Indoor Positioning: A Comparison of WiFi and Bluetooth Low Energy for Region Monitoring

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Keywords: Assistive Technology, Indoor Positioning, Bluetooth Low Energy.

Abstract: Mobile devices like smartphones equipped with several sensors make indoor positioning possible at low costs. This enables location based services, like mobile marketing, navigation, and assistive technologies in health-care. In case of supporting disoriented people, the exact position of the person has not to be known, but it is sufficient to inform a caretaker when the attended person enters a critical region. This is the so-called *region monitoring approach*. The paper presents results from region monitoring implemented as an app for Android smartphones using WiFi and the low power protocol Bluetooth Low Energy respectively. Both networks are compared regarding accuracy and the power consumption on the mobile device.

1 INTRODUCTION

With their widespread use, smartphones get interesting for indoor positioning in the context of assistive technologies. Thereby, disoriented people like demented people or people suffering from amnesia can be supported in their daily living. In case of demented people living in a house for elderlies, the patient, or a device like a wheelchair, is equipped with a smartphone. The smartphone periodically checks whether the person is still in a *safe* environment. In case the person leaves the home environment and seems to get lost, the smartphone will send an alarm message to the mobile of the caretaker.

At Potsdam University, the Kompass system is developed which investigates Ambient Assistive Living (AAL) technologies for the support of elderlies (Fudickar et al., 2011). The Kompass system uses smartphones for fall detection and adds localization information to the alarm message when a fall with unconsciousness is detected (Gimpel et al., 2015).

Further, indoor positioning is used for mobile marketing application and indoor navigation within complex buildings, like airports.

In our use case the need for accuracy is low compared with mobile marketing applications, where the application needs to know exactly in front of which product the user is currently standing, or compared with indoor navigation. To support disoriented people, it is sufficient to notify the caretakers in case the user leaves the safe environment and enters a critical region, like the corridor in front of the door.

Therefore, we proposed *region-based positioning* where the given environment is divided into regions (Fudickar et al., 2011). A so-called *region map* lists the beacons/routers which have to be received in each region.

Since most buildings today have a WiFi infrastructure, this protocol was an obvious first choice for positioning and was successfully tested in the Kompass project (Schindler, 2011; Scheffler et al., 2013; Kappel, 2014).

This paper compares region-based indoor positioning using WiFi versus Bluetooth Low Energy (BLE). The evaluation metrics are positioning correctness (percentage of correct localizations) and power consumption of the mobile device. BLE is available on most of modern smartphones and operates like WiFi in the 2.4 GHz license-free band. BLE may be an interesting alternative to WiFi, since modern WiFi-routers have a feature called *cell breathing* which makes accurate positioning much harder. A WiFi-router which uses cell breathing may change its transmit power dynamically. In case of a high number of users, the radio reduces its transmit power and hence its cell radius is decreased. Thereby, heavily loaded cells may hand over load to neighboring cells. While this approach is beneficial for load distribution and a good service quality, the dynamically changing transmit power makes the definition of region maps more difficult. Further, it is a serious problem for positioning algorithms which rely on Received Signal

Lindemann, A., Schnor, B., Sohre, J. and Vogel, P.
Indoor Positioning: A Comparison of WiFi and Bluetooth Low Energy for Region Monitoring.
DOI: 10.5220/0005704603140321
In *Proceedings of the 9th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2016) - Volume 5: HEALTHINF*, pages 314-321
ISBN: 978-989-758-170-0
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Strength values.

The remainder of this article is structured as follows: The next section discusses different approaches for wireless indoor positioning. In Section 3, related work is discussed. The region-based indoor positioning algorithm and its parameters are presented in Section 4. The results of our evaluation are given in Section 5. Finally, the article ends with a conclusion.

2 WIRELESS INDOOR POSITIONING

Due to the attenuation by walls and other obstacles, a Global Navigation Satellite System (GNSS) like GPS or Galileo is not usable for indoor positioning. Therefore, other approaches are investigated like localization via the *Received Signal Strengths* (RSS) in a wireless network. Typically, the environment is equipped with so-called *beacons* which send wireless advertisement messages with a beacon identifier. The smartphones are configured with the information about the beacons and their location within the environment. Further, the *Received Signal Strength Indicator* (RSSI) is used to estimate the distance of the smartphone from the beacon. This is done by comparing the currently received signal strengths with a *radio-propagation map* which contains the expected RSSI values. The location with the smallest error distance is estimated as *current location*.

A radio-propagation map is generated either by fingerprinting or by a model-based algorithm. In case of fingerprinting, time consuming measurements are done in advance, since the RSSI values have to be collected at every grid point. For example, in (Fudickar and Valentin, 2014b) the influence of the grid granularity between 0.5-5 m is investigated for the model-based approach using WiFi. The finest grid size of 0.5 m shows the best results in this study. Model-based algorithms calculate the radio-propagation map from a formula using different parameters like signal frequency, the distance from the beacons, and the number of walls between beacon and the position of interest. Typically, the influence of multi-path fading is not considered in these models. For example, the International Telecommunication Union (ITU) proposed a path-loss function for the radio frequencies from 900 MHz up to 5.2 GHz (ITU, 2012). Free delectable parameters in this model are the distance power loss coefficient and the floor penetration loss factor. The accuracy of the modeling depends on the tuning of these parameters for the given building.

In the region-based approach, regions are defined by a list of beacons which have to be received (*positive list*) or which may not be seen in the specified region (*negative list*). Hence RSSI values are not used and therefore no costly calculations have to be done to determine the position with the least error. This approach can be combined with a threshold for the RSSI values to exclude beacons which are only seen sometimes due to multi-path fading for example. The benefit of this approach compared to fingerprinting or model-based positioning is the higher usability, since it has the lowest setup-time - no time consuming fingerprinting is necessary, nor parameter tuning like in the case of the model-based algorithms.

The region based approach is already supported by the iOS API since iOS 4.0 and later[1]. iOS supports two kinds of BLE positioning, *geographical region monitoring* and *beacon region monitoring*, where a beacon region is an area defined by the device's proximity to Bluetooth low-energy beacons. This fits perfectly to our region concept. iOS also supports a *ranging* API to determine the relative distance between a beacon and a device, but the programming guide also informs about the well-known difficulties: "Beacon ranging depends on detecting the strength of Bluetooth low-energy radio signals, and the accuracy of those signals is attenuated (or lessened) by walls, doors, and other physical objects. The signals are also affected by water, which means the human body itself will affect the signals. It is important to be aware of these factors when planning your iBeacon deployment because they will impact the proximity value reported by each beacon."

3 RELATED WORK

A comparison of different indoor location systems is given in (Fudickar and Valentin, 2014b). The majority of the algorithms use either WiFi (Bahl and Padmanabhan, 2000; Gansemer et al., 2010), or the 868 MHz network typically used in sensor networks (Behnke and Timmermann, 2008; Fink et al., 2010; Fudickar and Valentin, 2014a). While the different algorithms show a good accuracy in their specific test environments, neither the influence of humans nor the influence of concurrent networks, like the campus-wide WiFi, on the Received Signal Strength (RSS) is tested.

[1] iOS Developer Library, Location and Maps Programming Guide

3.1 Fingerprinting and Model-based Positioning

Different model-based algorithms have been investigated by Fudickar and Valentin (Fudickar and Valentin, 2014b; Fudickar and Valentin, 2014a). The authors investigated the influence of different parameters on the accuracy of the positioning algorithm. The parameter tuning process is described in (Fudickar and Valentin, 2014b), while (Fudickar and Valentin, 2014a) compares the tuned algorithm for WiFi with a model-based algorithm tuned for the radio frequencies of 868 MHz which are typically used within low power sensor networks. The authors show that the 868 MHz network is well suited for indoor positioning in their test environment since it was more accurate than using WiFi, and extended the device runtimes from 3.39 h (WiFi) to 7.25 h (868 MHz). Since the energy saving features of current operating systems like Android may result in even longer runtimes, the results show the benefit of the low power network. But on the other hand, the lack of mobile devices equipped with this network is a hurdle.

3.2 Positioning with BLE

Bluetooth Low Energy was already evaluated for indoor positioning in (Faragher and Harle, 2014; Jianyong et al., 2014).

Fingerprinting: Faragher and Harle compare WiFi and BLE fingerprinting (Faragher and Harle, 2014). They use 10 Hz beaconing and a sample interval of 1 second on the mobile device. First, they investigated the impact of a human body on the RSS value. The experiment shows an influence of about 10dB. In a distance of 1 m between beacon and receiver, this results in a poor range estimate of 5-10 m. Next, the authors compare the two networks in a 45m by 12m section of a building which is covered by 3 WiFi access points and 19 BLE beacons transmitting at power level around - 20 dBm. They report that the error during the WiFi tracking was less than 8.5 m in 95% of the measurements, and less than 2.6 m in 95% of the measurements using BLE. They state that the WiFi performance was limited by the poor signal geometry afforded by the existing WiFi infrastructure available in the laboratory, and the higher BLE beacon density on the other hand. While these results are promising, the influence of human bodies on the positioning accuracy is not further investigated in the tracking test. Further, the power consumption was not in their focus.

Model-Based: Jianyong et al. present results from a model-based positioning system using BLE (Jianyong et al., 2014). They evaluated their algorithms in a very simple scenario where one room was equipped with one beacon in each corner without any obstacles. Under this laboratory conditions, they achieved an error less than 2 meters in about 96% of their test cases. Again, the power consumption was not investigated.

3.3 Power Consumption

In (Dementyev et al., 2013), the power consumption of the three low-power protocols, Bluetooth Low Energy, ZigBee and the proprietary ANT network, is compared in a cyclic sleep scenario. All three wireless networks operate in the 2.4-GHz-ISM-band. In the cyclic sleep scenario, Bluetooth Low Energy achieves the lowest power consumption (10.1 μA), compared with ZigBee (15.7 μA) and ANT (18.2 μA) on the mobile device. Since the energy consumption of sending and receiving messages is more or less the same, we expect a similar behavior for the location scenario, where the mobile device periodically gets into the listening mode. Therefore, BLE seems to be the most suited test candidate from these low-power protocols.

4 USING BLUETOOTH LOW ENERGY FOR INDOOR POSITIONING

Several BLE beacons have to be deployed within the environment. A tracked person is equipped with a smartphone which scans periodically for advertising messages from the beacons and identifies each beacon by its signature (Major/Minor/UUID). The *Scan Time* is also a parameter which has to be optimized. Since sending and receiving messages is a dominant factor in the power consumption, the Scan Time should be set as short as possible.

Typically, a beacon can operate in different modes:

- *Advertising Interval:* time between 2 beacon advertising broadcasts. Depending on the hardware, this time can be configured in the range from 50-2000 ms.

  A short Advertising Interval results in a higher power consumption of the beacon, but increases the probability to receive advertising messages during the Scan Time of the device.

- *Transmit Power:* is the physical power of the transmitted signals.

  Again, the Transmit Power is relevant for the power consumption of the beacon. A higher

Transmit Power results in a higher energy consumption of the beacon, but also in a higher receive probability during the Scan Time of the device.

As introduced in Section 2, a region map has to be configured with a *Beacon Positive* and a *Beacon Negative List*. An example is shown in Table 3. The localization algorithm is illustrated in detail in Figure 1. Periodically, the smartphone enables the Bluetooth adapter to scan for advertising messages and sleeps between. Since the Bluetooth radio needs some time to get ready, the smartphone gets for *Setup Time* seconds again in the sleep mode after starting the BLE radio. After localization, the smartphone sleeps for *Sleep Interval* seconds. Hence, localization is done about every *Sleep Interval* plus *Sleep Time* seconds. During localization, the received beacon signatures are compared with the region map entries and the first match is returned.

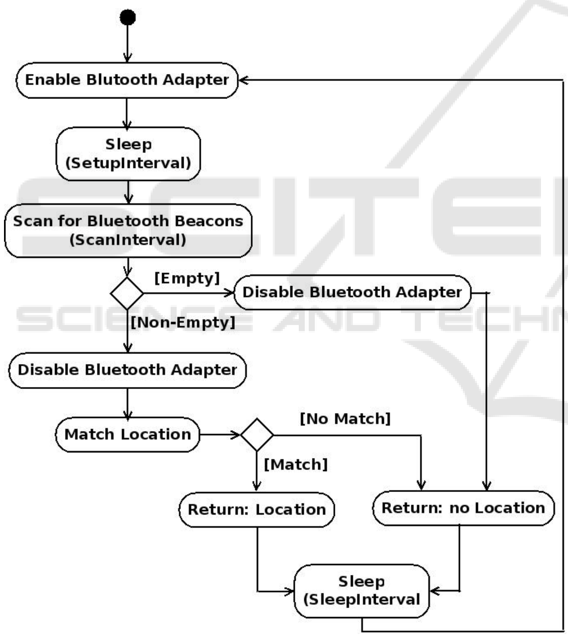

Figure 1: Localization algorithm.

In case a critical region is detected, the device sends a notification to a configured address (Kompass server or telephone number) via WiFi or SMS.

Privacy Concerns: Our location system uses 3 different *reporting modes* to support the privacy concerns of the user which have to be configured:

1. *alarm:* The localization information is only reported to the Kompass server in case of an emergency event, for example a detected fall with unconsciousness.
2. *tracking-alarm:* The localization is reported to the Kompass server when the user leaves the safe environment and enters a critical region.
3. *tracking:* The device reports periodically the localization to the server. This helps to find lost devices. Further, the localization is sent in case of the alarm messages.

5 RESULTS

5.1 Hardware and Software Parameters

In our test environment we used BLE iBeacons of BEACONinside, Model No. B0001-A[2] which is powered by two batteries from type AAA. Due to the manufacturer's data sheet, the beacons should operate about 1-year once deployed using the default (highest) Transmit Power of 0 dBm. The mobile device was the HTC ONE mini2 smartphone with Android 4.4.2 (KitKat) installed.

Figure 2: BEACONinside: Picture of the used Beacon[3].

First, we experimented with the parameters to set up a robust system. We measured a Setup interval of 2.5 s. Hence, we configured a Sleep Interval of 4.5 s to scan about every 10 s. The Advertising Interval was set to 200 ms and the Scan Time to 3 s. Theoretically, the device should receive up to 15 advertising broadcasts during one scan process. The chosen parameter values are summarized in Table 1.

5.2 Comparison WiFi and BLE

First Experiment: In our first test scenario we compared the results from (Kappel, 2014) for WiFi with a BLE setup. Kappel deployed three WLAN access points and defined four regions as shown in Table 2 and illustrated in Figure 3. The regions were defined according to the coverage of the WLAN access points. The access points did not support cell breathing. During a walk along the corridor, Kappel made 65 measurements and reports only one false localization (98.4 % correct localizations).

We repeated this experiment using three BLE beacons at the same positions, each sending with the

[2]http://www.beaconinside.com

[3]Picture from press kit of Beaconinside (Copyright 2014 BEACONinside GmbH. All right reserved.)

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Table 1: Parameter list of the localization algorithm.

Beacon Parameter	Value	description
Advertising Interval	200 ms	Time between two advertisements
Beacon transmit power	-23/-6/0 dBm	
Smartphone Parameter	Value	description
Setup time	2.5 s	Time until the Bluetooth radio is ready
Sleep Interval	4.5 s	Time between localizations
Scan Time	3 s	Time the Bluetooth radio is listening

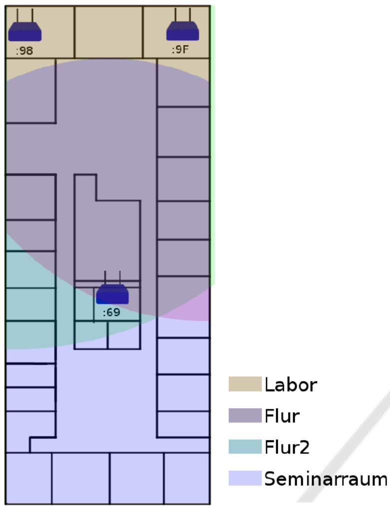

Figure 3: Regions with WLAN access points (Kappel, 2014).

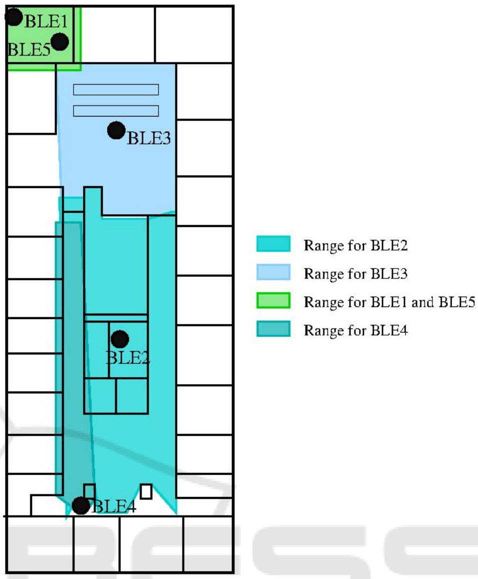

Figure 4: Regions with BLE beacons.

Table 2: Region map for WiFi from (Kappel, 2014).

Region	Positive List	Negative List
Lab	:9f; :98	:69
Floor	:69; :9f; :98	
Floor 2	:98; :69	:9f
Classroom	:69	:98; :9f

highest transmitting power of 0 dBm (three beacons instead of WLAN access points :98, :9F and :69 in Figure 3). Similar to the test from Kappel, 70 measurements were made during a walk along the corridor with the smartphone in the hand, but in only 28 measurements the correct region was detected. WiFi has a further range than BLE and does not fade out as fast as BLE. Obstacles as walls, doors and reflecting surfaces affect the signal strength of BLE more than WiFi. Hence, there have been areas in which no advertisement messages could be received and therefore no localization was possible.

Table 3: Region map for BLE test.

Region	Positive List	Negative List
Lab	BLE 1 or BLE5	-
Floor	BLE3	-
Floor2	BLE4 or BLE2	BLE1, BLE3, BLE 5

Second Experiment: In the next experiment, we increased the number of beacons and used different transmit powers. The beacon placement is shown in Figure 4 and corresponding region map in Table 3. The transmit power of the beacons is set as follows: beacon BLE1 and BLE5 are in the low transmit power mode (-23 dBm), beacon BLE3 in median (-6 dBm), and beacon BLE2 and BLE4 in high transmit power mode (0 dBm).

In our experiments, a low transmit power is beneficial for a more accurate localization due to the smaller cell radius (see the Lab region). On the other hand, beacon messages sent with a low transmit power are lost more often, since they are shielded by the body of the smartphone user. Therefore, we equipped the laboratory with two beacons to increase the receive probability.

Further, we added an additional beacon BLE4 behind the column which was no problem in case of WiFi, but shielded the BLE beacon signal of beacon BLE2.

We repeated the measurements and got 85 correct localizations out of 88 (96.6 %).

5.3 BLE Accuracy Tests

In the following test scenarios, we investigated whether it is possible to localize more accurate using BLE. Therefore, we defined smaller regions in the north part of the building. The test environment is about 19 m x 19 m. Again, we experimented with different beacon densities (3 resp. 5 beacons) and different beacon transmit powers. The beacons are deployed as shown in Figure 5 in a height of approximately 2,3 m. The 10 test positions where the smartphone user made the localization are also shown in Figure 5. For each test position, the localization was made 9 times which results in 90 measurements. At each test position, the test person turns around about 40° after each measurement. Hence, in some of the experiments there is a direct line-of-sight, and in the others, there is the human body as an obstacle.

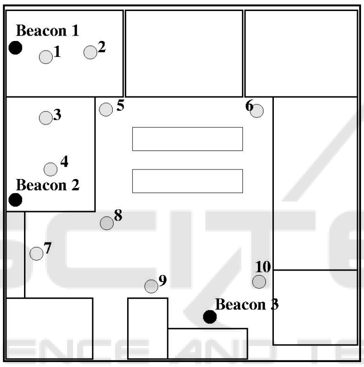

Figure 5: Three beacons with lowest Transmit Power.

Lowest Transmit Power - In our first experiment, we tested with three beacons (Beacon 1, 2 and 3) in the lowest transmit power mode of -23 dBm. The expected benefit of the low transmit power is a longer beacon life time due to energy savings and a more accurate localization due to smaller cells.

The goal of this test scenario was to determine whether it is possible to distinct two neighboring rooms (Laboratory 1 and 2), and further to identify the critical region with two exits (elevator and staircase). The region map is shown in Table 4. The region map was designed in such a way that position 1 and 2 are in the laboratory 1, position 3 and 4 are in laboratory 2, 9 and 10 within the critical region, and all other positions (5-8) are within the safe corridor.

From the 90 localizations, 70 were correct and 20 were incorrect. The results for each position are given in Table 5. Failures occur when the test person stands near a beacon and shields the beacon broadcast (Position 1,2, and 10). At position 9, the elevator shields the signal.

Medium Transmit Power - In the next step, we increased the transmit power to the medium mode of -6 dBm. The results are shown in Table 6. Due to the higher transmit power, the beacon cells are enlarged and overlap. Hence, lots of false localizations occur (55.5 %). It is notable that a high error rate occurs at positions 5, 6, 7, and 8 which belong to the safe corridor. Due to the higher transmit power, advertisement messages from beacon 1, 2, or 3 were received at these positions which results in a wrong classification.

Table 4: Region map for experiment with 3 Beacons.

Region	Positive List	Negative List
Lab 1	Beacon 1	empty
Lab 2	Beacon 2	empty
crit. region	Beacon 3	empty
safe corridor	empty	empty

Table 5: Low Transmit Power (-23 dBm).

Test place	correct	false
1	5	4
2	7	2
3	9	0
4	9	0
5	7	2
6	9	0
7	7	2
8	8	1
9	4	5
10	5	4
Total	70	20
Percent	77.8	22.2

Table 6: Medium Send Signal strength -6 dBm.

Test place	correct	false
1	9	0
2	9	0
3	2	7
4	4	5
5	0	9
6	1	8
7	0	9
8	0	9
9	7	2
10	9	0
Total	41	49
Percent	45.5	55.5

Higher Beacon Density - The key problem identified in the experiment with low transmit power was the inability to perform any localizations at all, due to the limited beacon range. In the experiment with medium transmit power, the key problem identified was the number of incorrect localizations due to the unexpectedly high range. This particularly affected positions in the corridor where we could not distinguish the safe corridor from other regions including the critical region.

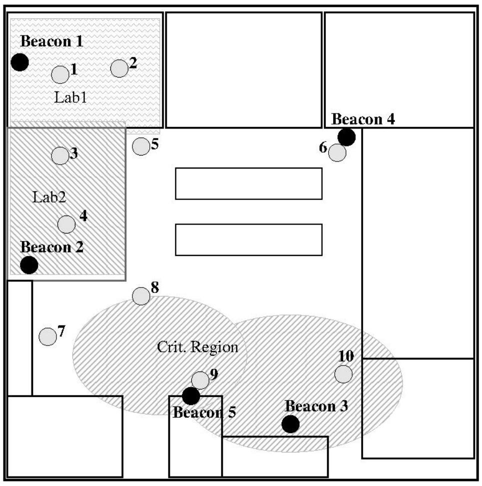

Figure 6: Five beacons with low transmit power.

Table 7: Region map with 5 beacons.

Region	Positive List	Negative List
Lab 1	Beacon 1	Beacon 4
Lab 2	Beacon 2	Beacon 4
Crit. Region	Beacon 3 or 5	Beacon 1, 2, 4
Safe Corridor	-	Beacon 1, 2

Hence, we increased the beacon density as shown in Figure 6. All beacons operated in the low transmit power mode. We added one beacon in the corridor to distinguish one area of the corridor from the other. Furthermore, we added a beacon at the elevator, since the beacon for that region could often not be seen due to a missing line of sight (elevator shaft). For that reason, point 8 is considered part of the critical region for this experiment. The region map is shown in Table 7.

As can be seen in Table 8, this improves the results for some positions only, while worsening the results of other areas. In particular, point 7 is now showing poor performance due to the high range of the added beacon at the elevator shaft. As expected, points 9 and 10 however achieve better results compared to the experiment with medium transmit power.

Table 8: Higher beacon density with 5 beacons.

Test place	correct	false
1	5	4
2	6	3
3	4	5
4	7	2
5	8	1
6	9	0
7	1	8
8	6	3
9	8	1
10	7	2
Total	61	29
Percent	67.8	32.3

5.4 Power Consumption

In a further experiment, we compared the power consumption of WiFi and BLE for region monitoring. Kappel reports experimental results for a HTC Evo 3D using WiFi (Kappel, 2014). He measured the runtime of the smartphone when the localization is performed every 10 or 30 seconds and compares this value with the runtime when no positioning is done. If the positioning app was not running, the battery was discharged after 185 hours and 31 min. With the running app and an interval of 10 s for positioning, the device runtime was 37 hours and 15 min, for an interval of 30 s, the runtime was 50 hours and 43 min.

Table 9: Power Consumption.

Localization	device runtime	
	WiFi (Kappel, 2014)	BLE
Without	185.5 hours	500 hours
every 10 s	37 hours	70.5 hours
every 30 s	80 hours	151 hours

We measured the power consumption of region monitoring for BLE on the smartphone HTC ONE mini2. Table 9 shows that BLE improves significantly the device runtime.

6 CONCLUSIONS AND FUTURE WORK

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Low power networks like Bluetooth Low Energy are attractive for indoor positioning due to the easy installation, the low power consumption and the long life cycle of the beacons. Therefore, we compared Bluetooth Low Energy (BLE) with WiFi in a region monitoring scenario where the localization is done on a mobile device like a smartphone. The region-based positioning was implemented as an app for Android smartphones.

Regarding power consumption, the benefit of BLE is impressive. BLE nearly doubled the runtime of the mobile device from 37 hours up to 70 hours when the device tries to localize its position every 10 seconds.

Regarding accuracy, the result is not so obvious. Even with the maximal signal strength, we did not get a coverage like WiFi. So we had to increase the beacon density. Since the costs per beacon is low compared with WiFi, this is no serious drawback. On the other hand, the higher beacon density combined with different transmit power modes allows the definition of smaller regions and hence a more accurate localization compared with WiFi.

In a coarse grain scenario, we achieved 96.6 % correct localizations with BLE. In a similar scenario, Kappel reported 98.4 % correct localizations in case of WiFi (Kappel, 2014). In a second test series, we tried to identify smaller regions with BLE. In these experiments, the best result was 77.7% correct localizations.

Another aspect for the usability of the presented approach is the setup time of the beacon infrastructure. While it is short compared with fingerprinting or parameter tuning for model-based algorithms, the effort for beacon positioning and test measurements is not neglectable.

In our use case, the caretakers are notified when a demented and disoriented person leaves the safe area. For sending notification messages, the BLE infrastructure is not suited. Hence, the existing WiFi infrastructure of the building or SMS messages via GSM have to be used.

In (Fudickar et al., 2011) a dynamic localization interval is motivated. For example, a resident may have lunch and is not moving. In this situation, the localization interval may be increased for further energy savings. Therefore, we will combine sensor data from the smartphone's accelerometer which are already used for fall detection with the localization system. Further, we will use thresholds for the RSS values and investigate their influence on the positioning accuracy.

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