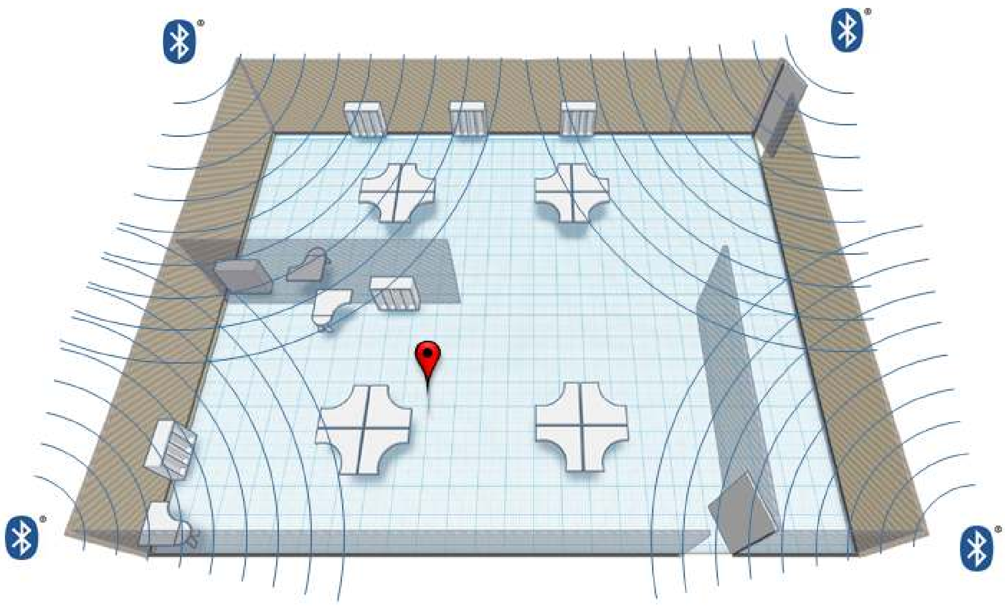

Evaluation of indoor positioning based on Bluetooth® Smart technology

Master of Science Thesis in the Programme Computer Systems and Networks

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Göteborg, Sweden, June 2014

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Illustration of Bluetooth® radio based positioning in action.
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Abstract

Nowadays, positioning technologies are used in a wide variety of areas such as providing driving directions and tracking valuable goods to name a few. Since the introduction of the global positioning system(GPS), it has become a de facto standard for outdoor positioning applications. In contrast to this, no similar widespread technique is available for indoor positioning or in areas where GPS is unavailable. Extensive research have been devoted to exploring the topic based on a variety of technologies such as Wi-Fi, Bluetooth, Zigbee and ultra wideband radio. None of these have successfully made it into a widely accepted standard, although significant progress has been made. In 2010 a completely new Bluetooth technology, referred to as "Bluetooth low energy" or "Bluetooth smart" was released that promises among other things ultra low power consumption, changed radio frequency properties and a completely new software stack. No academic work can be found that explores the usability of this new technology in the context of indoor positioning. This Master thesis is the first project to evaluate the suitability and the applicability of this new technology in the context of indoor positioning. A selection of algorithms and approaches are explored, tested, evaluated and compared in a testbed scenario designed for this purpose. Furthermore, the results of these tests are analyzed by examining the received signal strength indicator (RSSI) behaviour, which is the parameter used as basis for the positioning approaches. The evaluation shows that Bluetooth smart is a viable alternative for indoor positioning which offers widespread availability in society, reasonable accuracy and low cost deployment. The report also provides essential advice on some important pitfalls when using the technology for positioning applications.

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Abbreviations

AOA - Angle of arrival
API - Application programming interface
BER - Bit Error Rate
BF - Bayesian Fusion
BLE - Bluetooth low energy
BSE - Bayes static estimation
ESS - Effective sample size
GFSK - Gaussian frequency shift Keying
GLONASS - Globalnaya navigatsionnaya sputnikovaya sistema
GNSS - Global Navigation Satellite System
GRPR - Golden Receiver Power Range
GPS - Global positioning system
HCI - Host Controller Interface
ID - Identification
IRR - Inquiry response rate
ISM - Industrial Scientific and Medical
LD - Laying down
LOS - Line of sight
LQ - Link Quality
MAC - Media access control
PDU - Protocol data unit
PKF - Point Kalman filter estimation
RF - Radio frequency
RSS - Received Signal Strength
RSSI - Received signal strength indicator
SIG - Special interest group
SOC - System on chip
SU - Standing up
TDOA - Time difference of arrival
TOF - Time of flight
TPL - Transmit power level
TTL - Time to live
Tx - Transmission

Contents

1

Introduction

1.1 Background

Since the introduction of GPS technology, services that rely on positioning and localization data have emerged in a rapid pace. Today positioning technologies are used in a variety of areas such as providing driving directions, recording running routes during training and tracking valuable goods in real-time to name a few. While GPS has become a de facto standard for outdoor positioning applications, no similar widespread technique is present for indoor positioning or in areas where GPS is not available. The topic of indoor positioning does not lack research: Several approaches and suggestions based on different technologies have been developed and introduced over the last two decades. What is common for all of them is that no approach has made any big impact within the area. A number of systems have been commercialized, produced and installed in different quantities but none of these have yet made a big penetration into society. The systems are usually proprietary and used in very small scale installations based on requirements of the specific use case, resulting in that no common universal standard such as GPS exists in the area of indoor positioning.

One proposed radio frequency-based (RF) technique for indoor positioning is to use Bluetooth technology and provide positioning based on signal strength parameters that can be easily obtained. A major advantage of using Bluetooth is that it is a technology with high penetration in society. Devices such as cellphones, tablets and computers normally come equipped with the technology as standard. The large penetration rate also means that the required hardware is produced in large quantities, resulting in a very low unit cost. A Bluetooth chip combined with a microcontroller is typically available for less than 5$. Research on positioning based on Bluetooth has also made some progress in the past years, possibly making it a viable candidate for large scale deployment in several scenarios and applications.

In June 2010, the specification for the Bluetooth 4.0 technology was released[1]. This specification introduced a new technology, named "Bluetooth low energy"(BLE) or "Bluetooth smart". The new technology contains some major differences compared to traditional Bluetooth. A variety of new services and roles are introduced, the RF-band usage is changed, a new software stack is introduced and as can be guessed from the name, power consumption is greatly reduced to between 50-99% of the classic Bluetooth power consumption[2]. A Bluetooth smart device could potentially operate for years powered by a single coin cell battery.

1.2 Motivation

Indoor positioning based on traditional Bluetooth has been both carefully evaluated and improved. However according to the best of our knowledge, no academic work can be found which characterises and evaluates Bluetooth low energy in a positioning setting. Meanwhile, commercial systems using the technology are rapidly emerging on the market promising different performance and properties. The technology and algorithms behind the commercial systems are often vaguely described and kept secret due to competition. This project thoroughly evaluates and investigates the properties of Bluetooth smart and describes its suitability and applicability for providing inexpensive widely available indoor positioning. The project is based upon related theory about RF based positioning techniques and systems. The relevant techniques and approaches are evaluated within a Bluetooth smart setting in a testbed scenario set up to imitate a real world practical scenario. The collected results are carefully investigated, analyzed and explained with regard to properties of the Bluetooth smart technology. In addition the project provides ideas and pointers for future work within the area.

1.3 Research questions

Based on the motivation above, the following questions have been established for describing what the project depicts:

- When is Bluetooth smart a viable choice for indoor positioning systems?
- What algorithms/technologies are best suited for indoor positioning based on Bluetooth smart with requirements on the following properties:
  - accuracy
  - ease of use/ease of installation
  - scalability
  - response time
  - robustness

- Does using Bluetooth smart for indoor positioning achieve more or less benefits compared to related existing systems based on Wi-Fi or Bluetooth technology? Examples of benefits could be performance increase of the aforementioned properties.

- Does using Bluetooth smart for indoor positioning introduce more limitations compared to related existing systems based on Wi-Fi or Bluetooth Technology? Examples of limitations could be performance decrease of the aforementioned properties.

- What level of accuracy and precision can be expected from a positioning system relying on Bluetooth smart technology?

1.4 Limitations

The project has a number of limitations on the depth of the evaluation and analysis. The project does not provide an extensive analysis of antenna design or antenna characteristics. The basic antenna properties of the testbed system are briefly mentioned but no extensive investigation nor evaluation is performed. The evaluation of positioning is limited to a 2-dimensional setting considering x and y-axes for coordinates in space. Meaning that multi-storey applications requiring a z-axis to describe the height of an object is not considered. The evaluations are performed in a static setting where environment and objects do not change position or setting during measurements. The measurements are performed in ”real life” scenarios with furniture, competing RF technologies and other sources of obstacles or interference present. The evaluation does however not take people into account in the scenario. This means that a human body will never be in the way of a measurements during the evaluation, although this would most likely be the case in an actual real life scenario. Furthermore, no power measurements or evaluation have been performed to investigate the improvement in the power consumption. All mentioned statements regarding power consumption efficiency have been found in related material covering the Bluetooth smart technology.

1.5 Outline

The rest of the report is structured in the following manner:

- **Chapter 2 Bluetooth Technology**: This chapter is allocated to give an overview of Bluetooth technology, Bluetooth smart technology, and applicable Bluetooth signal parameters suitable and unsuitable for use in RF-based positioning systems.

- **Chapter 3 Positioning techniques**: Presents and explains the most commonly used approaches and techniques for indoor positioning.

- **Chapter 4 Theory**: Describes related work and literature on indoor positioning and does also present information regarding related commercial systems.

- **Chapter 5 Testbed**: This chapter describes the evaluation criteria used for positioning experiments, the test environment, and the hardware and software with which the testbed is implemented.
- **Chapter 6 Positioning results**: Presents results from the positioning system evaluation described in Chapter 5
- **Chapter 7 RSSI analysis**: Describes an investigation of the underlying RSSI parameter and how it is affected by distance, angle and environmental properties.
- **Chapter 8 Discussion**: This chapter contains a discussion about the obtained results, and what effect they would have on an indoor positioning system.
- **Chapter 9 Conclusion and future work**: Presents the conclusion of the evaluation and also provides pointers and advice for future work within the area.

2

Bluetooth Technology

2.1 Classic Bluetooth

Bluetooth is a wireless technology allowing electronic devices to perform short range wireless communication between each other. The technology operates between 2400 to 2485 MHz divided into different channels. The specified frequencies lie within the globally unlicensed "Industrial Scientific and Medical"(ISM) 2.4GHz band. Traditionally 79 different channels have existed with 1 MHz spacing, but the specification for Bluetooth smart introduces the use of 40 channels with 2MHz spacing instead[3]. While the ISM frequency band is unlicensed, the usage and development of Bluetooth technology are regulated by the Bluetooth special interest group, or Bluetooth SIG. The group, which has over 20 000 member companies is responsible for defining the Bluetooth specification as well as to certify that developed products conforms to these specified standards. The latest specification is currently at version 4.1 (Released December 3, 2013). Previously adopted specifications can be found in[4].

The specification defines a set of protocols and properties that devices may use to communicate. Some are mandatory and producers of Bluetooth technology enabled equipment or software must support them, while other properties are optional and manufacturers may freely choose if they want to implement them in their products. On top of the Bluetooth technology protocols, different application specific profiles are implemented. The profiles are standardized and described with requirements in the Bluetooth specification. A few examples of defined and commonly used profiles are:

- **Advanced Audio Distribution Profile(A2DP)**: A2DP profile defines how audio streaming is performed between two devices, for example playing MP3 files from a cellphone in a wireless Bluetooth enabled headset.
- **Phone Book Access Profile(PBAP)**: This profile defines how contact infor-

mation are transferred from one device to another. Examples include transferring phone-book contacts between a cellphone and an infotainment system in a car.

- **A/V Remote Control Profile(AVRCP)**: Defines a profile to remotely control audio and video devices, for example sending and receiving commands such as play, pause, fast-forward, next track etc.

All profiles defined in the Bluetooth specification are listed in[4].

2.1.1 Discovery and pairing

For two devices to be able to communicate a pairing is necessary to set up a bond between them. In the Bluetooth technology, two device modes are supported: Slave or master. A device in master role can potentially support up to 7 simultaneous connections with different slaves, although supporting that many connections is not a mandatory requirement. Before a connection is established, devices must discover each other and specify what profiles are to be used. Devices typically only support a small subset of all available profiles in the specification. To initiate a pairing, a master device will continuously broadcast "inquiry messages" which will be picked up by nearby devices that allow connections to be established. The devices that allow a connection to be made are named "discoverable" and they will answer to any inquiry message with a response message containing their name, what profiles they support as well as other technical information. With this information the master device can continue and initiate a pairing and establish the desired profiles. In addition connected devices can potentially change their roles from master to slave and vice versa upon agreement.

2.1.2 Bluetooth range

Bluetooth was designed to be used in short-range applications typically reaching a few meters. The effective range that can be practically achieved depends on several factors, for instance parameters such as propagation, interference, attenuation, signal reflection, antenna characteristics, transmit power, fading and obstacles. Bluetooth devices are divided into three different classes which specify their maximum allowed output power which in turn significantly affect the range. The different classes, power limits and theoretical ranges are listed in Table 2.1[5].

Class	Max range	Max Transmitter output power
Class 1	100 m (300 ft)	100 mW (20 dBm).
Class 2	10 m (33 ft)	2.5 mW (4 dBm).
Class 3	1 m (3 ft)	1 mW (0 dBm).

Table 2.1: Ranges and output power of different Bluetooth classes

2.2 Bluetooth smart

In June 2010 the specification for Bluetooth 4.0 was released. The specification did not only introduce improvements to the already well established Bluetooth technology, it also introduced a completely new technology: Bluetooth low energy or "Bluetooth smart". This new standard is not backwards compatible with the classic Bluetooth and introduces an entirely new stack. The new standard was introduced to facilitate communication within a short range for devices that do not require large amount of data transfer. Instead the main idea was to provide an efficient technology for monitoring and control applications where data amounts are typically very low: such as sending sensor values or control commands.

2.2.1 Bluetooth smart stack

The Bluetooth smart stack is as mentioned in the previous paragraph entirely new and is not compatible with the traditional Bluetooth stack. It is however common that new Bluetooth enabled devices support both the traditional Bluetooth as well as Bluetooth smart. These are commonly referred to as "Dual mode" or "smart ready" devices[6]. The Bluetooth smart stack does inherit a number of characteristics from its predecessor: The stack is composed of two parts, the host and the controller. The controller represents the physical layer and the link layer. It is typically a small chip with a radio, which is quite commonly implemented in a System-on-chip(SOC) solution[7]. The host consists of the the upper layer protocols and software and runs the following services:

- **Logical link control and Adaption protocol(L2CAP)**: The L2CAP layer is responsible for multiplexing data between the higher Host layers and the lower Control link layer. It has similarities with the L2CAP protocol used in traditional Bluetooth but has been optimized and streamlined for Bluetooth smart. The Bluetooth smart-L2CAP protocol works in a best-effort manner providing no retransmission or flow control as opposed to traditional Bluetooth. Furthermore it does not provide segmentation or reassembly since in Bluetooth smart, the higher layers are required to only send packets with sizes that fit into the L2CAP maximum payload size.

- **Attribute protocol(ATT)**: The ATT protocol is used to send attributes between two devices communicating with each other. An attribute can be described as a sort of data-structure which GATT profiles use to send and receive data.

- **Security manager protocol(SMP)**: The SMP protocol handles key exchange and encryption tasks when links are set up. The procedure to establish a connection is done in a number of steps that require several key exchanges to take place.

- **Generic attribute profile(GATT)**: GATT is a framework that describes different services and profiles. The profiles are standardized by Bluetooth-SIG and provides specifications for data formatting when communicating with the application layer. Each GATT-profile is designed for a specific functionality. Some examples of profiles adopted by Bluetooth-SIG are Glucose profile, Heart Rate profile and Proximity profile. A full list of adopted profiled is listed in[4]. The GATT profiles use attribute/value pairs which are predefined for each profile. The attributes are then handled by the ATT protocol.

- **Generic access protocol(GAP)**: Defines procedures used for pairing and linking with other devices. The procedures are generic and the application layer can then implement different Bluetooth smart modes, see Paragraph 2.2.2.

An illustration of the entire Bluetooth smart stack is presented in Figure 2.1. The communication between the host and the controller is similarly to classic Bluetooth performed by a standardized host controller interface (HCI) protocol.

Figure 2.1: Block diagram picturing the Bluetooth smart stack

2.2.2 Bluetooth smart modes

A new addition in the Bluetooth smart stack compared to traditional Bluetooth is the support for a completely new mode. When using Bluetooth smart for certain applications it is no longer necessary to do a pairing to be able to exchange data. Instead, a ”broadcast” mode is supported where data can be sent in the advertisement channels without establishing a connection. In Bluetooth smart a total of 4 different modes are supported: Central, Peripheral, Broadcaster and Observer. A complementary mode to the already mentioned Broadcaster role is the Observer role that receives the data that the Broadcaster transmits. The Central role which is similar to the traditional Bluetooth master role is designed for more sophisticated devices which initiate and manage several connections. The Bluetooth smart specification states that a Central role device may support up to infinite simultaneous connections against different peripheral devices. This is an improvement of the specification compared to traditional Bluetooth which supports maximum 7 connections. Although in reality, typically only a small number of simultaneous connections are supported. A peripheral device is typically a simple device that can only handle one active connection at a time against some central device. The peripheral and central device roles mean that the Bluetooth smart controller must provide support for both master and slave roles. Although a specific device does not have to support both of them. The different roles allow segmentation of the stack which allows for small lightweight devices to be created, which could for example only support the peripheral role. A device may support a single, several or all of the specified roles, but only one can be active at a time.

2.2.3 Discovery and pairing

The Bluetooth smart specification defines two different approaches to perform discovery of connectable nodes: active and passive scanning. In passive scanning, a central device passively listens on the advertisement channels to capture advertisement PDU packets transmitted by connectable devices. In active scanning, the central device similarly to passive scanning listens for advertisement PDU packets. When receiving a PDU packet, the device may examine what modes the advertising device supports. If the PDU packet indicates that the device is connectable or scannable, it may send a scan request packet to the device asking for more information. In Bluetooth smart, three dedicated advertisement channels have been defined. 37, 38, and 39 [8], which have been specifically allocated in the frequency spectrum to minimize collision with the most commonly used Wi-Fi channels 1, 6 and 11. This change in advertisement behaviour means that discovery of devices may complete much faster since it is no longer necessary to scan the entire frequency spectrum. In addition to this improvement, The Bluetooth smart technology also allows to define how frequently advertisement is set to take place. Devices may advertise as seldom as once every 10 seconds or as fast as every 20 millisecond. This means that the time it takes to discover a device is related to the advertisement interval. A complete overview of the Bluetooth smart frequencies and channels is presented in Figure 2.2. Similarly to traditional Bluetooth, an adaptive frequency hopping mechanism is used to counter interference and fading. A Gaussian frequency shift keying(GFSK) modulation is used to select which data channels are to be utilized.

2.2.4 Bluetooth smart range

The range of Bluetooth smart is similarly to traditional Bluetooth dependent on transmit power as well as different interference and obstacles in the environment. Although Bluetooth smart was primarily designed for low energy usage, transmit power up to +10dBm is supported. Typically Bluetooth smart devices operate on 0dB or less resulting in a peak current consumption of <15mA. Using the maximum +10dBm transmitting power gives a theoretical range of >300m, while the more commonly used 0dBm transmit power

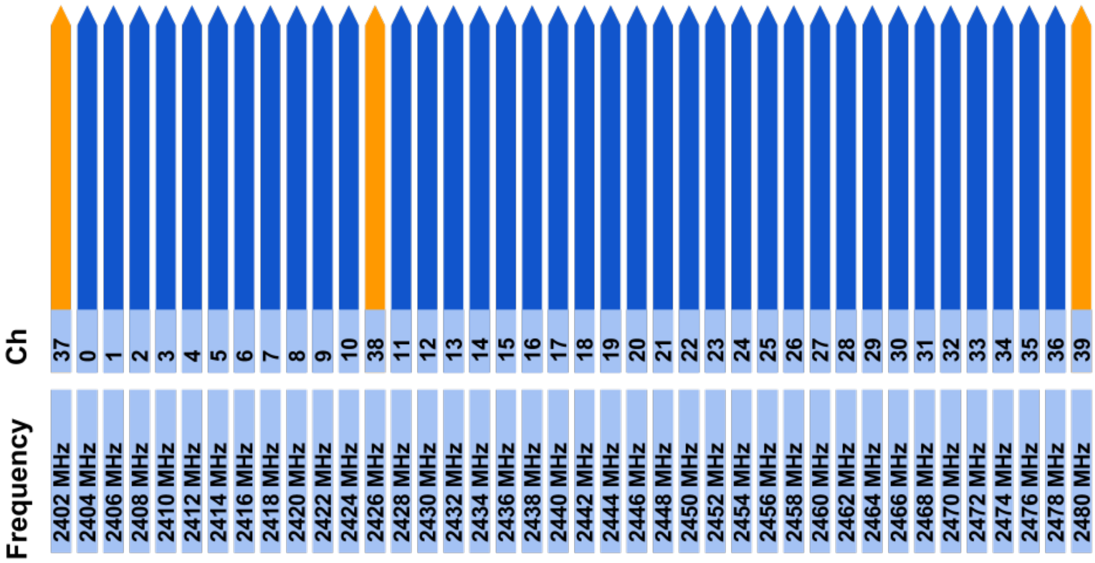


Figure 2.2: Overview of Bluetooth smart channel spectrum

gives a theoretical range of about 50m[9]. The effect of this power classification actually means that, despite its name claiming ”low-energy” consumption, Bluetooth smart has a longer effective range than traditional Bluetooth in the maximal power mode[10]. This is mainly explained by the simpler modulation scheme used by the radio combined with a more restricted packet size.

2.3 Signal parameters

In order to perform RF-based positioning, some form of characteristic is required for providing reference values. This section presents the various signal parameters available within classic Bluetooth and/or Bluetooth smart technology. Other applicable technologies to perform indoor positioning are discussed in Chapter 3.

2.3.1 Received signal strength indicator

The received signal strength indicator(RSSI) is an indication of the signal strength experienced by the receiver of a Bluetooth PDU. The value is a signed 8-bit integer value which for Bluetooth smart varies between -127 to 20dBm, where an increasing value indicates a stronger signal. The value can be retrieved both while scanning for devices as well as during an active connection with another device. An important difference between classic Bluetooth and Bluetooth smart related to this parameter is how the RSSI can be obtained. In classic Bluetooth two different variants was possible. The very early versions of Bluetooth only allowed to retrieve the parameter during an active connection between two devices. Later specifications(1.2 and later) allowed to retrieve the parameter during inquiries, e.g without establishing a connection beforehand. In Bluetooth smart this is further improved by providing RSSI also when passively receiving advertisements. The possibility to retrieve it during an active connection is still preserved. To convert RSSI to distance, several algorithms have been proposed. Where almost all of them rely on the fact that some reference value is known beforehand, examples of this could be Tx-power level of the transmitter or measured RSSI at a fixed known distance.

2.3.2 Link quality

Link quality(LQ) is a parameter that is available in traditional Bluetooth when a connection between two devices is active. The parameter is an bit unsigned integer which is most commonly related to the average bit error rate (BER). The parameter spans the entire space of the integer and thus varies between 0 to 255 where a higher number corresponds to a better link. The value is updated continuously as packets are received, meaning that the parameter is available at the receiving end. In practice, this means that both ends will have access to it since communication usually goes both ways. There is however no guarantee that both ends experience the same LQ. The Bluetooth specification documents do not specify how the BER is mapped to a LQ-value, the implementation of this is defined as vendor specific.

2.3.3 Transmitted power level

Class 1 Bluetooth devices with a maximum power level of +20dBm provide the foundation for yet another possible parameter to link against distance called Transmitted power level(TPL). The Bluetooth specification mandates that devices with Tx power between +4 to +20 dBm compulsorily have to perform power control. The reason for this is twofold, partly the power control is used to conserve energy when the transmitter is capable of using high power for radio output. Partly the power control is used to mitigate interference. Similar to RSSI, TPL is represented by an 8-bit signed integer. The TPL is measured in dBm and will as a result have a maximum value of +20dBm. The minimum value is not defined, rather it is vendor specific. However, the Bluetooth specification does advice that class 1 devices use power control even for values below -30dBm [11].

The core of this TPL variable is thus that Bluetooth chips with high output power scale down the Tx effect to save power when the link is good. Example of such a case could be when the communicating devices are close to each other-when the distance later grows the device will increase its TPL to compensate. Based on this, it could be possible to derive a distance metric. A factor that negatively impacts the precision of TPL as parameter is that it has different step sizes for adjustment between 2 to 8 dBm. This means that if a device performs power control between +20 to -60 dBm and has a step size of 4, only 20 unique identifiers will be available for mapping to a distance((60+20)/4).

2.3.4 Inquiry response rate

A suggested parameter for performing indoor positioning based on Bluetooth is the Inquiry response rate(IRR)[12]. The parameter is not something defined by the Bluetooth-specification or received in Bluetooth messages. Instead the suggestion is to use the characteristic of Bluetooth where inquiries are made to discover nearby devices. The nearby devices, which are set to discoverable mode will respond to such a request with an inquiry response message. The idea is that, in each location the inquiring device will receive responses from different nodes and also receive different number of responses from each node. Together these two parameters form an attribute that should possibly be unique for each position in the area where positioning is to be deployed. A positioning system employing this methodology is described in more detail in Paragraph 4.6.2.

2.3.5 Parameters in Bluetooth smart

In this section a number of signal parameters that could serve as potential candidates for a positioning system were described. The listed parameters are mainly based on traditional Bluetooth since no studies of Bluetooth smart in the context of positioning exist to this date. When it comes to Bluetooth smart, the choices immediately become more limited since the protocols and stack have changed significantly. In Bluetooth smart it is still possible to set up a connection between devices but this active connection is different from a traditional Bluetooth connection. While in classic Bluetooth the connection is always up and connected, in Bluetooth smart the taken approach is to put devices in sleep or passive mode whenever possible. The master device has control of how and when the slave is allowed to transmit. This means that neither LQ or TPL are normally available parameters. LQ is not defined for Bluetooth smart and will thus never be available for a positioning system based on the technology. TPL is not necessarily available either, instead it is quite common that devices use a fixed Tx power level. It is however still possible for a user application to perform TPL if it is desirable. Bluetooth smart hardware will typically support reprogramming the Tx power during operation, resulting in the possibility for users to implement a TPL mechanism manually if needed. A good parameter to decide on what power level to use is however required.

RSSI is still available and easily accessible in Bluetooth smart, both during a connection as well as when receiving broadcasts or performing scanning. It is also the parameter within Bluetooth that has received the most attention and consensus to be the one best suited for positioning applications even though it is not optimal. Especially in more recent research where inquiry RSSI is available[13]. The connection based RSSI in classic Bluetooth proved to be an unfavourable parameter[11] since power control mechanisms adjusted Tx power during active connections, causing the value to almost always return the value 0 dBm. Since the devices aimed to always stay within an optimal power range called "Golden Receiver Power Range"(GRPR)[14]. This is however a factor no longer used for Bluetooth Smart, here the GRPR is not used and RSSI will reflect the power that the receiver experiences without interference from power adjustments.

3

Positioning Techniques

In this chapter, the most commonly used algorithms and approaches for indoor positioning systems are presented and reviewed. RF-based positioning techniques can roughly be divided into six approaches, trilateration, filter based technologies, fingerprinting, cell based positioning, triangulation and Time of flight(TOF). In trilateration, distances to at least three beacon nodes have to be obtained in order to estimate a position. In filter based technologies, multiple positions are generated continuously and filtered based on observations from different inputs to the system. In fingerprinting, a map is divided into a grid and different attributes are associated with each grid-cell. In cell based positioning, a specific sub-set of beacon nodes is discoverable in each interesting area segment of the environment. The triangulation approach is based on getting angles to or from some known references and use them to calculate a position. TOF is used for measuring the time a signal takes for travelling to or from a reference point to the device being positioned and the distance is estimated accordingly. Similar to trilateration, at least three reference points are needed. All of these techniques are explained in an easy to understand fashion in this chapter.

3.1 Trilateration using RSSI

Trilateration is one of the most old and renown methods used in determining or estimating locations. It requires measurements of distances between the object for which a position is to be determined and a minimum of three reference points. The three or more reference points are considered as centers of three/several circles and the distances are treated as radii of these circles. The relative or absolute position then becomes the intersection point between these circles. As a result, an overdetermined system of at least three circle equations and two common unknown values (x, y) is obtained. Thus, least square approach is employed to estimate the position of least squared error.

In the context of wireless based positioning, the first step toward positioning is to measure distances to at least three known reference positions. In most positioning systems these reference points are made up of beacon nodes or access points. The distances can be estimated based on conversion of wireless signal parameters. Popular examples of such a parameter are RSSI or TOF. These measurements combined with knowledge of the beacons coordinates can form the basis for trilateration.

3.2 Filter technology

Filter based technologies are a mathematical methods used for predicting or estimating a hidden or unknown variable given some observations from the system known as observable variables. The hidden variable in the context of positioning is the position of the mobile node, while the observable variables for example can consist of: Measured distances to references, previously estimated position, sensor inputs such as compass or gyroscope and reference data such as orientation or movement. While the approach is not a concept dedicated to positioning, but rather used in a great variety of applications, it is very well suited for usage in positioning applications. The really useful property of the method is that it has the ability to fuse together several different data sources as input to estimate the hidden variable for output. A good example of this is presented in [15], An approach relying on an ultrasound positioning system combined with odometry readings achieves great accuracy and tracking abilities by combining data from both observable reference systems.

Several different mathematical concepts implementing filters exist where the two most commonly used are Kalman filter[16] and Monte Carlo filter[17], which is usually referred to as just "particle filter". In this report the emphasis is put on particle filters mainly because its advantage of being simpler to implement, it also has other advantages not directly specific to this work such as ability to represent multi-modal distributions and reduction of memory usage requirements compared to grid based approaches[14].

3.2.1 Particle filter for positioning

Within particle filters, thousands of particles are randomly and continuously generated during runtime, which in the context of indoor positioning are representations of positions. Thus, the distances or differences to each of the reference beacons or reference values/data can be calculated. Based on the observable variables, the particles that are unlikely to represent the current position are filtered out while particles likely to be true representations of the position are selected for calculating the estimation. The filtering process is achieved by giving weights to all particles based on how reasonable the particles values are taking observable variables into account. Gradually, most of the particles will assume negligible weights and will thus no longer contribute to the estimation, while few particles will have significant weights and contribute largely in the system. To mitigate this problem, the particles with high weight are resampled while those of negligible weights are not. Meaning that probable particles are duplicated while unlikely particles are removed from the system.

At initiation, no observed data is available and the first generated particles will as a consequence often be uniformly randomly distributed all over the map. Later, particles are generated based on the weights of earlier particles by duplicating those of high weights only. When the number of different particles decreases significantly, new particles are generated as in the first sampling step. Formally speaking, the objective of a Particle filter is to compute the density of the posterior as $p(x_k|z_{1:k})$. It means, computing the position $x_k = [x\ y\ \theta]^T$ at time t, given the estimated positions $z_{1:k}$ at times prior to t. This is done recursively in two steps: position prediction and position updating. In the position prediction step, if the previous estimation $p(x_{k-1}|z_{1:k-1})$is available, the current prediction can be calculated as in equation (3.1) and (3.2)

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1},z_{1:k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1} \tag{3.1}$$

If a Markov model of order one is assumed, then $p(x_k|x_{k-1},z_{1:k-1}) = p(x_k|x_{k-1})$, and the equation (3.1) becomes (3.2)

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1} \tag{3.2}$$

The predicted position is the probability density function or the current likelihood of the particle x_k including the coordinates and the orientation, given the previous estimated position, its orientation, and the previous trilaterated position(assuming distances to reference nodes are used).

While in the position update step, the position is updated to be available for use in the estimation of next iteration. This is done based on equation (3.3)

$$p(x_k|z_{1:k}) = \frac{1}{\eta}p(z_k|x_k)p(x_k|z_{k-1}) \tag{3.3}$$

Where $\eta = p(z_k|z_{1:k-1})$ is a normalizing constant.

3.3 Fingerprinting

This approach is performed by dividing a map into segments or grids. The approach consists of two phases. At first, a training phase or ”offline phase” is performed to associate each segment or grid cell in the map with some unique attributes to break the symmetry among them. In the context of wireless positioning, these attributes can be signal parameters, such as RSSI, IRR or LQ. In this phase, attributes are measured and assigned to each segment or grid cell. For example, if RSSI is used as an attribute, An average of RSSI values per beacon node is computed in each segment. Each fingerprint then consists of several RSSI averages and the position of the map segment or the grid cell that the fingerprint belongs to. In this way, a fingerprint database is constructed.

In stage two, an online phase is carried out where the actual position estimation is performed. Within which, a mobile node tries to determine its position based on the database values. Every time a mobile node wants to find its position, it collects measurements of the same kind of attributes stored in the offline phase and compare them against the values that are stored in the database. For example, in case when the RSSI parameter is used as attribute, the mobile node collects RSSI values from all the beacon nodes in its range and compares them to the fingerprints that are stored in the database. The position in question will be the one that is associated with the fingerprint of the best match or the geometric median of the positions of the K-closest n fingerprints.

3.4 Cell based positioning

Similar to the previous approach, this method consists of two phases, a training phase and an online phase. The beacon nodes are deployed in a way that makes each segment of the map covered by a different set of beacon nodes. In the training phase, the beacon nodes that cover each segment are registered and associated with it in a database. While in the online phase, the mobile node scans for any beacon node in range and stores the identifications of the discovered beacons. The discovered set is compared to other sets stored in the database and the best match is selected. In this approach, signal parameters can be utilized to break the symmetry among several segments that are covered by the same set of nodes. As an example, if two segments are covered by the same beacon nodes but with different signal strengths, the symmetry between these segments can be broken based on the signal strength.

The database search can be optimized by setting up some roles and conditions. For instance, if the coverage area of a beacon node is known to be within a bigger coverage area of another beacon node, then both nodes must be in the discovered set given that the first beacon is discoverable. On the other hand, if it is known for two beacon nodes that their coverage areas do not intersect, then they cannot be in the same discovered set. Thus, having this information about the network and the discovered set, the search can be optimized.

3.5 Triangulation

Another approach of positioning estimation is determining the position of an object or a mobile node based on the angle of arrival(AOA) of wireless signals. There are several methods of determining AOA by a receiving node, for instance, by equipping the nodes with a directional antenna, an antenna array, a compass model, or two ultrasound receivers. Measuring the angle of arrival at the receiver requires that the receiver has to be aware of a reference axis, against which, the angle of an estimated straight line passing through the sender and the receiver is measured.

Assuming that the angles of two incoming signals from two beacons of known positions can be determined, the position can be calculated by some mathematical effort. The simplest way of calculating a position in two dimensional environment is as follows: after determining the angle of arrival from two beacons of known positions (x_1,y_1) and (x_2,y_2), the position (x,y)can be solved by Equations 3.4 and 3.5, where θ_1 and θ_2 are the angles of arrival from beacons 1 and 2 respectively [18].

$$\begin{aligned}\tan(\theta_1) &= \frac{y - y_1}{x - x_1}\\ \tan(\theta_2) &= \frac{y - y_2}{x - x_2}\end{aligned} \tag{3.4}$$

$$y_i - x_i \tan(\theta_i) = y - x \tan(\theta_i) \tag{3.5}$$

Another triangulation method involves three beacon nodes, which are assumed as vertices of a triangle. Knowing the positions of the three beacon nodes and the angles of arrival of their signals at a mobile node located inside the triangle, the mobile node can determine its position. In comparison to trilateration, triangulation measures angle of arrival of beacon node's signals instead of measuring distances to the beacon nodes. After knowing the beacon node's position and measuring the angle of arrival of the received signals at the mobile node, what remains is to calculate the position. The position can be determined as the intersection point of three circles where each of them passes through a pair of adjacent beacon nodes and the mobile node. Least square error is also an effective tool in this kind of triangulation since in most cases angle of arrival measurements are not exact.

Triangulation can be reduced to trilateration in the following manner: For any pair of adjacent beacons of the three beacons that form the triangle, the angle of intersection at an interior node that is formed by two lines where each of them passes through a node of the adjacent nodes can be calculated based on the angles of arrival at the interior node. Then, the position of the interior node can be determined somewhere on a circle that passes though the two adjacent beacons and the interior node. Given that the positions of the beacons are known, the circle's center can be determined. Finally, the distance between the interior node and the center node can be calculated and utilized in trilateration. Thus, three distances and beacon positions are calculated, which is exactly what is required for executing the trilateration method[19].

To make triangulation applicable in indoor localization where RF-technologies such as

Wi-Fi or Bluetooth are used, customizing the hardware, or more specifically the antenna is necessary. It is important to mention that LOS between the mobile node and each of the respective beacons against which angle of arrival is to be calculated is necessary. By using a compass, angle of arrival can be calculated more accurately since the orientation of a mobile node can be determined.

3.6 Time of flight

This approach utilizes the propagation time of electromagnetic signals between two nodes. TOF works by estimating the distance between two nodes by counting the time required for a signal to travel from a node to the other. The travel time is the difference between the time when the signal is sent and the time when the signal arrives. Having in mind that RF-signal speed is close to the speed of light in vacuum(29.98cm/ns), the distance can be calculated as the speed and travel time are known/can be determined. Using this approach in a Time of Arrival fashion requires synchronizing the transmitter's and receiver's clocks with very high precision since each nanosecond difference will introduce an error of 0.3m.

If Time Difference of Arrival(TDOA) is used, two transmitters sends their signals to a receiver that wants to determine its position. Clock synchronization between the transmitters and the receiver is not required. Instead, the clocks of the transmitters have to be synchronized as tight as possible and for as long as possible[18]. Another way of using TDOA is by having the node that wants to calculate its position as the transmitter and the beacons as receivers. Also in the latter case, the receivers (beacons) need their clocks to be synchronized. After calculating the distances to at least three beacons, this approach can be followed by the trilateration method to determine a position.

4

Theory

In order to evaluate Bluetooth smart as a solution for indoor localization, several academic reports, scientific papers, and articles that focus on indoor positioning using Wi-Fi and classic Bluetooth with different approaches have been extensively studied. This chapter is devoted to describe and discuss this related material. They are categorized based on the underlying positioning theory and approach in use by respective work. The chapter is concluded by presenting the choices made for this project based on the results discovered herein.

4.1 Trilateration

With regard to the trilateration based positioning. Two high quality related scientific reports [20] and [21] have been selected. They are described respectively in detail in the following subsections.

4.1.1 Positioning using RSSI and Triangulation

In this subsection a Bluetooth based positioning system[20] is presented. In the presented system a new addition to the Bluetooth 2.1 specification was utilized. The addition is a new Host controller Interface(HCI) command called *Inquiry_With_RSSI*. The new HCI command allows for retrieval of RSSI values of all discoverable Bluetooth devices in range without the need to perform connection establishment beforehand. In the report, this interface command is called by an Android OS device that is to be positioned. The testing area is defined as a 6x8 meter rectangular room and the reference beacon nodes consist of four Bluetooth enabled Android mobile phones positioned in the four corners of the room. To obtain distances based on the measured RSSI the mathematical model in equation (4.1) is used.

$$RSSI = -(10n \log_{10} d \ + A) \tag{4.1}$$

$$d = 10^{\frac{A - rssi}{10 * n}} \tag{4.2}$$

A is here the absolute energy in dBm, which is the average RSSI value measured at the distance of one meter in LOS to the node. The n-variable is the propagation constant which is environment dependent. By estimating A as the average of several reads, coupled with reading the RSSI at predefined distances d, the propagation constant n can be solved. Because of the fluctuations in RSSI values, the average of several RSSI reads in each distance is substituted in (4.1) to get the propagation constant n. In the event that different values of n are obtained for each distance, n is calculated as the average of all obtained n values.

After determining the necessary constants, the distances to the beacon nodes can be obtained by rewriting the equation as equation (4.2) and using it for trilateration to solve the position of the mobile node. In the paper, three position estimation methods are used and compared. Firstly positioning based on a mathematical concept of *Least square estimation* using matrices is used. Secondly, *Three-border positioning*, which is referred to in most books and scientific papers simply as *Trilateration* as explained in 3.5 is used. Finally, we have *Centroid positioning*, which calculates the center of a polygon surrounded by the circles when there is more than a single intersection point between circles. In the last mentioned method, the mobile node is assumed to be outside the intersecting circles but in an area surrounded by them. This area forms a polygon, in which the vertices indicate the intersection points and the center of the polygon becomes the estimated position of the mobile node. According to the results and the plotted values, an accuracy of about 0.6 meter is achieved without considering the effect of the human body. A separate test in the work concluded that RSSI values drops by about 6-8 dBm when the LOS is obstruted by a human body.

4.1.2 Wi-Fi and Trilateration positioning

A Wi-Fi trilateration based indoor positioning system is presented in [21]. The distance is calculated based on the percentage of signal strength from beacon nodes experienced by a mobile node. Higher percentage indicates that the position of the mobile node is close to a beacon node, while lower percentage indicates the distance to the beacon node is farther away. The mathematical model shown in (4.3) is used to calculate distances based on the percentage of received signal strength.

$$d_i = p(1 - m_i) \tag{4.3}$$

Where d_i and m_i are the distance and the percentage for beacon node i. The variable p is the maximum range of beacon i.

After calculating distances between the mobile node and each of the beacon nodes in range respectively, trilateration is used to estimate the position in two dimensions. Thus a system of linear equations for two variables can be established. This system consists of at least three circle equations, where radii and center points are the calculated distances and the positions of the beacon nodes respectively. The circle equations are linearized before solving the position.

4.2 Particle filters

Particle filters are a recurring mathematical concept that is often used in different positioning applications and scenarios. In this section two high quality scientific papers presenting positioning performed with the aid of particle filters are described.

4.2.1 Robot indoor localization

A robot localization system that includes trilateration combined with a particle filter is presented in [14]. Moreover, the report uses a novel approximation method called iterative trilateration, for solving overdetermined systems. The distances are similar to previously described work calculated based on RSSI and equation(4.2). The system consists of four online steps. The trilateration approach means that no training phase is required but some signal parameters are needed for calibration. In the first step, the mobile nodes that should be positioned obtain RSSI measurements from beacons in range using *Inquiry_With_RSSI*. In step two, the system estimates distances to the beacons based on RSSI to distance conversion. Then in the third step, using a trilateration method referred to as iterative trilateration, the position of the mobile node is estimated. Finally in the last step, a particle filter is executed taking into account the estimated trilateration positions from the previous steps with a motion model derived from the robot.

In more detail, iterative trilateration consists of several steps and the goal is to solve an overdetermined system of equations iteratively, where the error is expected to be minimized in each iteration. The first step is to construct circle equations based on data from at least three beacons, this is done mathematically as described in equation (4.4).

$$(x - x_i)^2 + (y - y_i)^2 = d_i^2 \tag{4.4}$$

d_i, x_i, and y_i are the estimated distance based on RSSI to distance conversion and the coordinates of beacon i respectively. Then matrices are constructed based on these equations, where the hidden variables are: $s = (x^2 + y^2)$, x , and y. Ignoring the first variable results in a linear system of equations which is simpler to solve for retrieving the estimated coordinates x_e, and y_e of the position. Then the absolute error vector of the calculation can be obtained based on equation (4.5). This vector is recalculated after each iteration in the iterative trilateration but divided by d_i.

$$|f_i| = \left| d_i - \sqrt{(x_i - x_e)^2 + (y_i - y_e)^2} \right| \tag{4.5}$$

By using the error vector and Taylor series approximation, the step size of the adjustments $(\Delta x, \Delta y)$ can be calculated as $\binom{\Delta x}{\Delta y} = (B^T B)^{-1} B^T f$ where B is calculated as in equation (4.6). The error vector together with a reduction factor s are used to update the estimated coordinates after each iteration. The reduction factor is used for convergence purpose and is decided based on practical results, which in [14] is determined to be 0.05. Thus, new x_e and y_e are calculated by $x_e = x_e + s\Delta x$ and $y_e = y_e + s\Delta y$ respectively.

$$B = \begin{pmatrix} \frac{(x_1 - x_e)}{\sqrt{(x_1 - x_e)^2 + (y_1 - y_e)^2}} & \frac{(y_1 - y_e)}{\sqrt{(x_1 - x_e)^2 + (y_1 - y_e)^2}} \\ \vdots & \vdots \\ \frac{(x_i - x_e)}{\sqrt{(x_i - x_e)^2 + (y_i - y_e)^2}} & \frac{(y_i - y_e)}{\sqrt{(x_i - x_e)^2 + (y_i - y_e)^2}} \end{pmatrix} \tag{4.6}$$

The theory of particle filtering is applied by using Monte-Carlo Localization iteratively. First, an initial set of samples or particles are generated randomly. Then weights are given to the particles based on how close they are to the trilateration position. The weights are normalized after every update step so that the sum of all weights is equal to one. This followed by a prediction step, where each particle is moved based on the previous position and a control vector from the robot's motion model.

It is important to mention that the motion model predicts the next position based on a control vector of $[d\ \theta_1\ \theta_2]$, that is, rotation of θ_1 units followed by d number of steps then rotation of θ_2 units. After that, the weights are recalculated in the same way as in the first time. As a result, some particles lose weight when their probability of being likely the actual position decreases. If a particle weight becomes negligible, it will not be resampled or contribute to the position estimation in the system. To reduce the computational load on the system and to overcome the problem when the number of particles contributing to estimating the position becomes very small a threshold on the number of different particles that contribute in the system is set. When the number of these particles becomes less than the threshold, the system generates new particles by duplicating particles of high weights and discarding particles of negligible weights. An accuracy of 0.427 ± 0.229 meters is claimed to be achieved in a scenario measuring 6x8 meters.

4.2.2 Bayesian Filtering Positioning

An indoor Bluetooth positioning system based on particle filter and RSSI with the title *Bayesian Filtering for a Bluetooth Positioning System* is introduced in[22]. In the system a mobile node collects RSSI values from several beacons within range, followed by calculation of distances to the beacons using the mathematical relationship from equation (4.7).

$$RSSI(d) = RSSI(d_0) + 10n\log\left(\frac{d}{d_0}\right) + X_\sigma \tag{4.7}$$

$RSSI(d)$ and $RSSI(d_0)$ are here the RSSI values at distances d and d_0 respectively, d_0 is a reference distance, n is the propagation constant, and X_σ is a normal distributed noise with zero mean and standard deviation of σ.

The first step within the particle filter is as always initialization, N particles are generated with random states and equal weights w_i for each particle i. The state consists of position, velocity, and direction. The initial weights are calculated as $w_i = 1/N$. As the particle filter is run iteratively, weights are updated in each iteration based on a dynamic model. Two different dynamic models are tested, one without velocity and another which takes into account the velocity of a human being.

Each particle's position is updated by a Gaussian distribution random number generator and a time interval. In addition, the velocity is considered when updating the direction. For instance, When a person using the system begins to walk, any direction is possible. Whereas when the velocity increases to finally reach 1.3m/s, which in the article is considered the maximum velocity of a human. The trajectory is forced to follow a straight line. The motion model step is followed by an update step, where the weight $w_i(t)$ of each particle i at time instance t is updated based on the normalized weights at $t-1$ and the likelihood of the current estimated position using equation (4.7). After that the weights are normalized to $\overline{w}_i(t)$ based on the current calculated weights. The mathematical models for weighting and normalizing steps are performed according to equations 4.8 and 4.9 respectively.

$$w_i(t) = \overline{w}_i(t-1)p(z(t)|x_i(t)) \tag{4.8}$$

$$\overline{w}_i(t) = \frac{w_i(t)}{\sum_{j=1}^{N_p} w_j(t)} \tag{4.9}$$

These steps are followed by a resampling step. During resampling, the same number of particles generated at the beginning will be regenerated. This step is required since when the system runs, most of the particles will gradually lose their weights and will thus no longer contribute usefully in the position estimation, possibly leading to erroneous estimation. Resampling is done by duplicating particles of high weight and ignoring particles of very low weight. To determine whether resampling is necessary or not, the concept of effective sampling size described in equation (4.10) is applied to calculate and compare the size of effective samples to a threshold. If the result N_eff is less than the threshold, resampling is required. After this step, the position, the orientation, and the velocity are estimated by recalculating the weighted sum of the positions, orientations and velocity respectively that are given by the particles.

$$N_eff = \frac{N_p}{\sum_{i=1}^{N_p} \overline{w}_i^2(t)} \tag{4.10}$$

4.3 Fingerprinting

Two fingerprinting based localization systems which both rely on signal strength data as characteristic[23][24] are reviewed in this section.

4.3.1 Fingerprinting localization for ZigBee

In [23], an indoor localization system based on ZigBee Wireless sensor networks and fingerprinting is presented. The system consists of three phases, a fingerprinting database creation phase, a feature identification phase, and the actual position estimation phase. In the first phase, Received Signal Strength(RSS) values are collected in each position where a fingerprint is desired. Each fingerprint consists of x and y coordinates and RSS values of the beacons within range. Then the whole area is divided into subareas. In the second phase, a unique RSS based feature is associated with each subarea. For instance, a feature of a subarea is the range of RSS values of the nodes within this subarea.

Finally, in the estimation phase the mobile node collects RSS values to select the most similar subarea based on the subarea feature. For instance, a subarea is selected if the collected RSS values are within a certain RSS range if we choose the selected feature to be RSS range. After selecting the subarea, three fingerprints with least difference to the collected RSS measurements within the subarea are selected. Then the position is calculated based on the positions of the three selected fingerprints.

The system is tested in two environments with three beacons in each. One of them is (41.5 x 11.5) meters with walls and obstacles, and the other is a sport hall with dimensions of (30.5 x 11.3) meters. Fingerprints are collected in 70 and 60 distinct locations in the first and the second mentioned environments respectively. Then, the area is divided into subareas either manually or autonomously. In the manual way, a subarea is selected manually and the system is designed to check for a common feature. Whereas if the division is autonomous, the area is divided randomly into several subareas. The last mentioned method is applicable only in open environments and cannot be used in complex environments where obstacles and non-uniformly distributed objects exist. If a common feature exists, the selected area will be accepted and considered as subarea. If no common feature exists, the selected area will be reduced and analysis to find a common feature starts again. The report concludes that an accuracy between 1 to 3.5 meters is possible to achieve.

4.3.2 Bayesian Fusion Using Fingerprints

A method called *Bayesian fusion for indoor localization using Bluetooth and fingerprinting* is proposed in [24]. As the proposed method utilizes fingerprinting, it consists of two phases, training or offline phase, and position estimation or online phase. In addition, it utilizes a motion model. In the same manner as other RSSI based approaches, RSSI measurements are collected at several reference points in the training phase to build the fingerprint database. Each fingerprint that refers to a position consists of the coordinates of the center of that position together with beacon information for all the beacons in range. Each beacon information entry consists of the RSSI value of that particular beacon, the statistical mean and the variance obtained from the RSSI values of that beacon. In this way, a radio map is constructed for the area that should be enabled for positioning.

In the online phase, a mobile node powered by a USB connection connected to a laptop by a serial port is used. The mobile node collects RSSI measurements while moving and sends them to the laptop via the serial port. The sent information is processed by an application on the laptop that estimates the positions based on the mentioned methods. When calculating the position, two approaches are used, static Bayesian estimation and estimation with a motion model. In static Bayesian estimation, the position is estimated based only on the current RSSI measurements that are collected from beacon nodes in range. When the motion model is utilized, earlier positions and the velocity are applied in the calculations. When initializing the estimation a uniformly distributed prior such is used since no previous data is available in the firs iteration

The proposed method of Bayesian Fusion (BF) is compared to both Bayes static estimation (BSE) and point kalman filter estimation (PKF). These estimations are based on Gaussian distributions and the results become Gaussian density functions. To use BF and PKF, an initial position is required, which is supplied by using the first obtained position from BSE. In the experiment, the estimated positions in each of the three aforementioned methods are compared to the real position that is obtained by a high accuracy GPS system for evaluation purposes. According to the attained results, the accuracy of using BSE is about 5 meters. When using PKF, an improvement of 0.1 meters is observed. Whereas, the accuracy of the proposed BF method is 4.7 meters on average. In comparison between all methods, the accuracy of BF is better than both BSE and PKF with about 0.4 meters and 0.3 meters respectively.

4.4 Cell based positioning

In this section a cell based localization system[25] is reviewed and explained.

4.4.1 Low-latency cell based positioning

In [25] an indoor positionung system that is based on the visibility of beacons is presented. The system consists of several short-range beacons that are deployed in an indoor environment in a way such that each beacon covers a specific segment. The coverage range of the beacons is very limited, typically reaching only a few meters. Making it very likely that a moving user will discover different beacons in a short time while moving.

In addition, geometric and topological relations are represented in the system as a *location graph*, where vertices represent locations and edges represent connectivity or neighborly features between locations and associated with weights equal to the distance between the adjacent vertices. Two vertices are connected by an edge if there is a direct route between their locations that does not pass through any other location. In addition, the ranges of the beacons are expressed as sets of vertices that represent locations that the beacons cover and are connected by hyperedges. Thus a *beacon hypergraph* is constructed. By combining the *location graph* and the *beacon hypergraph*, a *beacon map* is generated.

Furthermore, a path between two locations is represented as a sequence of locations at a sequence of discrete time points, with fixed time intervals between them. Thus each two locations that are separated by only one time interval are adjacent. Each mobile device contains a map of interesting locations and beacon identifications. Determining the location of a device is done by using the beacon map, the previous position, and the visibility of the beacons. By taking into consideration the adjacency relationship between the locations on the map, earlier position fixes are utilized in current position estimation and the current estimated position is utilized in the subsequent estimations.

In order to optimize the beacon visibility probing time and cost, a probing plan is introduced and expressed as a binary tree that is arranged based on the probability of traveling from a location to another and the probability of a location being in range of a beacon given that it is in the range of another beacon. Several approaches to design the binary tree are presented in the report. Based on the example used by the authors, the most optimized approach is something based on so called balanced plans. Related work on the optimization of cell based positioning systems is presented in [26]. The cited report focuses on the problem of beacon placement decision and presents a solution based on a greedy approach.

4.5 Triangulation

Determining the position of a node using Triangulation requires measuring the angle of the arrived signal, referred to as "Angle of Arrival". One related paper using the concept has been selected. The selected paper is described and explained in the following subsection.

4.5.1 Ad Hoc Positioning System Using AOA

One of the triangulation based positioning systems that utilizes Angle of Arrival in a ad-hoc network is presented in [19]. The network in this system consists of ad-hoc nodes that are able to communicate directly only with their immediate neighbor nodes within their range. Further, at each node, angles can be determined against the node's reference axis, which identifies the heading or orientation. Landmarks are nodes that are aware of their positions and headings based on external references such as manual configuration. Two angle measures are used in the report at each node: bearing and radial. Bearing is the angle of arrival that is determined at the receiver, or in which angle the receiver sees the sender. Whilst, radial is the reverse of bearing but at the sender, in other words, in what angle the sender sees the receiver. In this system, not all of the nodes are aware of their positions and their orientation.

For a node to be able to calculate its position, it needs to determine the angle of arrival of signals from its direct neighbours. Neighbors may also be assessed by their neighbors to calculate their positions and orientation by getting information about neighbours' orientations. A node can determine the angle of arrival from two neighbours and find out one angle of the triangle constructed by the node and its two neighbours. Also, a node can find out its orientation if it is aware of the orientation of one of its neighbors.

As a result, nodes will find their orientations and positions gradually by propagating landmarks information. For a measurement of bearing at a node to be forwarded, the node needs two neighbors that are neighbors of each other to be present. Some error avoidance is also applied, for instance, applying TTL on the propagation of packets that contain orientation information. A node determines its position by calculating the intersection point of three circles that are determined by the angle of arrival and the landmarks. More details about triangulation is presented in 3.5.

The evaluated system, an ad-hoc network consisting of 1000 nodes was evaluated. All of the nodes were capable of measuring AOA and only a small part of them had initial awareness of their positions. To make the experiment more realistic, Gaussian noise was applied to AOA measurements. Worthwhile to mention is that the system was tested with static nodes, where the nodes were fixed or moved a negligible distances.

4.6 Signal Parameters

This section reviews two different articles regarding what parameters are suitable to use for a Bluetooth based positioning system. More sources and parameters are described in Paragraph 2.3

4.6.1 The reliability of RSSI

Valuable effort has been put on evaluating the reliability and applicability of using the RSSI parameters for indoor positioning. In [27] a thorough evaluation is performed examining the suitability of using RSSI as parameter for positioning. The hardware that was used in the evaluation is a Texas Instruments CC2420 chip. The mathematical model used is in fact the same as (4.1). The A and n constants were calculated using two approaches. In the first approach, the constant A was calculated in the same way as before, namely by measuring RSSI at a distance of one meter. By using A in the mathematical model with different pairs of measured RSSI values and distances, several values of n could be obtained, the average of them was inserted in the mathematical model when calculating distances based on RSSI. When A and n were calculated, a reference curve of the relation between RSSI and distance was established.

In the second approach, a linear relationship between RSSI and a distance dependent value $x = (-10)\log_{10} d$ was established and inserted in equation (4.11)

$$RSSI = nx - A \tag{4.11}$$

Later, for different *RSSI* and x pairs, a polynomial curve fitting model was used to compute the values of n and A. A test of the effect of human body on RSSI was also carried out and showed that the sensitivity of RSSI increased as the relative distance decreased. Moreover, the RSSI value was also examined while moving away from a beacon node with an average speed of 1.4m/s up to a maximum distance of 27.5m. Then a mathematical relation between RSSI and the distance was established. This relation was applied when calculating distances based on RSSI values. The relation took into account the time when the test began and ended and the time when the RSSI was read as shown in (4.12). Having in mind, *tmax*, *tmin*, *t(i)*, and RSSI were known, distance *d(i)* could be calculated.

$$d(i) = \frac{RSSI}{tmax - tmin} t(i) \tag{4.12}$$

Several RSSI values were read at different distances and points in time, whereafter distances were calculated and compared to the actual distances in order to evaluate the reliability of RSSI. Four approaches were carried out to process and analyze the collected data. At first, by plotting the raw sampled data, it was shown that the RSSI could not be used as a distance indication due to its high fluctuation. Secondly, by taking at each time point the average of all the previously collected RSSI values. The result of this approach showed that the collected data samples were smoothed, but result was still not accurate enough. In the third approach, the previous method was used but instead of treating all the previous collected samples evenly, different weights were given to the sampled RSSI values. Higher weights were given to previous samples which were closer to the sample that is to be calculated. The result of this approach showed that the distance could not be determined based only on RSSI due to large differences between the calculated distances and the actual distances. Finally, by predicting the sample at the next time point using curve fitting of all the previous collected samples. According to the outcome of this approach, the error margin of the calculated distances is minimized as the time went by and the mobile node moved further away. In the end, the authors concluded that it is unsuitable to determine distance based only on RSSI measurements due to the high and unpredictable fluctuation in the calculated distances vs RSSI and the large errors obtained for calculated distance vs actual distance.

4.6.2 Inquiry response rate fingerprinting

Another parameter which does not have connection to signal strength is inquiry response rate(IRR). In [12] Bargh et al describe a system which provides room level precision with an IRR-fingerprinting approach. The IRR is defined by the authors as: "the percentage of inquiry responses to total inquiries". The nature of Bluetooth is that a device scanning for nearby devices continuously broadcasts inquiry messages as described in Section 2.1.1. A number of these inquiries will be responded to by different discoverable devices in the vicinity. This functionality is then utilized to create a map of the area that shall support positioning where the unique fingerprint is based on the fact that this IRR will be different for different positions. When calibration is performed, an online phase is carried out to do the actual position estimation. During the positioning phase, inquiries are again performed to get measurements. These measurements are compared to the fingerprints in the database and the difference is calculated and used with Kullback-Leibler divergence[28] and the related but modified Jensen Shannon divergence[29] to get a position estimation. The result of the system is a positioning approach which achieves a 98% accuracy of providing the correct position on a room level. The mentioned accuracy is achieved provided that the room in question is fully covered by nearby Bluetooth beacons and that the device being positioned remains stationary for a duration of 3 minutes.

4.7 Commercial systems

The development of Bluetooth smart and related applications has made a big leap in the past two years. Currently there exist commercial products on the market that at least partly rely on Bluetooth smart technology to perform indoor positioning. The commercial systems are divided, both with respect to which technology is used to provide positioning but also with respect to the use case. Some are focused on providing a positioning system with the aim to provide good characteristics for such an application. While other systems are more concerned with ”proximity” rather than actual positioning. In these systems, it it not strictly necessary to provide an exact position with x and y coordinates(or latitude/longitude). Instead, focus is put on location awareness, for example if a user is near a store, or if the user are standing right next to an article inside the store. In either case, the technology can then be used to provide the user with relevant information. For instance, popping up a message offering some discount to attract the user into the store. Or if the user is standing next to some article, provide the user with detailed technical data/video/reviews to enhance the shopping experience. Some of the existing systems also combine both these applications (as well as adding others, such as customer movement tracking) and offer a complete solution with both positioning, location aware services as well as tracking.

4.7.1 iBeacon

iBeacon is the name of Apple Inc’s trademarked positioning technology based on Bluetooth smart technology[30]. The system is not only concerned with location estimation but also interaction and engagement for retail applications as the most commonly cited use case. The system can detect when a user carrying another Bluetooth smart enabled device such as a smartphone is in the vicinity. It can also send a notification or a message to the device, for example to offer a special discount depending on what department in a store the user resides in. The technology is not only designed for retail purposes and can be used in a variety of other contexts such as museums, airports, and sport events to name a few. The beacons are not primarily designed to provide high precision localization, instead distance estimation to each beacon is considered. The system defines three different range areas, Immediate (a couple of centimeters), near (a few meters) and far (10+ meters). The positioning is typically made against a single beacon and will thus provide an approximate position in a large area if several iBeacons are deployed. The technology is also used as basis in systems that aim to provide high precision positioning. Examples of such systems are listed in paragraphs below. Although developed, trademarked and patented by Apple, the technology is also available for use with Google’s competing Android operating system as well as other systems with support for Bluetooth smart. The only requirement (so far, might be subject to change) is that a registration has to be made with Apple’s MFi-program[31].

4.7.2 Estimote

Estimotes[32] is similar to the iBeacon system and does in fact use the licensed iBeacon technology. The system consists of Bluetooth smart-chips wrapped in waterproof soft silicon casing. With the motes come an application programming interface(API) which developers can use to easily develop their own tailored applications and use cases. The motes have the same properties as described for iBeacons and are mainly marketed towards retail solutions. The vendor does state that high precision localization is not the primary goal. Instead the range areas defined for iBeacon are used to give an estimate location of where in a building a user is located given that the beacon position is known.

4.7.3 SenionBeacon

SenionBeacon is a positioning product from SenionLab[33]. The company provides indoor positioning systems which rely on sensor fusion. The SenionBeacon is a Bluetooth smart chip which a user installs in the area that shall support indoor positioning. Then a calibration app is used by the customer to collect data samples within the area. The data together with a map are sent to SenionLab which provides the customer with an API and an indoor positioning app that customers can further develop to suit their needs. The SenionBeacon, although built on iBeacon technology (the beacon, much like Estimote uses iBeacon technology), has focus on providing high precision real-time positioning. This is achieved by a combination of a fingerprinting-based localization system using Bluetooth smart or Wi-Fi combined with sensor data obtained from sources such as accelerometer and compass. The calibration app which the customer uses collects a database of fingerprints that SenionLabs uses to create calibration data for the positioning system.

4.7.4 indoo.rs

Indoo.rs provides a similar system as SenionBeacon with a number of differences. All of the tools needed to create, maps, positioning, etc. are already built and the customers will use the tools themselves to create a positioning system. Much like the SenionBeacon, the system depends on either iBeacons for a Bluetooth smart implementation or Wi-fi. It does also rely on the fingerprinting approach where sampling and measurements are required before the system can be used for positioning. Indoo.rs guarantees an accuracy of <5m radius in 95% of the cases[34]. The company also adds that accuracy can be inexpensively improved by adding more beacons and states 2m as a potentially achievable accuracy.

4.7.5 Quuppa-HAIP

HAIP is an indoor positioning system that uses Bluetooth smart as the core technology and exists in two different variants[35]. The first is a mobile-centric system that analyze RSSI parameters to determine a position. An app developed for cellphones broadcasts a special Bluetooth smart request, which causes all nearby HAIP-locators (Bluetooth smart beacons) to respond to the inquiry. When the app receives the response, a request is sent to a locator database server that responds with the position of the discovered beacons. The information about the locator position together with the RSSI parameters which were received in the broadcast response allow the app to estimate a position. Quuppa, the company behind the products claims an accuracy of 5-10m is achieved by the system.

The second variant of the system, is a network-centric solution which also uses Bluetooth smart for sending radio packets and offers much better accuracy. Quuppa states that customers can expect 0.3-1m accuracy which is significantly better than all related systems as of today. This technology, however, is not standardized yet and requires special tags to be functional. The system does not rely on signal strength, instead angular estimation is used where the locator's beacon is equipped with an antenna capable of determining the angle of arrival of incoming radio packets. This angle together with information about locator position and the known height of the tag allow the system to estimate a position with good accuracy. The only requirement for the positioning to work is that the tag should not deviate in height of more than 1m.

4.7.6 Insiteo

Insiteo is a french company which has been working with indoor localization since 2009. The company has several interesting technology approaches pipelined, where the newest addition is an indoor-GNSS(Global navigation satellite system) with hardware that retransmits GPS and Galileo signals indoor. The new system requires almost no setup and calibration work while providing high precision accuracy better than 1 meter[36]. The system will also work without these GNSS repeaters and is then similar to systems like indoo.rs and SenionLab. RF-signals such as WiFi and Bluetooth smart are fused together with internal sensors such as accelerometer, compass and gyro in a smartphone to provide indoor positioning with high precision and responsiveness. The system supports multi-storey buildings and Insiteo claims to achieve an accuracy of 2 meters or better. Insiteo also combines the positioning service with several other business oriented use cases such as geofencing, location aware push-messages and visitor monitoring.

4.8 Justifying choices

This section explains and motivates the decisions and choices that have been taken based on the literature review including scientific papers, Bluetooth smart documentation, and commercial products. The area of RF based indoor localization is rich with respect to documented studies and information although not in the context of Bluetooth smart. The only references of Bluetooth smart based positioning are the several existing commercial systems promising different properties.

Based on the information presented in Chapter 2. It is appropriate to conclude that using RSSI as parameter is the most suitable selection. Of the available parameters, RSSI is the one with the most examined relation to distances. RSSI is also obtainable in Bluetooth smart by simply receiving a broadcasted message. In other words, the choice of RSSI will allow connectionless positioning possibly supporting multiple nodes without increasing RF spectrum demands.

When it comes to the matter of selecting positioning approaches it seems like a reasonable decision to pick trilateration as one of the approaches since it is one of the simplest. Further, the literature review reveals that the concept of iterative trilateration could be an interesting choice. No literature uses the approach straightforwardly, instead it is combined with a particle filter, which fuses it with other sensor data. It would therefore be interesting to test it alongside traditional trilateration and see how much improvement it possibly adds. When it comes to the other approaches, two of them stand out when it comes to usage and presented results, namely particle filters and fingerprinting. Both of the concepts are used in a wide variety of systems and implementations, of which some are mentioned in the literature review. Thus fingerprinting and particle filter are added to the list of interesting positioning approaches to be evaluated in a Bluetooth smart setting. Another advantage of selecting these systems is that comparison against similar systems that uses other technologies such as traditional Bluetooth or Wi-Fi is simplified.

Some algorithms of course have to be eliminated for the evaluation. Some are eliminated because they do not offer adequate performance such as cell based approaches and IRR-fingerprinting, which both only target room level accuracy. Others are eliminated since they would be infeasible to actually implement in a Bluetooth smart testbed. Specifically the AOA and TOF approaches approaches are left out. The motivation behind this is that AOA requires advanced hardware modifications adding a directional antenna or an array of antennae which is beyond the scope of this work. When considering TOF, the distance between two objects is calculated based on the time the signal takes to travel from one object to the other by multiplying it by the signal speed. Since signal speed is similar to the speed of light traveling in vacuum, which is about 0.3m/ns an extremely precise clock synchronization would be required. Something which is not expected to be feasible using inexpensive Bluetooth smart hardware in the price range of a few US dollars per unit.

How the aforementioned approaches are implemented, tested and evaluated is described in Chapter 5.

5

Testbed

This chapter describes the evaluation criteria for evaluating Bluetooth smart based positioning systems as well as the configuration and architecture for the testbed setup used for evaluation. Four different positioning algorithms are evaluated: trilateration, iterative trilateration, a particle filter, and a fingerprinting approach. Technical details and explanations are provided for each approach.

5.1 Evaluation criteria

To evaluate positioning based on Bluetooth smart technology, We define a set of evaluation criteria which positioning will be evaluated against. A number of important characteristics can be defined in the context of indoor localization and different types of systems comply in different degree with these characteristics. The characteristics selected as important for indoor positioning in this report are listed below:

- **Accuracy and Precision** - A positioning system should provide good accuracy, where the user with high probability and precision can locate himself in the environment. We emphasize that the definition of accuracy is not synonymous with the definition of precision. Definitions of both concepts can be found in[37].
- **Calibration complexity** - The system should be as easy as possible to install and setup. If a lot of effort is required for the system to be operational, it is not deemed to have good calibration complexity.
- **Scalability** - The system should allow for easy expansion into several rooms and areas, for example if the system is installed in a certain room or area, it should require as little effort as possible to expand the area. This criterion also governs

the ability for the system to support several simultaneous users. E.g if the system supports expanding from 5 to 50 simultaneous users.

- **Liveliness and response time** - Defines how responsive the system is, for real time tracking the update rate for the positioning needs to be quite high with at most a few seconds between each update.
- **Robustness and Adaptability** - A positioning system should preferably be able to cope with changes in the environment without requiring extensive reconfiguration or experiencing performance degradation. Examples include when furniture is moved or when an empty configured area is filled with a lot of people.

Accuracy and precision can be measured quantitatively by calculating the exact error for each estimation. In the evaluation of Bluetooth smart in a positioning context the following data will be presented:

- Average error for each approach in each scenario.
- Standard deviation of estimation errors in each approach and scenario.
- Largest error in estimation.
- Smallest error in estimation.
- Precision confidence, e.g with what precision is a certain accuracy achieved. The defined errors in accuracy presented is <2m, <3m, <4m, <5m and >5m.

The other four characteristics are more difficult to evaluate strictly with numbers and statistics. Each of them will instead be analyzed individually based on the perceived performance in relation to the relevant characteristic. Each score will be analyzed and motivated in relation to properties of Bluetooth smart technology and/or relation between properties of the positioning approach and properties of Bluetooth smart. It is important to emphasize that all the characteristics listed are treated independently from each other. This means that even though the system provides poor accuracy, it could still achieve high performance for all the other characteristics. It is therefore important to specify and reflect on which characteristics that are important to consider for a specific system. This project does not perform evaluation for a specific use case, rather it performs evaluation on a broad level with several characteristics. A use case may after all hold all of these criteria, or only a subset in high regard.

5.2 Test environment

The evaluation is performed in a typical office environment at the premises of Cybercom Ab's Gothenburg office. Two different scenarios are tested, a small scale scenario in a rectangular open plan office environment measuring 8x11 meters and a larger scenario consisting of an entire wing of the office in the shape of a triangle measuring 20.5x16x25.5 meters. In both scenarios the areas is furnished although the type of furniture differs somewhat. The open plan office contains desks, chairs and filing cabinets while the wing consists of a large kitchen and an adjacent living room furnished with couches, stand tables, a conference table and kitchen furniture. A picture of each test area is presented in Figure 5.1. The overview floor plans are presented in Figure 5.8. The radio spectrum in the area is not free from competing technologies, a number of Wi-Fi networks are active in the area and it is possible that other Bluetooth enabled devices are active within the premises. The environment that in no way is free from noise or obstacles represents a typical real life scenario in which an indoor positioning system could be deployed where furniture and radio transmitters are expected to in a non-negligible way affect the system performance.

5.3 Testbed setup

The system used for evaluating the positioning approaches can be divided into two parts, hardware components and software components. This section provides a description of the components and decisions on implementing each of the two parts.

5.3.1 Hardware

The main hardware required for evaluation is the reference Bluetooth smart nodes to be deployed as beacons in the test environment and a mobile node to gather data to be used for positioning algorithms. Both these components are described below.

5.3.1.1 Bluetooth smart beacons

To facilitate the beacons, Bluetooth smart chips combined with microcontrollers, software stacks and RF-components including antennae are required. Currently several different System on chip(SOC) solutions including all the required parts are available from electronic component vendors. The reason to use dedicated embedded systems hardware instead of using easily accessible Bluetooth smart enabled smartphones is that smartphones do not yet support the Bluetooth smart broadcast mode which is particularly suitable for usage as beacons. The choice of Bluetooth smart-chip fell on Bluegiga's BLE112[38] chip with an integrated 8051 microcontroller complete with an assembled 0.7mm ceramic antenna. The reason for choosing this particular SOC was threefold: (1) It enables really easy development of simple applications with a proprietary script language called BGScript. While several of the competing SOCs require a proprietary compiler from IAR Systems[39]. (2) The size of the chip is (18.15x12.05 mm) which makes it relatively easy to work with in respect to soldering and assembly. (3) The chip comes with excellent documentation and support.

To be able to work effectively with the relatively small SOC, the decision was made to construct a Printed Circuit Board(PCB) to allow easy access and handling. The PCB

(a) Open plan office scenario

(b) Office wing scenario

Figure 5.1: Visual representaion of the two test areas

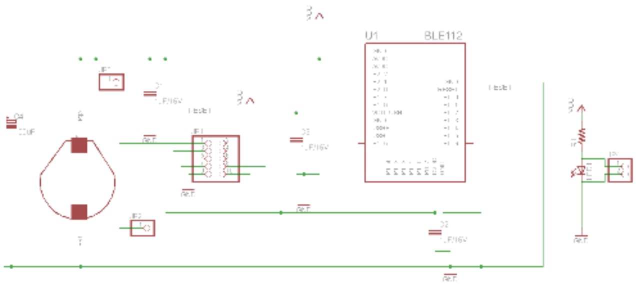
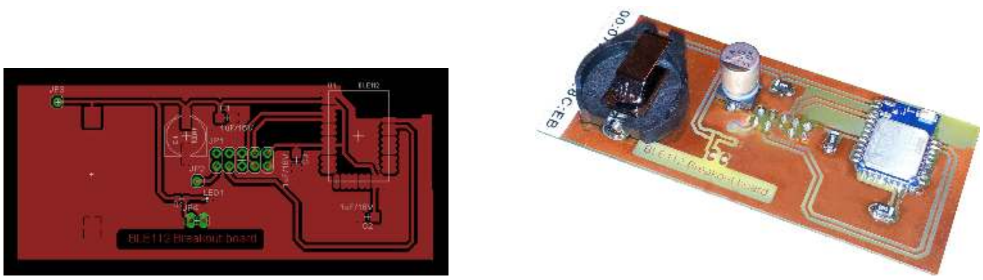


Figure 5.2: Breakout circuit board schematic



(a) Circuit board design

(b) Printed circuit board

Figure 5.3: Breakout board for BLE112

also allowed to mount capacitors in recommended places to improve battery performance[38]. The schematics of the PCB and a figure demonstrating a completely assembled beacon can be seen in Figures 5.2, 5.3(a), and 5.3(b).

5.3.1.2 Mobile node

To collect data broadcasted by the beacons, a mobile node is necessary for retrieving the desired RSSI measurements. The easiest solution was determined to be using a smartphone with Bluetooth smart support. By coincidence, one of the authors had a Sony Xperia ZR (C5503) running android 4.3 with support for Bluetooth smart. It was decided early that calculations and evaluation should be performed on a PC, the reason for this is described further in the paragraph below but as a result of this decision, a PC is also a necessary hardware component in the testbed.

5.3.2 Software

The software in use by the testbed can be divided into three parts, Bluetooth smart beacon application, mobile node application(s) and PC applications implementing positioning approaches combined with data gathering code. The beacon's application is implemented using BGScript. The same application is used throughout all evaluations in this report. The objective of the application is simple, broadcast advertisements periodically with a customized time interval which in the tests performed is set to every 0.25s.

The mobile node application is an android application which exists in two simple variants. Its task is to scan for Bluetooth smart beacons within range, register the measured RSSI value for each beacon and forward the data via Wi-Fi to a PC for analysis and estimation. The reason why several versions exist is because the gathering of RSSI values are different for different applications in the testbed. The first version of the application simply scans for devices within range for a specific time interval. When the scan time interval is reached, data consisting of all discovered beacons MAC addresses together with the measured RSSI for each one is sent in a packet to a PC. A second version of the application does almost the same thing as the first, except that instead of sending data when the scan completes, the application performs several scans and then sends the average of the gathered RSSI for each node based on all the scans in a packet. How many scans to perform when constructing the average value is configurable, but will typically be 20 for offline/configuration purposes and 5 for online/positioning purposes.

The last part of the software suite is the program running in the PC which is used to perform the actual positioning estimations and calculations. The software tool used for data collection, implementing algorithms, evaluation and visualizing results is Matlab. Matlab receives UDP packets sent from the mobile node containing beacon IDs and associated RSSI values and then runs the applicable code. The reason for using Matlab instead of executing algorithms and evaluations directly in the android device is due to implementation complexity. Matlab is a high level tool with extensive support for implementation of complex systems, support for saving data in several formats, API calls for common mathematical functions and competent tools to create visual reports and elements such as graphs or defining maps with coordinate systems.

5.4 Positioning algorithms

This section presents the four implementations of positioning algorithms that are evaluated.

5.4.1 Trilateration algorithm

The simplest approach to do positioning is to use the trilateration algorithm to estimate a position. The algorithm requires knowledge of the beacons positions to be known by the mobile node or the application that performs positioning. It also depends on measuring the distance to each beacon to be able to determine the position. The theory behind this approach is described in Paragraph 3.1 and a flowchart of the algorithm is shown in Figure 5.4. To estimate distance against a node based on measured RSSI, Equation 5.1 is used.

$$RSSI = -(10n\log_{10} d \; + A) \tag{5.1}$$

A and n are the absolute energy in dBm and the propagation constant respectively. The Equation 5.1 is rewritten to get the distance as output since we will be able to measure the RSSI value. The resulting Equation 5.2 is written as:

$$d = 10^{\frac{A-rssi}{10*n}} \tag{5.2}$$

Which is the same equation seen in 4.1.1 and several other related reports.

Trilateration in this approach is combined with least square error estimation since trilateration generates an overdetermined system that is recommended to be solved precisely using the least square error method.

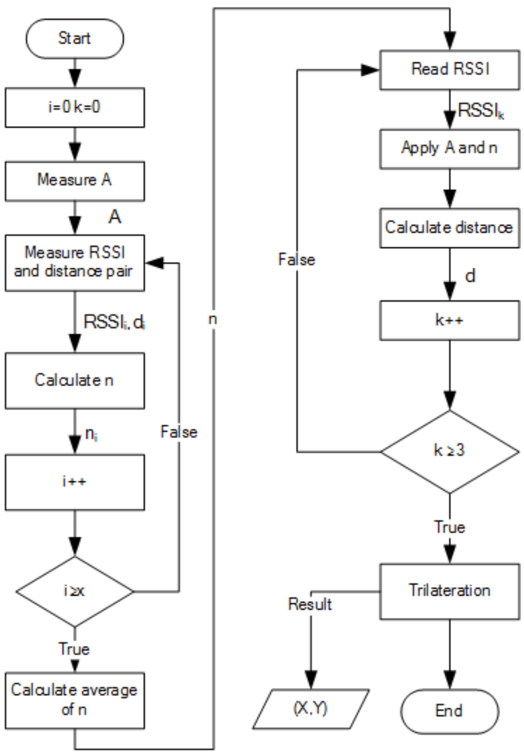


Figure 5.4: RSSI based trilateration algorithm. Distances are calculated based on RSSI, A, and n using Equation 5.2. x is the number of pairs, which is a customized value

5.4.2 Iterative trilateration

As a further step towards a possibly more accurate positioning approach is to use the principle of iterative trilateration. To use this method, an initial estimation is required as the first input in the first iteration, which can be calculated using trilateration a single time. In each iteration the previous estimated position is updated. In addition, the difference between the RSSI based distance measurement and the distance calculated based on the estimated coordinates is calculated for each beacon. Based on these differences and by using Taylor series approximation, the adjustment to the previous estimation can be calculated. The calculated adjustment is multiplied by a reduction factor before calculating the new estimation for convergence purpose. The steps of iterative trilateration are shown in Figure 5.5. All details regarding iterative trilateration and the mathematics behind it are described in Paragraph 4.2.1.

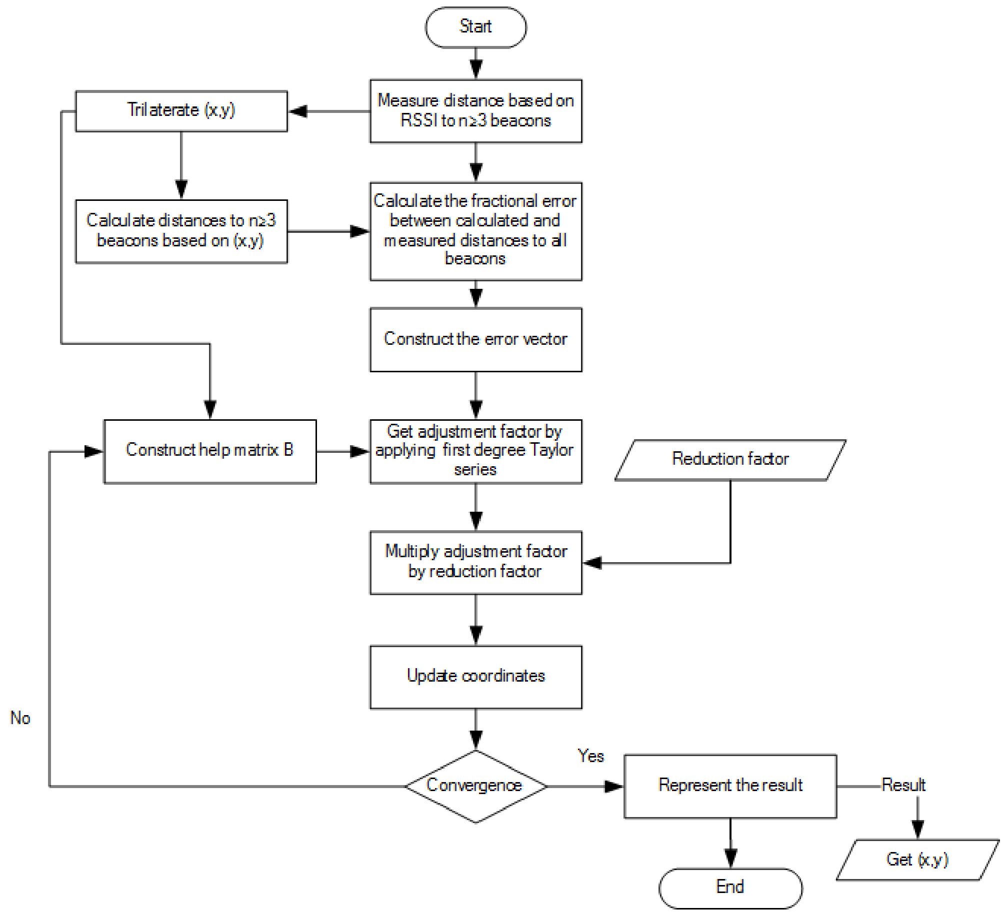


Figure 5.5: Iterative trilateration

5.4.3 Particle filter algorithm

A Matlab implementation of a particle filter based on the theory and the concepts explained in Chapter 4 has been utilized. The observable variables are the distances to the beacons that are calculated based on RSSI. At the other end, the hidden variable is the position of the mobile node. Compared to other related work that utilizes compasses or motion model that give observation about the orientation, the orientation information is generated randomly without utilizing a compass or a motion model. By randomly generating several thousands of particles and then testing each particle for likelihood of being accurate or not based on the observation variables, weights are given to each particle. Particles that are likely to be accurate given the observations are awarded high weights, whilst those that are unlikely to be accurate given the observations are awarded low weights. The likelihood is determined as follows: The mobile node collects RSSI from each beacon and calculates the distance to each beacon based on RSSI. At the same time, distances between each particle and each beacon are calculated. By comparing the distances of each particle to each beacon with the distances calculated based on RSSI the weight is determined. A small difference in distances will result in high weight, while a large difference will result in low weight. The filter is executed recursively over time and as a result most of the particles lose almost all their weight. Which leads to the effect that they do not contribute to the positioning estimation. On the other hand, some particles gain more weight, which results in making them contribute significantly in the estimation process.

Consequently, the system may end up in a situation where there are very few contributing particles. By deciding a threshold on the number of contributing particles and weights, the aforementioned issue can be resolved. When the number of the significant particles decreases below a certain limit, new particles can be generated and old ones discarded. This step is called re-sampling. Equally importantly, no re-sampling is required if the number of particles is above the threshold, which attenuates the load. In addition, Gaussian noise is applied on the measurement estimation and move processes to account for uncertainty. A flow chart that illustrates the general steps of the particle filter in this project is presented in Figure 5.6.

In each recursion step, the quantity of particles of considerable weight is tested to check whether to generate new samples or not. Each sampling or re-sampling step is followed bya weighting step and a normalization step, where weights are normalized for comparison purpose. In addition, in each recursion step, particles are moved in random directions and get new positions. Later, the most probable particles to be accurate are considered as basis for determining the position of the mobile node.

5.4.4 Fingerprinting algorithm

Indoor positioning using fingerprinting is similar to a ”look up process”. A mobile node collects some RSSI values and then searches a database for some data that satisfies the

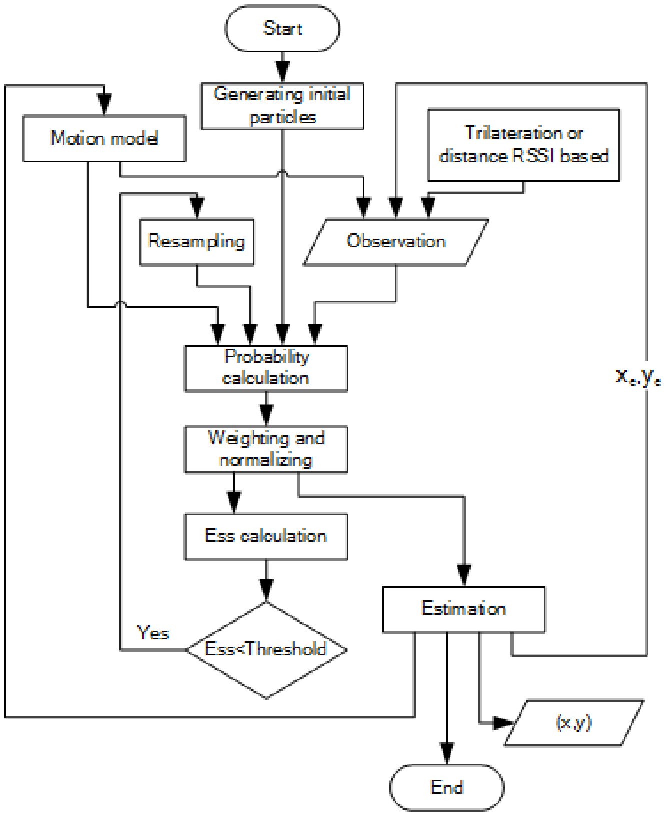
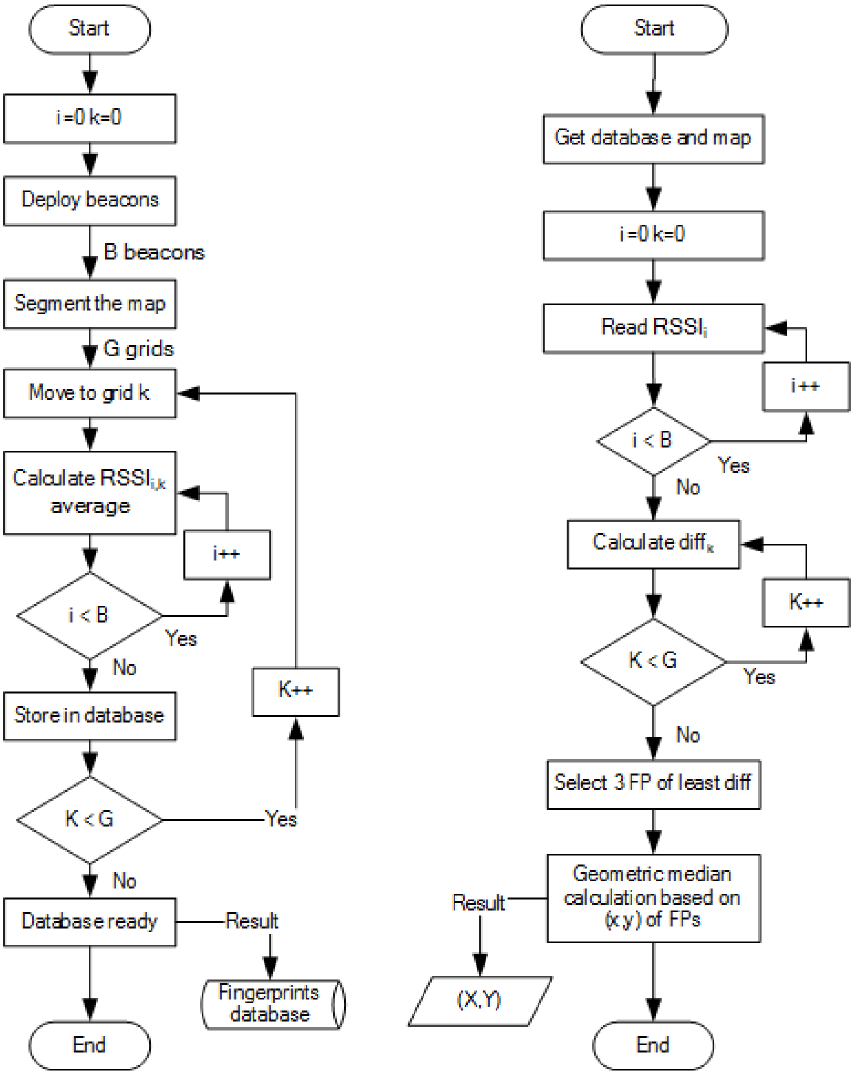


Figure 5.6: Particle filter

same characteristics as the measured data. A database needs to be available before any positioning is performed. Thus, this approach requires two phases, a training phase and a positioning phase. Before the database can be created, the map of the indoor environment where the system will be deployed must be divided into several segments. It can be divided symmetrically into grids, or asymmetrically by selecting some interesting locations on the map. By deploying the beacons in a way that guarantees best coverage and signal strength diversity, the performance in terms of accuracy and precision can be increased. A description of the fingerprint algorithm for both training and positioning phases is presented in Figure 5.7

In the training phase, at each segment or cell the RSSI values of all the beacons in range are collected. A fingerprint thus consists of the coordinates of the center of the segment or the cell and the RSSI values, where each of them is the average value of several reads and associated with a MAC address or ID that belongs to different beacons. As a result, a database that consists of the fingerprints is constructed. This is done simply by placing a mobile node at the center of these locations or cells for a reasonable period of time while an application that is run on the mobile node collects RSSI values. The mobile

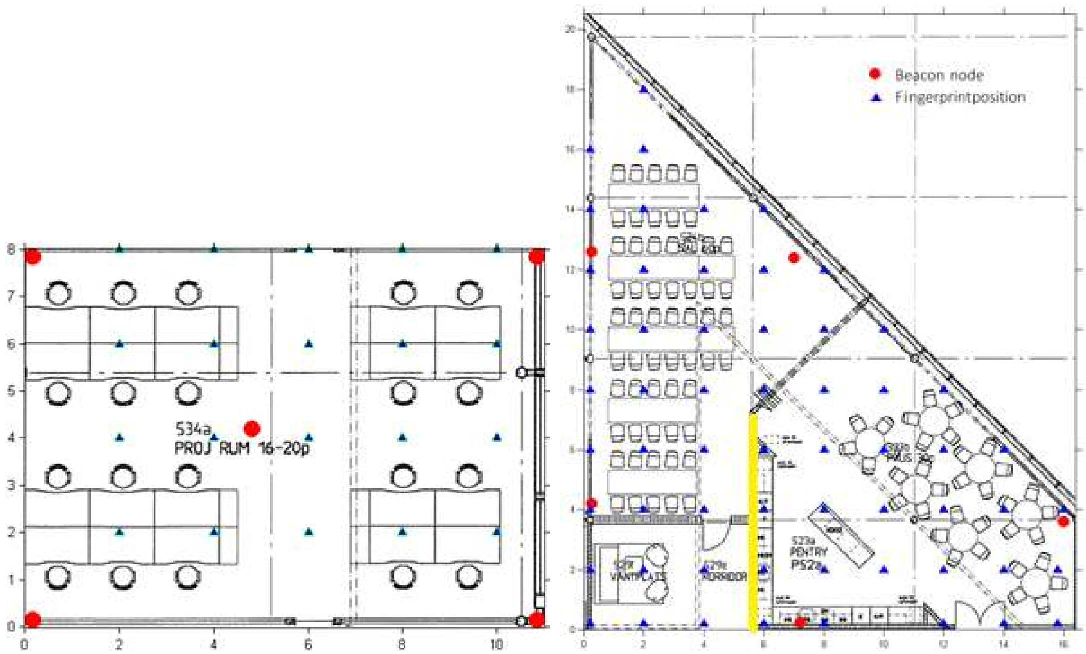


(a) Training phase (b) Positioning phase

Figure 5.7: Fingerprinting flowchart

node is an Android device explained in 5.3.1.2. A flowchart that illustrates the general steps of the training phase is shown in Figure 5.7(a). The number of fingerprints and the number of beacons in each fingerprint depend on the environment. On the laptop a Matlab application receives the sent data and appends them to the database. The database is located in a text file that can be updated by the Matlab application. Whenever the training phase is completed and the database is constructed, the online phase and the positioning process can be started.

In the positioning phase, a mobile node that wants to estimate its position needs to collect RSSI values of all the beacons in range in the same way as in the training phase. The RSSI collection can be done in two ways, collecting single a RSSI value per beacon, or computing the average of several measurements per beacon. Choosing which method to be used depends on the real-time requirements and the update interval requirement. A flowchart that illustrates the general steps of positioning phase is shown in Figure 5.7(b).



(a) Office room (b) Living room

Figure 5.8: Environments where fingerprinting has been deployed

To determine the position of the mobile node, the gathered data and each of the fingerprints in the database are compared. Figures 5.8(a) and 5.8(b) show where fingerprints have been recorded in the two different environments. The comparison is done by computing the total difference between the gathered data in the online phase with each of the fingerprints in the database according to equation (5.3).

$$Diff_i = \sum_{k=1}^{n} \sqrt{(RSSI_{k_{online}} - RSSI_{k_{offline}})^2} \tag{5.3}$$

where $Diff_i$ is the difference between a fingerprint i and the online gathered data, n is the number of RSSI values in each fingerprint, which is a common value for all of the fingerprints in the database, and k is the beacon unique identifier. The next step is to calculate the coordinates of the mobile node. This is done by selecting the nearest

x neighbours among the fingerprints, which gives the least x *Diff*s. In the event that each fingerprint contains the coordinates of the cell or the segment that it is associated with, the position of the mobile node will be determined as the position of least total of distances to the positions of the selected fingerprints. More specifically, the x and y coordinates of the mobile node are the geometric median of the xs and ys of the selected fingerprints respectively.

6

Positioning results

6.1 System results

This chapter presents the results from the testbed evaluations described in Chapter 5. Two different scenarios was tested, one small 8x11m office room and one large 20.5x16x25.5m triangle lounge inside the office building.

6.2 Small area Scenario

The four selected positioning approaches have been tested in 10 different positions in the office scenario, see Figure 5.8(a). In each position, 20 positioning estimations are done where each estimation is calculated based on the average RSSI value from all beacons in the vicinity. To calculate each single estimation, the average RSSI is based on 5 single measurements. This means that each average error (AvgErr) and standrad error deviation (StErDe) is derived from 100 datapoints (20 unique position estimations). Finally the average error and error deviation combining all positions for each approach is calculated. The reason for using the average RSSI instead of basing the analysis on single readings is to mitigate the effect of fluctuation in RSSI values. The results of the measurements are presented in Table 6.1. It is important for analysis purposes to know that LOS is always guaranteed in this scenario.

In addition to the average error in estimations, the least and the worst error for each approach and position are presented and compared to each other. The result of this comparison is presented in Table 6.2 to give a view of outliers for each approach.

As can be concluded from the Tables 6.1 and 6.2, the results differ in accuracy significantly between approaches but also from position to position for the same approach. When it comes to the small Office scenario, the conclusion that can be drawn is that the

Coord.	Iter.		Particle.		Tril.		FP	
(X,Y)	StErDe	AvgErr	StErDe	AvgErr	StErDe	AvgErr	StErDe	AvgErr
(8.9,3.6)	0.318	5.744	0.107	2.446	0.068	2.426	1.285	2.401
(8.8,2.1)	0.316	7.063	0.064	3.670	0.081	3.230	0.763	4.002
(6.9,2.9)	0.478	4.209	0.031	1.870	0.152	1.421	0.505	3.037
(6.9,5.9)	0.616	4.656	0.132	3.356	0.839	3.312	0.620	1.553
(5.3,1.3)	0.269	3.227	0.137	2.130	0.386	2.417	0.832	2.421
(3.7,4.8)	0.691	2.481	0.303	1.087	3.130	3.042	0.775	1.914
(5.6,6.4)	0.346	2.556	0.067	1.813	0.237	1.898	1.042	3.039
(1.9,4.8)	0.319	1.799	0.168	3.626	1.129	4.758	1.451	3.846
(2.9,2.9)	0.354	1.030	0.033	1.971	0.215	2.502	0.895	3.023
(2.1,7.0)	0.876	4.214	0.338	1.404	2.297	3.716	1.111	2.319
Total	**0.458**	**3.6980**	**0.138**	**2.337**	**0.853**	**2.872**	**0.928**	**2.756**

Table 6.1: Standard error deviation and average error of 4 approaches in 10 different positions in a room with size of 11x8 meters, where Iter means iterative trilateration, Particle means particle filter, Tril means trilateration, FP means fingerprinting, StErDe means standard error deviation, and AvgErr means average error. The first two columns are the real x and real y coordinates

particle filter approach provides the best accuracy and least estimation error in comparison to the other approaches. The worst approach with quite significant margin is the iterative trilateration approach.

Finally the confidence of different accuracy intervals are presented in Table 6.3. This table confirms the previous conclusion which presented the particle filter approach as the one providing best performance with regard to precision and accuracy. It is worth pointing out that the trilateration and particle filter appraoches provide similar results for the different intervals.

Coord.	Iter.		Particle.		Trilat.		FP	
(X,Y)	Best	Worst	Best	Worst	Best	Worst	Best	Worst
(8.9 , 3.6)	5.149	6.467	2.307	2.718	2.247	2.503	0.985	4.866
(8.8 , 2.1)	6.403	7.720	3.555	3.849	3.072	3.374	1.905	5.218
(6.9 , 2.9)	3.276	5.176	1.759	1.905	1.050	1.633	1.782	3.821
(6.9 , 5.9)	3.366	5.784	3.020	3.548	2.356	5.479	0.801	3.593
(5.3 , 1.3)	2.844	3.910	1.969	2.551	1.194	2.908	2.150	4.854
(3.7 , 4.8)	1.359	3.671	0.208	1.361	0.752	13.169	0.880	4.213
(5.6 , 6.4)	2.035	3.157	1.737	2.056	1.557	2.275	1.099	3.883
(1.9 , 4.8)	0.784	2.344	3.343	3.914	3.527	8.153	0.778	5.459
(2.9 , 2.9)	0.316	1.875	1.912	2.032	2.128	2.875	1.819	4.772
(2.1 , 7.0)	3.775	7.710	0.878	1.889	0.369	8.825	1.278	6.032

Table 6.2: distances between best and worst estimated positions and the actual positions in 10 different positions in a rectangular room with dimensions of 11x8 meters, where Iter means iterative trilateration, Particle means particle filter, Trilat means trilateration, and FP means fingerprinting. The real coordinates are presented in the first column

Error in estimated position					
Algorithm	<2m	<3m	<4m	<5m	>5m
Iter	21.4%	50%	64.3	78.6%	21.4%
Tril	21.4%	50%	71.4%	85.7%	14.3%
Particle	28.2%	67,5%	92.5%	100%	0%
FP	21.4%	50%	64.3%	85.7%	14.3%

Table 6.3: Confidence for positioning accuracy in 8x11m office scenario

6.3 Large area scenario

Similarly, to the small area scenario tests has also been performed in a larger environment, see Figure 5.8(b). The new environment is a triangle shaped room with an area of 202± 2 square meters. The room is partially separated by a wall in the middle. The setup is presented in Figure5.8(b) where the mentioned wall is marked by a yellow line. Five beacon nodes are placed in the positions represented by red circles. Similar to the small office scenario in 6.2, the standard error deviation, average error, best and worst estimated positions and accuracy confidence are presented in Tables 6.4, 6.5 and 6.6

respectively. Important to note for analysis purposes is that in this scenario, LOS is not guaranteed. Instead it is often the case that at least one beacon is hidden behind a wall or some other obstacle.

According to the the results in this scenario, the fingerprint approach gives with signif-

Coord.	Iter.		Particle.		Trilat.		FP	
(X,Y)	StErDe	AvgErr	StErDe	AvgErr	StErDe	AvgErr	StErDe	AvgErr
(2.9,14.0)	0.424	8.042	0.416	12.888	1.670	7.906	2.837	3.810
(1.2,12.0)	0.628	8.281	0.205	9.853	0.349	7.571	1.352	3.623
(1.3,8.0)	0.343	1.127	0.159	7.519	0.191	5.747	0.249	1.936
(14.5,3.2)	0.251	8.542	0.089	9.053	0.243	6.463	0.856	2.632
(4.0,9.0)	0.448	3.083	0.139	6.540	0.825	3.176	0.826	1.858
(4.0,5.0)	0.416	3.322	0.441	3.461	0.364	2.963	0.878	4.202
(7.1,9.0)	0.298	6.610	0.168	6.378	0.156	1.584	1.110	2.568
(10.2,4.1)	0.166	4.431	0.088	3.019	1.053	3.360	0.654	1.331
(10.3,8.5)	0.604	8.425	0.174	7.130	0.598	2.893	1.759	1.815
(7.1,4.0)	0.401	1.939	0.326	3.164	1.270	3.622	1.949	3.350
Total	**0.398**	**5.398**	**0.221**	**6.901**	**0.672**	**4.529**	**1.247**	**2.713**

Table 6.4: Standard error deviation and average error of 4 approaches in 10 different positions in a triangle shaped room with with an area of about 202 square meters, where Iter means iterative trilateration, Particle means particle filter, Trilat means trilateration, FP means fingerprinting, StErDe means standard error deviation, and AvgErr means average error. The real coordinates are presented in the first column

icant margin the best accuracy and precision amongst the tested approaches. The worst approach is no doubt the particle filter which gives an average error in estimation close to 7m. The results are further confirmed looking at the confidence for different accuracy intervals. The particle filter does only provide accuracy better than 5m in 24% of the estimations while the same accuracy is achieved in 85% of the estimations for fingerprinting.

Coord.	Iter.		Particle.		Trilat.		FP	
(X,Y)	Best	Worst	Best	Worst	Best	Worst	Best	Worst
(2.9,14.0)	7.324	8.744	11.857	13.251	5.738	13.924	0.233	11.281
(1.2,12.0)	7.296	9.156	9.511	10.168	6.865	7.975	1.147	6.981
(1.3,8.0)	0.395	1.724	6.986	7.657	5.360	6.044	1.538	2.142
(14.5,3.2)	8.134	8.895	8.795	9.209	5.911	6.880	1.344	3.870
(4.0,9.0)	2.411	4.159	6.113	6.655	0.087	3.755	0.745	3.569
(4.0,5.0)	2.555	3.992	2.042	3.755	2.102	3.422	2.553	6.846
(7.1,9.0)	5.850	7.064	5.822	6.512	1.366	2.052	0.547	5.548
(10.2,4.1)	4.054	4.788	2.799	3.171	2.437	6.399	0.477	3.184
(10.3,8.5)	7.471	9.511	6.822	7.491	1.307	3.905	0.583	6.816
(7.1,4.0)	1.065	2.579	2.095	3.492	2.034	8.381	0.233	6.893

Table 6.5: distances between best and worst estimated positions and the actual position in 10 different positions in a triangle shaped room with an area of about 202 square meters, where Iter means iterative trilateration, Part means particle filter, Tri means trilateration, and FP means fingerprinting. The real coordinates are presented in the first column

Error in estimated position					
Algorithm	<2m	<3m	<4m	<5m	>5m
Iter	7.7%	23.1%	21.1%	46.2%	53.9%
Tril	7.7%	7.7%	38.5%	61.5%	38.5%
Particle	7.7%	21,5%	22.7%	23.5%	76.5%
FP	23.1%	69.2%	84.6%	84.6%	15.4%

Table 6.6: Confidence intervals for positioning in 16x20.5m scenario

6.4 Characterization results

Based on the evaluation criteria in Chapter 5.1 the following subsections describes the achieved results and conclusions for each of the characteristics. Each characteristic is evaluated and motivated based on the properties of Bluetooth smart technology and properties connected to each positioning approach. For each category a five-point score system is used: Excellent, Very good, Good, Fair, Poor. Excellent of course means that an approach provides great performance for the characteristic and Poor would respond to very bad performance for the characteristic. If further mapping between a score and the characteristic is required, it is defined for each subsection respectively.

6.4.1 Accuracy

Several interesting conclusions can be found in the performed measurements. First of all, no single approach provides the best results for both scenarios. In the small scenario with LOS, the particle filter approach achieved the best performance with regard to accuracy and precision whilst in the large scenario the fingerprint approach outclassed the other tested approaches. Interesting to notice is that the fingerprinting approach was the only one who scored a quite consistent performance with an average error of 2.7m in both scenarios. The other approaches experienced significant performance degradation in the larger scenario where LOS was not guaranteed. Interestingly the iterative trilateration approach which was tested mainly for comparison with standard trilateration performed worse in both scenarios. The performance related to particle filter is also interesting, in the small scenario with LOS it was the best approach while in the large scenario it attained the worst performance. The results on a five-point scale: Excellent, Very good, Good, Fair, Poor is presented in Table 6.7. The mapping are defined as follows: Excellent: <2m, Very Good <2.5m, Good: <3m, fair: <4m and Poor: >5m.

Accuracy and precision performance

Algorithm	Small scenario	Large scenario
Iterative trilateration	Fair	Poor
Trilateration	Good	Poor
Particle filter	Very good	Poor
Fingerprinting	Good	Good

Table 6.7: Accuracy for different positioning approaches

6.4.2 Calibration complexity

Considering the calibration complexity criteria, a common calibration process among all of the tested approaches except fingerprinting is the fact that they require calculation of the propagation constant and the average RSSI in dBm at 1 meter before putting the system into mission. This is because all these approaches are dependent on converting the measured RSSI value into a distance. This calibration step can be considered very lightweight and could possibly be automated in production. Measuring the RSSI at one meter to determine A and later do a couple of more measurements at different distances to find an acceptable value for n. Both of these values can later be programmed into the advertisement message, putting minimal effort for central configuration of the system or the need for keeping a database to store these values. The only thing the positioning really has to know about the reference beacons is their position in the scenario. Since all beacons require manual configuration, the performance is not considered excellent. It would have been more advantageous if all beacons could be deployed with the same configuration. But nevertheless the conformance with the complexity characteristic must be considered very good for all the three approaches requiring the same configuration effort.

When it comes to the fingerprinting approach the picture is a bit different. This approach requires quite significant manual effort which not necessarily can be automated very easily. An entire map consisting of unique characteristics, which in this project is Average RSSI for different locations needs to be created. This configuration step is not considered complex or complicated but it is time consuming. The configuration can be simplified, collecting fingerprints directly in a smartphone and measuring coordinates with for example a laser range finder. As a result the calibration performance for fingerprinting can be considered adequate since even if it is demanding in comparison with the other approaches, it is not a factor that in itself would hinder the deployment of a fingerprinting based positioning system. The calibration performance for all approaches are listed in Table 6.8.

Calibration performance

Algorithm	Score
Iterative trilateration	Very good
Trilateration	Very good
Particle filter	Very good
Fingerprinting	Fair

Table 6.8: Score related to calibration for different positioning approaches

6.4.3 Scalability

The scalability characteristic can be divided into two separate parts. One that concerns how the system would be able to scale with regard to the number of users. E.g how complex would it be to scale from 5 to 50 to 500 simultaneous users? The other part is how well and easy will the system scale if the configured area is to be expanded into multiple rooms or a larger area. The resulting scalability performance for all the approaches and properties are listed in Table 6.9.

The first property regarding support for an increasing amount of users is the same for all approaches. All approaches relies on reading RSSI values from advertisements for position determination. This is done by passively scanning for advertising beacons as described in Paragraph 2.2.3. Since the scanning is passive, an increasing amount of users will not have any effect on the system or the RF-spectrum. Resulting in an excellent compliance with this property for all approaches.

The second property related to scalability does introduce some differences between approaches. Again the fingerprinting approach stands out compared to the others which have common performance also for this characteristic. In the case of fingerprinting, if the covered area should be expanded new beacons will be deployed and the database with fingerprints has to be expanded to also cover the new areas. The problem here comes in the case where beacon coverage areas overlap. This would render the old database entries a poor match, especially if the overlap is large. As a result, it might be the case that the entire configuration would have to be done from scratch. A fact which compensates for this disadvantage, is the fact that expanding the approach to cover several rooms or a larger area instead of only the one already configured will not result in any performance degradation for accuracy and precision. From the tests performed it can be concluded that lack of LOS will not affect the system negatively. These properties combined for the fingerprinting approach leads to the conclusion that the conformance to the scalability characteristic can be considered fair for fingerprinting.

When it comes to expanding the other approaches to cover a larger area than what is already configured, the amount of effort is at first sight minimal. The only operation required would be to update the application with the positions of the newly deployed beacons. There is however a pitfall for this property which is not directly connected to scalability although it has a major impact on this characteristic. The fact that when LOS is no longer available the accuracy of the system decreases significantly. This means that if beacons are deployed in new neighboring rooms, a device positioning in an existing room will acquire the RSSI through the wall resulting in significant performance degradation. Something which is exactly what was seen in the large tested scenario in the testbed. As a result, trilateration, iterative trilateration and particle filter can all be considered having poor performance in conforming to the scalability characteristic.

Scalability performance

Algorithm	Increase in number of users	Area expansion
Iterative trilateration	Excellent	Poor
Trilateration	Excellent	Poor
Particle filter	Excellent	Poor
Fingerprinting	Excellent	Fair

Table 6.9: Score related to scalability for different positioning approaches

6.4.4 Liveliness and response time

The response time of the system is defined as how fast new position estimations can be generated. Since all tested approaches rely on the same data for calculating a position, all tested approaches achieve the same conformance with respect to this characteristic. In Bluetooth smart, three dedicated advertisement channels are defined: 37,38, and 39 [8]. The time it takes to find all beacons in the vicinity is as a result of this dependent on with what time interval the beacons are programmed to perform advertisement. Since the beacons can advertise several times per second, a very good response time can be achieved. Collisions in the radio spectrum are handled automatically on a low level by the Bluetooth stack described in Paragraph 2.2.3. As a result, no issues related to collision was observable in the tests. It was possible to discover all testbed beacons and gather RSSI measurements as well as discover other beacons not belonging to the testbed in less than a second. Resulting in a very good conformance to the Liveliness characteristic. The results are outlined in Table 6.10.

Response time performance

Algorithm	Liveliness and response time
Iterative trilateration	Very good
Trilateration	Very good
Particle filter	Very good
Fingerprinting	Very good

Table 6.10: Score related to response time for different positioning approaches

6.4.5 Robustness and adaptability

When it comes to adaptability and robustness, all the approaches again share the same property of relying on RSSI. The evaluation of this characteristic is thus completely related to the robustness of RSSI. It is worth mentioning that fingerprinting does not rely on RSSI exactly in the same way as the other approaches which relies on converting the measured RSSI into a distance. But both approaches will be very sensible to eventual fluctuations in the RSSI parameter.To be able to draw conclusions for this characteristic it is thus required to further evaluate the RSSI properties. The result which is based on the analysis performed Chapter 7 is that all approaches has poor conformance with the robustness characteristic. The result is outlined in Table 6.11.

Robustness performance

Algorithm	Robustness and adaptability
Iterative trilateration	Poor
Trilateration	Poor
Particle filter	Poor
Fingerprinting	Poor

Table 6.11: Score related to robustness for different positioning approaches

7

RSSI analysis

This chapter presents the characteristics for measured RSSI values which is central when performing localization with Bluetooth smart technology. The section begins with a brief description of what characteristics are expected in relation to related work and literature on RF-based positioning. This is followed by measurements and results from several settings: investigating of RSSI behaviour in a static setting, RSSI in relation to distance, angle and variance over distance. To characterize the RSSI readings for Bluetooth smart a testbed is set up to measure values for different scenarios. Two Bluegiga BLE112[38] chips powered by coin cell batteries with full power(3.3V) is programmed to send an advertisement packet every 500ms. Two different units with MAC-addresses ”00:07:80:78:8C:EE” and ”00:07:80:78:8C:3E” are used to mitigate any temporal disturbances or chip deficiencies. The packets are received by the Sony Xperia ZR smartphone described in5.3.1.2. The RSSI value is sent from the smartphone over Wi-fi to a laptop running Matlab where data is aggregated and processed.

7.1 RSSI characteristics for Bluetooth smart

Based on conclusions from related work, it is expected that RSSI values are not necessarily a good indicator of distance between a positioning beacon and a ranging device. Some literature suggest that RSSI in traditional Bluetooth is in fact a very poor measure of distance[27], while other work concludes that it is in fact quite acceptable[13]. Even with the changes introduced in the Bluetooth smart stack compared to traditional Bluetooth, it is expected that the characteristics could be quite similar. Based on results from traditional Bluetooth it is expected that RSSI values for Bluetooth smart will have the following characteristics:

1. RSSI values for a device in a static setting (device is not moving), are not giving static readings, instead the values differ within a limited interval.

2. There exists a correlation between distance and the average RSSI value measured in a static setting with increasing distance.

3. The variation of measured RSSI-values increase with distance to the node aginst which measurement are performed.

4. A formula of the form:

$$RSSI = -(10n \log_{10} d \ + A) \tag{7.1}$$

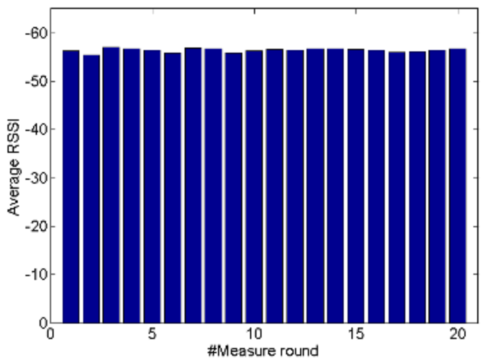
exists where constants A and n can be determined to give a reasonable relation between RSSI and distance.

7.2 Static RSSI measurement

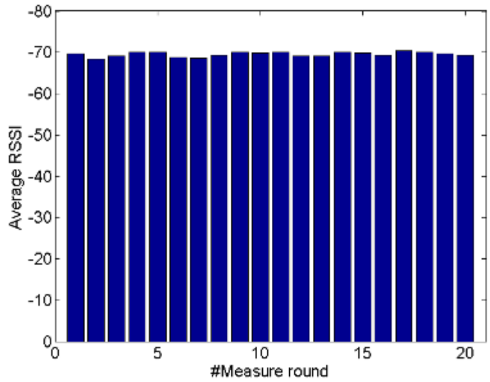
To be able to draw conclusions from measured values in different settings, a baseline needs to be established to determine how much values differ when measurements are performed in a static setting where no external factors are changed. This will give an approximation of how much multipath propagation, interference in the radio spectrum and similar disturbances affect the measured results. Related literature[14] suggests that individual RSSI readings tend to vary quite significantly. To counteract this effect, a number of RSSI-values are collected and then the average of these values are calculated and presented. Measurements are performed at a distance of k meters where *k=1,3,7*. At each distance 20 average values are calculated where each average value is composed of 30 measurements. The results are presented in Figure 7.1. From the results it is observable that average RSSI has small variations when no external factors are changed. To get a usable metric, the variance and standard deviation for the measured RSSI-values at each distance are calculated. The formula used to calculate the standard deviation is presented in Equation 7.2, where $\overline{x}$ is is obtained using Equation 7.3. The observant reader will recognise this as the definition for the *corrected sample standard deviation.* From the results, it can be observed that the variance and standard deviation are quite small and that the measured average RSSI are quite similar even though single measurements vary quite significantly.

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})^2} \tag{7.2}$$

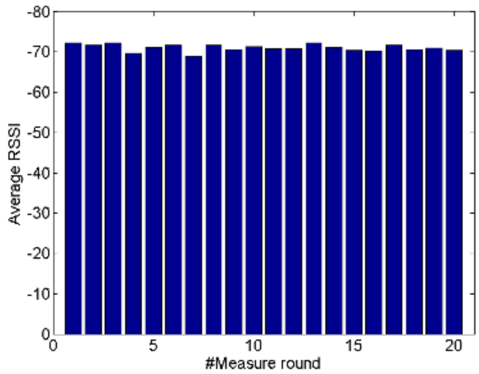
$$\overline{x} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i)} \tag{7.3}$$



(a) Variance of measured RSSI at 1m



(b) Variance of measured RSSI at 3m



(c) Variance of measured RSSI at 7m

Figure 7.1: RSSI variance in static settings

Distance	Variance	Standard deviation(σ)
1m	0.1541	0.3925
3m	0.2950	0.5431
7m	0.7847	0.8859

Table 7.1: Variance and standard deviation for static measurements

7.3 RSSI vs Distance in Bluetooth smart

To investigate the relation between average RSSI and distance, measurements are performed at k meters where *k=(0, 1, 2, 3...19, 20)*. At each distance 30 samples are collected for each node. The orientation of the device is kept static during the entire experiment and thus only distance is changed. The measured values are presented in

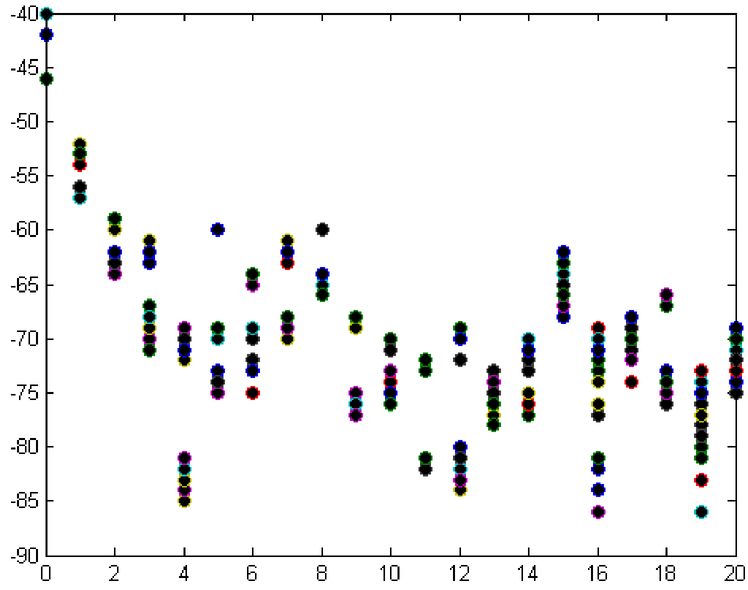
Figure 7.2. Here it is observable that 30 unique sample values are not obtained at each distance, instead the same RSSI is measured several times at each distance, represented by different edge colors. The collected average for each position k is calculated with Equation 7.4

$$\frac{1}{\mathrm{m}}\sum_{i=1}^{m} x_i \tag{7.4}$$

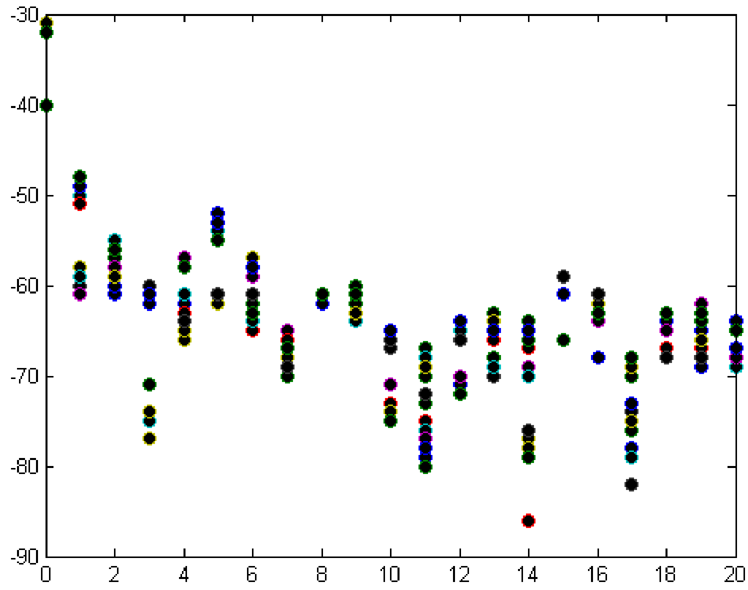
Where m is the number of collected values and x_i is the measured RSSI value. The result is presented in Figure 7.3. It can be observed that as predicted, each location shows a great variance in measured RSSI values. When looking at the calculated average for the different distances, a quite unfavorable result is found. Between 1 and 3 respective 4 meters, the curve follows the predicted behaviour where the signal strength is decreasing almost linearly with distance. However after 3 respective 4 meters, the curve makes a sudden veer and the measurements are suddenly increasing and starts flipping up and down.

To rule out any chip related problem such as antenna placement, antenna design and similar hardware specific factors, the same measurement are also performed with another chip model, Bluegiga BLE113[40] which is based on a different core system(Texas instrument 2541, compared to BLE112s: Texas Instrument 2540). The measurements of average RSSI in relation to distance are presented in Figure 7.4. A similar behaviour is observed with different peaks and dips when the distance increases. It is however necessary to emphasize that the characteristics have a slightly better, more positioning friendly slope than what was observed for the TI 2540-chip. It is not necessarily well suitable for accurate positioning resulting in coordinates. But from the graph it is possible to estimate the distance between the beacon and the measuring device at least with coarse precision which can be seen in Figure 7.6. Similar to the distance classification used by the the Estimote system[32].

This of course presents a great challenge and means that two of the expected characteristics does not hold. Characteristic 2 and 4 does not hold since a nice correlation between distance and RSSI will not be possible to find. The measured results allow a RSSI value to potentially correspond to two or more locations. For example, an RSSI measure of -65dBm could with the BLE112 chip correspond to 6.5, 7.5, 9.3, 13.0, 14.5, 16.1, 17.9, and 18.2 meters as shown in Figure 7.5. It is easy to conclude that between 5-20 meters there exists no clear correlation between distance and RSSI. The RSSI reading oscillates between -60 and -75 during the entire distance. This means that in the end, it would be impossible to find constants for A and n in characteristic 4 such that the formula can fit the measured results.



(a) Variance of measured RSSI of node 00:07:80:78:8C:EE



(b) Variance of measured RSSI of node 00:07:80:78:8C:3E

Figure 7.2: RSSI measurements for two Bluegiga Bluetooth smart nodes

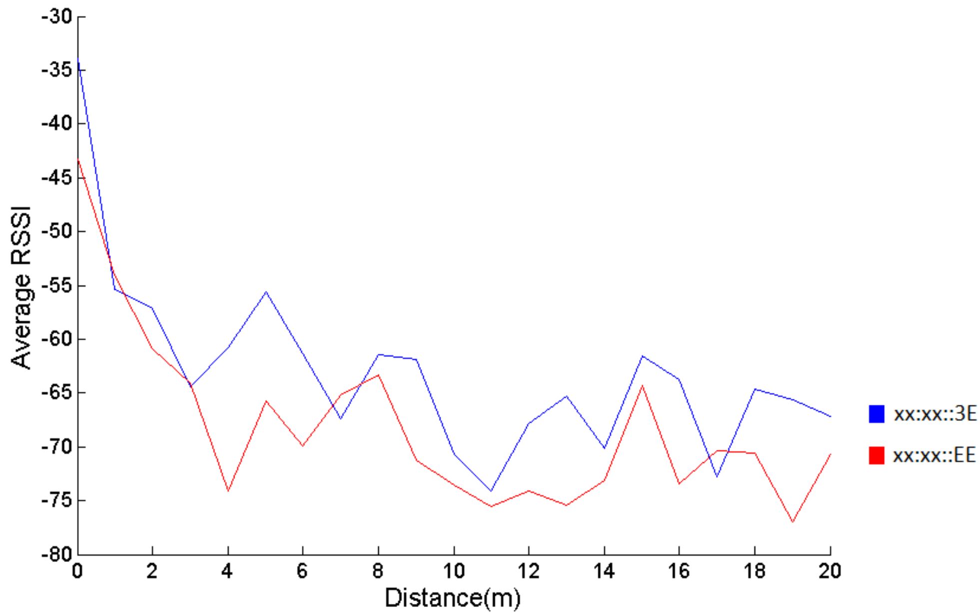


Figure 7.3: Average RSSI versus distance

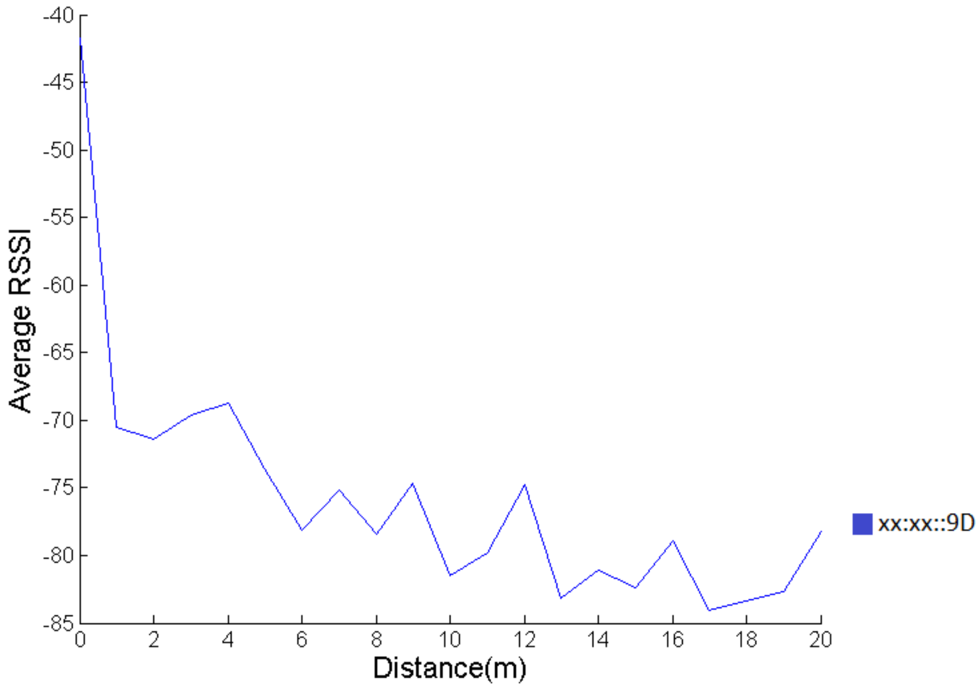


Figure 7.4: Average RSSI for TI2541 Bluetooth smart-chip

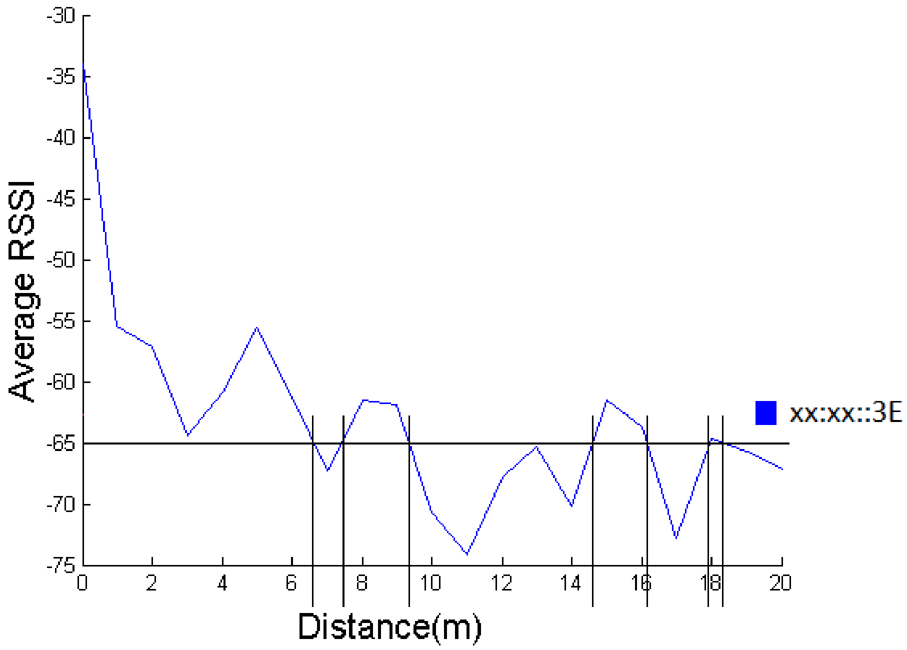


Figure 7.5: Diagram showing RSSI of -65dBm corresponding to several distances

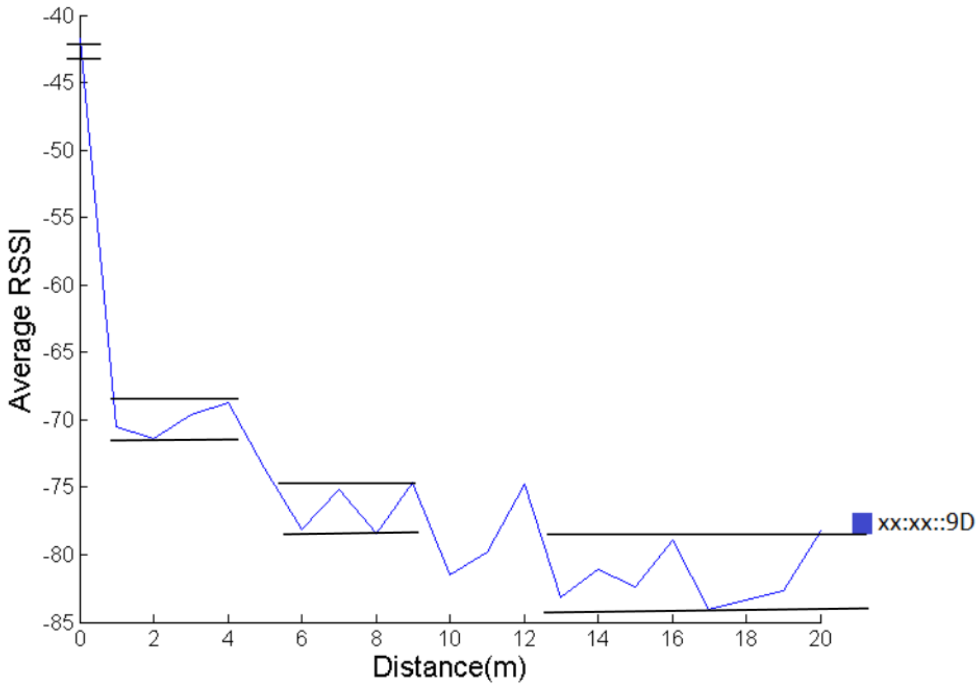


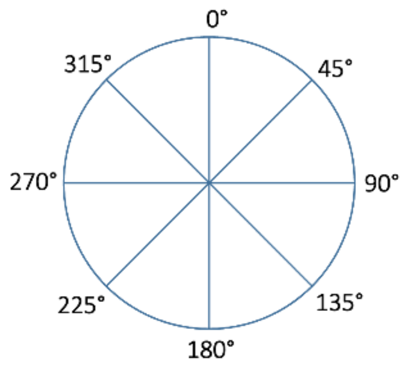
Figure 7.6: Distinguishably different distance zones can be defined for the BLE113 chip

7.4 RSSI vs angle

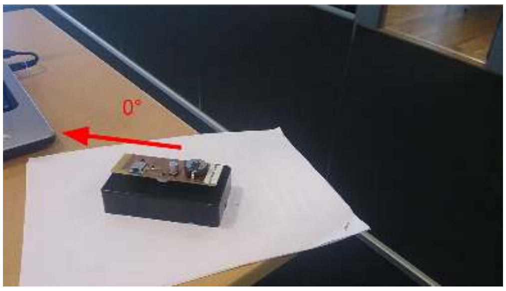
In the previous section the relation between RSSI and distance was explored. During all the measurements, the angle between the beacon and the smartphone was constant at 0°. For a positioning system, it is also important to know how much the angle between devices could affect the RSSI readings. The beacons are expected to be deployed on walls or in the ceiling inside a building and positioning against them will be performed with 360° of freedom. A report related to this project[41] expresses that the angle does have a non-negligible effect on RSSI measurements. To investigate how large variance the angle introduces we use a test area shown in Figure 7.7. The BLE112 Beacon is used with two different orientations: Standing up (SU) and Laying down (LD) as displayed in Figures 7.8(b) and 7.8(c). The Beacon is placed statically in the test area and the smartphone is moved around the beacon in 360° as shown in Figure 7.8(a). The smartphone is always kept at a fixed distance of k meters from the Beacon. Measurements are performed for *k=1,3,7* meters. This results in 8 measurements with different angles for each orientation(SU,LD) with a difference in angle of 45° between each position. As the test-setup in previous section, an average of 30 values in each position is calculated. To mitigate any temporal environmental effects, each measurement is performed 3 times. In the results only one of the measurements rounds are presented to save space, but the measurements can easily be repeated with similar results. The measurements are presented in 3 figures, one for each distance in Figures 7.9(1m),7.10(3m) and 7.11(7m).

Figure 7.7: Test area for orientation measurement's

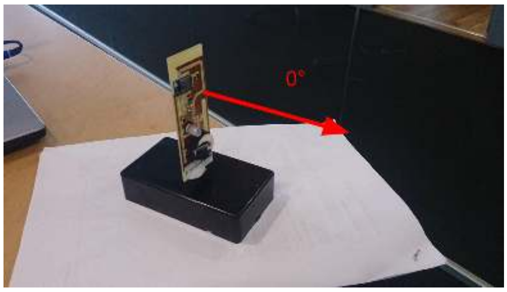
Looking at Figure 7.9 reveals great differences in RSSI related to different angles. For SU orientation, 90° and 270° stand out with much weaker signal than the other angles



(a) Angle orientation



(b) LD position



(c) SU position

Figure 7.8: Chip orientation for angle vs RSSI measurement

for the same orientation. In LD orientation, 0°, 180° and 135° stand out with much weaker signal strength than other measured angles. Comparing the two orientations at the distance of 1m reveals significant differences when the orientation changes. The differences are well above the amplitude of any coincidental variations. The variance and deviation for measured averages have been calculated in Table 7.2.

The results at a distance of 3 meters are presented in Figure 7.10 and show distinctly different values. Here the variance and deviation between both angle and orientation are much smaller. No angles significantly stand out for any of the orientations and also the differences between orientations are quite limited. But looking at the calculated variance and deviation in Table7.2 still reveals that they are well above the corresponding values for background noise/interference/multihop influences measured in the static setting. It appears that the angle has a considerable impact also at a distance of 3 meter, although it is significantly smaller than what was observed for 1 meter.

The results from measurements at a distance of 7 meters confirm the findings from the two previous tests at 1 respective 3 meters. The difference between angle and orientation does have an impact on the RSSI reading, The result is presented in Figure 7.11. It is necessary to emphasize that the variance between RSSI in LD-orientation at 3 meters is

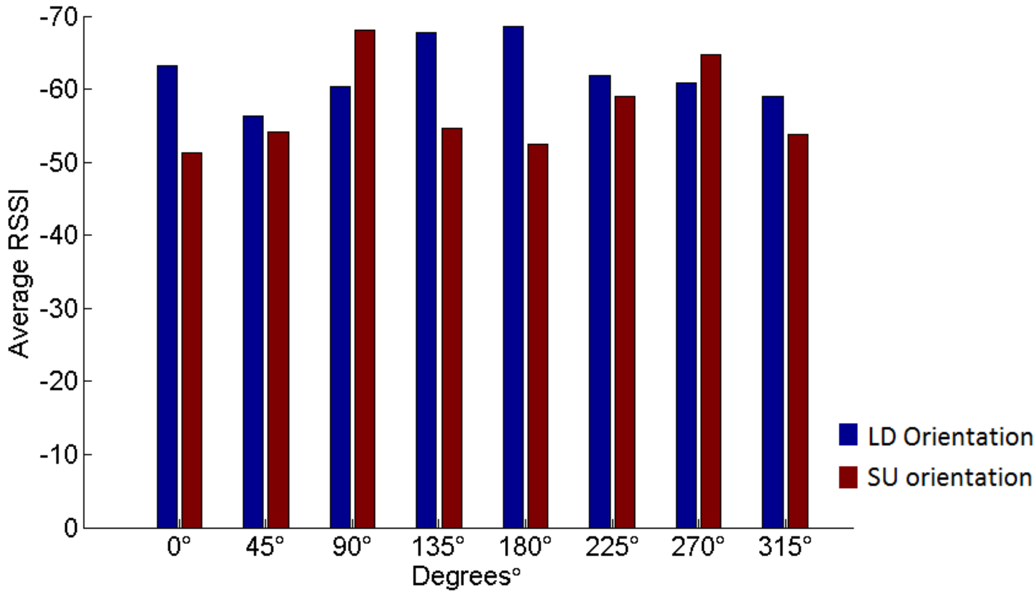


Figure 7.9: RSSI results for different orientation and angle at 1m distance

significantly smaller than any of the other obtained results and does not position itself far away from background interference measured in the static measurements setup in Paragraph 7.2. The difference for SU-orientation is in line with the results of the 3 meter measurements. The conclusion that can be drawn from the angle measurement evaluation is that the angle does impact the average RSSI measurement, especially for a close distance where the difference in values are large. When the distance increases the difference between values decreases, both between angles and between orientations. They still however make a non-negligible impact on the readings which is in line with expected results based on findings in related literature.

Distance and orientation	Variance	Standard deviation(σ)
1m LD	17.3543	4.1658
1m SU	37.5078	6.1244
3m LD	5.3501	2.3130
3m SU	5.9025	2.4295
7m LD	1.6180	1.2720
7m SU	5.4198	2.3281

Table 7.2: Variance and standard deviation for different angle measurements

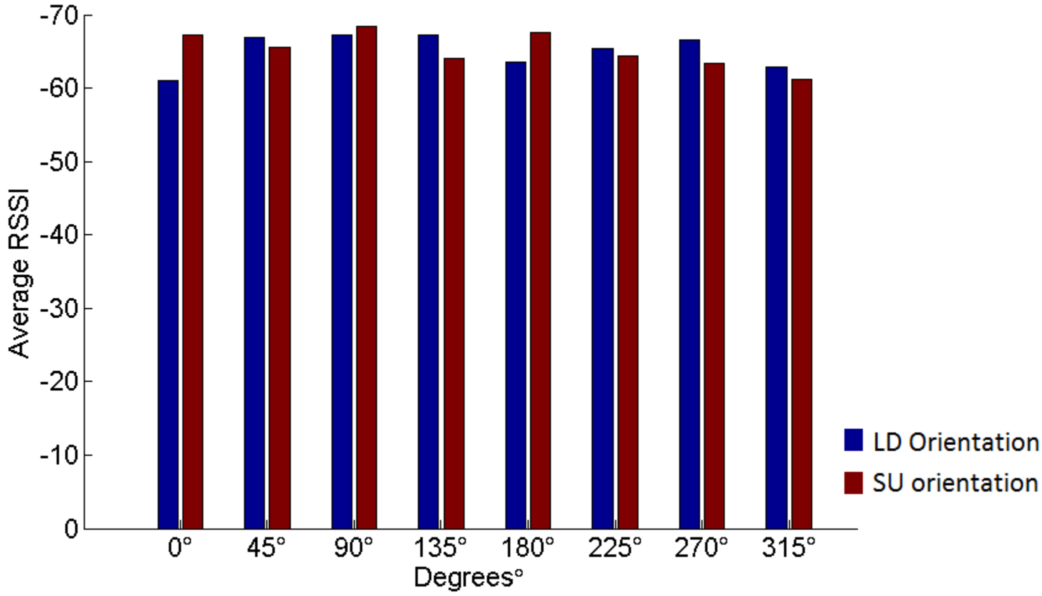


Figure 7.10: RSSI results for different orientation and angle at 3m distance

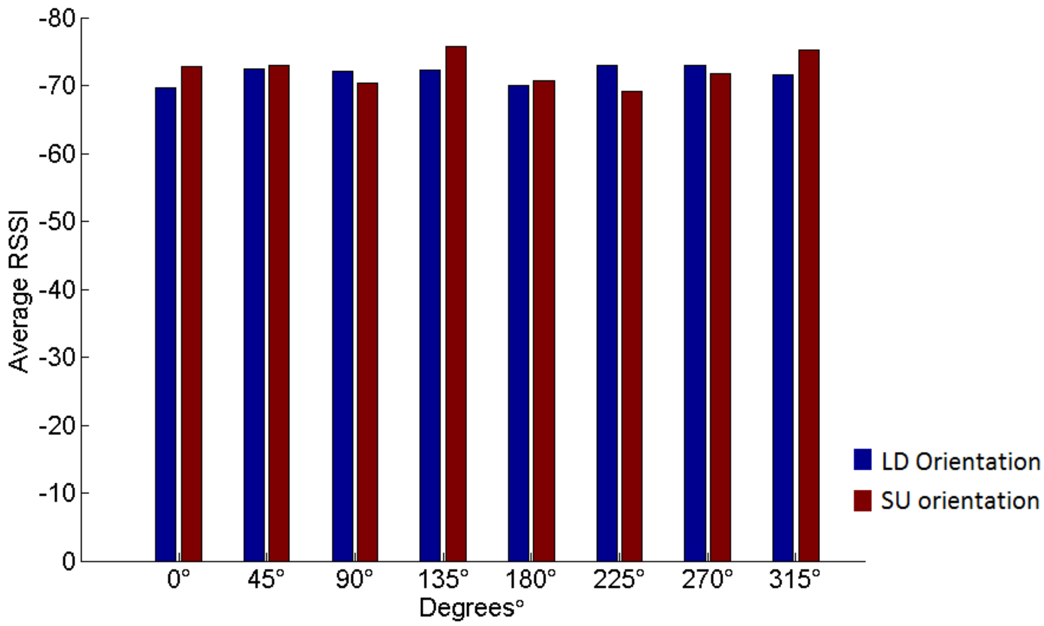


Figure 7.11: RSSI results for different orientation and angle at 7m distance

7.5 RSSI variance over distance

One of the predicted characteristics for RSSI was the variance in measured values in static settings increases with distance. To validate whether this is the case we use data collected in Paragraph 7.3 and calculate the deviation and variance for each distance. The calculated Variance and deviation is presented in Table 7.3. A visual representation of the measured values was presented in Figure 7.2. From the results it can immediately be established that variance of values does not increase with distance. Instead the variance similar to the average RSSI oscillates up and down when the distance increases.

Distance	Variance	Standard dev(σ)	Distance	Variance	Standard dev(σ)
1m	2.8517	1.6887	11m	19.7023	4.4387
2m	3.4299	1.8520	12m	30.0517	5.4819
3m	11.9644	3.4590	13m	2.3920	1.5466
4m	28.8374	5.3701	14m	6.1946	2.4889
5m	40.5621	6.3688	15m	3.8724	1.9678
6m	9.2057	3.0341	16m	23.3575	4.8330
7m	11.1540	3.3398	17m	2.1609	1.4700
8m	5.4713	2.3391	18m	14.8057	3.8478
9m	14.9437	3.8657	19m	9.9644	3.1566
10m	5.1506	2.2695	20m	2.2862	1.5120

Table 7.3: Variance and standard deviation for different distances

7.6 RSSI conclusions

The results from the RSSI measurement experiments in this chapter reveal several challenging and unfavorable characteristics for RSSI as parameter to perform positioning. A relation between distance and RSSI is only observable when a beacon and the positioning device are very close to each other. After the first meters, the values oscillate up and down for quite a long distance. The same behaviour is observed when Tx power is decreased in the beacons, the same pattern is observable, although the duration is decreased. Furthermore properties such as angle and obstacles have major impact on measured values. Combining these characteristics means that RSSI for positioning is not a very robust parameter. Comparing measurements in different scenarios such as Paragraph 7.2 and Paragraph 7.3 also reveals that even for the same distance, the measured RSSI can vary significantly when the environment is changed. Meaning that not only will the RSSI depend on factors within the positioning system such as angle and distance to beacons, but also if the environment such as walls, furniture and ceiling are changed (e.g one room has walls out of plaster, another room has lots of windows). The Measured values will vary greatly.

There is also an observable difference in measurement from different devices even if they have exactly the same design. in Paragraph 7.3 two different devices show similar trends, but the measurements against the different devices at exactly the same distance vary significantly in amplitude. It is easily observable that different chips with the same design will have difference in measured RSSI between them, since RF-devices are highly sensitive to even minimal irregularities in chip construction[42]. This means that if two chips of the same type is used, they will likely not give exactly the same results even if all external conditions are the same.

The results from the RSSI investigation disclose that trilateration based positioning, where a distance is needed to calculate a position in a Bluetooth smart system seems to be a poor approach unless the area is very small and the distances fall within the linear distance/relation part of the curve. This explains the results from Chapter 5 well. Algorithms and approaches which rely on a correlation between RSSI and distance are likely to achieve poor results simply because no such correlation when the distance increases exists. Coupled with, sensitivity for changes in environment, orientation, and obstacles renders such approaches less favourable.

The characteristics, although at a first glance appearing discouraging do however seem to enable fingerprinting based approaches to positioning quite well. It is observable that within an environment where calibration is made, measurements will not vary greatly. This is observed in Paragraph 7.2 where measurements could be repeatably performed with similar results. This means, a database of fingerprints could be saved and used for positioning since values at a certain position do not change significantly over time. The approach would still be vulnerable to changes in environment, node failures and broken LOS. But since positioning is based on a radio map and not conversion of RSSI to distance it can be explained why this approach achieves much better and consistent results than trilateration and distance based algorithms.

8

Discussion

This chapter provides a discussion of questions related to indoor positioning based on Bluetooth smart technology, its pros and cons, its applicable use cases as well as limitations and possible improvements.

8.1 Advantages and disadvantages

8.1.1 Advantages

From the evaluation it is clear that the use of Bluetooth smart technology in the context of indoor positioning brings several advantages compared to previous attempts made with traditional Bluetooth. One of the major improvements is the introduction of the new Bluetooth smart mode ”Broadcasting” or advertisement which was described in Chapter 2.2.2. The new feature makes it easy to implement a system which would scale in satisfying manner when the number of clients increases. If the system is supposed to work with a mobile centric architecture, the deployed beacons within the building would simply need to broadcast their messages within a defined interval. All clients in the vicinity can then intercept these messages and base their positioning either directly on the received RSSI which is available when the message is received, or combine the RSSI with extra data which can be sent in the payload of the message. The mobile nodes perform passive scanning, meaning that the radio spectrum will only contain the advertisement messages from beacons. Comparing this with the traditional Bluetooth technology that requires all mobile nodes to perform active scanning, and all beacons to explicitly respond to each inquiry trivially, leads to the conclusion that the Bluetooth smart technology is a much better suited candidate technology than traditional Bluetooth. This development is very convenient in the context of indoor positioning. Different approaches and technologies developed with traditional Bluetooth started with different connection based solutions where the mobile node had to connect to beacons to get access to parameters for performing positioning. When inquiry based RSSI was available, this presented another improvement since scalability would be better when no connections needed to be set up, also the accuracy was significantly improved since the GRPR could be avoided. The new modes and radio definition of Bluetooth smart further improve the suitability for a positioning application.

Another Bluetooth smart characteristic which is related to the effect on the radio spectrum is the defined advertisement channels, which are specified to 37, 38, 39 in the Bluetooth smart tecnology. From the experiments conducted in this project it can be concluded that the discovery time for finding reference beacons can be considerably shortened compared to Traditional Bluetooth. With traditional Bluetooth requiring 10.25 seconds for a complete scan and 4-6 seconds in practice for finding most nodes. Bluetooth smart can easily be configured allowing mobile nodes to find beacons in less than a second. This is a major advantage if responsiveness and real-time tracking capabilities are desirable within a system. It is also a characteristic which can be used to improve precision of a Bluetooth smart positioning system. Since the quick update rate allows for a system to collect an average of several individual values and perform positioning on the average value. Instead of performing it on single values individually which for Bluetooth and other RF technologies has the property of oscillating considerably.

Another factor speaking for Bluetooth smart within an indoor positioning setting is its widespread global penetration in devices and in society. This is not an improvement from traditional Bluetooth which has an even deeper penetration in society and devices. Bluetooth smart is however a technology which is being rapidly integrated in different areas of society as well as in different devices. A clear example of this is the fact that almost all high and middle end smartphones today, independent of manufacturer or operating system comes equipped with built in Bluetooth smart module. This is a major advantage in several ways. First, the fact that the technology is widespread and mass-produced means that unit costs are very low(1-5$/unit). Even if hundreds or thousands of units are necessary to complete a big indoor positioning installation, the hardware costs could be considered very reasonable or even inexpensive. In addition to the fact that hardware is inexpensive, the fact that the small amount of power required to power the beacon can be provided for years by a coin cell battery. Means that, a system could easily be deployed even in areas where supporting infrastructure is missing, such as, power outlets, network equipment, etc. The widespread penetration also imply that deploying a system based on any smartphone platform means that the solution can be quickly deployed and available to almost all users today.

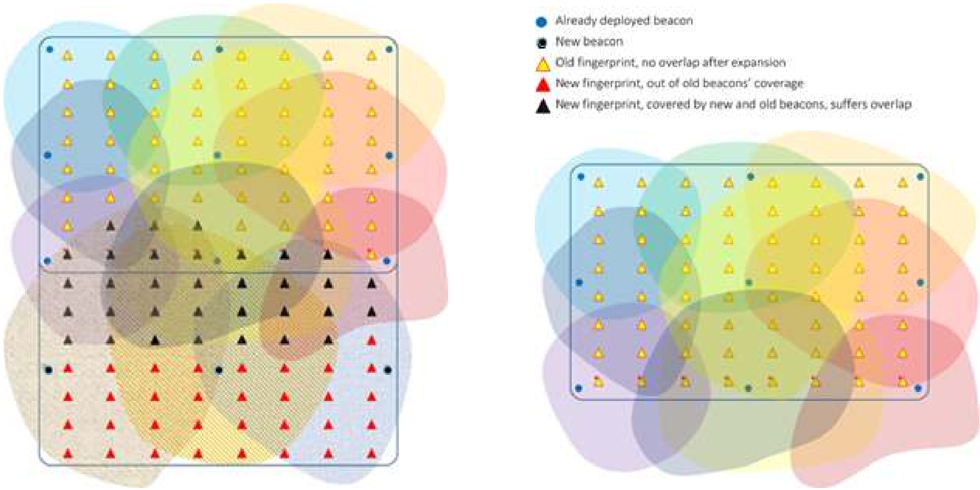
Furthermore the smartphone approach also means that a number of other sensors will be available to improve the positioning systems performance. Smartphones normally come equipped with sensors such as gyroscope, accelerometer and compass which provide data that is very useful in a positioning context. This is in fact something that is widely used in leading commercial systems in the market today, which was previously described in section 4.7.

8.1.2 Disadvantages

Based on the findings in this project, it can be established that Bluetooth smart does not add any new disadvantages for usage in a localization context. Compared to traditional Bluetooth, it seems that only advantages and improvements are added. This does however not mean that there are only advantages of using Bluetooth smart as technology for developing indoor positioning solutions. This project does reveal a number of undesirable properties with the technology, which need to be carefully considered if anyone wishes to use it in a positioning context.

The two most apparent problems are the lack of relation between RSSI and distance and the problems related to robustness. Both these properties have a major impact on both accuracy and precision. This implicates, careful consideration is needed when planning to use a system based on Bluetooth smart technology. This project has established that an accuracy of a few meters is possible to achieve using only Bluetooth smart RSSI. Meaning that usage in applications requiring very high accuracy, such as robotics, may be unfitting. This is further motivated by the fact that robustness to interference or changes in the surrounding environment are very low. Both conducted experiments in this work as well as related work suggests that signal strength parameters in RF-based solutions are very sensitive to obstacles and/or changes in the environment.

Another problematic factor depending on what technology and algorithms are used to implement a Bluetooth smart positioning system is scalability. If a trilateration or distance based approach is used which relies on only knowing positions of reference nodes and presence of LOS, scalability is after careful consideration not very good as described in Paragraph 6.4.3. The fingerprinting/radiomap approach does also suffer from quite serious scalability problems although it was deemed a bit better than the distance based approaches. The problems with the approach are several. The first is how to handle an expansion of a system after initial configuration have been performed. Problems are very likely appear in areas where beacons overlap each others coverage areas. An example of this has been constructed in Figure 8.1. in 8.1(b), a fingerprinting system has been deployed and reference data has been collected in areas marked with yellow triangles. Now looking at 8.1(a), where the plan is to extend the reach of the positioning system. It is notable that several of the newly deployed beacons overlap in their coverage with the old beacons. This means that several of the old fingerprints in the twofold covered area will be quite wasted. The fingerprints in this area is represented in Figure 8.1(a) by black triangles. A fingerprint collected at any location in the twofold covered area will now has major differences to any fingerprint in the database. A possible solution could be engineered in two ways, either perform recalibration of most or all of the system, which is resource consuming especially for large systems, or deploy the new beacons in such a way that overlap between old and new beacons are minimized, which is difficult to do in practice. Neither of theses approaches are optimal since both imply either significant



(a) After expanding the calibrated area by adding new beacons and deciding new fingerprinting positions

(b) The already calibrated area where the training phase is already finished

Figure 8.1: An illustration of fingerprinting based positioning system before and after expantion where the covered areas by the beacons overlap each others.

amounts of manual work or the introduction of significant error vectors. As an example, selecting the second approach of minimizing radio overlap means that an area is introduced between the old and the new area where system performance can be expected to be significantly degraded, see Figure 8.1(a). The radiation pattern for an antenna is rarely symmetric, which combined with effects of multihop and reflection, means that it is very difficult to draw a line where a beacon coverage area ends. This means that both uncovered areas as well as twofold covered areas are likely to exist between a new and an old fingerprinting database, resulting in degraded performance in terms of accuracy and precision. The same problem is present also in the case when a reference node fails. This project has demonstrated that different chips with exactly the same design and implementation have small but not insignificant differences. For a system which relies on radiomap/fingerprinting technology, this could result in performance degradation.

8.2 Suggested improvements

In the section above, advantages and disadvantages of a Bluetooth smart based positioning system was listed and discussed. In this section some possible improvements and solutions for listed problems are presented. The focus of this project has been entirely on the evaluation of a system based solely on Bluetooth smart without any other technologies, furthermore not all possible algorithms and techniques to mitigate potential problems have been discussed in detail since the number of such solutions are immense. In this section, a number of such techniques and suggestions are briefly described to allow the reader to get an understanding of the available options and opportunities.

8.2.1 Machine learning/self adjustment

One of the major disadvantages of fingerprinting based positioning approaches is the poor scalability, how to handle failed nodes and how to handle changes in the environment. The problem has its root in the fact that the database or map that is the core of the solution is static, it is thus only valid at configuration time and for as long as no changes or failures occur. To mitigate this problem, the suggestion is to make use of machine learning approaches and neural networks. An example of system with redundancy is presented in [43]. The system does not really manage all of the mentioned problems but it clearly demonstrates a usable principle for dealing with them. By adding redundant nodes the ability to mitigate node failures naturally improved. A possible extension to this described in several related papers suggests to make a positioning systems self-calibrated or self-adjusting. By adding a new calibration mode to beacons in addition to the positioning/broadcasting mode used for localization the system can be designed to continuously recalibrate itself. This is not a small technical challenge and will likely require a fully connected infrastructure for all nodes in the system as well as a connection to the database containing all calibration data. The idea is that the system recalibrate itself all the time and updates the database with reference data. The solution could be implemented either by deploying dedicated calibration nodes in the system which will require more nodes. It could also be provided if nodes support the ability to change between modes. Which makes it possible for a positioning node to switch into a calibration node temporarily to update the system's database. The idea for a system with these mentioned properties has been suggested in several papers although to the best of our knowledge, no system exists today which satisfies the requirements well.

8.2.2 Additional data sources

A popular approach already extensively used to improve performance of indoor positioning systems is to fuse data from several sources and sensors into the positioning determination. This approach is commonly used by the state of the art commercial systems today and is also a principle widely used in academic projects on indoor positioning. The idea is a viable option for improving the performance of several key characteristics for positioning applications such as accuracy, precision and responsiveness. The topic of sensor fusion and related mathematical foundation and models such as Bayesian theory[44], Kalman[16] and Monte-Carlo[17] -filters are already well established and large amount of literature and material is available on the topic. The concept is to use several different data sources to calculate the actual position. Even though some of the sources temporarily deliver bad data, an example in the Bluetoth smart case could be an obstacle preventing LOS measurement, the system will still be able to estimate a fairly accurate and precise location since Bluetooth smart is only one of several inputs to the system.

Another advantage of this approach besides increased performance, is the fact that the potential additional data sources are widely available today. Wi-Fi, which is a commonly used secondary radio parameter or primary when using Bluetooth smart as secondary, is widely deployed in today's society. This makes it easy to incorporate it in a positioning system, since the infrastructure is most likely already deployed. Other potential and highly available data sources are different kinds of sensor data such as compass, gyroscope and accelerometer. These sensors are available both individually if the plan is to create the positioning system entirely from scratch with construction of both hardware and software. They are also commonly available and already integrated in most modern smartphones today making it easy to access them and obtain the relevant data. The data delivered by the sensors can be used to get information about heading, acceleration and movement which can be useful for calculating and estimating the position.

8.2.3 Hybrid solution

A quite interesting approach which could be worth investigating would be to create a hybrid system of the fingerprinting approach and the particle filter. But instead of using the full fingerprint approach, use a cell based approach. The result would be a system which would use a database and a single beacon with quite low Tx power in the middle of each room that should support positioning. The positioning process would work in two phases, first determining a room level position based on the database and weak cell beacons. Followed by a more high accuracy position determination by running the particle filter against several powerful deployed beacons in the specific room. This would solve complexity problems for both the fingerprinting approach and the distance based approaches. Since no real fingerprints would have to be configured. Instead the database would consist of information mapping a specific room to a specific cell beacon, combined with information about which powerful beacons have LOS for the room in question and should thus be used for position estimation by the particle filter. The complexity for the distance based approaches is solved since the system will now only perform measurements against nodes with LOS, and not take nearby nodes which transmits through walls or obstacles into account.

Although the solution might provide a significant performance increase related to both accuracy, precision, complexity and scalability. It is not a quick fix suitable in all applications. There are still some problems since the approach will not work if rooms are very large. The evaluation performed in this report showed that for a 8x11 meter room with LOS, a particle filter based approach was superior to the fingerprinting approach. However, if the room gets bigger and distances end up beyond the linear relationship found for the first meters when the distance between nodes increases. It would no longer achieve better results since there is a lack of relation between distance and RSSI at larger distances. Looking at the RSSI evaluation in Chapter 7, it is possible to at least expect a nice property when Tx power is increased. For the BLE112 chip with transmit power of 3dBm, a linear relationship existed between 0 to 4 meters. The same relationship was true for the BLE113 chip which has a lower Tx power of 0dBm, with the difference that the linear relationship existed only between 0 to 1.5 meters. The Bluetooth smart specification allows for Tx power up to 10dBm and if the same pattern can be observed, it is possible that the distance with linear or almost linear relationship can be extended several meters. Allowing deployment in larger rooms.

It is necessary to emphasize that this is a theoretical hypothesis, but it could be an interesting topic to investigate for increasing Bluetooth smart positioning performance.

8.2.4 Hardware considerations

A very interesting approach that has been found during this project but not practically evaluated is the possibility to design hardware which would improve Bluetooth smart for use in a positioning context. Most commercial systems as well as academic research have put a lot of effort on software and algorithm development. During the project two important factors related to hardware was found, at first it was concluded that RSSI measurement which is the parameter used in the evaluation varies greatly between different hardware and chips. The difference is not only observable between hardware with different design and configuration, it is also indeed observable between hardware with the same manufacturer and exactly the same design and configuration. This needs to be carefully considered while designing a localization system based on Bluetoth smart technology. This is also a characteristic that is actually considered in the iBeacon technology covered in Paragraph 4.7.1. The trademarked technology which actually describes a GATT-service, contains the parameter A, which is the measured RSSI at 1 meter as described in Paragraph 4.1.1 in the payload, which the iBeacon nodes broadcast.

The second important factor related to hardware was the fact that a specialized hardware solution seem to outperform all "software-heavy" solutions which relies on sensor fusion and RSSI values. In Paragraph 4.7.5 a system able to determine AOA is described which provides performance that exceeds both commercial Bluetooth smart solutions as well as academic research based on Bluetooth and/or Wi-Fi. This implicates that a more hardware based solution could be a viable alternative. The knowledge about antenna arrays and the principle of determining AOA has made good progress in the last couple of years[45] and may be an interesting possibility.

Another more theoretical idea which surfaced during the project is to perform localization based on TOF or TDOA. It is important to emphasize that this is only in the idea stage and no practical evaluation of the possibilities with relation to Bluetooth smart exists. Although other systems exists which successfully relies on TOF/TDOA such as GPS. The reason why it might be a plausible idea is the fact that high precision embedded atomic clocks are being introduced on the market[46]. If the clocks in systems allow for synchronization with precision of a few nanoseconds, TOF could, at least in theory be a possible alternative for a high accuracy Bluetooth smart indoor positioning system.

8.3 Proximity applications

An application that is related to localization and positioning is the concept of proximity detection and location awareness. It is not really positioning in the sense of providing exact coordinates or an exact position in a reference geographical coordinate system. But it is highly current in the context of the Bluetooth smart technology and also rather simple to implement. The application is interesting because in many cases it is not necessary to know an exact location, instead it is fully sufficient to know roughly in which area something is located. This thesis concludes that Bluetooth smart is highly suitable for such applications. While using Bluetooth smart-RSSI for high accuracy positioning has several challenges, using it for coarse distance estimation is simple. In chapter 7, the properties of RSSI in relation to distance was thoroughly explored. The result confirms the properties that for example the popular iBeacon technology promises. Separation of distances in three zones: immediate, near and far can be easily made no matter which hardware is used. It is also a very popular approach to combine location awareness/positioning with different kinds of information services. This is of course something for which Bluetooth smart also is a very suitable technology. With the changes in the stack and the introduction of, for instance, the broadcast mode with voluntary data payload, it becomes easy to think of a location aware application running on a smartphone. Depending on distances to beacons and some unique IDs embedded in the advertisement messages, the system will present the user with different information or data, which it can fetch online or from a database in the application itself.

8.4 Privacy aspects of positioning

An important topic related to positioning and location awareness is the matter of privacy. With the prospect of including indoor positioning functionality in smartphones and gadgets to enhance and provide services for users in retail, museums, hospitals, industry and airports to name a few. It is important to clearly elaborate on how this data is and can be used or shared. Positioning systems can potentially provide users with improved service and experience, but the same data can also be used by others to perform live tracking and monitoring of the users.

A distinct example of such a use case is when deploying an indoor positioning system in a shopping mall. The system will help a user navigate within the premises and might also offer advantageous discounts and offers. But the entity controlling the application can potentially also perform real-time tracking of the user and in detail map the users movements and behaviour. The privacy topic is not new and positioning services such as GPS and GLONASS are already able to track users and devices outdoors with high accuracy and precision. A key aspect is thus to make users aware about how positioning data is used.

Returning to the smartphone scenario, if an application demands access to high precision positioning data from GPS or coarse position data based on cell tower information. A user can clearly understand that the location will in some way be shared with the entity behind the application. If an application instead just demands access to use the smartphones built-in Bluetooth chip, it might not be as clear to understand that this could allow high/coarse precision tracking and monitoring capabilities. The same reasoning can also be further extended, just because the application provides positioning abilities locally for the user, it will not automatically make the user aware that the application at the same time provides both the entity behind the application and potentially third parties with information about movement and behavior.

9

Conclusion and future work

This chapter presents the conclusions reached by the evaluation and does also provide some advice for future work that would be of interest in the area.

9.1 Conclusion

Indoor positioning based on Bluetooth smart technology has been tested and evaluated based on several known algorithms in the area of positioning. The goal was to evaluate the suitability and the applicability of using Bluetooth smart technology in the context of indoor positioning. Furthermore tests where performed to analyze RSSI behaviour in indoor environments. The practical experiments were preceded by a comprehensive study of earlier research in RF based indoor positioning. The conclusion of the evaluation is that Bluetooth smart can be considered a viable candidate solution depending on the requirements. The approach can deliver accuracy of a few meters with relatively high precision which is enough to facilitate navigation and tracking of humans and goods. The response time is good or even excellent with the changes done to the RF properties. The deployment is simplified by low cost of beacons combined with the fact that no extra stationary infrastructure needs to be deployed, since beacons run for years on batteries. A couple of pitfalls was also discovered during the evaluation which will be important to consider before deploying a system. In particular, the utilized RSSI parameter has poor correlation with distance, making distance dependent approaches unsuitable. This can be surmounted by relying on characteristic based approaches at the cost of deployment complexity. The exhibited sensitivity of RSSI also results in low robustness to environmental changes regardless of positioning algorithm. In the end, it can be concluded that Bluetooth smart introduces several improvements to inexpensive indoor positioning. Faster response time, independence from fixed infrastructure, advertisement support and power efficiency are important and worthy to mention improvements. Particularly in static scenarios where the environment does not change and an expansion of the system is not forthcoming.

9.2 Future work

Even though the evaluation was done according to plan, several improvements could be added if the time and the budget would have permitted. Some limitations in Bluetooth low energy and Bluetooth in general are caused by implementations done by vendors. An example of this is the filtering behaviour of discovered nodes by the Bluetooth smart module in the Android smartphone. In the phone, the *onLeScan* method does not report the same device multiple times in the same scan even if the advertisement interval is really small. A potential improvement in the future is to have a mobile node as an independent module or a customized system rather than a mobile phone which does impose limitations in the lower layers.

Another potential improvement that can provide significant improvements could be to evaluate a Bluetooth smart based positioning system using AOA. This can be achieved by customizing hardware such as using directional antennas or an antenna grid. The performed literature study seems to support such an approach

Another related topic of great interest would be to evaluate strategies for beacon positioning. We have seen that both the amount of beacons used as references as well as their position affect primarily the accuracy and precision of the positioning. A formal strategy for good beacon positioning would be a helpful tool.

A related concept to beacon placement is the hybrid solution discussed in Paragraph 8.2.3. It would be interesting to combine a characteristic based approach with the distance based approach, to potentially introduce a significant performance increase for several characteristics in Bluetooth smart based positioning. Especially if the systems were to be deployed in a scenario with not too many large open areas.

Finally the topics of scalability and deployment complexity could benefit largely by future evaluation and development. Machine learning approaches and data fusion algorithms to allow simple deployment, expansion or repair of deployed systems could improve RF based positioning significantly.

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