieve room-level localization. All different implementations have had to balance the technologies used in terms of cost, precision, accuracy, portability, ease of installation, deployment and use.

One of the first indoor badge positioning systems is the Active Badge system [8]. Active badges were used to emit a globally unique infrared signal and were carried by people. Sensors were placed in each located place such as a room, in order to detect the signals sent by the active badges and to infer a position for each badge. Although the sensors and the badges were cheap, the sensors had to be connected to a central server and the cables raised the cost of the system, despite the room-level accuracy that it provided. The use of a central server is also not suitable for our application.

Another way of indoor localization is by using ultrasound signals. Inspired by bats that use those signals to navigate at night, several such systems have been developed. The Active Bat positioning system [9] is using tags that periodically broadcast a short pulse of ultrasound. Ceiling mounted receivers at known positions receive the aforementioned pulses. Using the TOA measuring method and trilateration, a 3D position for every tag can be calculated. Generally, the performance of the ultrasound technology is hindered by reflections and by obstacles between receivers and transmitters. Although the system has achieved an impressive accuracy in positioning, the use of a large number of receivers by the Active Bat and the interconnection between them, limit the scalability of the system.

Conversely, the Cricket indoor localization system [2] uses ultrasound emitters attached on the walls or ceilings at known positions and receivers attached to objects to be located. The system uses again TOA and the trilateration location technique to infer a location. On top of this, radio frequency (RF) signals are used for the synchronization of TOA and for proximity positioning to address fault tolerance issues. Although the system was not targeting room-level accuracy, less ultrasound emitters can be used to achieve this, leading to a proportional decrease in both cost and accuracy. The problem with this approach though, is that both the transmitters and the receiver need more power, since they have to handle both ultrasound and RF signals at the same time.

A large body of indoor localization approaches use the Wi-Fi technology, as to take advantage of the spread of wireless access points in urban areas. The RADAR system [10] uses the existing WLAN technology and employs RSSI and SNR with the triangulation localization technique. Another system named WILL [11] also uses the existing Wi-Fi infrastructure and mobile phones to localize the user indoors. On this occasion site survey is not needed and thus the deployment is easy and rapid. Although Wi-Fi positioning is one of the most popular indoor positioning techniques, most of the times the Wi-Fi access points are not deployed with the ideal geometry and density for positioning, and thus are not optimized for indoor localization.

Another wireless sensor network based indoor location estimation system uses the ZigBee communication standard for room detection [12]. It considers the behaviour of the RSSI through walls, floors and ceilings, and using a decision algorithm estimates a position. A blind node is located by using the reference nodes, that are placed one per room. The system exhibits good performance for its simplicity, although a wrong room indication often occurs when the blind node is located in the vicinity of a wall, due to the unpredictable indoor multipath effects and the potentially small path loss through the intersecting material. The boundary locations were also the biggest challenge that we faced in our approach.

The use of Bluetooth technology for positioning has been evaluated more than a decade ago [13]. Since then, the introduction of the BLE radio protocol provided even more opportunities for indoor localization. BLE beacons are flexible in the sense that they are small in size, they do not need to be plugged in and are power efficient. Either deriving a location from fingerprinting techniques [14], or ranging techniques that use path-loss models [3], researchers have focused on increasing the accuracy of the positioning. Although a room estimation can often be derived from such systems, they are usually not optimized for it. Our research has focused on developing an easy to set up BLE-based system for room localization, while keeping the cost as minimal as possible.

III. System overview

A. RSSI and propagation model

In RSSI-based localization, the signal sent from the anchor beacon to the mobile device is used to map the RSSI to a distance by means of a propagation model. The correct calibration of the propagation model is crucial, since the way RSSI is transformed into a distance significantly affects the accuracy of the positioning. The widely known method we use to model wireless signal propagation loss [15], is expressed as:

$$r = r_0 - 10nlog_{10}(\frac{d}{d_0}) + X_\sigma \quad (1)$$

where r and r_0 denote the received signal power at the real distance d and at a reference distance d_0 respectively. X_σ is a random variable representing the noise in the measured r and n is the path loss exponent, that depends on the transmission channel, the transmitter and the receiver. Using $d_0 = 1$ meter as the reference distance, and assuming X_σ to be a zero mean Gaussian distribution, the simplified model is used as follows:

$$r = p - 10nlog_{10}(d) \quad (2)$$

where r is the received signal power at the distance d, p is the received signal power of the receiver from a transmitter one meter away and n is again the path loss exponent.

B. Room dimensions and RSSI thresholds

Let S be the surface area of a room and h be the height of it. Assuming a square room as on Figure 1, the radii of the inner and the outer tangent circles are calculated with Equations 3 and 4 respectively.

$$r_{in} = \frac{\sqrt{S}}{2} \quad (3)$$

$$r_{out} = \sqrt{\frac{S}{2}} \quad (4)$$

Now using the Pythagorean theorem, the hypotenuses are calculated with Equations 5 and 6 respectively.

$$d_{in} = \sqrt{h^2 + \frac{S}{4}} \quad (5)$$

$$d_{out} = \sqrt{h^2 + \frac{S}{2}} \quad (6)$$

Eventually, by substituting the calculated distances of the hypotenuses into the propagation model of Equation 2, the expected RSSI values at those distances are obtained. Defining the inner and the outer RSSI thresholds as the expected RSSI values at the inner and the outer tangent circles of the aforementioned square room respectively, the thresholds are calculated with Equations 7 and 8.

$$threshold_{in} = p - 10nlog_{10}(\sqrt{h^2 + \frac{S}{4}}) \quad (7)$$

$$threshold_{out} = p - 10nlog_{10}(\sqrt{h^2 + \frac{S}{2}}) \quad (8)$$

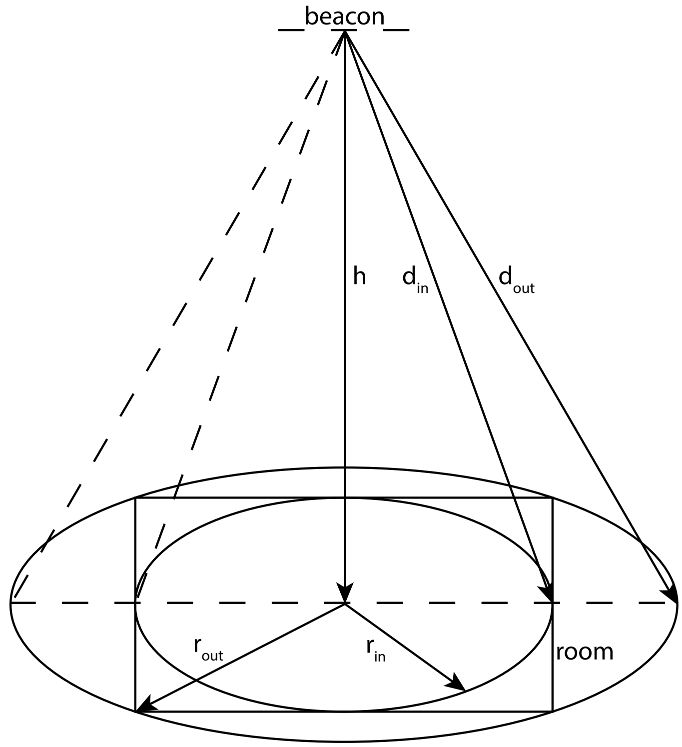

Fig. 1. Dimensions in a square room.

C. RSSI classification and localization algorithm

In our approach, one BLE beacon is attached to the ceiling in the center of every room. For every beacon, the $threshold_{in}$ and $threshold_{out}$ are calculated as described previously, taking into account the dimensions of the rooms. Based on the RSSI readings of the beacons, they fall into one of the following categories. The "Strong" category (S) when $RSSI > threshold_{in}$, the "Medium" category (M) when $threshold_{in} > RSSI > threshold_{out}$, the "Weak" category (W) when $threshold_{out} > RSSI$ and the "Not found" category (NF) when there is no reading for a specific beacon. The ordering of those categories based on their significance is the following: S > M > W > NF.

At any given moment, for every beacon, a set of its N latest RSSI readings is averaged, before every beacon can be classified into one of the aforementioned categories. While a relatively large N may increase the robustness of the system, in the sense that it copes with noise and signal variations, this particular choice may introduce lag to the localization method, because older readings are taken into account for a longer period of time. This can be confronted though by giving more weight to the latest readings than to the old ones.

After the classification of the beacons, the most significant non empty category is picked. If only one beacon falls into this category, then the procedure ends and presence is assumed in the room that this specific beacon was placed in. When multiple beacons fall into this category, then a score is calculated for every beacon that is equal to the difference of its measured RSSI and its lower threshold. The

TABLE I
RESPECTIVE LOWER THRESHOLD FOR EACH CATEGORY.

Category	Requirement	Lower threshold
Strong	$RSSI > threshold_{in}$	$threshold_{in}$
Medium	$threshold_{in} > RSSI > threshold_{out}$	$threshold_{out}$
Weak	$threshold_{out} > RSSI$	-127
Not found	no RSSI reading	N/A

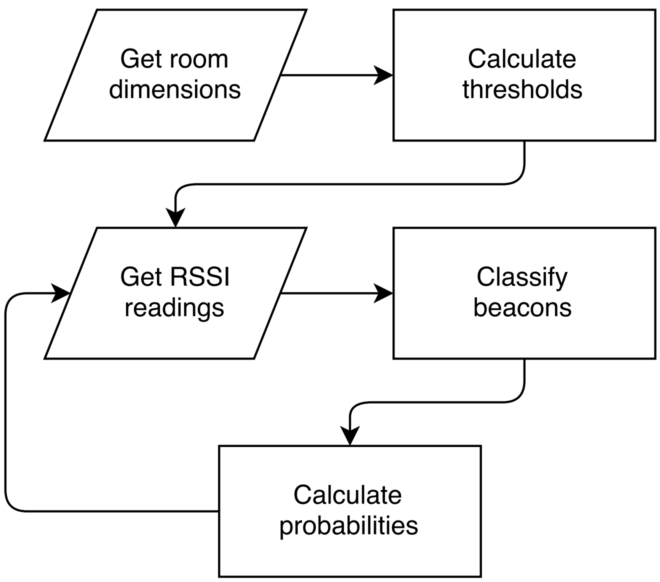

Fig. 2. Steps of the localization method.

lower threshold is equal to $threshold_{in}$ when S is the most significant non empty category, $threshold_{out}$ when M is the most significant non empty category and when W is most significant non empty category, it is the global minimum of the RSSI readings set by the BLE specifications, which is -127 [16]. The corresponding lower threshold for every category, along with the requirements for the beacons to fall into each one of them, are given in Table I.

Then, a probability is calculated for every beacon as the fraction of its score by the sum of all the scores of the beacons that fall into the aforementioned most significant non empty category. In case a single room estimation is needed, the beacon with the highest probability obviously dominates and in the final case of a draw, the beacon that is placed in the biggest room does. The whole procedure is depicted in Figure 2.

The way the algorithm is designed, it intrinsically favours presence in bigger rooms, in the sense that when the same RSSI is received by two beacons, the one in the bigger room will have lower thresholds and will either be in a higher category, or if not it will have a higher probability than the beacon in the smaller room. For this reason, the algorithm works best for the boundary locations in a room that are farther away from the center of the room, than the center of a smaller adjacent one.

IV. EXPERIMENTS AND EVALUATION

A. Experiment methodology

For our experiments, we used a Samsung Galaxy S6 (the SM-G920F international variant) smartphone as the receiver and the Kontakt.io Smart Beacons as the transmitters, set in their default configuration settings (transmission power = $-12dBm$ and interval between transmissions = $350ms$).

We gathered RSSI readings at grid locations in every room throughout the floor. At every point, we collected a total of 200 averaged RSSI readings for every beacon. For our tests we have empirically set $N = 10$, where N is the size of the set of the latest RSSI readings of every beacon that is averaged. The receiver was placed on a non conducting surface at roughly one meter from the floor.

B. Propagation model calibration

In order to construct the specific propagation model for our application, we placed a BLE beacon in the center of a corridor. Then, we took multiple measurements at several points with a known distance from the beacon, ranging from 0.5 to 7 meters. By constructing the line of best fit described by Equation 2, the estimated values of the propagation model parameters were $p = -70.09$ and $n = 1.95$.

C. Deployment in two locations

We have deployed our indoor positioning system in two different environments. The first is a typical office environment composed of three rooms as seen in Figure 3, housing eight people. The area is divided by thick concrete walls and wooden doors. The second is a house environment composed of five rooms of different sizes and one corridor as seen in Figure 5. Due to the corridor being oblong in this occasion, we have divided its total area into two equal ones, so that we can abstractly consider that the house is composed of a total of seven rooms. The area is divided by thin concrete walls and wooden doors.

D. Comparison

We compare the performance of our indoor positioning system with room-level accuracy with the one without the thresholds our algorithm introduces. That is a naive system that only considers the magnitude of the RSSI readings and assumes presence in the room with the highest one. Due to the result of the naive system being discrete, only the room with the highest probability given by our system is taken into account. The same dataset was used for the comparison.

E. Office environment

In this experiment, RSSI readings were collected at 27 different points (9 for every room) as depicted by the circles in Figure 3. The green points are the ones for which the error was improved with the introduction of the localization algorithm, while for the red one the error deteriorated. Table II presents the average error per room and Table III presents the specific locations in the office for which the error has changed. For the rest of the points that the error remained unchanged (white

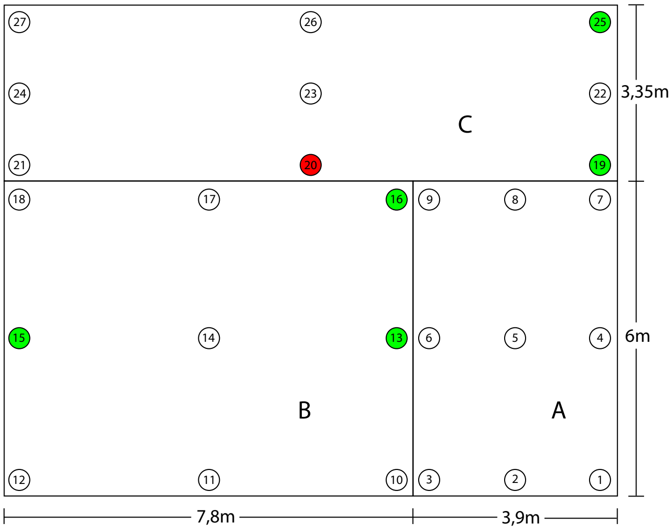

Fig. 3. Office evaluation area and targeted locations (green for the points with an error improvement, red for an error deterioration).

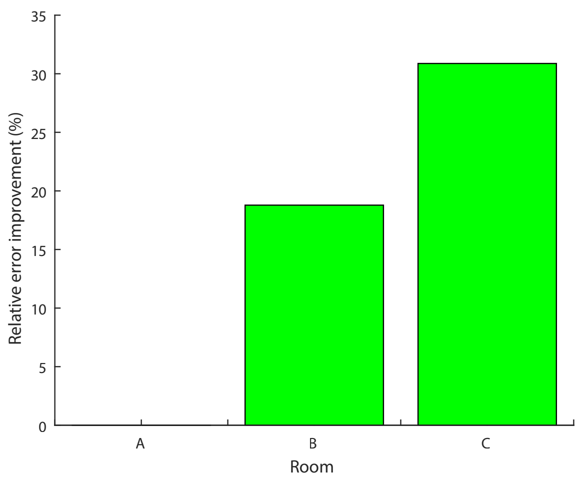

Fig. 4. Relative error improvement in the office evaluation area.

points), the average error was 0.29%. As seen in Figure 4, the average error of the points of room B has improved by 18.79% and the average error of the points of room C has improved by 30.88%.

F. House environment

In this experiment, RSSI readings were collected at 63 different points (9 for every room) as depicted by the circles in

TABLE II
PER ROOM ERROR COMPARISON IN THE OFFICE.

Room	Error without the algorithm (%)	Error with the algorithm (%)	Relative error improvement (%)
A	0	0	0
B	10.06	8.17	+18.79
C	12.06	8.33	+30.88

TABLE III
LOCATIONS IN THE OFFICE WITH AN ERROR CHANGE.

Point	Error without the algorithm (%)	Error with the algorithm (%)	Relative error improvement (%)
13	53.5	40	+25.23
15	11.5	10.5	+8.7
16	19.5	17	+12.82
19	86.5	50	+42.2
20	21.5	25	-16.28
25	0.5	0	+100

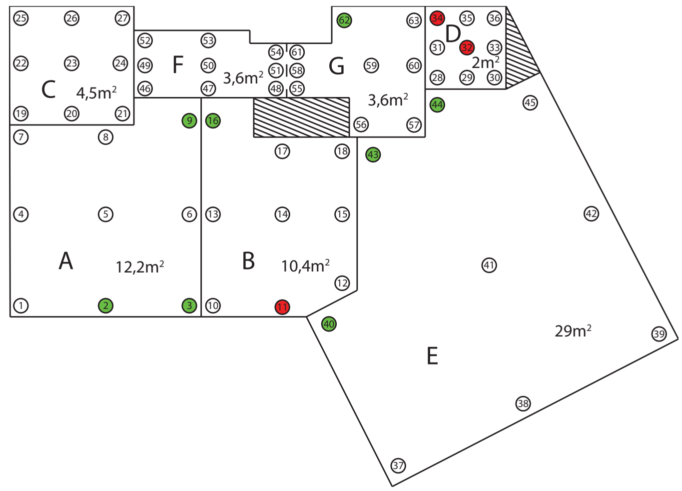

Fig. 5. House evaluation area and targeted locations (green for the points with an error improvement, red for an error deterioration).

Figure 5. Once more, the green points are the ones for which the error was improved with the introduction of the localization algorithm, while for the red ones the error deteriorated. Table IV presents the average error per room and Table V presents the specific locations in the house for which the error has changed. For the rest of the points that the error remained unchanged (white points), the average error was 6.07%. As seen in Figure 6, the average error of the points of room A has improved by 8%, of room B by 18.91%, of room E by 13.52%, of room G by 8.9%, while the average accuracy of the points of room D has deteriorated by 9.09%.

G. Discussion

The presented algorithm was designed in order to improve the accuracy in the boundary locations. These are the locations

TABLE IV
PER ROOM ERROR COMPARISON IN THE HOUSE.

Room	Error without the algorithm (%)	Error with the algorithm (%)	Relative error improvement (%)
A	9.72	8.94	+8
B	8.22	6.67	+18.91
C	0	0	0
D	1.83	2	-9.09
E	21.78	18.83	+13.52
F	15.33	15.33	0
G	18.72	17.06	+8.9

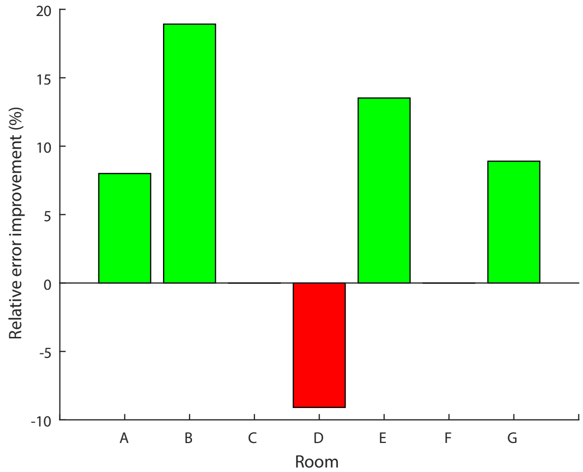

Fig. 6. Relative error improvement in the house evaluation area.

TABLE V
LOCATIONS IN THE HOUSE WITH AN ERROR CHANGE.

Point	Error without the algorithm (%)	Error with the algorithm (%)	Relative error improvement (%)
2	2.5	2	+20
3	25	24.5	+2
9	29.5	23.5	+20.34
11	9.5	10	-5.26
16	54	39.5	+26.85
32	7.5	8.5	-13.33
34	0.5	1	-100
40	46.5	44.5	+4.3
43	45	24	+46.67
44	100	96.5	+3.5
62	45	30	+33.3

in a room that are farther away from the center of the room, than the center of a smaller adjacent one. As seen from the measurements, accuracy was improved in the following such locations: points 13, 16 and 19 in the office evaluation area and points 3, 9 16, 40, 43 and 44 in the house evaluation area.

The deterioration of the accuracy in some points was mainly due to the combination of the RSSI fluctuating and the fact that the presented algorithm intrinsically favours presence in bigger rooms. This especially holds true for the point 20 in the office evaluation area, where although the RSSI from the beacon in room C was in average higher than the RSSI from the beacon in room B, the fluctuation of the signal along with the thresholds introduced by the algorithm eventually decreased the localization accuracy.

V. Conclusion

In this paper we have presented an easy to deploy BLE-based indoor positioning system with room-level accuracy. The system only requires the geometry of the rooms and BLE beacons attached to the ceiling in the center of every room. The presented algorithm computes two RSSI thresholds for every room, and based on them, categorizes the RSSI readings and finally estimates a room location.

We have deployed our system in two different locations, an office environment composed of three rooms and a house environment composed of six rooms. After comparing it with the no-threshold approach, we saw an improvement of room estimation accuracy, especially in the boundary locations of the rooms. These are the locations in a room that were farther away from the center of the room, than the center of a smaller adjacent one. Overall, out of the 90 points that measurements were taken, the algorithm managed to improve the localization accuracy of 13 of them, decreased the accuracy of 4 and did not affect the rest.

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