Robin Christian Braggaar

Wi-Fi network-based indoor localisation

The case of the TU Delft campus

TU Delft

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Wi-Fi network-based indoor localisation

The case of the TU Delft campus

by

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Abstract

The current trend towards the use of smart tools within universities open up new opportunities. Insight in the location and daily rhythms of users within the building form valuable input for many decision-making processes within campus management. Unlike the outdoor environment, where the position is easily obtained through omnipresent satellite-based positioning systems such as GPS, the use of these systems in indoor environments is limited. Various implementations of indoor positioning systems try to fill this gap and provide indoor positioning capabilities. However, the complex indoor environment presents its own challenges regarding positioning. The effectiveness of current implementations varies depending on techniques and methods used, while often being limited to function only within small test bed environments. Privacy, cost, scalability, ease of integration in the environment and many other decisive factors steer the choice for certain indoor positioning systems. Within this research the focus is on the development of a non-intrusive network-based indoor positioning system using Wi-Fi. Wi-Fi has clear advantages over other measuring techniques in that these systems are ubiquitous, cost-effective and their use is multi-faceted. Now over 85% of the users carry a smartphone. These off-the-shelf, unmodified smartphones and other Wi-Fi-enabled mobile devices can be used as mobile stations to indicate user locations through an iterative positioning process. Besides the mobile stations, existing Wi-Fi infrastructures and networking equipment can be re-used with minor adaptations. The following research question was addressed in this research: 'To what extent can indoor Wi-Fi positioning be used for indoor localisation in order to determine occupancy rhythms and movement patterns within and between rooms to support campus management?'. The research question was approached starting with exploring the different techniques and methods suited for indoor positioning or localisation. The case study was used to review and develop a system suitable for indoor campus environments. As the case study requires a non-intrusive and low-cost solution that functions without active user participation a signal propagation-based technique was chosen. Distances were estimated employing the signal strength metadata extracted from various 802.11 management frames originating from user mobile devices. Various influences on the Wi-Fi signals were identified and a solution to counteract those influences was designed in the form of a differential Wi-Fi system using a grid of interconnected reference stations. With the use differential Wi-Fi correction parameters the positioning improved by mitigating for temporal environmental influences that are continuously present in indoor environments. Next, based on a comparison of different methods, a multilateration method was developed as the core of the positioning system. The multilateration algorithms combined with various filtering algorithms provide for a highly maintenance-free system with minimal manual set-up required. As the environment changes new training data is automatically acquired for ready-use. All algorithms were designed to work both in (near) real-time as well as non real-time, with configurable processing delays of at least 10 seconds. The longer delays allow for more observations, while the shorter delays are better for moving users and fast updates. Accuracies of 2 meters at the lower bounds are reported, ranging up to the 10 meter mark due to Wi-Fi characteristics. Various filtering and post-processing mechanisms were designed to generate accurate mappings from mobile devices to user counts. Furthermore, in the preparation phase different geometries were tested with reference stations 10 to 20 meters apart from each other. Preferred spatial geometries were matches as closely as possible for the deployment of the system in a real-world test case scenario. The designed reference stations were deployed in the Architecture faculty building to monitor occupancy and movement patterns before, during and after a fire drill. Ground truth was acquired using BLE wrist bands and manual counting. The fire drill had different elements: counting the number of users per m^2 and per room, the occupancy rhythms over time and the movement patterns. Overall during 48% of the uncontrolled testing a 100% match between BLE wrist band equipped user counts and Wi-Fi counts was achieved. In 77% of the cases there was a 1 person difference in counting, where in more than 95% of the cases the maximum difference was 4 persons. In conclusion, with this localisation system the occupancy rhythms and movement patterns of users can be measured to a large extent to aid in the various tasks of campus management, e.g. planning, and safety evacuations.

Preface

Before you lies the thesis ”Wi-Fi network-based indoor localisation”. It represents a study on localising users within rooms in indoor campus buildings, through the Wi-Fi-enabled devices they are carrying. It has been written in partial fulfilment of the graduation requirements of the Geomatics for the Built Environment programme at the Delft University of Technology. The research has been conducted from April 2017 to January 2018, following a precursor project on Wi-Fi monitoring concluded in spring 2016.

The research took place within the university as they kindly let me use their building as a living lab. The focus on accuracy and the level of detail in describing user occupancy rhythms and movement patterns soon expanded from a data analysis challenge to a combination of also designing a whole new set of sensors capable of retrieving a suitable dataset. The research was difficult and at times legal aspects could delay me for weeks on end. However, in the end the formulated research questions could be answered successfully. This wouldn’t have been possible without my mentors: Stefan van der Spek, Edward Verbree and Alexandra den Heijer.

I would like to thank my mentors for their excellent guidance and support during this process. I am also indebted to Marianne de Vries, who took the time to proof-read this thesis and to provide fruitful suggestions. Furthermore I also wish to thank all of the volunteers that have participated during the data collection and validation stages. Next I would like to thank Dick Hoeneveld and the people from the TU Delft Safety & Security Institute DSys for their assistance and financial support.

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I hope you enjoy your reading.

Robin Christian Braggaar
Delft, January 2018

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1

Introduction

1.1. Motivation

Nowadays Location-Based Services (LBS) are frequently used by many people, for purposes ranging from navigation to getting current location-specific information. One of the upcoming areas where the need for LBS is becoming more present is the indoor environment. In indoor environments not only the individual user can benefit from added value of LBS, this environment is also increasingly interesting for deploying management applications and tools. Indoor management LBS could potentially benefit from a stream of (near) real-time information about the building, that provides new opportunities to aid management decision making. Traditionally however, most of the LBS are meant to function mainly in outdoor environments. The techniques behind these services are often using satellite-based systems such as the Global Positioning System (GPS) in order to determine the user's position as a starting point for providing LBS. The various satellite constellations, together the Global Navigation Satellite System (GNSS), are adequate for outdoor environments, because the relative weak signal these satellites emit can often be received at the user's side due to a clear line of sight with the satellite system. Indoor environments however are preventing these types of systems from being used reliably, limiting the use to outdoor environments (Ogaja, 2011).

The indoor positioning research field focuses on research dedicated to providing accurate information about the indoor position of users. Often this involves using local sensor systems in order to provide LBS that work in the more complex indoor environment. By combining the principles and techniques of the indoor positioning research field with the potential value of LBS this could provide valuable insight to further extent the field of indoor positioning. However, if location-based information is to be used within management environments it should be reliable and suitable, to avoid basing (critical) decisions on wrong data. Within this research the application and testing will be done in the light of university campus management as a case study. So by asking questions such as ”what requirements should the data meet in order to support campus management” this can give a direction to the research.

The need to manage university buildings in a cost effective and smart way is becoming more apparent. Not only due to the high costs of real estate, but a 'green image' is also increasingly important. Furthermore, the increase in user mobility and technological advancements also open up new ways of studying. The traditional study environments become adaptive, smart and pervasive environments (Atif et al., 2015) further adding to information demands about the environment. In relation, within the university management a trend towards using and exploring smart tools (tools based on IT technology), can be identified (Valks et al., 2016). A rising demand for (near) real-time information, within or near university buildings, can also be noticed from the user perspective. This trend can be largely denoted by the fact that now more than 80% of the users are using a mobile smartphone and are very much connected to the surroundings in a digital way (Steemers et al., 2016).

Combined this creates a large demand for (real-time) geo-spatial information about the building and activities within the building, that may be used to manage the building more effectively. Such information may include information about the occupancy of different parts of the building (rooms, lecture halls, study areas and offices), but also data from monitoring events (fire drills, maintenance, meetings). Currently such information is not yet available and that is the main motivation of this research. To accurately provide this information the capabilities of a Wi-Fi-based localisation system will be investigated.

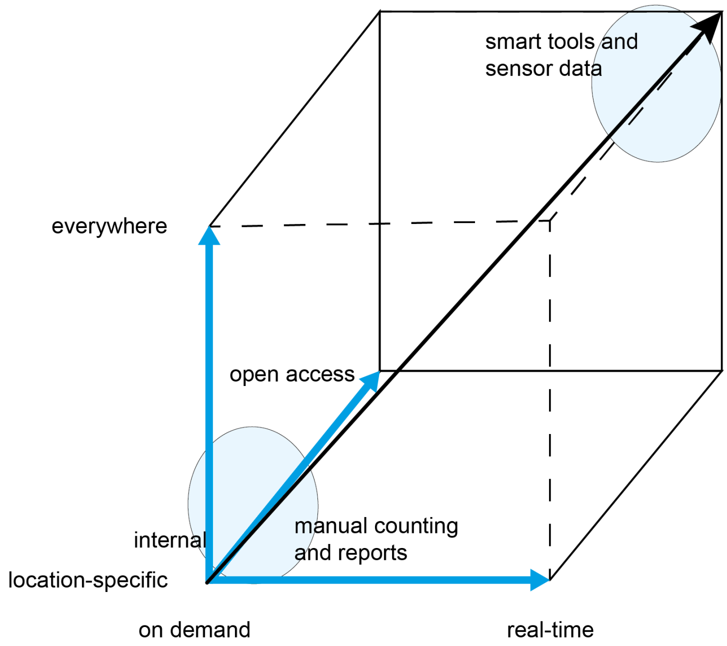


Figure 1.1: Reports and manual counting positioned together with smart tools and sensor data in a framework. Figure adapted from Valks et al. (2016).

Wi-Fi is omnipresent in modern indoor environments and therefore Wi-Fi signals can be classified as one of the signals of opportunity. In indoor environments users also tend to turn on their Wi-Fi, instead of resorting to costly mobile networks. Due to the high number of smartphone and mobile device owners together with the existing infrastructure Wi-Fi-based systems have a potential for solving the campus management information needs.

1.2. Current practice in university campus management

Within university campus management a good planning, among other things, is essential to avoid operational problems. Planning tasks include creating schedules for the different rooms to be used by staff and students, but also maintenance tasks, preferably during quiet times. Besides operational aspects it is also important to make sure that in the long run the right amount of space is available. Too much space and the cost will cause for budgetary problems, too little space and spaces become cramped contributing negatively to the primary goals of the university. Besides quantitative aspects, problems can also arise when different types of rooms are used for purposes they were not designed for (e.g. 2 people having a meeting in a lecture hall).

Currently the information to support these tasks is derived from occupancy rate counts manually performed several times a year. A team of employees of the building will count the number of people inside specific rooms and areas and during specific times. Usually this process takes place on several days spread over two weeks to get a better impression of the average occupancy. Information from the scheduling department is also used (number of reservations, guest lists etc.). With the current source of information it is however not possible to respond to real-time events and the information may get outdated quickly or not be representative at all due to errors in counting. Not to mention the current data capture process is also labour intensive and therefore expensive.

1.3. Problem statement

Indoor positioning and localisation based on Wi-Fi systems is a much researched topic. The gap between outdoor and indoor positioning has now been largely bridged by solutions that use Wi-Fi, Bluetooth or other kinds of Radio Frequency (RF)-signals. However currently there is a gap between the required performance a WPS can deliver in terms of both temporal resolution as well as in terms of accuracy and reliability. For the envisioned purposes (monitoring campus rhythms and movement patterns) it is important that users can be identified on the level of individual rooms. Furthermore, to enable management applications it should be possible to position the users from a central point of view, not from within the individual users' device, so that central monitoring can take place to aid information demands of campus managements. This research presents a network-based system using Wi-Fi reference stations for an accurate (near) real-time overview of the amounts of users in different rooms at all times.

1.4. Potential value for university campus management

University campus management would like to have more insight in the actual usage of space in terms of occupancy rates and rhythms during the day. Campus management could use these types of information to learn more about possible vacant spaces or the opposite, overcrowded spaces. The information provided by a WPS could also be used to monitor specific events, for example during open days and fire drills. The results can lead to valuable knowledge to predict possible congestion and aid in planning purposes, avoiding vacant rooms and decrease costs.

However, this information is not yet available to campus management, as is also shown by the current practice, manual counting. Simply increasing the frequency of manual counting cycles is too expensive and still would not solving the problem. Aside from the the inconvenience caused by manual counting (the room has to be opened, potentially disturbing important meetings) a higher frequency of manual counting also still only provides the data in an interval and not in real-time. By using the mobile devices of users (smartphones, laptops and tablets) as sensors to detect their presence, the same occupancy information might become available to campus management in real-time and at a fraction of the cost (figure 1.2).

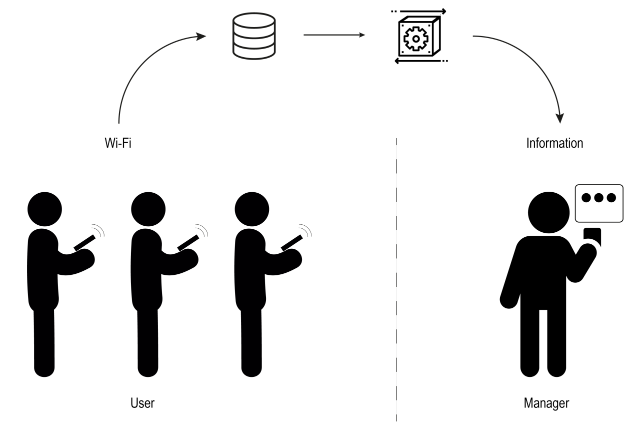


Figure 1.2: WPS serving up-to-date information about occupancy and exploitation.

1.5. Scientific relevance

The indoor positioning field has seen a lot of research already. Mautz (2012) presents a comprehensive overview of all indoor positioning technologies currently available. A lot of different systems are available, but at the same time the limitations of current systems are well known. These specialised systems are much different from the systems used outdoor, however the demand for a seamless transition between the outdoor and indoor environment pushed the indoor positioning research mostly towards systems centred around navigation applications. Research on systems tailored to the field of university campus management is still a challenging field. According to interviews the information about occupancy (space use) and programming remains hard to reliably collect (Den Heijer, 2011). This field provides new challenges where data in real-time is crucial and where the positions need to be calculated on a large scale, allowing for aggregation.

Despite the differences in application, the main positioning techniques that are at the core of each of system stay mostly the same. For the positioning techniques themselves, mostly RSSI-based techniques are employed such as fingerprinting or trilateration. Recently Retscher (2017) demonstrated that a combination of the two by using different elements from each method is also possible in order to improve the accuracy of one technique. Retscher (2017) also introduces a differential technique to further increase the positioning accuracy compared to conventional techniques. However these techniques are limited to the device of the user in question and therefore cannot be used directly for large scale network-based Wi-Fi tracking.

This research takes a different approach where the initial focus is on developing a connected differential WPS that allows for accuracy indoor positioning. Then the data acquired by the system will be analysed and processed centrally with a focus towards application within university campus management. The requirements for the prototype design will be based on a requirements analysis centred around campus management. The other focus in this research is on analysing the data in real-time in order to provide direct information about occupancy, exploitation and activity.

1.6. Research question

Based on the problem statement, describing the need for accurate (near) real-time occupancy rates within academic facilities, the following research question is defined:

> To what extent can indoor Wi-Fi monitoring be used for indoor localisation in order to determine occupancy rhythms and movement patterns within and between rooms to support campus management?

This question covers different research problems, namely: the creation of a WPS capable to capture and provide data with a suitable accuracy to make statements about the occupancy on the scale of individual rooms; the analysis of the data in order to describe patterns and rhytmhs and the presentation of the data in order to support campus management. The Wi-Fi monitoring by the use of a users' mobile device should be passive. No additional software or hardware should be necessary on the user side and the system should work fully autonomously.

The data capture will be done through both existing APs and through a new WPS prototype. Within this research the goal will be to test the suitability of a WPS to support campus management with information about occupancy and exploitation on the scale of individual rooms. The information can be used in different ways, e.g. maintenance or rebuilding purposes, scheduling or event monitoring. Applying the information within applications will not be the main focus in this research, but rather the steps before that: data collection, data storage, data analysis and the data visualisation.

1.6.1. Sub-questions

To break down the research question a number of sub-questions are defined. The first sub questions pertain to the data analysis part, the latter questions are of a more technical and detailed nature and deal with the WPS itself.

1. *How can information about occupancy rhythms and movement patterns support university campus management and what are the requirements of this information?*

   To understand the value of occupancy rates for the business processes of campus management it is first necessary to look at how this information is currently used by the campus management and what the requirements are for this information. This sub-question is answered in chapter 3 through literature research.

2. *How can devices be linked to building users?*

Devices that are connected over the wireless network are not always mobile devices and can also be unrelated to users, such as printers and other static devices. Different devices might also belong to a single or multiple users. Therefore it is important to analyse the data to be able to define what an individual user is (with a degree of uncertainty).

3. *How can the sensors be calibrated to adapt to the indoor environment and its influences?*

   One of the goals within this research is to develop a WPS that is able to provide information about occupancy on the level of individual rooms. Therefore the accuracy needs to be sufficient. As the RF-signal can fluctuate due to external temporal influences the WPS needs to be calibrated to adapt for these influences.

4. *How does base station distribution affect the indoor positioning accuracy?*

   As the RF-signal degrades exponentially over distance it is imperative to look at the static positioning of the APs and the effect their positional distribution has on the positioning performance.

5. *To what extent can a user be positioned or localised within a room or area as defined by the campus management?*

   When the user sends out RF-signal through their mobile device the device can be positioned. This position can be translated to a space or room in the building to tell something about the users' position and location.

6. *Which occupancy rhythms and movement patterns can be recognized and how to acquire them?*

   When the positions of users over time have been established occupancy rhythms in different spaces or rooms can be derived. This information can tell something about the usage of rooms during the day. Analysing the change in places of users visit during the day can provide insight in the movement patterns within the building. These patterns can also lead to a better understanding of the use of spaces.

1.7. Objectives and scope

The objectives of this research are to explore the possibilities of Wi-Fi-based tools as a way to support university campus management. Therefore, this research focuses on developing a prototype of a network-based Wi-Fi positioning system that can be used to study occupancy rates through performing indoor positioning. Special attention was paid to implement a novel solution in order to achieve a high accuracy of positioning. Where previous studies focussed on acquiring wing or floor level information, this research focuses on the room level. Next to the development this prototype system was also used for the data capture and storage of Wi-Fi metadata packets. Another part of the thesis research addresses the data analysis and presentation. Through data analysis this research provides near real-time information about the occupancy rhythms and flow patterns within university buildings. The information was also made presentable in a dashboard for the user.

The thesis does not cover indoor wayfinding based on the data. The interpretation of the data in a management context is also limited, and aimed towards occupancy and exploitation rates. Furthermore the test site location was limited to one location on the campus of the Delft University of Technology. The research considered indoor positioning by the use of mobile devices; i.e. users that exclusively make use of desktop computers (without carrying mobile devices) were excluded from the research. Finally, the time frame of data capture was limited to the time frame permitted by campus management.

Table 1.1 presents an overview of the prioritisation of the different requirements to be met in this research.

1.8. Research strategy

The research was conducted in several phases as described in figure 1.3. First both Wi-Fi measuring techniques and positioning and localisation methods were researched. From a selected case study the system requirements were set to build a prototype WPS. Next the WPS was deployed on a test

Table 1.1: MoSCoW requirements prioritisation

Must have	Should have
Build WPS-prototype	Build data visualisation tool or presentable outcomes
Capture and collect data with the prototype through multiple experiments	Build (near) real-time working prototype
Analyse data in database to define and position users, calculate occupancy, exploitation and movement	Deploy WPS within the university 'Eduroam' network
Implement differential technique in order to attain sufficient accuracy for room-level statements	Make prototype fully autonomous
Keep system time synchronised	
Respect user privacy with regard to data capture and storage and conform to local legislation	

Could have	Will not have
Test different methods of positioning	Production-ready application
Create algorithms that identify and correct for different types of devices/antennas	Install system in other places than the test location or university network
Iterate data visualisation tool development through interviews with stakeholders	Raw data exchange with third parties
	Research campus management business processes intensively

site to capture data required by the use cases. Conclusions were drawn based on the results obtained through testing the prototype and the data capture in the case study. The data acquired through this WPS will be subject of further research to determine the data's value for university campus management application.

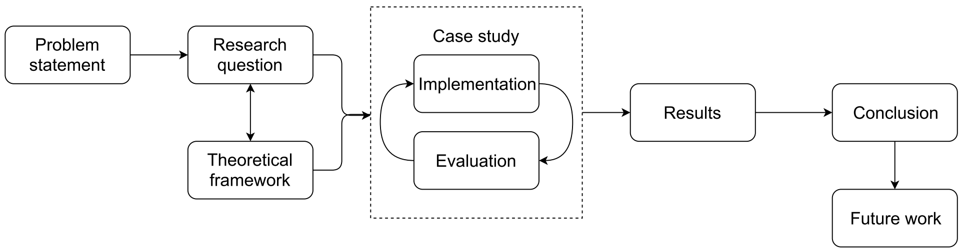


Figure 1.3: Research methodology

1.9. Thesis outline

Chapter 2 discusses the theoretical framework around the field of indoor Wi-Fi positioning and indoor tracking. Chapter 2 also contains information about the use and value of occupancy information within campus management. Finally examples of some current applications for occupancy monitoring are presented. Chapter 3 focusses on the case study information needs and system requirements as well as privacy regulations. Chapter 4 will go into detail about the research design of this thesis. In chapter 5 the implementation is presented. The results obtained within the research are presented in chapter 6. Chapter 7 will contain conclusions drawn based on the results and discusses the limitations as well as opportunities for future work of this research.

In addition to previously described chapters, this thesis contains the following appendices:

- Appendix A, which contains a reflection on the research
- Appendix B, which contains an overview of the time planning used during the research
- Appendix C, which contains information about the way users were informed about the data collection process

2

Theoretical framework: technical aspects

The following chapter will provide an overview of the relevant literature for this research, focussed on the technical aspects. The next chapter will focus more on the case study (chapter 3). The first section of this chapter will present some of the core terminology related to the field of indoor positioning and localisation (section 2.1). Section 2.2 presents a brief overview of some of the most commonly used wireless measuring techniques and the sensors related to them. Subsequently, section 2.3 goes in depth on the Wi-Fi measuring technique and its characteristics related to the indoor environment. Section 2.4 continues on the possible ways of acquiring a position using the obtained measurements. As positioning is never without error, section 2.5 explains the statistical quantities that define the performance of the system. Finally literature suggested options are given to improve the system performance (section 2.6).

2.1. Definition of terms

2.1.1. Concepts of placement

In this work the subject of indoor positioning and localisation using Wi-Fi monitoring is investigated. The core of each LBS always starts with a location or a position. In the research field a distinction is made between a position and a location (Mautz, 2012), and in addition also places and areas (Sithole and Zlatanova, 2016). And although sometimes these concepts are used as synonyms, there are subtle differences. These concepts, or referential expressions, describe the placement of objects, users and things (Sithole and Zlatanova, 2016). The expressions of placement are always relative to things in space, or the space itself (expressed in a coordinate reference frame). When using a coordinate reference frame the position is called an absolute reference. According to Sithole and Zlatanova (2016) three categories of spatial relationships between objects can be defined:

- Topological relationship: neighbourhood relationships between two objects
- Directional relationship: linguistic relationships such as 'in front of the reference object', including relationships using the Euclidian reference frame
- Metric relationship: using geometrical metric parameters of point sets, such as the coordinates, distance, area and circumference.

Absolute referential expressions can also be defined as a type of physical location information, and relative references can be called symbolic (in natural language) (Mautz, 2012). In the context of indoor environments both relative and absolute referential expressions can be used to give describe placement within the indoor space. When using relative references the reference depends on the given context at hand. Therefore, because of the ambiguity there is a risk of assigning spatial information to the wrong

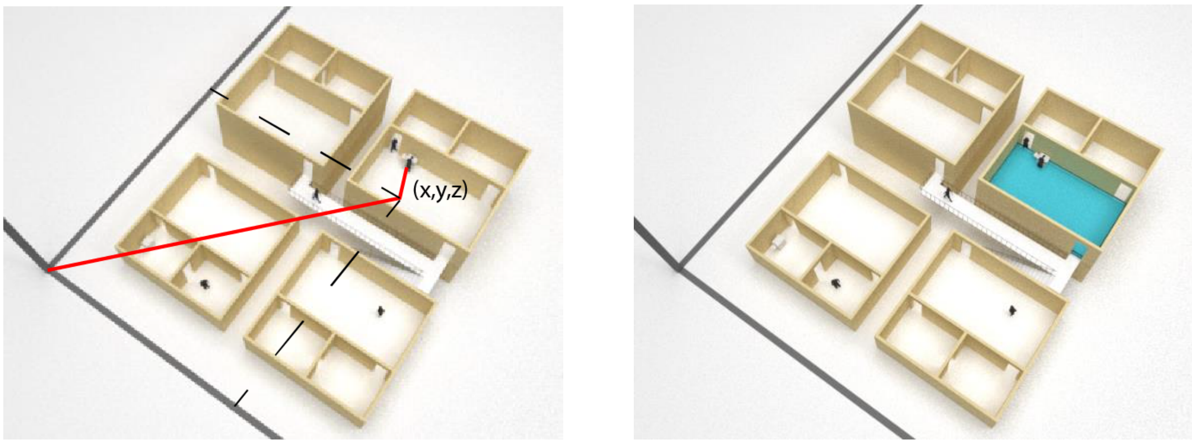
Table 2.1: Distinction between different types of addressing Sithole and Zlatanova (2016)

	Position	Location	Place	Area
Reference	Absolute, i.e. using a coordinate reference system	Absolute, e.g. room number	Relative, placement in a room (inside)	Relative, placement in an aggregation of rooms
Specificity/ Uncertainty	Depends on the device providing the position	Certain, defined by the physical borders (walls)	Uncertain, defined by the functional space of an object, e.g., a desk	Uncertain, defined by a more general notation (floors, parts of buildings)
Scope	Defined by a reference frame	Contains places	Contained in locations	Contains locations
Context	There is no context besides the coordinate reference frame	Context	Context	Context
Example	I am at 28.2314°, -33.4577°	I am in the living room	I am at the photocopier	I am on the second floor

space. Depending on the use case of the information, the context should be described unambiguously to avoid problems. For example, computer algorithms might work differently than the way humans think and therefore yield other results. In such cases a mapping from absolute references, that a computer can understand (i.e. coordinates), to relative references (room numbers, space designators) is necessary.

An overview of the different types of addressing (position, location, place and area) and the different aspects (reference, specificity, scope and content) can be found in table 2.1. In this context reference specifies the type of reference (absolute or relative). Specificity refers to the extent of the addressable space, comparable with the accuracy or uncertainty. Scope declares how the terms relate to each other specifies the topological nesting. For example, a location can be in a larger area, whereas a position can only reside within a coordinate reference frame.

In short, the position is expressed in coordinates and can be either absolute or relative, depending on whether a local or global reference frame is used (figure 2.1a). Furthermore in this work a location will be defined as the smallest space physically restricted by walls or other building parts (e.g. a room) (figure 2.1b), or sometimes as a clearly identifiable sub-space as defined by campus management. The place further reduces the possible extent of a location (e.g. room A) down to a certain sub-part of the location (e.g. in the center of room A) and thus is more specific than a location and requires the location to be known. Finally areas are less specific than locations and can cover multiple locations including partial locations (e.g. a wing or floor of a building).



(a) An absolute position (coordinates). Figure adapted from Sithole and Zlatanova (2016).

(b) A location. Figure reprinted from Sithole and Zlatanova (2016).

Figure 2.1: Position and location.

The placement of a user always consists of the quartet of a position, location, place and area at the same time, however some aspects are dominant while others are auxiliary Sithole and Zlatanova (2016). In the case of Wi-Fi localisation in indoor environments the accuracy is not likely to be suited to accurately pin-point users on a certain position. On the other hand, as will be demonstrated in the next chapter, precise placement of users is not of interest to campus management. The dominant treat of the users' placement is thus likely to be that of a location (or sub-space).

Table 2.2: General overview of different techniques and their common accuracies by Mautz (2012).

Technology	Typical accuracy	Coverage [m]	Typical measuring principle	Typical application
Cameras	0.1mm – dm	1 – 10	angle measurements from images metrology	robot navigation
Infrared	cm – m	1 – 5	thermal imaging, active beacons	people detection, tracking
Tactile & Polar Systems	μm – mm	3 – 2000	mechanical, interferometry	automotive, metrology
Sound	cm	2 – 10	distances from time of arrival	hospitals, tracking
WLAN / Wi-Fi	m	20 – 50	fingerprinting	pedestrian navigation, LBS
RFID	dm – m	1 – 50	proximity detection, fingerprinting	pedestrian navigation
Ultra□Wideband	cm – m	1 – 50	body reflection, time of arrival	robotics, automation
High Sensitive GNSS	10 m	global'	parallel correlation, assistant GPS	LBS
Pseudolites	cm – dm	10 – 1000	carrier phase ranging	GNSS challenged pit mines
Other Radio Frequencies	m	10 – 1000	fingerprinting, proximity	person tracking
Inertial Navigation	1%	10 – 100	dead reckoning	pedestrian navigation
Magnetic Systems	mm – cm	1 – 20	fingerprinting and ranging	hospitals, mines
Infrastructure Systems	cm – m	building	fingerprinting, capacitance	ambient assisted living

In this research the term positioning refers to the process of obtaining a position through a positioning method. The position can be 2D or 3D in any coordinate reference system. With localisation the process of acquiring the location (e.g. room) of a person or object is meant. In this respect, positioning (point coordinate) is more specific than localisation (room). Finally, as is the case in this research, multiple positions can be used to estimate a fitting location, thereby accounting for the error margin the estimated position may have. So in this case localisation is performed through repeated positioning.

2.1.2. Positioning and tracking

Within this research the locations of users are estimated by positioning them with Wi-Fi. Once individual locations are estimated, aggregates can be derived to provide information about the location at a certain point in time or time range. Tracking on the other hand is more focussed on the movement trajectory of (individual) users. Mautz (2012) defines tracking as ”the process of repeated positioning of a moving object or person over time”. When Wi-Fi signals from mobile stations are captured over prolonged amounts of time, i.e. the network is monitored, the users could also be tracked if their unique identifier is known and remains unchanged during the repeated positioning. Mautz (2012) also adds ”tracking is used when the infrastructure is determining the location of a passive mobile device, where the information about the current position is not necessarily known at the mobile device”. This adds two important elements, namely the user does not necessarily need to be actively involved in the positioning process and therefore the positioning can be performed silently. Also the infrastructure is determining the position, rather than the device itself.

2.1.3. Techniques and methods

Techniques are commonly referred to as processes that involve the use of some kind of technical equipment (such as a measuring device for distances). In this context techniques are used to gather data that can be used as input for positioning methods. A method in turn uses or processes the input data provided by the technique to provide enriched data or information, not necessarily using the same specialised technical equipment.

2.2. Overview and comparison of wireless measuring techniques

For different applications different techniques can be used. In order to understand the strengths and weaknesses of Wi-Fi compared to other methods a general overview is presented here. Measuring techniques for indoor environments can be classified based on the type of measuring principle used. The most common types of measuring techniques are the distance and angle observations. Table 2.2 shows an overview of the different techniques currently in use and their common accuracies (Mautz, 2012).

Some of these technologies are already used in universities for different purposes. Cameras are often present for security reasons. However, optical crowd monitoring and tracking is becoming more viable in open public spaces due to the increase in computing power and network capacity. Camera-based methods of localisation are subject to very strict regulations as user privacy can easily be harmed. Other disadvantages are the need for good lighting conditions, and the high cost of the system installation. Additionally, cameras require line of sight in order to position a user. The presence of cameras is also not preferred in some places. Cameras equipped with infrared sensors overcome the problem of poor lightning conditions, but at the cost of extra expenses.

Bluetooth is usually present on the mobile devices of users, such as smartphones and laptops. Bluetooth is a short range (typically less than 10 meters) bi-directional communication standard. Monitoring crowds with the use of Bluetooth has seen succesful applications e.g. by Basalamah (2016). An accuracy of around 1 meter can be achieved by using a dense network of Bluetooth scanners (van der Ham et al., 2016). Bluetooth is also energy efficient and works well with mobile platforms, however tracking of pedestrians can be unreliable since users often deactivate the Bluetooth connection on their mobile devices in order to reduce energy consumption. The usage of Bluetooth tags increases reliability and can achieve good accuracy (Faragher and Harle, 2015). Tags can be integrated in access or campus cards for example. The use of Bluetooth is not suitable for large-scale prolonged application considering the requirement of additional tags.

Similarly, Radio-frequency identification (RFID) based methods use short range radio signals to detect tags. The tags are passive objects influencing radio signals that hit the tags. These tags are commonly integrated in credit card-sized cards. The transmitting devices can recognize the tag according to the signal it receives back. Because of the very short range it has limited use for crowd monitoring. This method is at the same time subject to shadowing and fading. Common applications are the integration of RFID chips in campus cards (Khamayseh et al., 2015).

Considering the research objectives and the characteristics of the different aforementioned technologies, a Wi-Fi-based approach has lots of opportunities. Other techniques may however be used to validate the data after and during the data collection stage. The fact that Wi-Fi monitoring systems can be deployed using the existing network infrastructure and the fact that unmodified Wi-Fi-enabled devices can be monitored with a Wi-Fi monitoring system are clear advantages of the Wi-Fi system over the other techniques. Another key requirement is the possibility to collect data over longer periods of time and centralised information storage and visualization. However, also certain challenges have to be faced with Wi-Fi-based systems, such as dealing with fluctuating signal strength, environmental and geometrical influences. Also different methods for localisation by Wi-Fi have to be compared and suitable algorithms have to be developed. Hybrid systems using more than one technique, e.g. combining Bluetooth and Wi-Fi have also been successfully deployed (Baniukevic et al., 2011). Figure 2.2 shows the global bandwidths of coverages and accuracies of the different techniques.

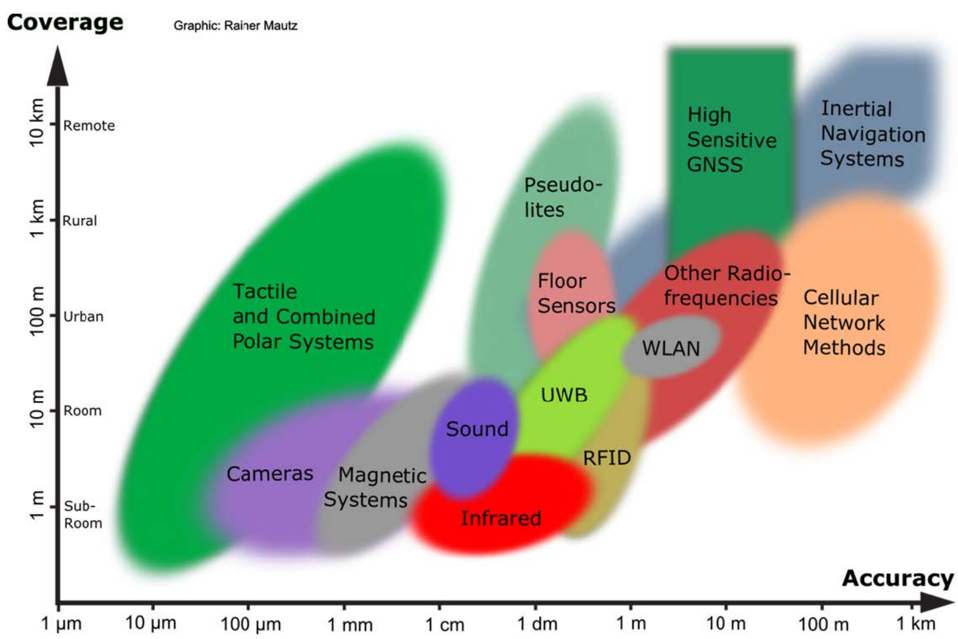


Figure 2.2: Coverages and accuracies of different remote sensing techniques that can be used for positioning. Figure reprinted from Mautz (2012).

2.3. Wi-Fi

Wi-Fi-based positioning systems need to be capable to accomplish a couple of different tasks: data collection, data processing and data transmission. This section will explain how data can be collected using Wi-Fi techniques. The next section will present the possible methods of data processing in order to derive locations.

2.3.1. Introduction to Wi-Fi

Wi-Fi is a communication standard for wireless two-way communication, typically between an access point and a user station. The development of Wi-Fi goes back to 1971 as a way to connect the Hawaiian Islands by means of a Ultra High Frequency (UHF) data connection. 1974 Marked the start of the actual development of the Wi-Fi as we know it now under the lead of Vic Hayes. Further shaping the developments of Wi-Fi were the changes in 1985, when the U.S. Federal Communications Commission released the Industrial, Scientific and Medical (ISM) frequency bands for unlicensed use. Wi-Fi in its previous iterations was called WaveLAN. The first version of the 802.11 Wi-Fi protocol was released in 1997 Stephen McCann; Alex Ashley (2015). However, the name Wi-Fi was only officially used in commercial applications from the moment the Wi-Fi alliance formed as a trade association around 1999.

From the initial role of connecting remote islands, Wi-Fi soon spreaded out to become one of the most used technologies for wireless local area networking. Wi-Fi is built into many products nowadays, including many types of portable devices such as smartphones, tablets, smart watches and music players. The development of Wi-Fi sees constant improvements, mainly the networking speeds have been drastically improved. Currently the Wi-Fi standard (IEEE 802.11) has incorporated several subsequent amendments to improve the standard and to adapt to the increasingly demanding requirements. Each of those amendments is sometimes treated as a standard on its own in the commercial market (such a the N-standard). However, all Wi-Fi devices are backwards compatible. This means that for example a station working on the N-revision of the standard can also receive packets from station working on the B-revision of the standard.

2.3.2. Properties of the Wi-Fi technology

Infrastructure and network components

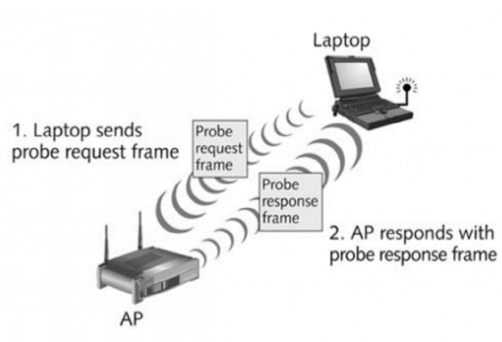
Wi-Fi networks are composed of several different components. APs are Wi-Fi-enabled base stations that extend the wired local area network wirelessly and provide access to the Wireless Local Area Network (WLAN). Depending on the network size and intended coverage one or multiple access points can be set-up. Client stations are any devices that host a wireless network interface controller. Between the AP and client stations such as mobile phones and laptops a wireless two-way communication can be set up and together they form the main components of wireless networks.

In this research a further distinction between different base stations will also be made. In contrast to an AP, a reference station (beacon) is equipped with hardware and software that enables it to form a mesh network with other reference stations for the purpose of improving the network's positioning performance (e.g. better tracking). Reference stations involve active signal emission at all times, even when there are no nearby mobile stations. Differential Wi-Fi (DWi-Fi) networks are those networks that can make use of such reference stations. For the process of positioning the measurements' base station position is often called an anchor position or anchor node, irrespective of the type of base station (AP or reference station).

Network discovery and data communication

The network discovery process enables Wi-Fi client stations to connect to APs, either passively or actively. Passive discovery occurs when the client station starts listening to beacon frames, sent out by APs on a regular interval (figure 2.3b). Once a broadcasted beacon frame contains a matching Service Set Identifier (SSID) to the SSID configured on the client device, a connection will be established. Active network discovery can be initiated by the client device by sending a network management probe request frame that lets the surrounding network know that the client station wants to establish a connection (figure 2.3a). If the probe request contains a specific network it is a directed request. The alternative, a null probe request can be used to discover any available networks in the area. Once the probe request gets received at one or more APs a response in the form of a probe response frame is sent back, containing all necessary network parameters. When multiple APs reply to the probe request the network with the best signal reception will be connected to.

Beacon frames are always sent on the same Wi-Fi channel as the AP operates on (CWNP, 2016). Active probe requests are sent out across all channels, because the target network channel is unknown.



(a) Probe request and response between access point and client station. Figure adapted from CWNP (2016).

(b) Beacon frames broadcasted from an access point. Figure reprinted from CWNP (2016).

Figure 2.3: Mobile-based probe requests and network-based beacon frames.

A user does not have much control over the network management frame sent out by their devices other than turning off Wi-Fi or in some cases they may have access to roaming and power settings that can be used. The management frames are required to organize and manage traffic over wireless connections between wireless clients and APs (Musa and Eriksson, 2012).

Frequency and channels

Wi-Fi signals are EM radio waves in the frequency range of 2.4 to 5 GHz (figure 2.4). The range of these signals is typically between 10 to 90 meters for normal Wi-Fi radios (as those found in mobile devices).

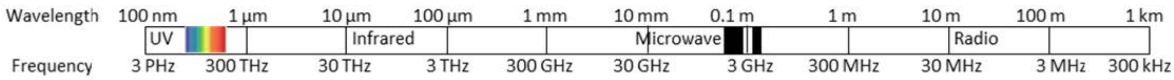


Figure 2.4: Wi-Fi in the EM spectrum. Figure reprinted from Mautz (2012).

Wi-Fi can use multiple frequency bands and each band is subdivided in a number of channels. The 2.4 GHz band is subdivided in 14 channels that are 22 MHz wide. The channel width is optimised between data transmission and scalability so that any Wi-Fi connection on a specific channel also occupies the two neighbouring channels (figure 2.5). Thereby, to avoid overlapping a minimum spacing of 5 channels should be used between networks, such as 1 and 6. In Europe there are 4 non-overlapping channels: 1, 5, 9 and 13. All communication, including management frames such as probe requests and beacon frames can be received by all stations that are within reach, however only the addressed devices will actually process the data.

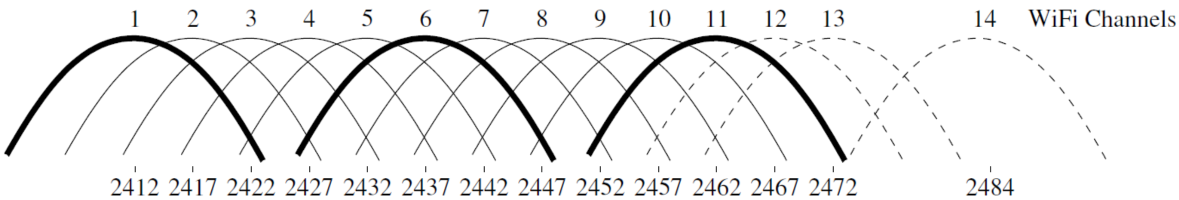


Figure 2.5: Wi-Fi channels in the 2.4 GHz band. Figure reprinted from Liang et al. (2010).

According to one of the most fundamental equations in antenna theory, Frii's free space transmission equation, signals with a longer wavelength (or lower frequency, e.g. 2.4 GHz as opposed to 5 GHz) are less affected by objects (Kulachi, 2008).

Tracking with Wi-Fi infrastructures

Tracking with the use of Wi-Fi infrastructures and mobile devices is a form of network-based or centralised positioning. The network base stations (e.g. access points or reference stations) capture signals transmitted from mobile stations (blind nodes) whose position or location needs to be determined. In network-based positioning the process of position determination is carried out on the network or server side, rather than at the mobile side (Mautz, 2012). Therefore, the positioning can be performed centrally, without the user having to be actively involved. This allows for data collection and data aggregation on a large scale, however user privacy regulations around this topic are becoming more strict lately. Network-based positioning commonly rely on active systems. Active systems or sensors work on the principle of emitting signals that are then returned and captured by the sensor itself or are captured at a different sensor. Contrary to network-based positioning, mobile-based positioning systems perform positioning on the mobile device side. These type of systems are often passive as they will consume signals (e.g. satellite radio waves), but do not actively emit signals on their own (Rees, 2001). For passive systems the user can not control the signals that are captured, as that is regulated by the infrastructure entirely.

The use of Wi-Fi is potentially very interesting as the main infrastructure is often already present in buildings. In addition, for network-based positioning standard Wi-Fi-enabled devices can be used without modifications, limiting the amount of preparation needed. Therefore, Wi-Fi is also classified as one of the major signals of opportunity and its use is currently heavily in development. Research among universities has also shown that Wi-Fi is the most suitable for application in a university setting (Valks et al., 2016).

Wi-Fi measures

For Wi-Fi tracking different measuring techniques can be used. The most common techniques are either based on time, angle or signal strength. Time of Arrival (TOA) is a technique that compares the time of signal destination on the senders' clock with the time of arrival on the receivers' clock. The absolute difference in time can be related to the distance by multiplication with the wave speed. This technique requires very accurate clocks on both the receiver and the transmitter side. Furthermore the wave speed differs when it passes through different types of materials. The clocks in current Wi-Fi equipment are not capable of providing accurate time readings suitable for time-based ranging. A 1 micro-second delay can already introduce a 300 meter positioning error. Combined with the different travel speed in different materials this technique is not feasible for indoor network-based positioning. Time Difference of Arrival (TDOA) solves the problem of receiver clock bias and the need for very accurate clocks as the relative time difference between receiving multiple pulses is measured. However, this technique requires very precise synchronisation between the base stations. Lastly, the Round trip time (RTT) techniques also eliminates any clock bias between base stations as it works on the principle of two-way ranging. A pulse is sent to a base station and returned back to the mobile device. The total time duration can then be used for distance estimation. The drawback to this method is that the delays can cause inaccuracies (e.g. the time it takes for a receiver to respond to the pulse and the amount of sequential measurements needed).

Angle-based techniques rely on the Angle of Arrival (AOA) of the pulse from the receiver. This data can be used with triangulation to estimate the user position, but AOA-based techniques require specialised direction-sensitive antenna arrays that make this method less common for use in conjunction with Wi-Fi.

Finally techniques based on signal strength are not prone to clock errors as they employ signal attenuation to estimate distances. RSSI-based techniques are cheap because of the possibility to use off-the-shelf networking hardware, making this one of the most used Wi-Fi-based ranging techniques. This research will only consider this technique for distance estimation.

Smartphones, tablets, laptops and other devices that have Wi-Fi enabled periodically send out probe requests. When these packets are captured their metadata can be extracted to provide access to some useful properties that can be used for indoor positioning and device recognition. The following metadata can be retrieved from the probe requests:

- Timestamp: the time at which the probe request arrives at the Wi-Fi base station
- MAC address: the Media Control Address or unique identifier of the device on the network
- RSSI: an indicator for signal strength
- SSID: the name of the network the client is currently connected to
- (optional) Requested SSID: the name of the network the client station wants to connect to
- Vendor: the manufacturer info of the device's chipset

The timestamp is added to the metadata of the received packet as soon as it is received. Therefore the timestamp indicates the time of arrival at the base station. The MAC address-address helps identify the mobile device on the WLAN and can be used to uniquely identify individual devices. The RSSI is a measure for the amount of RF-energy, consisting of an 8-bit integer that can take up to 256 different values (usually 0 to -255). These values are indexed and dependable on the antenna hardware of the base station, i.e. they are not absolute measures. The mobile device also presents the name of the current network it is connected to. The device may also be looking to connect to a specific preferred wireless network and may optionally include the SSID or the name of the WLAN in the packet. Lastly, the vendor or manufacturer information can be extracted as from the MAC address-address, if it is included by the manufacturer.

2.3.3. Wi-Fi signals and the indoor environment

Sight lines in the indoor environment

Indoor environments are very heterogeneous compared to outdoor environments. The layout of the building is unique to each building and can be further differentiated by any furniture or objects placed in the indoor environment. Generally there are two scenarios for positioning users in indoor environments. Line-of-Sight (LOS) comprises situations where there is a direct straight and unobstructed path between the mobile device and the base station. However, because of the objects and indoor geometry a clear LOS is usually not the case and therefore Non-line-of-sight (NLOS) situations have to deal with damping and other effects on the signal propagation.

Signal propagation of Wi-Fi signals and antennas

Signal propagation Wi-Fi signals are attenuated by objects, human bodies and building elements, and the strength of the signal also degrades over distance. Therefore distance estimation can be based on the degradation of the signal strength. When using the signal strength as a ranging technique, the signal propagation becomes an important factor determining the quality of the whole positioning system. As noted before, the RSSI-values are included in the probe request packet metadata. Each wireless interface manufacturer has its own parameters that slightly affect the attenuation model for the received signal strength, therefore the RSSI-values among different brand interfaces are not directly comparable. However, this is not a problem when using a network consisting of a single type and brand of transceiver. The signal strength usually tends to degrade quadratically over distance. The received signal strength received (in dBm) can be modelled through a free-space attenuation model:

$$P_R \propto P_T \frac{G_T G_R}{4\pi d^p} \tag{2.1}$$

Where P_R is the received signal strength as returned in the packet metadata that can be used for ranging. P_T is the unknown transmitting power of the mobile device. The power gains that specify the antenna's directivity and electrical efficiency are G_T and G_R for the transmitter and receiver respectively. d is the distance between the two antennas and p is the path loss exponent that dictates how quickly the signal will attenuate over distance. p can vary between 2 for open areas or indoor environments with direct LOS to values as much as 10 or more for NLOS. On average values between 4 and 6 are common for indoor environments (Mautz, 2012).

For indoor environments however, the free-space path-loss model is not adequate. Therefore a path-loss designed for indoor environments can be used to account for environmental influences. The free-space path-loss model forms the basis for the indoor path-loss model. This model describes the degradation of the signal strength over distance travelled in free space (Kulachi, 2008). Equation 2.2 describes the path loss of a signal sent from a distance.

$$P_L(d_i) = P_L(d_0) + 10(2)\log_{10}\left(\frac{d_i}{d_0}\right) \tag{2.2}$$

$P_L(d_i)$ is the signal strength in decibels at the receiver. d_0 is the reference distance at which a known path loss is recorded, $P_L(d_0)$ [db].

To take into account the environment of the scanner, equation 2.2 can be adapted according to Oguejiofor et al. (2013) with a parameter n as in equation 2.3.

$$P_L(d_i) = P_L(d_0) + 10(n)\log_{10}\left(\frac{d_i}{d_0}\right) \tag{2.3}$$

n can then be empirically determined by setting up a test environment and using equation 2.4 to obtain an environment specific value for n.

$$n = \frac{(P_L(d_i) - P_L(d_0))}{10\log_{10}\left(\frac{d_i}{d_0}\right)} \tag{2.4}$$

With Frii's equation the relation between the free-space path-loss model and antenna characteristics are expressed in relation with received and transmitted powers in watts.

Antennas Antennas with different characteristics can be used to achieve different goals. The gain of the antenna, as mentioned in previous equations, is by default expressed in a unitless number and is relative to a hypothetical lossless isotropic antenna that radiates its energy equally in all directions (equation 2.5).

$$G = E_{antenna} \cdot D. \tag{2.5}$$

Where G is the gain, $E_{antenna}$ the efficiency of the antenna and D the directivity. Gain and other properties are the same for receiving as well as transmitting antennas. When the antenna gain (designated by G_{dBi} to denote its relation with an isotropic radiator) is specified in decibels the following equation can be used:

$$G_{dBi} = 10 \cdot \log_{10}(G) \tag{2.6}$$

The type of antenna used for this research is the common dipole antenna, a type of omni-directional antenna. As opposed to omni-directional antennas directional antennas increase or decrease the received signal according to the antenna direction. When the electrical energy is transformed into EM waves it will radiate the energy in a specific pattern. Figure 2.6 shows the radiation pattern for the dipole antenna used in this research. The antenna pattern for dipoles is non-directional for the azimuthal plane (the horizontal direction with the antenna pointing upwards). The elevation pattern is somewhat flatter, with cut-outs (nulls) at the top and bottom. The dipole antenna has a slight gain of 2.2 dBi in the horizontal direction (stronger horizontal radiation) and the dipole antenna radiates equally in all directions for the horizontal plane. Therefore, for optimal ranging purposes and to achieve optimal coverage, this antenna should be used mainly in the azimuthal plane in order to optimise signal reception, i.e. the antenna needs to be mounted vertically. By using a floor-based or per-floor positioning approach only measurements from the same floor are used for positioning (i.e. the signals arrive in the azimuthal plane).

Influences on indoor signal propagation

Indoor Wi-Fi localisation systems operate in dynamic environments, where many factors can influence the system's performance. The signal propagation in indoor environments depends on a number of factors, some of which mentioned before. Seybold (2005) distinguishes 6 main effects that can have an influence on the signal propagation in indoor environments. Figure 2.7 shows a visualisation of RF-signals in indoor environments and some of the identified influences (Callaerts (2016) in Haagmans et al. (2017)). Multipath, shadowing and diffraction can be seen in the figure.

Multipath reflection The main influence on the signal propagation are obstacles and sight lines. Signals arriving from line-of-sight are generally much stronger than signals arriving from reflection paths. Multipath is the term used for the phenomenon where signals travel in different paths from the transmitter to the receiver, e.g. echoes. NLOS multipath signals are series of multiple versions of the same signals, that arrive at different times. The travel trajectories have different lengths and therefore a different signal strength (amplitude) level for each of the signals. Especially metallic surfaces are

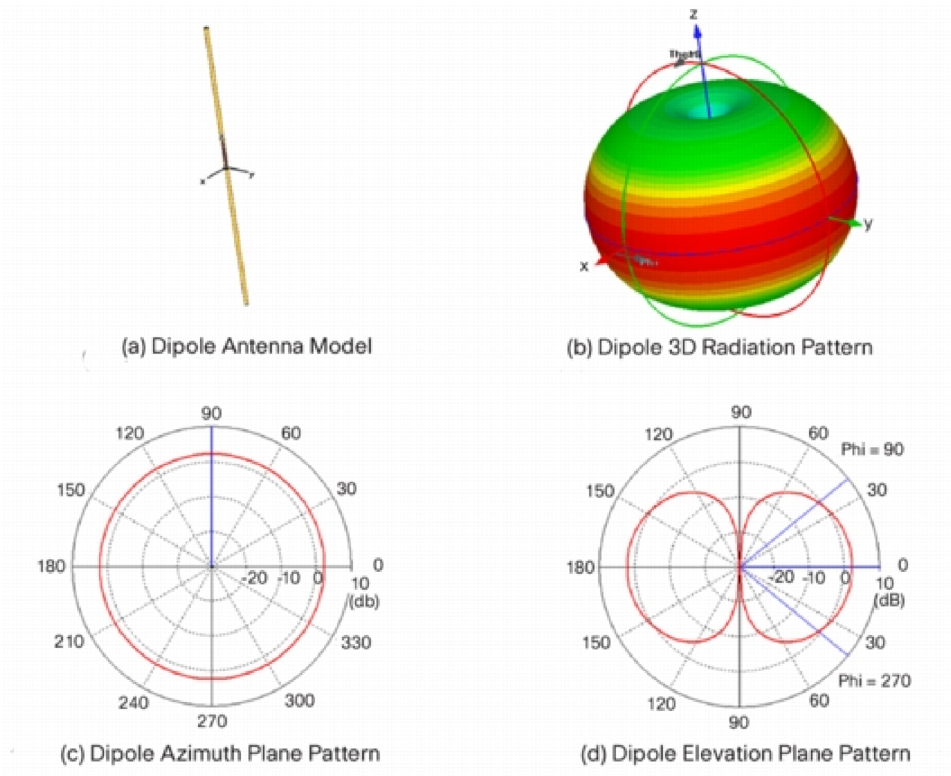


Figure 2.6: Radiation pattern of a dipole antenna. Showing the antenna model (a), the 3D pattern (b) as well as the two principal planes (c and d). Figure reprinted from Cisco (2014).

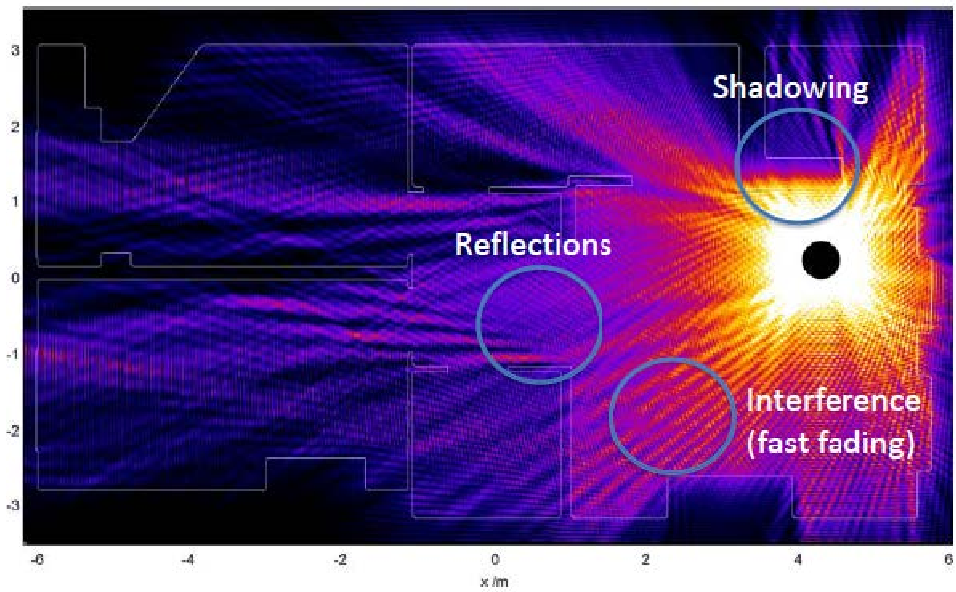


Figure 2.7: Influences on RF signals in indoor environments. Figure reprinted from Callaerts (2016) in Haagmans et al. (2017).

Table 2.3: Absorption rates for different materials (Cook) & King et al. (2006).

Material	Absorption rate
Plasterboard/drywall	3-5 dB
Human body	15 dB
Glass wall and metal frame	6 dB
Metal door	6-10 dB
Window	3 dB
Concrete wall	6-15 dB
Block wall	4-6 dB

known to be reflective for Wi-Fi signals. The multipath issue can be resolved by averaging the RSSI-values over a pre-defined time interval. This kind of influence is called the fast fading term in many literature. Especially time-based positioning methods are sensitive to the effects of multipath, as little variations can cause large offsets in the estimated position.

Absorption Besides multipath reflection, the signal can also be (partly) absorbed by different types of obstacles and their materials. Indoor environments are very dynamic with a lot of moving agents and resources. For example, human bodies, consisting for a large part of water can strongly reduces the strength by absorbing energy. King et al. (2006) reported a decrease of around 15 dBm in reception power as consequence of the blocking effect of the human body. The dampening effects by objects in the propagation path are called shadow fading or slow fading. Table 2.3 shows an overview of some of the most common causes of Wi-Fi signal absorption.

Refraction, diffraction and scattering Obstacles can also cause diffraction when their size is in the same order as the wave length. Diffraction is the phenomenon where waves curve or bend around the obstacles' edges, (e.g. stairs and balconies), causing the waves to change direction. When an obstacle is actually blocking the signal refraction or scattering can occur. Refraction and scattering both cause the signal to change direction, but in different ways. Refraction effects are more predictable and occur when the signal passes through objects of different materials, e.g. glass and then air. Each transition changes the angle of the signal propagation path a certain degree. Scattering happens in multiple unpredictable directions.

The rooms that host the network and the mobile devices may be inside the same room or in different rooms. Signal propagation in the same room allows for easier signal propagation modelling, closer to the free-space model. However, even for open space the walls are reflecting the signal and also absorption and penetration are possible.

When the signal travels to other rooms the signal might travel through unknown material types and objects giving different reflection, absorption and penetration values making the signal propagation much more complex. Therefore, in real-world cases often empirically determined models and parameters are used (Mautz, 2012).

Depolarisation For certain types of waves, e.g. waves that are circularly or elliptically polarised, the polarisation can change upon impact with the surface.

2.4. Wi-Fi-based positioning and localisation methods

Different methods may be used to acquire a user location or position. The following sections will address the theory behind the different methods. Recently Retscher (2017) demonstrated that a combination of multiple positioning methods by using different elements from each method is also possible in order to improve the accuracy of one method.

2.4.1. Cell-based localisation

Cell-based localisation is the most basic way of determining the approximate location of a Wi-Fi device or its owner. This method can be used when the application only requires a very coarse or rough estimation of the user location. This accuracy of this method is limited to the decametre range at best. Cell-based localisation can work based on either network- or mobile-based approaches. For both approaches the signal strength to one or multiple base stations is measured using either a mobile device or the network-side hardware to obtain the signal strength reading, that in turn relates to the distance between the device and the base station(s). Network-side measurements can be obtained through the probe request metadata. For mobile-side measurements various custom applications can be used, but the process requires active participation on the user side and is therefore not passive. In the case of multiple base station within reach, the base station with the highest RSSI-value is assumed to be the users' position. When there is just one base station within reach, that stations' position is estimated as the users' position. As the position refers to the coordinates of the base station in combination with the low accuracy this method is a form of localisation. Figure 2.8 illustrates that the user is in reach of three APs, but the strongest receiving AP will determine the estimated user position.

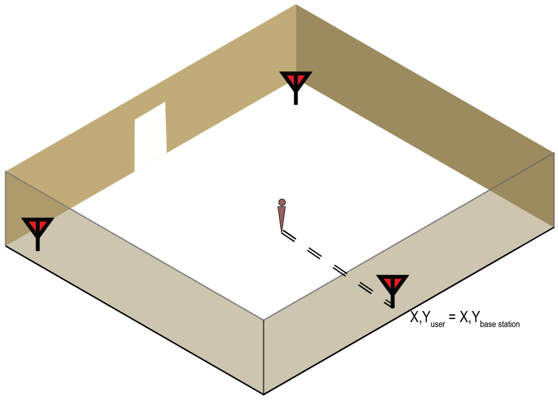


Figure 2.8: Wi-Fi cell-based localisation.

The research of Bot et al. (2016) has shown that when a pure cell-based localisation method is used, the resulting location is not consistent. For example, when estimating the vertical location of a user the most nearby base station to the user might be on a different floor, assuming the user to be on a different floor. Therefore single AP cell-based localisation techniques are unreliable and the possible applications of this method in real-world scenarios are limited for indoor use.

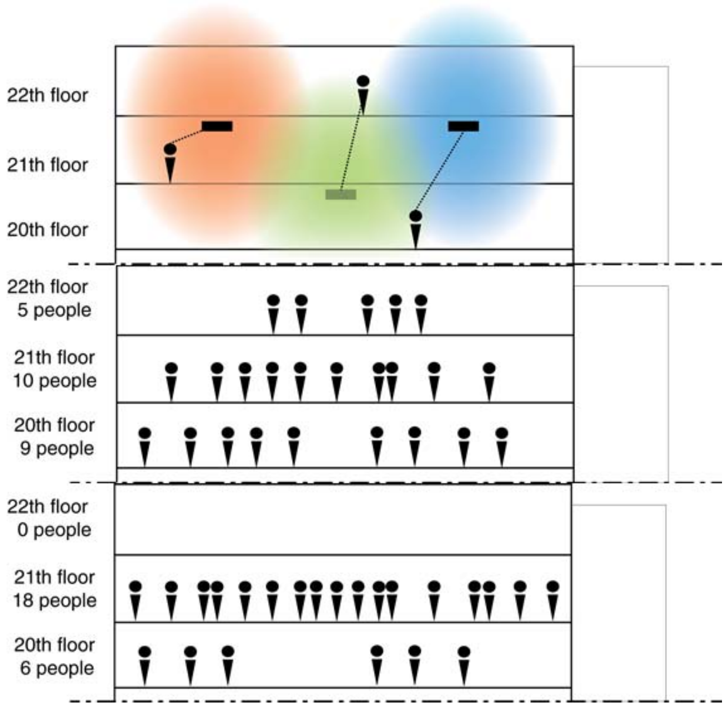


Figure 2.9: Cell-based localisation errors: users assumed to be on a different floor leading to wrong counts. Figure reprinted from Bot et al. (2016)

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2.4.2. Dead reckoning or trajectory estimation

Dead reckoning is a method that is usually used in conjunction with other methods and techniques. It is a way of predicting the next position of a user following a certain path. Various algorithms have been designed to predict user modelling. The Viterbi algorithms is one of the most common methods. The Viterbi algorithm predicts the travelling trajectory of the user (Cypriani et al., 2010) based on historic or simulated data. The advantage of this method is that it can be used in environments where other methods cannot be applied, such as environments where the the infrastructure network is very sparse. As this method does not yield a high accuracy on its own, it is best used in conjunction with other methods or to stimulate pedestrian flows or other large flows where individual errors are cancelled out due to the large population.

2.4.3. Fingerprinting

With the fingerprinting method two types of fingerprinting can be distinguished: analytical fingerprinting and empirical fingerprinting. The differences between the two types will be discussed shortly here.

Analytical fingerprinting

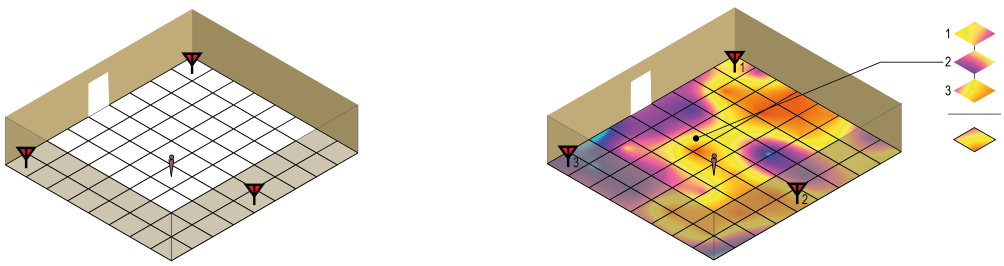
With analytical fingerprinting advanced signal propagation models are used to predict the distance based on a given RSSI measurement. The goal of this method is to minimize the calibration and preparation needed through the use of models. Commonly used signal propagation models are the free-space signal propagation model (2.9). With this model the signal degradation is used to estimated the distance. As the signal propagation is largely depending on the characteristics of specific indoor environments, theoretical models often face the difficult challenge to accurately predict the signal propagation in practise. Derived versions of the free-space path-loss model, that account for the the various effects that influence signal propagation in indoor environments, are also commonly used. Example of these models are the indoor path-loss model (2.3). Other models such as the Multi Wall

Model and various ray-tracing methods were developed in order to develop models better suited for the indoor environment by taking into account the geometry of the environment (Mautz, 2012).

Empirical fingerprinting

Empirical fingerprinting is often used in favour of analytical fingerprinting as it is easier to match empirical training data to live measurements than it is to match a theoretical model to live measurements. Empirical fingerprinting, as opposed to analytical fingerprinting, requires an offline preparation phase in the target environment (building, area, floor) that the system will be deployed in. The first step of the learning or preparation phase consists of subdividing the indoor space in recognisable measuring cells, usually rectangular grid cells for simplicity (figure 2.10a), but irregular-sized cells as large as a full room are sometimes also used. For each of the locations the RSSI values are measured from one or more base stations to the mobile measuring device. The combination of the measurements for each cell together with the coordinates of the cell (x,y,z) form the fingerprints or ground truth. In the operational phase of the system the live measurements are compared to the training database. The calibration measurements are correlated with the live measurements in order to get the best matching fingerprint using a probability distribution (Navarro et al., 2010). The coordinates of that fingerprint are assumed to be the user's position.

Fingerprinting works well in environments where direct line-of-sight with an access point is not always possible (He and Chan, 2016). Accuracies within meters are reported using this method, depending on the density of calibration points and available base stations (Mautz, 2012). A combination of fingerprinting techniques, orientation information and using multiple frequency bands can provide a better result (Jekabsons and Zuravlyovs, 2010). In 2.10 the user is in a room with 3 base stations, each having a distinct signal strength at the user cell at different epochs. The fingerprinting method requires up-to-date radio maps which are usually time consuming and therefore expensive to obtain. Even small changes to the indoor environment might require recalculation of the radio map. Hansen et al. (2010) concluded that static fingerprinting is not capable of localising users within rooms as the radio maps age quickly. Costilla-Reyes and Namuduri (2014) therefore proposes the use of dynamic fingerprints to account for outdated radio maps.



(a) Example room subdivided in a regular grid of measuring cells with 3 base stations.

(b) RSSI measurements from different base stations are taken for each of the cells. The measurements per cell are combined to create a radio map.

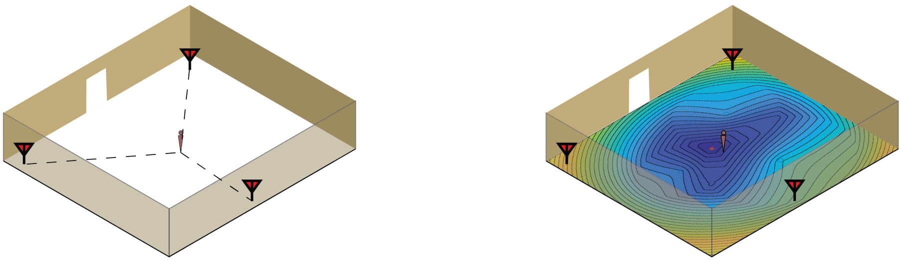
Figure 2.10: Empirical Wi-Fi fingerprinting using a radio map.

2.4.4. Lateration (trilateration/multilateration)

Lateration is a positioning method that uses the distances from a mobile devices to multiple base stations in order to calculate an intersection point. The distance for Wi-Fi lateration can be derived from the RSSI. The RSSI is an indicator of signal strength, based on the amplitude of the incoming signal. The RSSI-value is usually an average of multiple pulses and can be extracted from Wi-Fi management frames. By using a signal propagation model the signal attenuation can be related to the distance between the sender and receiver. Common signal propagation models for lateration are again the free-space path-loss model (equation 2.9) and the indoor adapted indoor path-loss model (equation 2.4).

Trilateration

With trilateration the RSSI to at least three base stations has to be known. Trilateration based on signal strength can give meter accuracy, however environmental factors can severely decrease the accuracy and reliability (Oguejiofor et al., 2013). For localisation by trilateration a trilateration model can be used to estimate a position based on the measurement of the RSSI of a client's probe request, measured by 3 different base stations. This model is based on the intersection radii of spheres whose radius is equal to the distance found using the free-space path-loss or the indoor path-loss equation 2.3 (figure 2.11a). Based on the equation for circles at three different points in 2D Euclidean space, the 2D intersection coordinates can be found by using equation 2.8 (Oguejiofor et al., 2013), where x and y are the client's x and y coordinates and x_a is the x-coordinate of the center of circle a etc. v_a And v_b are given by equation 2.7.



(a) Distance estimation to 3 base stations.

(b) Positioning through optimisation/minimisation of the estimated distances.

Figure 2.11: Lateration multi distance estimation and positioning.

$$\begin{aligned} v_a &= \frac{(d_b^2 - d_a^2) - (x_b^2 - x_c^2) - (y_b^2 - y_c^2)}{2} \\ v_b &= \frac{(d_b^2 - d_a^2) - (x_b^2 - x_a^2) - (y_b^2 - y_a^2)}{2} \end{aligned} \tag{2.7}$$

$$\begin{aligned} y &= \frac{v_b(x_c - x_b) - v_a(x_a - x_b)}{(y_a - y_b)(x_c - x_b) - (y_c - y_b)(x_a - x_b)} \\ x &= \frac{v_a - y(y_c - y_b)}{(x_c - x_b)} \end{aligned} \tag{2.8}$$

Following previous equation 2.8 the last step is to obtain the unknown distance of the client in relation to the scanner. Equation 2.9 can be used to obtain the distance from the RSSI, where A denotes the RSSI at 1 meter distance from the scanner.

$$RSSI = -10n \log_{10}(d) + A \tag{2.9}$$

Rewriting equation 2.9 into equation 2.10 gives the distance, obtained from the measured RSSI.

$$d = 10^{\frac{RSSI - A}{-10n}} \tag{2.10}$$

Multilateration

The term multilateration is used when more than 3 distances are used to calculate a point of intersection. Because multilateration uses a higher number of anchor nodes, the accuracy can be higher than trilateration. When n number of base stations are used the optimisation of the distance residuals can be used in order to find the position. This process is commonly referred to as cost-function minimisation (Seco et al., 2009). A multilateration approach can be based on the Levenberg Marquant algorithm (Dias, 2016). With this algorithm the sum of squared residuals will be minimized, where each residual is the difference between the measured distance (based on RSSI) and the distance to the estimated position. In figure 2.12 the cost-function minimisation is plotted for 3 distances as received by the 3 base stations. The optimum is where the distance residuals are all minimised to give a position as close to the real position as possible.

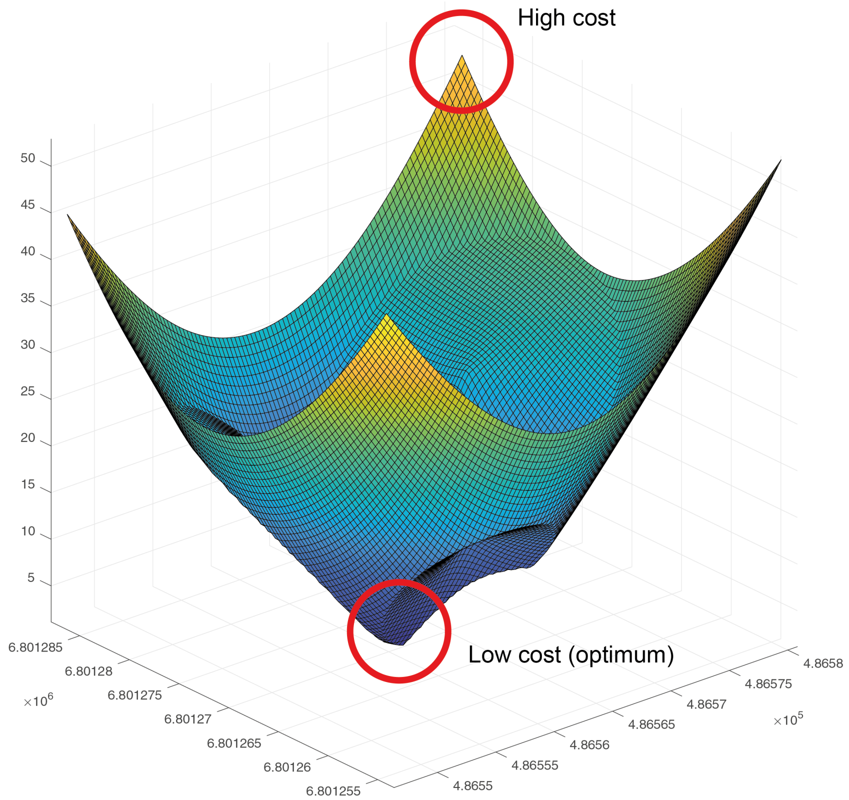


Figure 2.12: Cost-function optimisation of distances measured by three base stations using the Levenberg-Marquardt algorithm.

2.5. Technical performance parameters

The combination of the techniques and methods, the system, can be evaluated based on a set of parameters. An overview of the possible parameters has been presented by Mautz (2012), see figure 2.13.

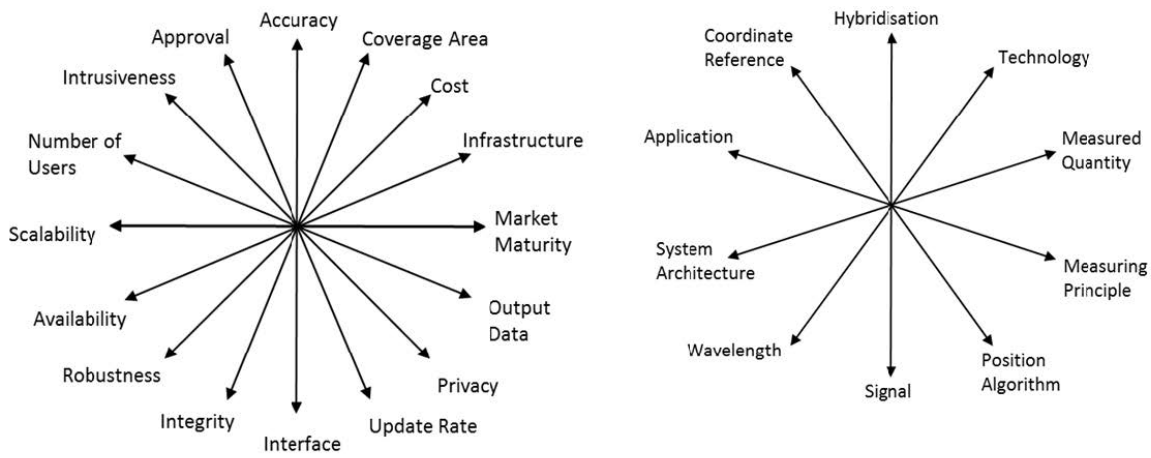


Figure 2.13: User and technical parameters overview (Mautz, 2012).

Accuracy has been defined as the closeness of agreement between a measured quantity value and a true quantity value of a measurand by the Joint Committee for Guides in Metrology (JCGM). The accuracy can be expressed as the distance from the estimated user position to the actual position of the user. Closely related is the precision which refers to the the closeness or spread of the position estimations. A higher precision indicates that the results are more consistent. The coverage area is the area that guarantees positioning capability. Usually the coverage can be extended, i.e. the system is scalable. The cost is always an important factor when comparing different systems and when looking at Wi-Fi network-based positioning is related to the amount of access points and other hardware required, aside from the costs of software. Other important parameters are the number of users, which in the case of network-based positioning is only limited by the available processing power, and the intrusiveness, i.e. the impact on the users (which should be weighted to the gains of using the system). In life-saving use cases such as fire alarm monitoring the availability (is the system working), continuity (does it keep working) as well as the integrity (does the system keep performing within tolerable limits) are also important parameters. Furthermore, the latency to which the information can be communicated to the operators is important in such cases, as well as the processing intervals or update rates.

2.6. Prerequisites and positioning performance improving strategies

Several strategies can be employed to improve positioning performance of an indoor positioning system. As mentioned before, the range can fluctuate if there are objects obstructing the signal. Another problem for indoor localisation can be the adaptive transmit powers of the radios used in Wi-Fi, causing a large RSSI variation.

General prerequisites

Foremost it is important that the base station positions are well-determined. Without a location the data is meaningless. When the scanner location is accurately mapped it will generally improve all aspects of the system that further built upon this location.

Another way to improve the system's quality is by ensuring there is enough signal activity, e.g. by acquiring enough wireless data packets such as probe requests. This is especially important when considering real-time applications such as LBS. The roaming settings of clients can have a big influence on this factor. For navigation purposes the frequency of passive probe requests might not be high enough to be usable. However, for localisation and subsequent monitoring of occupancy rhythms and flow patterns the frequency can be lower.

Adding additional information sources

To improve the indoor monitoring system additional data can be added about the users' digital activities. For example certain types of network traffic can be distinguished (Kotz and Essien, 2005) that can help identify different user groups within the campus. Traffic type can be related to the user through the MAC address of the users' device. The type of network traffic can help in determining whether multiple devices belong to one person.

2.6.1. Differential Wi-Fi

A big influence on the accuracy and precision of indoor Wi-Fi-based positioning systems are the environmental and temporal factors. Influences such as the background signal noise and moving objects affect the positioning capabilities. Even the human body, which largely consists out of water can have a significant damping effects on the signal propagation (Retscher, 2017). Information about the specific environment is thus necessary to adjust the model and to provide reliable results for any RSSI-based method. By implementing dynamic correction parameters provided by a differential reference system the temporal influences can be partly accounted for. A differential system — termed DWi-Fi — using reference stations can be set up and used to continuously adjust and compensate for these temporal and environmental aspects (Retscher and Tatschl, 2016). These kinds of systems are well known in the field of satellite-based positioning, but their use for indoor wireless positioning systems is still a topic of ongoing research.

Retscher (2017) introduced a differential method to increase the positioning accuracy and demonstrated the use of reference stations to predict the signal propagation and to dynamically update the fingerprinting radio map. The positioning however is limited to mobile-based positioning on the device of the user and therefore rendering it unusable for data aggregation and management applications. Also Lassabe et al. (2009) proposes a context-aware system based on reference points and trilateration to mitigate the environmental factors. Figure 2.14 illustrates a set-up where access points and reference stations communicate with each other while monitoring the users. This set-up can be termed a Continuously Operating Reference Station (CORS).

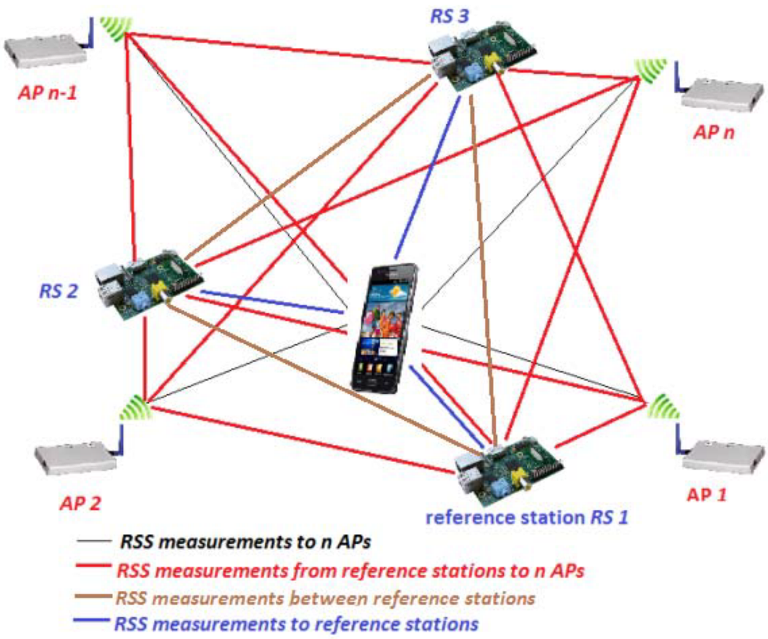


Figure 2.14: Wi-Fi positioning system with reference stations. Figure reprinted from Retscher (2017)

Within this research a differential system will be deployed through a mesh network of Wi-Fi base stations. Each of the reference stations collects signal propagation data from other nearby stations, based on known distances and calculated distances. This data can be further used on the server to aid the positioning capabilities of the system. The differential approach can automatically adjust the propagation model, so that manual intervention or recalibration is not necessary once the system is in place (Chang et al., 2010).

3

Theoretical framework: case study

This chapter focusses on the application of Wi-Fi-based positioning systems in a case study and looks at the requirements that go with some of the various tasks of campus management. Section 3.1 will present insight in the way smart tools are used by campus management and what requirements are placed on these smart tools. Finally the relevant literature for privacy and data protection is discussed (section 3.2).

3.1. Case study

Indoor positioning systems and (wireless) sensor networks have become widely deployed due to the mass production of cheap, reliable and (wireless) connected sensors with the ability to collect environmental data. The Internet of Things (IoT) and smart cities are present examples of these developments. With the evolving technology this also provides new opportunities for deploying such connected sensor networks in different environments and for different applications. Examples of these environments include campus buildings and facilities. The campus management aims to achieve a positive effect (or prevent a negative effect) on the performance of the campus real estate, e.g. in terms of finances or in terms of social goals such as user well-being (Den Heijer and De Jonge, 2012).

Indoor localisation methods are potentially very interesting for campus application. Not so much the position of users is important, but rather their location: how many people are inside a certain room. Since the location can be aggregated from positions, the focus is on delivering the information on an aggregated scale of the room level. Wi-Fi-based systems have seen a lot of interest recently, mainly because the infrastructure is often already (partly) present in the form of Wi-Fi access points (Li et al., 2008). As with other indoor localisation systems the system needs to have a suitable density in order to provide full building coverage. Increasing the density of Wi-Fi access points improves the systems' positioning capability and at the same time can provide a better network to the campus users, so additional deployment will have multiple benefits.

3.1.1. Smart tools in campus management

The terms smart campuses and smart tools are becoming more common within university campus management since universities have started to expand their virtual services. Atif et al. (2015) describes a smart campuses as environments (ambient learning spaces) which consist of physical learning resources augmented with digital and social services. This section will address the data and information demands by the different stakeholders of campus management. With knowledge about the demands certain requirements are then established so that the models of this thesis can be tested in a case study for suitability. Smart tools can help with measuring occupancy and exploitation. In this thesis the following definitions are used for these terms:

- Occupancy: number of persons per room at a specific time and date

- Exploitation: Relative indication for square meters [m^2] per person [n], according to ideal occupation. The ideal is set at 14.5 m^2/n, which is represented by a percentage of 100% (Spek et al., 2016)

Stakeholders in campus management

Corporate Real Estate Management (CREM) applies for a large part for campus management as well and has 4 main stakeholders (figure 3.1a). Asset management and project management focus on the real estate, while general management and facility management focus on the institution. As facility management operates on the operational level this stakeholder benefits from real-time information to steer operational processes. For the strategic level asset management focuses on aligning the supply and demand. In figure 3.1b the stakeholders are translated into perspectives showing their main interests.

To understand the value of smart tools the goals within the different perspectives can be defined. Figure 3.2 shows an overview of the goals for each perspective Den Heijer (2011). According to Valks et al. (2016) tools that support universities to make more efficient use of space are in high demand. On the other side, current tools are often aimed towards supporting the student, e.g. facilitating collaboration with co-students and finding a suitable workspace (Valks et al., 2016).

Valks et al. (2016) defines 4 different levels or resolutions on which smart tools can gather data and information to support campus management.

- frequency: how much the space is used in relation to the availability
- occupancy: the amount of users in a space
- identity: whether the user can be identified based on the data collected
- activity: whether the users' movement patterns can be tracked

Most of the current tools gather information about the occupancy and none of the universities in the study seem to be focussing on individual users or their identity.

3.1.2. Requirements for the Wi-Fi monitoring system

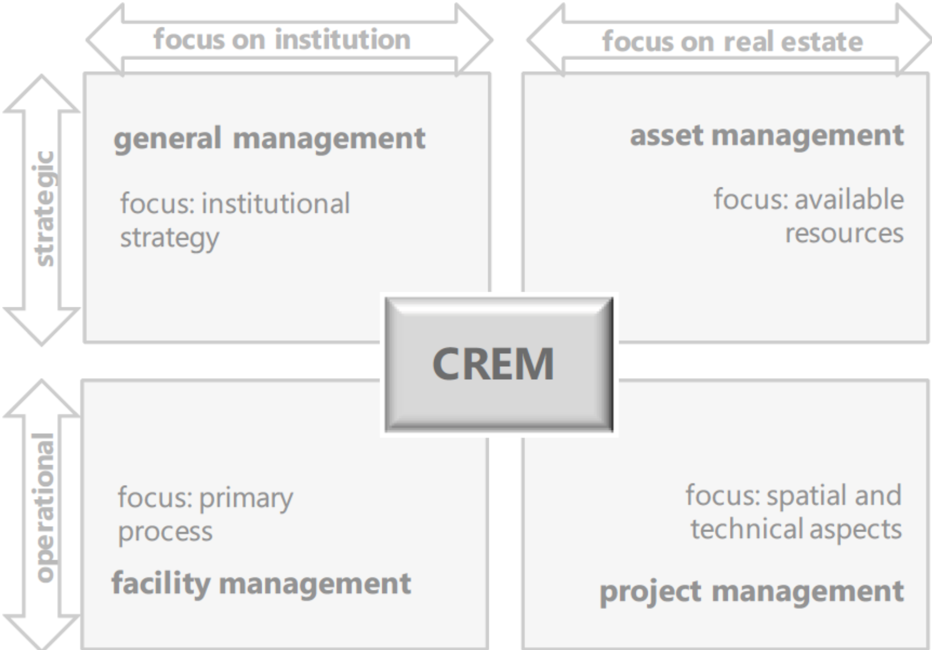
The different stakeholders as identified in the previous paragraph have a wide range of information demands to support various tasks as pointed out in figure 3.2. With the focus on space use (occupancy) a link will be explored between the technical possibilities of Wi-Fi monitoring and the ways how this can support campus management.

Previous research on smart tools in campus management has led to several recommendations and open questions which can be leading requirements for a new prototype. According to Valks et al. (2016) more information is needed on the usage of study spaces; especially the study spaces where occupancy measurements are not possible through desktop logins. Other functionalities that universities are interested in are measuring the user flows throughout and outside the building. The research also shows a demand for a smart tool that can measure occupancy and exploitation in real-time.

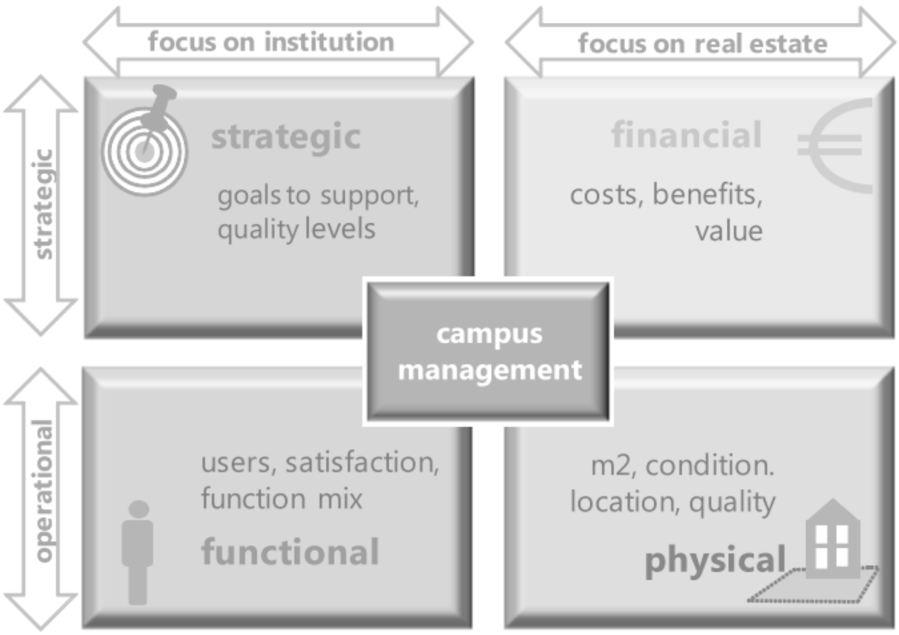
Based on the goals and recommendations of previous research on smart data tools the most important requirements for this research to consider are:

- resolution
- coverage, the amount of space that can be monitored
- cost
- integration, the ability to integrate the smart tool and its components with current real estate
- availability and robustness
- privacy and data protection
- latency and accuracy

Figure 3.1: Stakeholders and perspectives



(a) Stakeholders in CREM. Figure reprinted from De Jonge (1997) in Den Heijer (2011, p. 106)



(b) Perspectives in campus management, derived from CREM. Figure reprinted from Den Heijer (2011, p. 108)

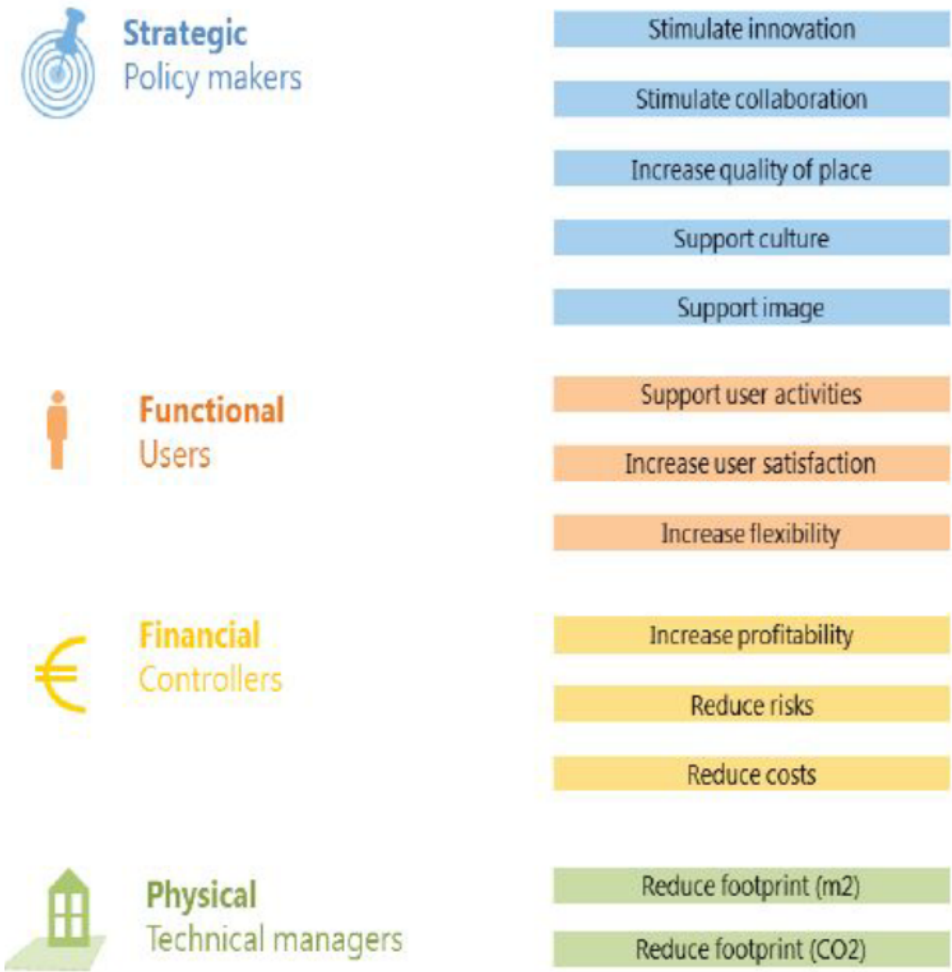


Figure 3.2: Goals within each of the campus management perspectives Den Heijer (2011)

For the information to be used in the decision-making process it needs to be communicated to the user, possibly in a dashboard or application. Figure 3.3 shows that information is required in the decision-making process to solve certain problems. To find out what information is required some sample applications are given.

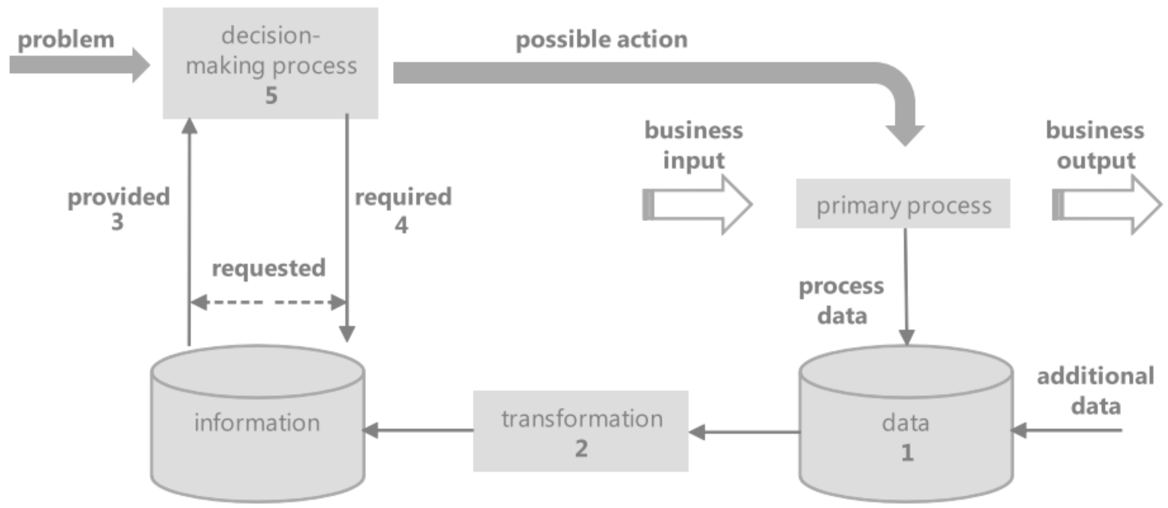


Figure 3.3: Information and decision making. Figure reprinted from Den Heijer (2011)

Real-time occupancy and exploitation measurements

Real-time occupancy and exploitation measurements are on the top of the wish-list for most universities. This information can be useful to decrease the footprint and thereby the cost of real-estate. Insight is needed on the amounts of people making use of the different rooms.

Table 3.1: Requirements for real-time occupancy and exploitation measurements.

Criteria	Criteria Description	Requirement
horizontal accuracy	need for specific room determination	room detection
vertical accuracy	need for determination of a specific floor in a building	floor detection
privacy	maintenance of the user privacy	in accordance with GDPR
latency delay	delay with which position are available to the management	none
availability	the amount of time the information can be accessed	during office hours

Increase flexibility and supporting user activity

The performance of real-estate can also be improved by guiding the user towards a suitable room for working or studying. Such applications generally require the same information, in real-time without delay. Flexibility can be improved by adding a multi-functional character to the space and can be measured be the types of users visiting the room.

Table 3.2: Requirements for information to increase flexibility and support user activity

Criteria	Criteria Description	Requirement
horizontal accuracy	need for specific room determination	meter
vertical accuracy	need for determination of a specific floor in a building	floor detection
privacy	maintenance of the user privacy	based on software agreement
latency delay	delay with which position is available to the user	none

Measure user flows within and outside the building

Campus managers would also like insight in the movement patterns of users within and outside the building.

Table 3.3: Requirements for information to gain insight in movement patterns (indoor/outdoor)

Criteria	Criteria Description	Requirement
horizontal accuracy	need for specific room determination	room/area detection
vertical accuracy	need for determination of a specific floor in a building	floor detection
privacy	maintenance of the user privacy	in accordance with GDPR
latency delay	delay with which position is available to the management	post occupancy analysis

3.1.3. Examples of current systems based on Wi-Fi monitoring

During a research on smart campus tools 26 different tools have been identified Valks et al. (2016). Currently there is only one Wi-Fi-based smart tool used within Dutch university campuses, made by Lone Rooftop.

Lone Rooftop

Lone Rooftop is an application aimed at campus management. It can provide real-time occupancy information for all rooms that are equipped with Wi-Fi access points. The monitoring system makes use of existing Wi-Fi infrastructures and does not introduce any special hardware itself. Not all Wi-Fi infrastructures can be used with the Lone Rooftop system however: a special interface is required in the form of a licensed computer made by Cisco. The positioning method relies on trilateration of Wi-Fi RSSI-values. Additional elements such as Bluetooth beacons and door tags can be added to the system. However, due to the heterogeneous nature of the indoor environment the accuracy could be further improved by using a differential augmented system to compensate for the environmental factors. Figure 3.4 shows an overview of the occupancy dashboard.

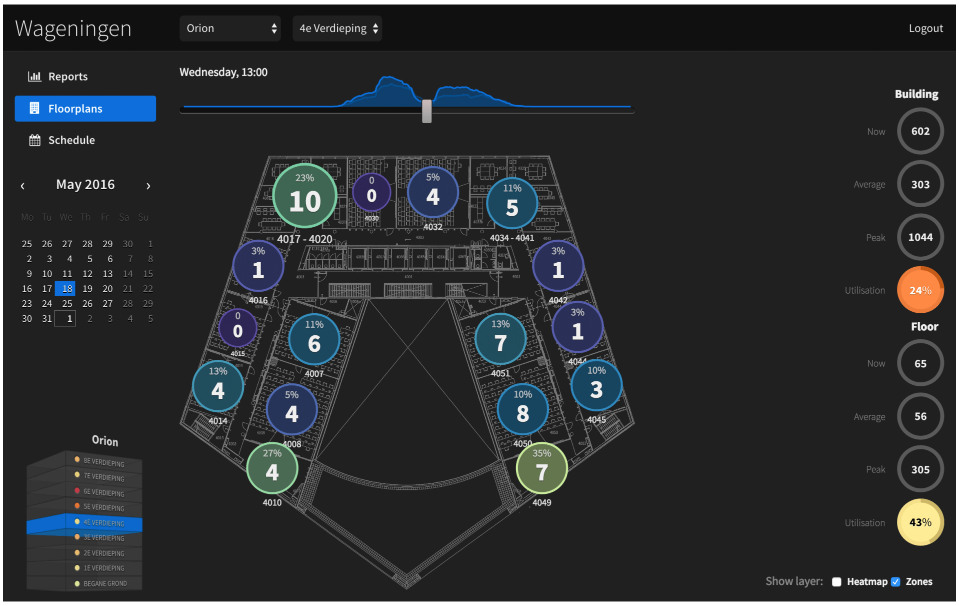


Figure 3.4: Lone Rooftop PIE

3.2. Privacy and data protection

The Netherlands, as a European Union (EU) member state has to conform to guidelines or directives regarding privacy and data protection. In 1995 the EU adopted the Data Protection Directive or officially:

"Directive 95/46/EC on the protection of individuals with regard to the processing of personal data and on the free movement of such data" Parliament (1995). The directive incorporates seven main principles:

1. Notice: data subjects should be given notice when their data is being collected
2. Purpose: data should only be used for the purpose stated and not for any other purposes
3. Consent: data should not be disclosed without the data subject's consent
4. Security: collected data should be kept secure from any potential abuses
5. Disclosure: data subjects should be informed as to who is collecting their data
6. Access: data subjects should be allowed to access their data and make corrections to any inaccurate data
7. Accountability: data subjects should have a method available to them to hold data collectors accountable for not following the above principles.

The definition of the personal data in question is broad: "Personal data is defined as "any information relating to an identified or identifiable natural person ("data subject"); an identifiable person is one who can be identified, directly or indirectly, in particular by reference to an identification number or to one or more factors specific to his physical, physiological, mental, economic, cultural or social identity;" (Parliament, 1995, article 2 a). In 2011 a study has been done to what extent the data obtained through Wi-Fi tracking is actually personal data. It was concluded that the MAC address-address is considered to be personal data because it is a unique number that can be used to identify a natural person (Kranenborg and Verhey, 2011). According to this study even the (dynamic or temporary) IP-address is considered to be personal data.

The directive also states that the articles apply for both manual and automatic data acquisition and processing. Furthermore the controller, or the person controlling the data process should state their identity (personal or company name), purpose for data collection and the destination of all data, including any other information that is assumed to be necessary for a fair understanding of the data processing. Lastly, any data that is gathered for one purpose (e.g. research) may not be used for any other purposes (e.g. advertising). For non-sensitive data (such as information about health) these are the most important rules.

Each member state is obliged to set up a supervisory body to maintain conformity with the directive. For the Netherlands, and thereby the area of study, this is the authority of personal data. Through this authority the directive is transposed in the internal Law for the Protection of Personal Information (LPPI) (Autoriteit Persoonsgegevens, 2000). This implementation is not significantly different from the European directive. Some articles however are relevant for researchers. Article 8.f states that personal data can only be collected if it serves a justified interest. Article 30 (Scientific Research and Statistics) of the LPPI then continues with some exclusions from the LPPI law under certain conditions. Researchers do not have to report the data collection to the functionary of the LPPI. The data also has to be used exclusively for scientific purposes (article 30.2) and the data can have a maximum retention time of 6 months (article 30.5). So the data can be collected for this research as long as the users are notified of the identity of the controller, the purpose and as long as their data stays safe.

From May 2018 a new regulation, the General Data Protection Regulation (GDPR), will be enforced on a European level European Parliament (2016). The law is currently in a two year transition period and is not enforced until May 2018. As this research is conducted before that date the old law still applies.

4
Research design

This chapter will provide an overview of the methodology and approaches used in this thesis. Section 4.1 then continues to describe the design of the conceptual framework. Within the conceptual framework the schematic concepts and workflows developed for this research are discussed.

During the research the main research questions is answered through a series of sub questions. The technical sub questions are answered through experiments with the prototype in a case study, while other research questions are answered directly through the theoretical framework. Figure 4.1 shows an overview of the methodology used in this thesis. The theoretical framework together with the research questions are used in the conceptual phase to set up a conceptual framework and to define requirements for the prototypical system. The theoretical framework is also used to answer sub-question 1 (see 1.6.1).

Various types of hardware and data sources were available during the writing of this thesis. Therefore, an iterative process was used to select the most opportune type of hardware and data source in a case study. The intermediate outcomes determine and further shape the requirements for the final prototype and results. The build process of the final prototype was again cyclical where various approaches were weighted and where the results were refined after each iteration until a minimum viable product was reached (questions 2, 3 and 6).

The final results were acquired in a real-world case study environment, the applied environment of smart tools and campus management. These results were used to answer questions 4 and 5.

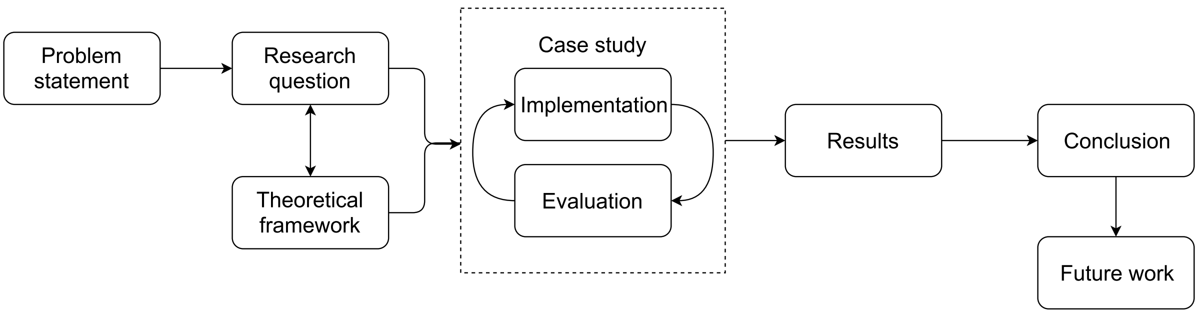


Figure 4.1: Research methodology

4.1. Conceptual framework

As this research is mainly based on Wi-Fi tracking data, obtained from scanning environments with Wi-Fi-enabled devices, an important part of the research consists of data acquisition. Different scanner devices are used during the research to test their tracking performance and quality (the level of deviation from the real-world environment).

Within the research there is an order of steps that was undertaken:

1. Data collection with Wi-Fi scanners (with an area defined through a case study)
2. Real-time and post-processing of raw data
3. Analysis of occupancy rhythms and movement patterns
4. Validation of the measured data including calibration of the system
5. Visualisation and presentation

As the research starts from data acquisition and goes all the way up till data visualisation, the process follows the Geomatics way of working as depicted in figure 4.2 (Lemmens, 1991).

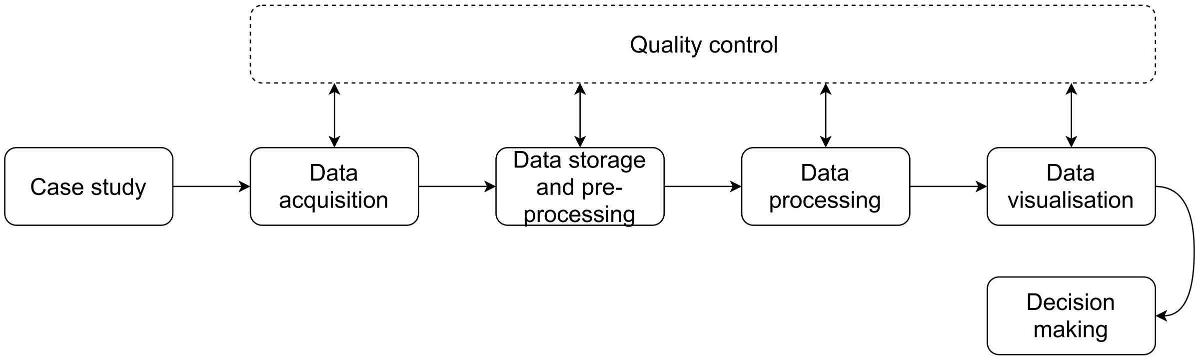


Figure 4.2: The Geomatics process. Figure adapted from Lemmens (1991)

4.1.1. System overview

To conceptualise the data flow the different steps are matched to hardware and data processing steps in a system overview. Figure 4.3 shows an overview of the system used in this research and shows how each step (data acquisition, data storage, data processing and data visualisation) relates to the system.

The used hardware in this research ranges from commercial networking equipment to low-cost custom-built equipment that is easy to install. The choice for different types of hardware is based on the different capabilities and limitations of the hardware.

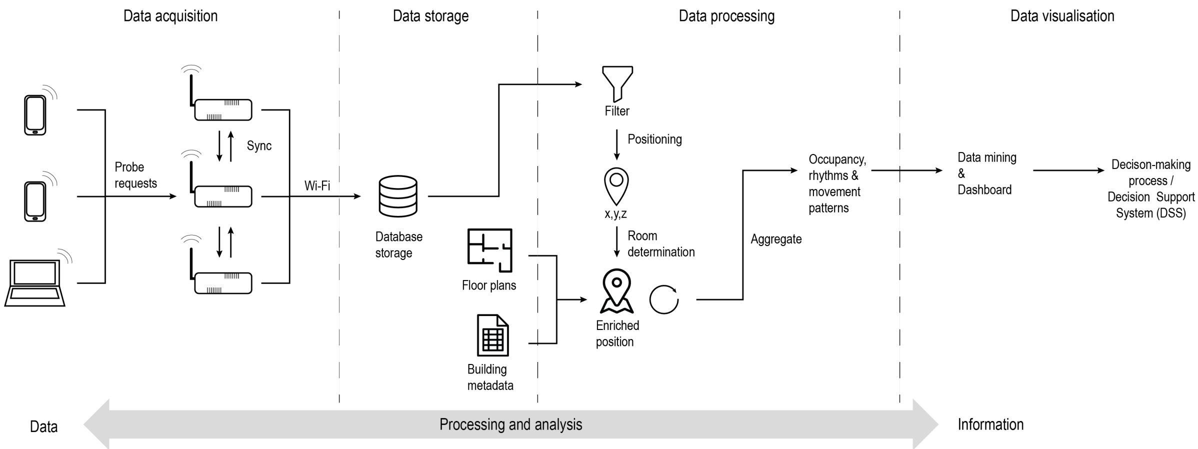


Figure 4.3: System overview of the WPS.

4.2. Methodology

4.2.1. Data acquisition

Data can be acquired in a number of different ways. The different methods will be discussed shortly here. In the implementation chapter the chosen hardware is implemented in the process.

Existing Wi-Fi infrastructure

Covering the whole indoor TU Delft campus a Wi-Fi network infrastructure is already present. This network consists of Cisco Aironet access points (see figure 4.4), with integrated or external antennas.

Figure 4.4: Existing Wi-Fi infrastructure APs

The software of these wireless APs is configured to save records of all connected wireless devices. The records only exist for devices that are connected, which means users without wireless devices are not included. The following information is provided with the records Bot et al. (2016):

- Timestamp: the timestamp a specific record is associated with. It is the starting time of a session and contains a date of format yyyy-mm-dd and a time of format hh:mm:ss.
- Username: the hashed organisation-defined user ID
- MAC address: the hashed (anonymised) MAC address Address or unique identifier of the device on the network. The hashing process converts each username and MAC address-address in a hashed string. For each given username the hash will always yield the same results, therefore the hashing does not provide protection against tracking as soon as the hashed username is linked to a certain individual through analysis.
- Access point name: a TU Delft specific name for the AP in question of the following format: A-X-Y-ZZZ, where X stands for building number, Y stands for floor or wing in select faculties and Z stands for a specific AP number
- Map location: A description of the AP location with building number, building name and floor, which may be as specific as “ground floor+” or as unspecific as “2nd, 3rd and 4th floor”. Many of these descriptions contain spelling mistakes and discrepancies
- Session duration: the duration of the recorded session, on a time interval of around five minutes
- Signal-to-noise ratio: Signal to noise ratio as a measure of signal quality emitted from the AP
- RSSI: an indicator for signal strength
- Import file name: a specification to which file added the data on which data

The advantage of using these access points are that it is not necessary to invest in new hardware and the fact that the network is already widespread available. The system is however limited in that it cannot record visitors or users that are connected over a LAN. Other limitations include the data accessibility and temporal granularity.

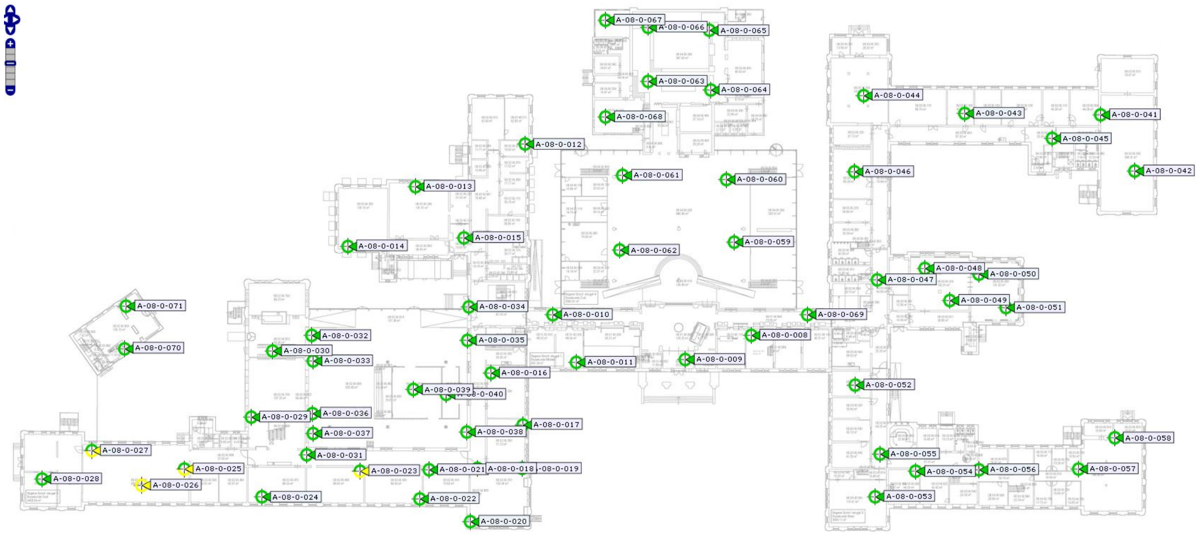


Figure 4.5: Distribution of existing Wi-Fi access points

Libelium Meshlium scanners

Meshlium devices from Libelium (see figure 4.6) are built for deployment in public environments and they can be used to capture probe requests from Wi-Fi-enabled devices in range. Besides Wi-Fi the Meshlium scanners also include a Bluetooth radio that supports monitoring. The device operates on the 2.4 GHz frequency range. The scanner is equipped with an internal memory of 8 Gb, but also comes with a network connection for database synchronisation. The Meshlium scanners are able to record visitors, but users that are using a LAN connection are not recorded with this device as the device only records wireless activity.

The biggest limitation of these scanners is the limited amount of records that can be synchronised concurrently with the database (maximum of 100 per batch). The limit of 100 records means that in practise a latency is introduced in crowded areas, and in the worst case data loss. For real-time applications the synchronisation interval of several minutes is also relatively high. Other drawbacks of the Meshlium scanners are frequent overheating of the processing and unstable internal clocks that could cause problems with the timestamps. Finally the high cost is another major limiting factor.

Figure 4.6: Libelium Meshlium Wi-Fi and Bluetooth scanner

Custom-built Wi-Fi scanners

To be able to create a dense network of Wi-Fi scanners that does not have before mentioned limitations a cheaper solution can be found in custom-made scanners. These scanners are created using a combination of microcomputers and low-cost network equipment. The advantages are the low cost of the hardware, the full control and open source software and ease of modification to fit a certain use case.

The following requirements are set for implementing the scanner station:

- Portable
- Wireless network connection
- Low-power and low network obtrusion
- High detection rate of user devices
- Ability to synchronise with a mesh network of similar scanners
- Low-cost, 50-100 euro

4.2.2. Data storage and pre-processing

Addressing privacy and data protection

According to 3.2 the MAC address can be considered personal data. Therefore precautions are taken to ensure user privacy. Before the data collections started users were informed of the data collection, the identity of the data collector and the purpose of the data collection. An opt-out possibility is not given as this would require the collection and storage of personal data, defeating the purpose of protecting user privacy.

The personal data is encrypted before storing. The Secure Hash Algorithm (SHA)-family is used to encrypt the data in a non-reversible process. Data access is also limited to a select group of researchers.

4.2.3. Data processing

The overall data processing workflow is depicted by figure 4.7. Elements in green represent stored data. Elements in blue represent intermediary volatile datasets that are used inside processes, but are not physically stored on disk.

The process starts by data filtering to produce clean input data which in turn is used to estimate distances. The distances are estimated with the aid of differential correction parameters. In subsequent steps the vertical location is determined and only the relevant data for that elevation will be used as input for the horizontal position estimation. The user positions are stored to be used as input for occupancy and exploitation rates. Positions from individual users are also tied together to form movement patterns.

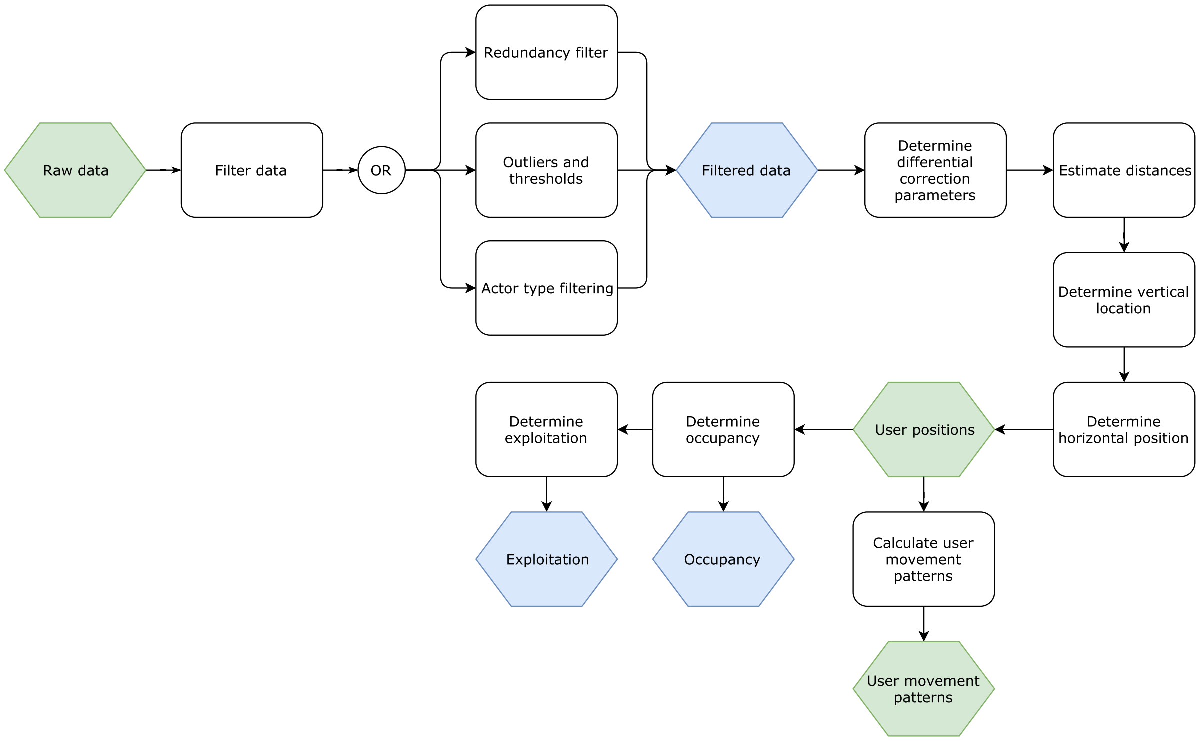


Figure 4.7: Data processing flowchart

Data filtering

The data filtering is a crucial process as there are several cases where unwanted data can be captured. On top of that probe requests captured usually consist of group of redundant measurements so that a selection can be made from a burst of packets. On a high level three different types of filtering will be applied: redundancy filtering, outlier and threshold filtering and user type filtering. The user type filtering can be further split in three different sub cases.

1. Redundancy filter
2. Outliers and thresholds
3. Actor type filtering:
   (a) Static devices
   (b) Anonimised traffic
   (c) One-hit traffic

Redundancy filter

All probe requests are stored at first. Then 10-60 second windows can be created in which the measurements can be grouped per scanner on the highest RSSI-value. The purpose of grouping is two-fold: first and foremost the grouping discards the measurements suffering from fading by picking only the strongest measurements. The second concept behind this type of filtering lies in the data capturing process. Wi-Fi devices are very likely to switch channels during operation (e.g. during roaming). The scanners account for this by also switching in short intervals, however this process can never be synchronous with all possible client devices as the areas are not clearly subdivided per channel. When the scanner is out of sync, i.e. on another channel, it is almost certain that the packet will be lost (otherwise the device would not be fully Wi-Fi-compliant).

Outliers and thresholds

For each interval window the highest RSSI values are used as these are less affected by the effects of multipath and fading. Outliers that may be caused by erroneous readings are also discarded. Furthermore a lower and upper threshold are set. The threshold values can be changed dynamically in order to support a lower density of scanners at the cost of a lower accuracy.

Actor type filtering

Static devices The observations are a measure for the amount of devices in the area. It is not a direct representation of the amount of users inside the room. Therefore training data is collected to help filter out devices that are static, i.e. they are part of the environment (printers), they are not carried by users (laptops) or the devices show activity outside opening hours.

Anonimised traffic Privacy protection features are limiting the tracking possibilities of users through their devices. To avoid overestimating the amount of users a so-called purge time is set for anonymous devices. After the purge time the device is not considered to be in the area any longer. The purge time is set empirically and is based on the average amount of probe requests sent during a certain period of time. A higher number of probe requests leads to a higher number of device positions and therefore will typically result in a lower purge time. Devices connected to networks behave differently and do not randomise the MAC address during network sessions.

One-hit traffic For occupancy the amount of users that actually use a room is leading. Therefore the devices that might accidentally be registered during passing by movement patterns are not interesting for occupancy rates, however these devices are still important to understand the whole of movement patterns.

Table 4.1: Filtering input and output

Input	Output
Observations	Observations fit for positioning

Differential correction parameters

The reference stations are deployed in a network consisting of at least 3 scanner nodes. Within these networks the scanner nodes emit beacon packets, similar to the probe requests of client devices. The beacon frames act as a counterpart of the probe requests and are usually used to advertise wireless network availability. In this case the measurements of such signals at other scanner nodes than the sender are used to construct differential correction parameters. The beacon interval is set to around 104 milliseconds and thus generates a way of quickly and continuously adapting the network for dynamic changes that may occur on the network, e.g. signal noise or large moving objects.

Figure 4.8 schematises the process of adjusting distances through the use of differential correction parameters. In the figure the nodes are numbered 1 to 3. Between all the scanner nodes beacon packets are mutually send and received. As the sending is a single-directional the problem of optimalisation is reduced to single node adjustments.

In this example scanner node 1 observes the calculated distance between itself and node 2 and 3. Node 2 is apparently observed as 7 meters away from node 1 (according to node 1). The distance is estimated 3 meters short. For node 3 the distance is estimated 1 meter short. The reverse (from 2 to 1) is not necessarily the same as the antennas only capture what is sent by the sending station.

The final output of this step are the correction parameters that are used in conjunction with the signal propagation model to estimate the straight-line distances between the scanner node and the client device.

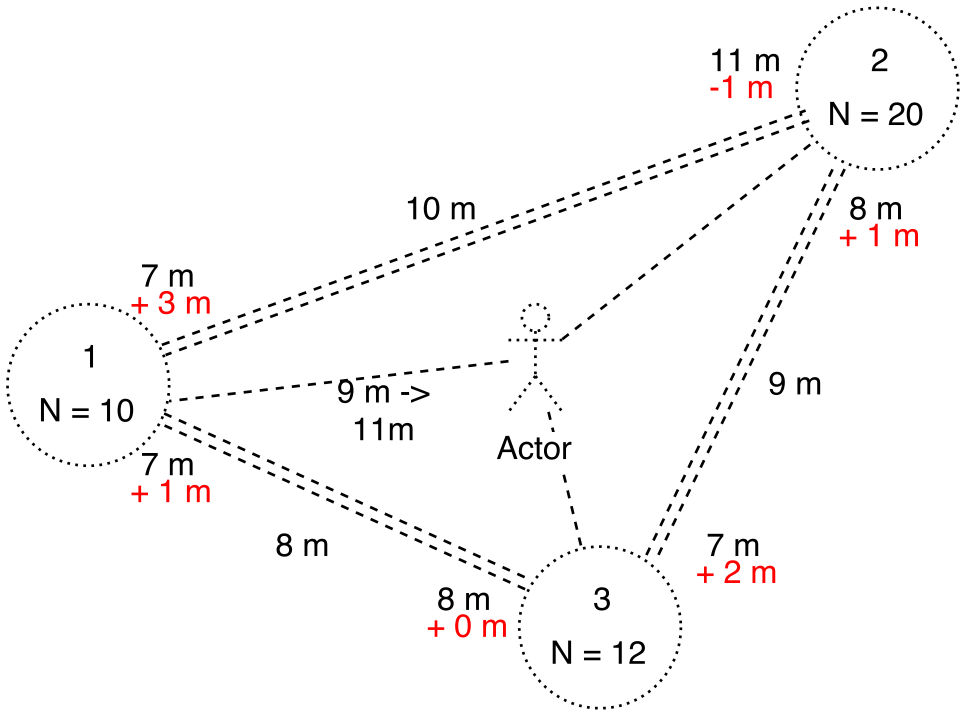


Figure 4.8: Beacon frames between differential reference stations in order to calculate correction parameters.

Table 4.2: Differential correction process input and output

Input	Output
Beacon observations	Correction parameter N (e.g. 5)

Estimating distances

The next step in calculating the user positions is to use the input of the previous step in conjunction with the signal propagation model to estimate the straight-line distance. By applying the differential correction parameters the distances are less likely to deviate from the ground truth. The estimated distance difference between correction parameters can vary from decimeters to meters. Figure 4.9 shows a plot of three parameters and their effect on the distance estimation.

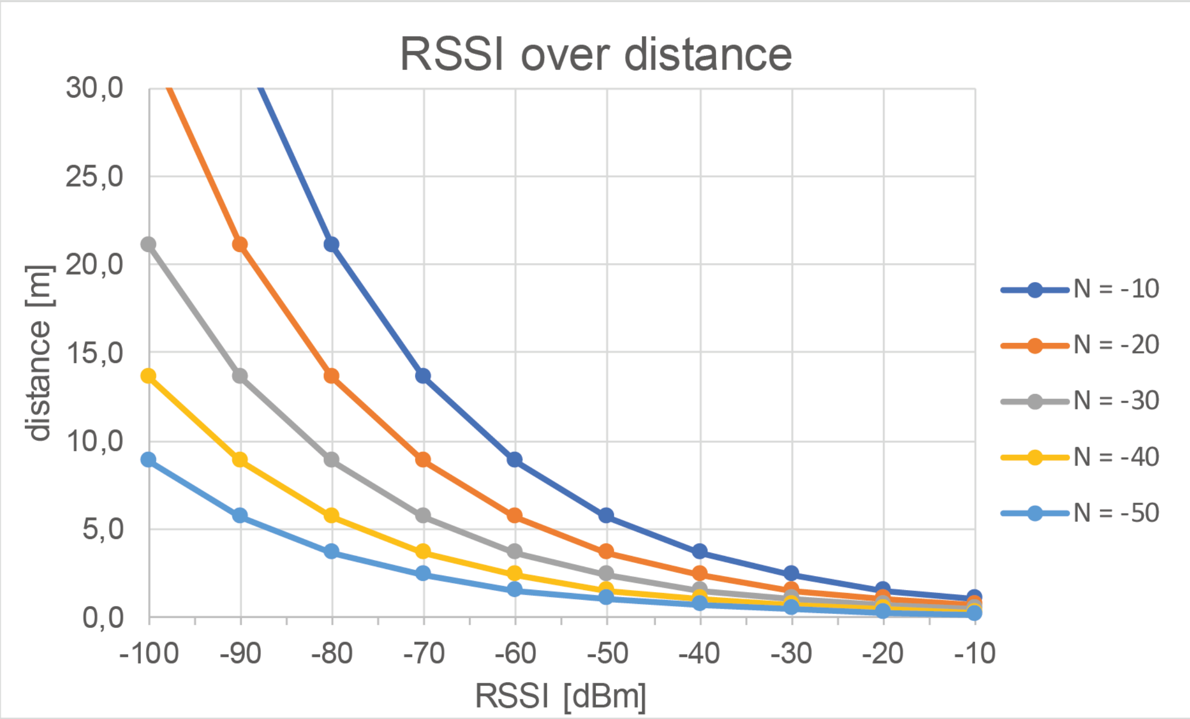


Figure 4.9: RSSI over distance using three different correction parameters

Table 4.3: Distance estimation process input and output

Input	Output
RSSI-measurements, Differential correction parameter	Distance in meters

Determining the floor level

During this step the vertical position of the user is estimated. Multiple approaches can be taken at this point. One option would be to create a multilateration algorithm that outputs 3D coordinates. The benefits of this approach are that the position will be calculated in an absolute way. To be able to acquire the z-coordinate of a user, at least 4 input values (range measurements) are needed, as opposed to 3 for in-plane multilateration. Moreover, because a building is usually vertically separated into distinct floors, and users can only be on the floors, a relative approach makes more sense in this case.

During initial experiments in the test building with two different types of popular smartphones the measurements as shown in figure 4.10 were found. Repeated experiments showed similar results.

The elevation of the user can be estimated by combining results from multiple rooms. The statistics show the average, minimum and maximum values of the probe requests sent from room '1.2' and captured by scanners in all six rooms. By combining the average values of multiple observations and grouping them per the floor where they were captured a total average per floor can be calculated. For device #1 the average on floor 1 is -49.7 and -58 for floor 2. The likelihood for the user to be on floor 1 is thereby greater as the distances are shorter.

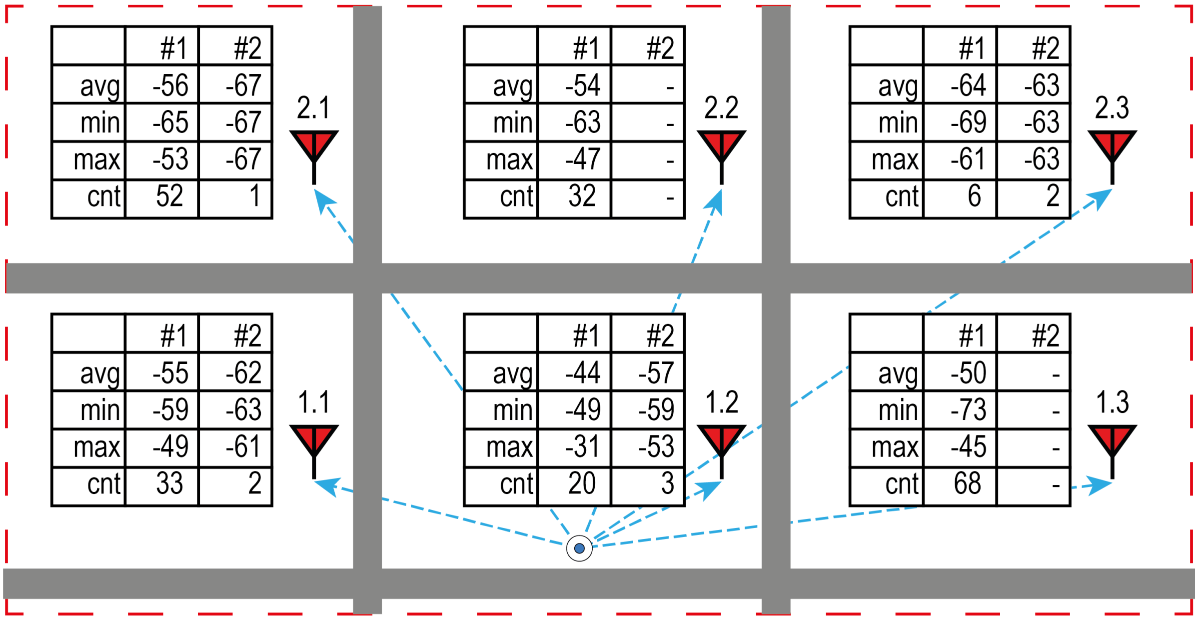


Figure 4.10: Signal strength statistics as recorded from different positions. Device #1: Android 7.1 smartphone, device #2 iOS 10 smartphone. Signal strength as measured from lower central room, values in dBm.

Table 4.4 shows the input and output of this step.

Table 4.4: Vertical position input and output

Input	Output
Observations	Floor level (e.g. 0 or 1)

Determining the horizontal position

During this step the horizontal position of the user is estimated. Table 4.5 shows the input taken and output produced during this step. To obtain the position of a user a multilateration algorithm is applied to each matched set of observations (observations belonging to one device, at different base stations). The observations are filtered based on the floor of the user, i.e. a user cannot be on multiple floors within the same time frame.

At least 3 observations are first converted to distances (D_1, D_2 and D_3) through the use of a signal propagation model. Next the multilateration is performed for each set using the distances. The position coordinate is found by minimising the quadratic distances from each circle to the possible position (R_1, R_2 and R_3), see figure 4.11. The coordinates of the scanners (AP_1, AP_2 and AP_3) form a minimum bounding rectangle. In order to be able to position users also outside of this rectangle the limits of the rectangle can be enlarged with a distance AD, the allowed distance in which the users can be positioned.

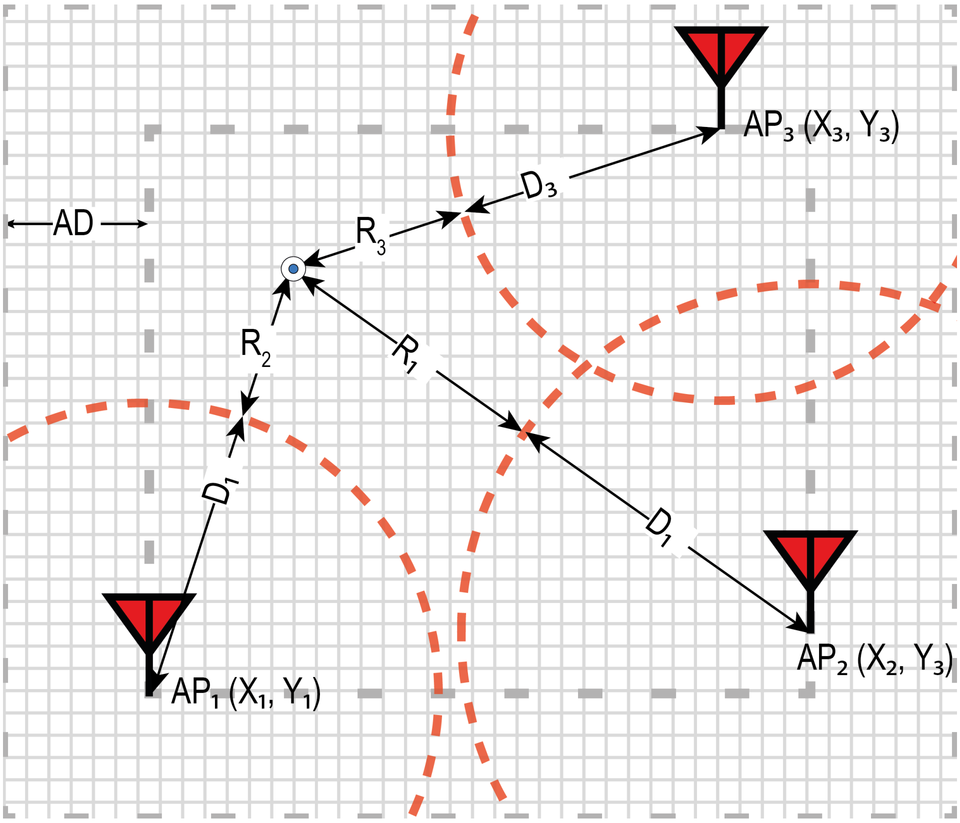


Figure 4.11: Trilateration optimalisation of distances

Figure 4.12 and 4.13 illustrate how the corrected distances lead to a more accurate position in the multilateration process.

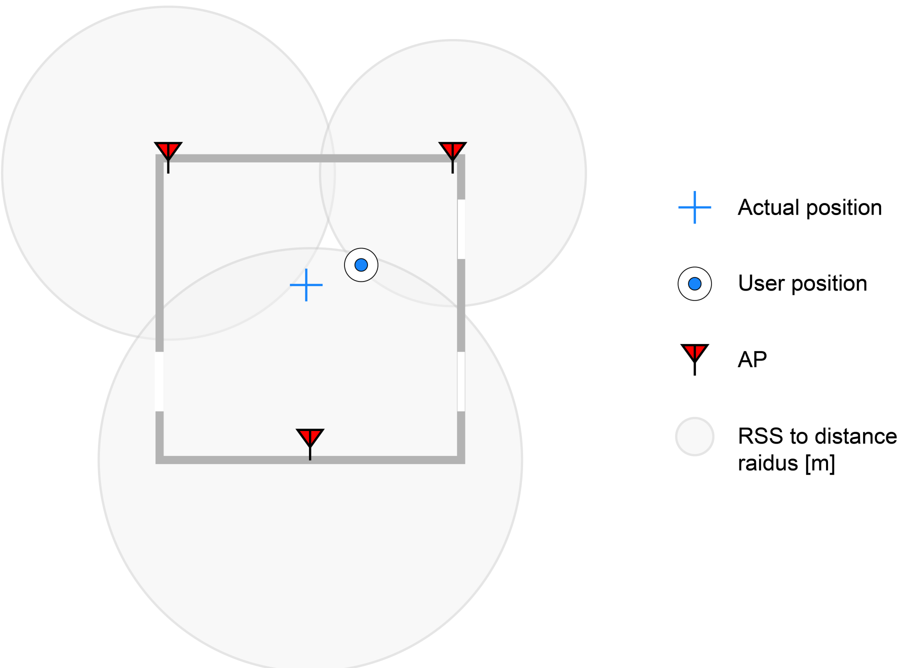


Figure 4.12: Trilateration with differential measurement corrections applied

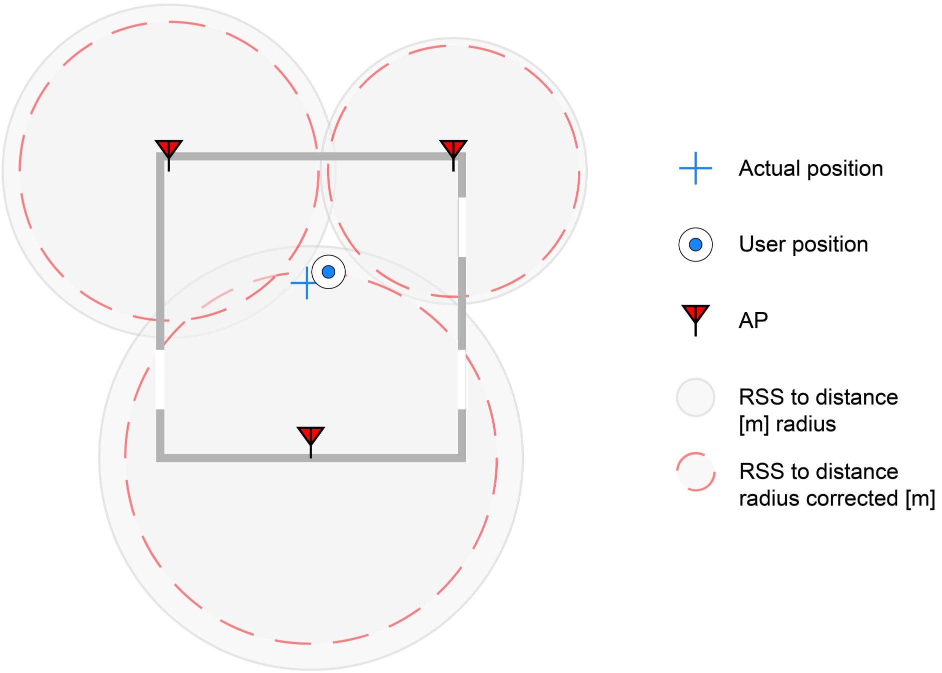


Figure 4.13: Trilateration without differential measurement corrections applied

Table 4.5: Horizontal position input and output

Input	Output
Observations	Position on a specific coordinate reference system (e.g. (X, Y))

Calculating occupancy

The stored position results can be further processed together with vector polygon features stored in the database in order to obtain the occupancy per area as pre-defined by the campus management. Figure 4.14 shows a closed valid polygon containing 5 points (duplicated start and end) which in a given timeframe yields the occupancy in combination with the spatial point in polygon function.

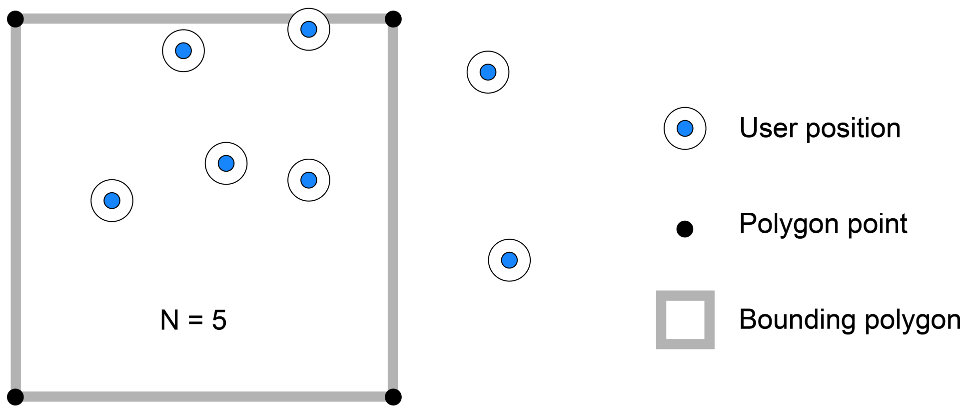


Figure 4.14: Calculating occupancy

Table 4.6: Occupancy input and output

Input	Output
Positions	Occupancy per location (e.g. 'room A: 10')

Calculating exploitation

From the occupancy results the exploitation can be obtained as by-product by using an additional table containing the same pre-defined areas (rooms) and their capacity in terms of number of persons, usually work places and the floor area of the rooms.

For example if a room can provide work places for 10 users at 50 m^2, and 5 users are inside the room, the exploitation is said to be 10 m^2 per user.

Estimating user movement patterns

Movement patterns are created with the results of the horizontal positions and vertical elevation data. The positions are sorted in order of ascending time before creating linestrings to form user movement patterns.

4.2.4. Data visualisation

Real-time data

The main output of previous steps are the positions of users and their aggregates: occupancy, exploitation and movement patterns. Positions require a spatial representation to better understand the data, while for the aggregates graphs are used.

The data is processed automatically so that real-time visualisation is possible without manual intervention by the user.

4.2.5. Data validation

In order to determine to what extent the prototype generates data that replicates the real-world, validation will be done with additional hardware.

Bluetooth bracelets

An additional network of Bluetooth scanners will be used in conjuction with Bluetooth-enabled bracelets. The bracelets emit a high frequency of beacon frames that can be captured by the Bluetooth scanners at different places on the test location. Figure 4.15 shows the bracelet that can be worn by users to track them between different endpoints.

Figure 4.15: Bluetooth-enabled bracelet as used for data validation during uncontrolled testing.

4.2.6. Case study: Faculty of Architecture

The case study to test the prototype is the Faculty of Architecture. Within the faculty the west wing is defined as area to conduct the pilot. During a fire drill the behaviour of users was monitored with Wi-Fi and some randomly selected users were given Bluetooth bracelets in order to track their movement patterns. Figure 4.16 shows the locations of Wi-Fi and Bluetooth scanner nodes. In addition validation was done through manual counting and observation.

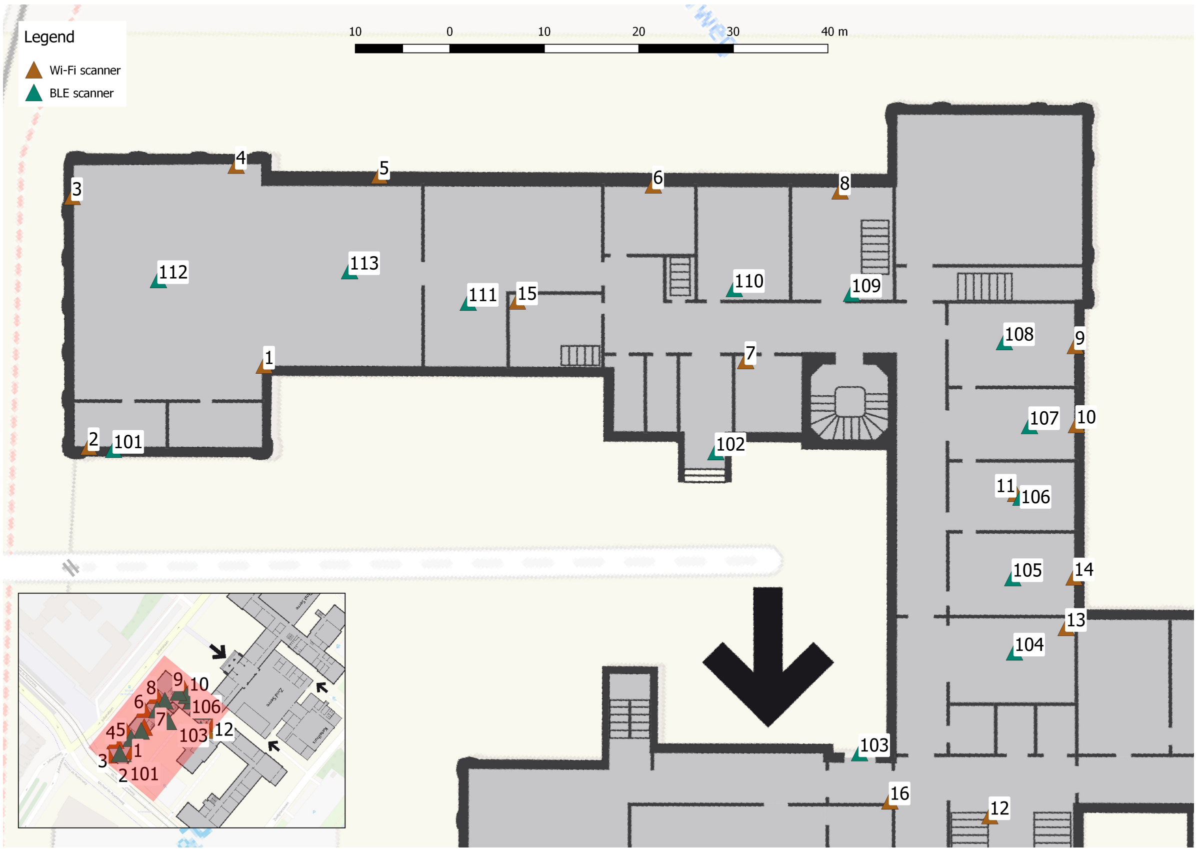


Figure 4.16: Placement of Wi-Fi and BLE scanners

5
Implementation

This chapter describes the implementation details of the conceptual framework described in chapter 4. It will describe the techniques, tools and data used within the research. First the tools and data used will be introduced, followed by the implementation of the workflow. The implementation is split in 3 separate parts: the sensor part (section 5.2), the server-side algorithms (section 5.3) and finally the client-side part (section 5.4).

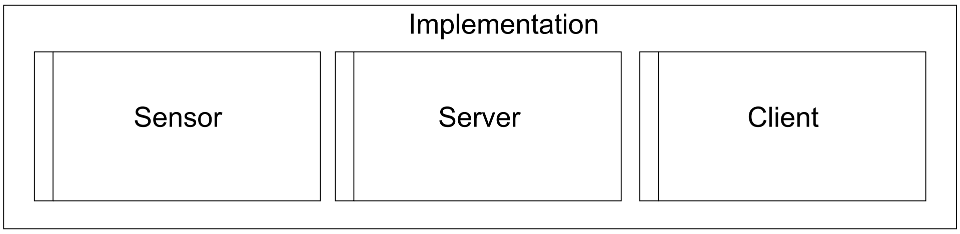


Figure 5.1: Overview of the implementation parts

5.1. Tools and libraries

For the implementation a set of algorithms is written, mostly in Python and Javascript. A distinction of used tools can be made between server-side and client-side tools and libraries. The server uses the MySQL (5.7) object-relational database management system used together with the SQL-language. The following non-standard modules have been used for realizing the conceptual framework:

- ScaPy Biondi (2008)
- Trilat Dias (2016)
- Chart.js Timberg (2017)
- OpenLayers Schaub (2017)

Other software packages used during the research include QGIS 2.18.14 for managing spatial features in spatial database tables, managing geographic data and plotting the results; MySQL Workbench for database modelling and creating SQL-queries and Adobe Illustrator for vector graphics.

5.2. Data acquisition

5.2.1. Selection of data source

During the research several types of scanner hardware and data source options were available. The differences between each were weighted and a selection was made based on the specifications. Table

5.1 shows an overview of the results of the comparison made between the available hardware in this research.

Table 5.1: Comparison of hardware

Device	accuracy	method	latency	aerial coverage of the system	cost	availability	integrity	data richness	integration / placement flexibility	detection percentage
Meshlium Libellium	10 - 50 m	cell-based	1 - 5 min	area	high	low, <95%	poor	good	mobile (lan/power)	70% mobile users
Eduroam	10 - 30 m	cell-based	7 days	building	n/a	high, >95%	poor	excellent	fixed	network users online
Custom-made stations	2 - 10 m	lateration	seconds	floor	low	high, >95%	good	good	mobile (wlan or lan/ power)	80% mobile users

To develop a prototype WPS that can monitor in real-time and support mesh networking a custom solution is built, see figure 5.2. An omni-directional antenna was used in order to minimise the directional dependency of signal reception from the transmitter to the receiving base station, caused by any rotation in the position of the antenna.

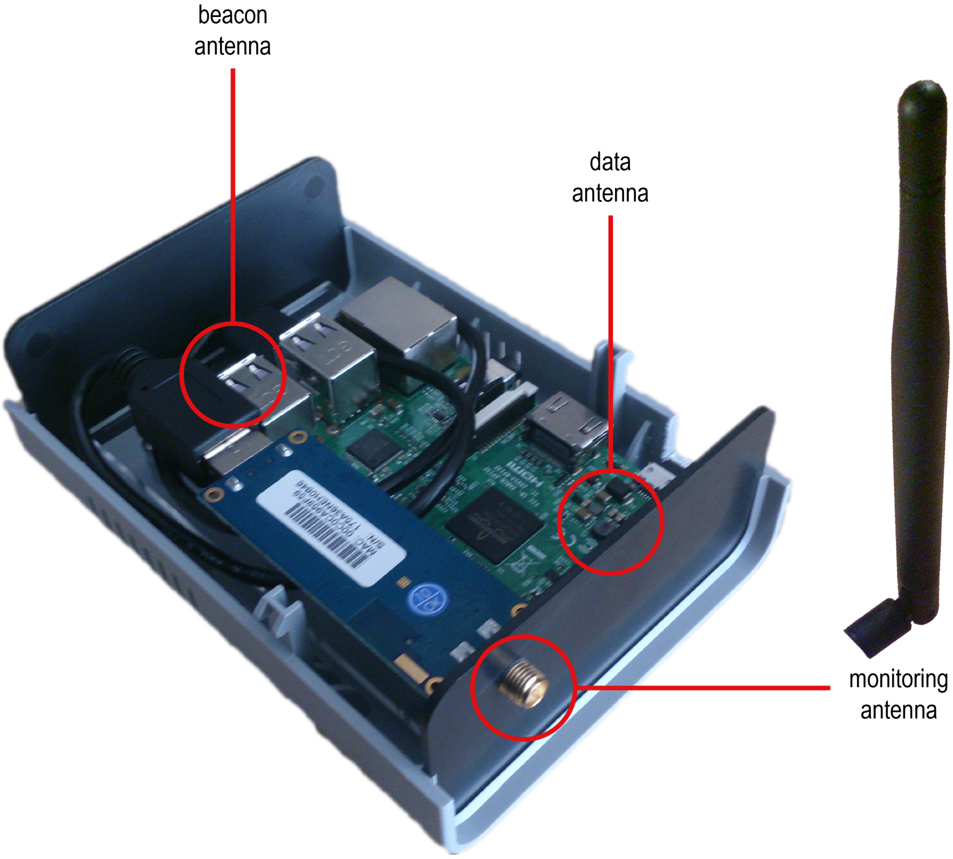


Figure 5.2: Raspberry Pi scanner node

Reference station software

Algorithm 1 shows the generalised algorithm running on the scanner nodes.

Algorithm 1 Scanner node generalised algorithm

```
function scan(interfaces, channelHopTime)                          ▷ starts the device
    configure interfaces                          ▷ networking, monitoring and beaconing
    while running do                                     ▷ as long as the device runs
        for channels to scan do
            set channel
            capture 802.11 frames for channelHopTime
            if frame is of type 'probe request' then                     ▷ user devices
                write frame metadata to database
                write frame metadata to logbook
            end if
        end for
    end while
return logBook              ▷ finally return a copy of the logs in case of network errors
end function
```

5.2.2. Capturing probe requests and beacon frames

Figure 5.3 show a snapshot of the Wi-Fi channel graph as measured in the building. The figure demonstrates that all the APs are either on channel 1, 5, 9 or 13. Therefore these are the channels that would have to be monitored for probe requests. All other channels can be skipped to maximise uptime on the selected channels and to minimize packet loss on those channels.

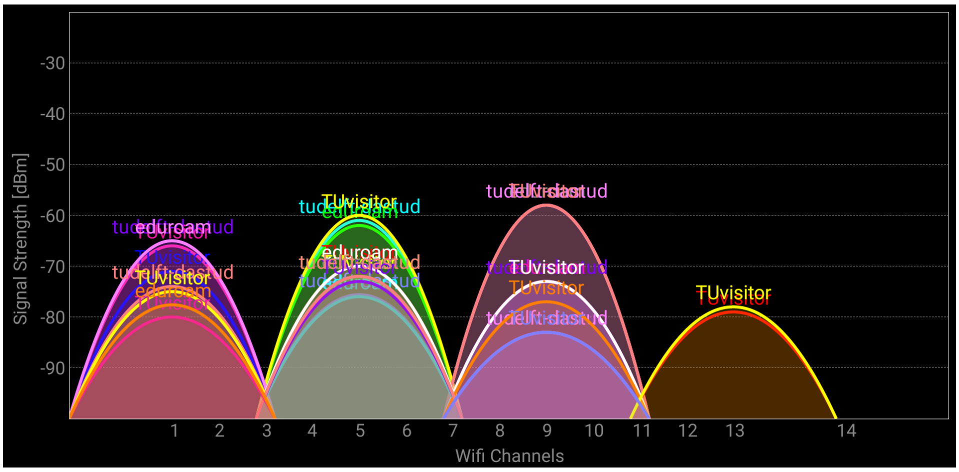


Figure 5.3: Snapshot of the channel distribution on the TU Delft campus.

To calibrate system parameters and to build the initial signal propagation model, reference data is gathered. The test bed as shown in figure 5.4 consists of markers placed on the ground in a 1-meter interval, a Wi-Fi scanner station and an emitting device with different antenna options. The emitting device is kept at each interval for 5 minutes so that enough data can be collected to get a statistically valid reference value for each distance. Outliers beneath -20 and above -90 dBm were discarded. Two tests were ran, one with a surface mounted antenna that can be commonly found in mobile devices. The other measurements were conducted with an external omnidirectional style antenna.

Figure 5.4: Collection of free-space reference data

5.3. Server

5.3.1. Data storage

Database structure

Figure 5.5 shows the relations of the different tables used to store the data. The raw data is all stored in a single table on which different views are created to prepare the data for real-time processing. The central tables contain the geometric shapes of the rooms and also the positions of the different scanners. Preliminary results are stored in the positions table, where the $date\_time$ column indicates when the user was estimated at a certain position. Metadata that may be used to display additional information about the rooms of the building is stored in the building table. The final tables includes some of the processed data to speed up data retrieval, such as the occupancy values and the user movement patterns in the traces table.

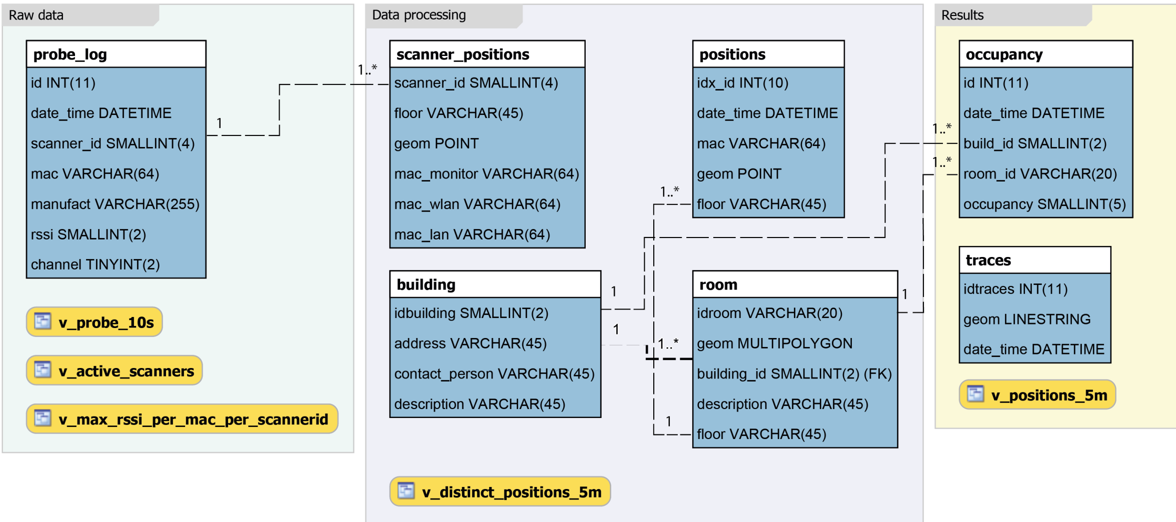


Figure 5.5: Entity relation diagram of the wifi_log database schema.

Addressing privacy and data protection

The data encryption is done on the server upon insertion. The built-in SHA-2 function provides a strong one-way encryption. This hashing algorithm always produces the same result for equal input. Therefore tracking users is still possible, despite the fact that the MAC address is not directly known. However, the data is only collection in a limited timeframe.

Figure 5.6: One-way encryption of personal data

5.3.2. Data processing

Data filtering

The data is first filtered by selection: a threshold on the RSSI-values is applied. This will remove outliers and outlier measurements. During the data retrieval the data is also grouped on the hashed MAC address-value and the id of the scanner node.

Algorithm 2 Generalised filtering algorithm

function filterData(data, lower, upper) ▷ filters the data before processing
    Group $data$ by $scannerId$ and mac
    for $hashedmac$ in $data$ **do** ▷ compare with table $outside\_office\_hours$
        if $hashedmac$ not in tableOut and $hashedmac$ rssi between $lower$ and $upper$ **then**
            append $hashedmac$ to $filteredData$
        end if
    end forreturn $filteredData$ ▷ Data prepared for processing
end function

Differential correction parameters

The correction parameters are calculated for each of the scanner nodes. The validity of the correction parameters is limited to measurements obtained by the scanner node for which the parameters are calculated.

The straight-line distances between the node and other nodes are fed into the function. The straight-line distance is based on the coordinates of that make up the two points of the scanner nodes, as defined in QGIS (EPSG:3857, cartesian coordinate system).

Algorithm 3 Calculating correction parameters generalised algorithm

function correction(observations(scannerId, rssi), distances)
    Initialise $correctionList$
    for scannerId **do**
        Calculate $correction$ nSeek($distance$, $rssi$)
        append $correction$ to $correctionList$
    end for
    group $correctionList$ by $scannerId$
    $correctionParameter$ = $\sum_0^n correction * weight$
    return $correctionParameter$
end function

Distance calculations

To transform the RSSI measurements into distances a function $calcDistance$ (algorithm 4) was implemented, using the signal propagation model to go from signal strength to distance.

Algorithm 4 Calculate distance

function calcDistance(rssi, n)
    $dist = E^{((rssi-n)/A)}$
    return $dist$
end function

Determining the floor level

Based on the distances of the client device to all receiving scanner nodes an estimation is made on the floor of the user (algorithm 5).

Algorithm 5 Estimate floor

READ scannerFloors
function estFloor(measurements(mac, rssi))
    group measurements on $floor$, mac
    return $floor$ ←floor having max(avg(rssi))
end function

Multilateration

The horizontal position is calculated based on the measurements of the client devices related to the floor on which it is localised. An extended version of the trilat algorithm by Dias (2016) is used.

The algorithm considers the Minimum Bounding Rectangle (MBR), or envelope as [MINX MINY, MAXX MINY, MAXX MAXY, MINX MAXY, MINX MINY].

Algorithm 6 Calculate position

READ latInput ▷ measurements to different scanner nodes, on $floor$
READ scannerCoords ▷ coordinates of scanner nodes
function trilaterate(scannerCoords, allowedDistance)
    return coordinate(x,y)
end function

5.3.3. Occupancy per room

The saved positions can be geometrically compared to the room polygons to check their relationship (algorithm 7). All computations are done assuming SRID 0, regardless of the actual SRID value. SRID

0 represents an infinite flat Cartesian plane with no units assigned to its axes (MySQL, 2016).

Algorithm 7 Calculate room occupancies

```
READ userPositions, roomGeometry
function occupancyCalculation(userPositions, roomGeometry)
    if userPosition in roomGeometry then
        roomOccupancy = roomOccupancy + 1
    end if
    return occupancyRoom
end function
```

Exploitation

The exploitation can be obtained per room by joining some extra metadata of the room capacity. The exploitation is the quote of occupancy and floor area.

Algorithm 8 Calculate exploitation

```
function exploitation(roomOcc, roomArea)
    READ roomOcc                                  ▷ results of previous algorithm
    JOIN table capacity                           ▷ Room metadata such as floor area
    exploitation = roomOcc/roomArea
    return exploitation
end function
```

Movement patterns

Movement patterns are obtained by sorting the positions over time and creating linestrings from them (algorithm 9).

Algorithm 9 Create traces

```
for mac in point table do
    READ points traces(points, mac, datetime)     ▷ create linestring
end for
function traces(points, mac, datetime)
    SORT points on datetime
    return return pointList as linestring
end function
```

5.4. Client

5.4.1. Data visualisation

The data visualisation is implemented as a separate desktop visualisation tool. The OpenLayers package is used in combination with other libraries running on the Node.js Javascript run-time and visualised through the Electron wrapper.

6 Results

In this chapter the results obtained through the implementation are presented.

6.1. Preparation results

6.1.1. Signal propagation model

In order to develop a signal propagation model the distances on a straight line were measured over prolonged duration in order to calibrate the signal strength to distance conversion. The RSSI-values are measured in different configurations at varying distances. The RSSI-values are measured in free space over a distance of 10 meters, with a 1 meter interval. The client is equipped with an integrated antenna similar to the types used in smartphones.

Figure 6.1 shows that when monitoring multiple probe requests, the RSSI can be defined as a logarithmic function of distance. The effect of changing the correction parameter is also shown.

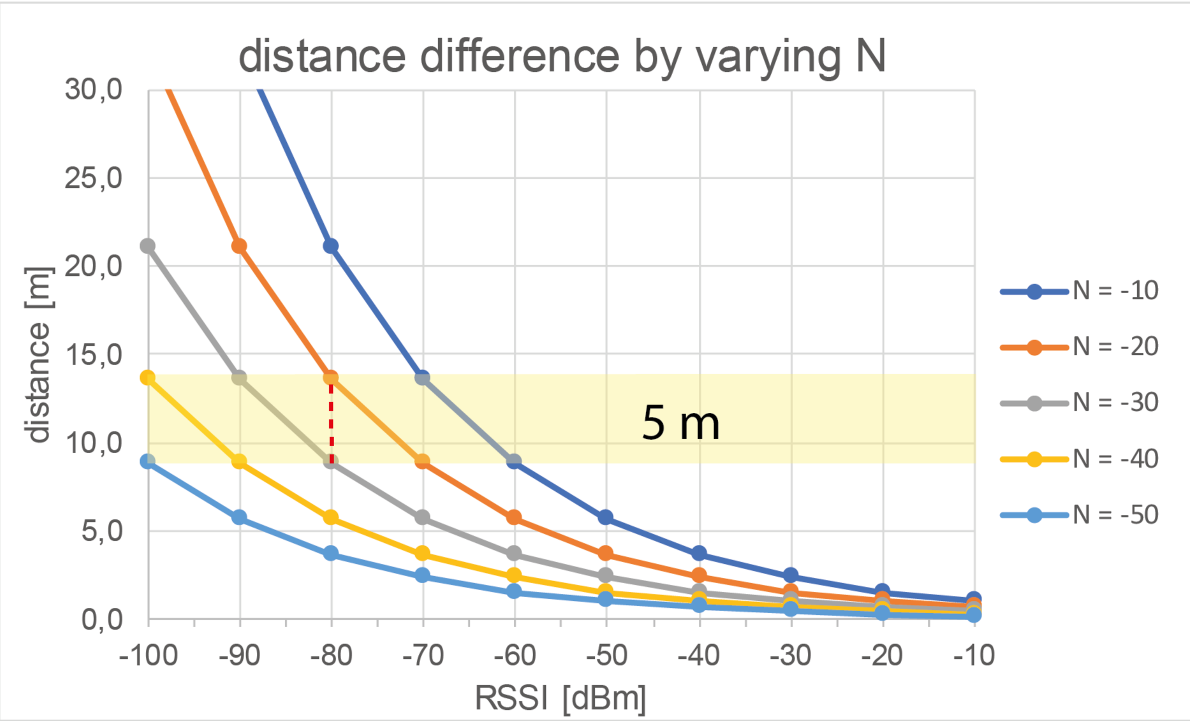


Figure 6.1: RSSI over distance difference.

6.1.2. Controlled test environment

Static positioning

The prototype is tested in a static test environment as described in figure 4.10. Figure shows the estimated positions of two different types of smartphones (Android and iOS). The scanner nodes were placed on two different floors. Both devices remained in a fixed position during the test. Table 6.1 displays the relative deviation of the estimated position from the ground truth. The best positions have a deviation of around 2 meters, but some positions deviate by around 10 meters or more (iPhone). The accuracy in this case was sufficient to localise both users in the same room, through matching the positions with the room geometries. The devices were also estimated to be on the correct floor. However, the horizontal accuracy for smaller rooms would most likely require a different distribution of the base stations in order to achieve sufficient horizontal accuracy.

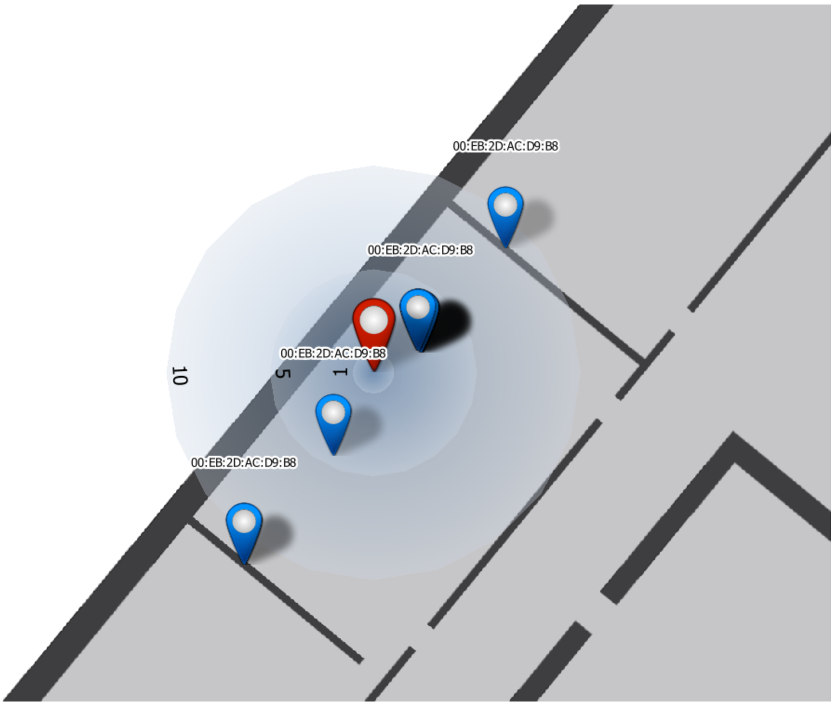


Figure 6.2: Accuracy in test environment

Table 6.1: Deviation from ground truth

	Distances to reference point [m]
Android	2.17 2.54 4.60 8.54
iOS	11.54

Bluetooth bracelet calibration

To count ground truth numbers the participants in the test environment were handed Bluetooth bracelets. Before the test a signal strength threshold was established in order to use cell-based localisation. Based on the figure 6.3 the threshold was set at -70 dBm. With this threshold it is possible to distinguish whether a user is inside or outside of a room by using signal attenuation to a single closest base station.

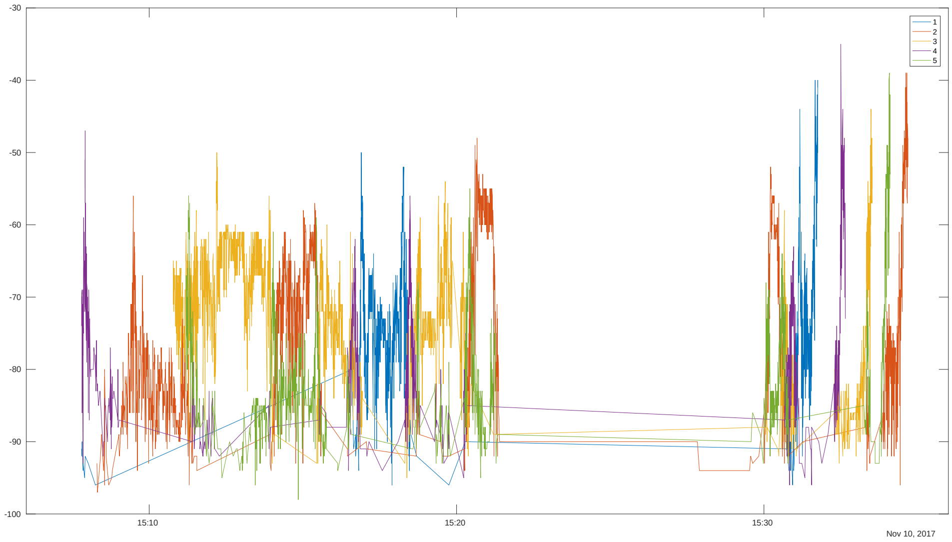


Figure 6.3: Bluetooth signal strength controlled test for varying distances

Tests with different base station distributions

In order to determine the effect of the base station distribution on the positioning performance, some tests were performed in a controlled environment. On average the positioning accuracy improved by 2-5 meters when the base stations were set up with a high Dilution of Precision (DOP)-value (figure 6.4).

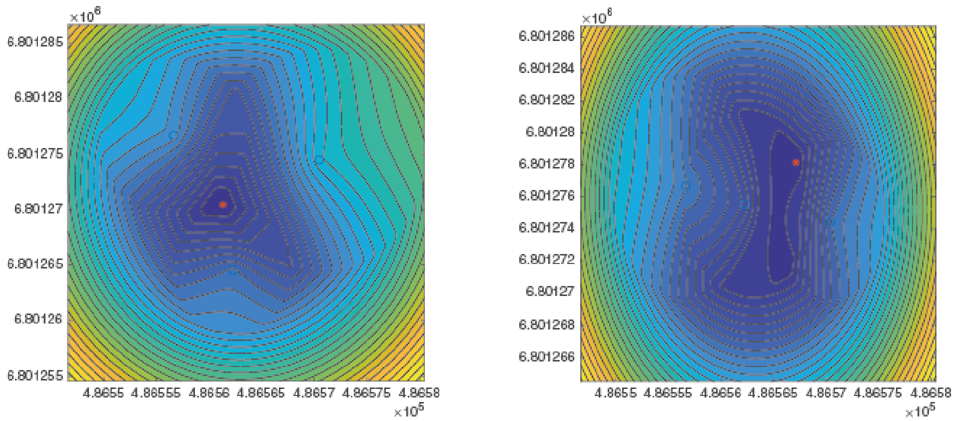


Figure 6.4: Distribution of base stations and the effect on positioning accuracy

6.2. Position data

The raw data produced by the tracking system results in positions with coordinates in the WGS84 Web Mercator projection. This projection uses meters as units in x- and y-direction.

Figure 6.5 shows the positions of client devices that were generated during the timeframe of the fire drill.

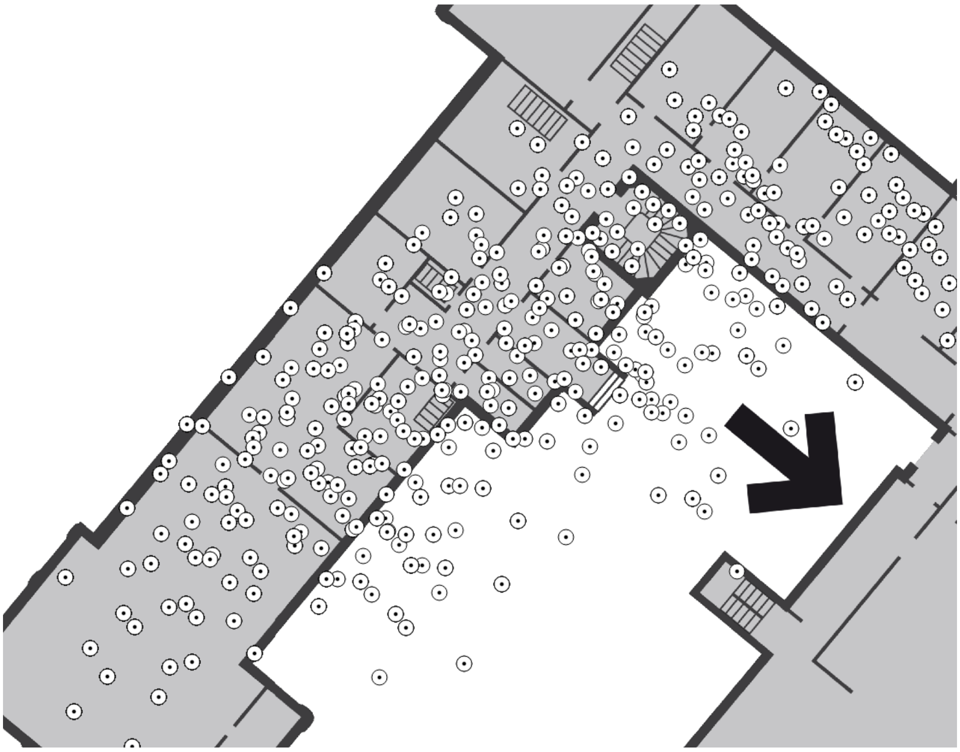


Figure 6.5: Devices positioned

6.3. Occupancy

The raw data can be aggregated by location, by time, by MAC address, by device type or by the scanner which registered the device's signal. Figure 6.6 shows occupancy within the Faculty of Architecture during a fire drill. The evacuation started at 11:05 and lasted approximately 10 minutes.

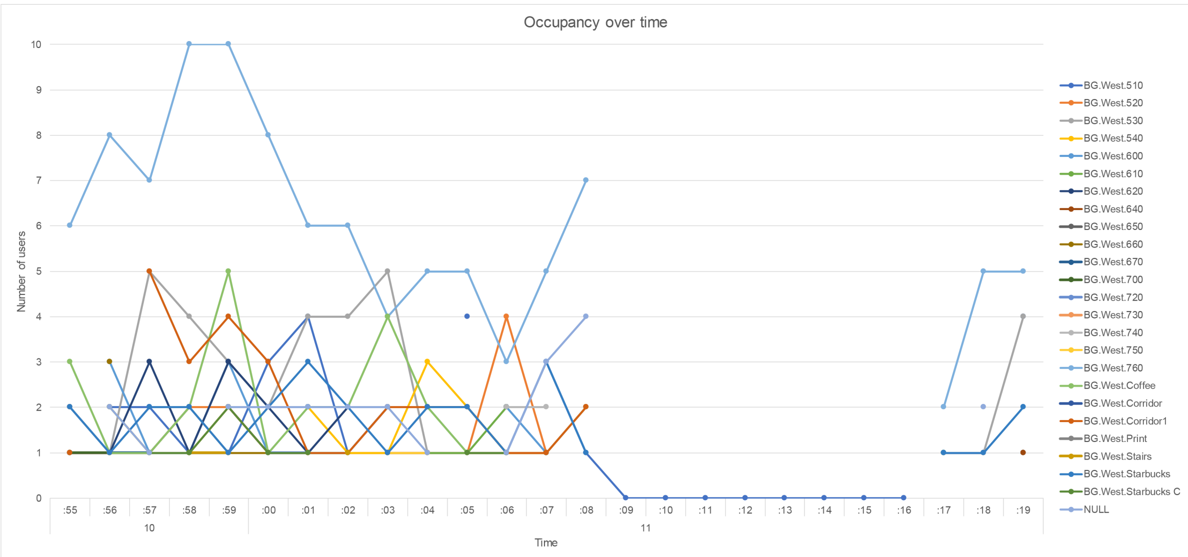


Figure 6.6: Occupancy of the Faculty of Architecture west wing during a fire drill.

The number of unique devices observed (figure 6.7) is much higher than the occupancy rates of the rooms. Therefore, this figure shows that not all devices are considered to be users.

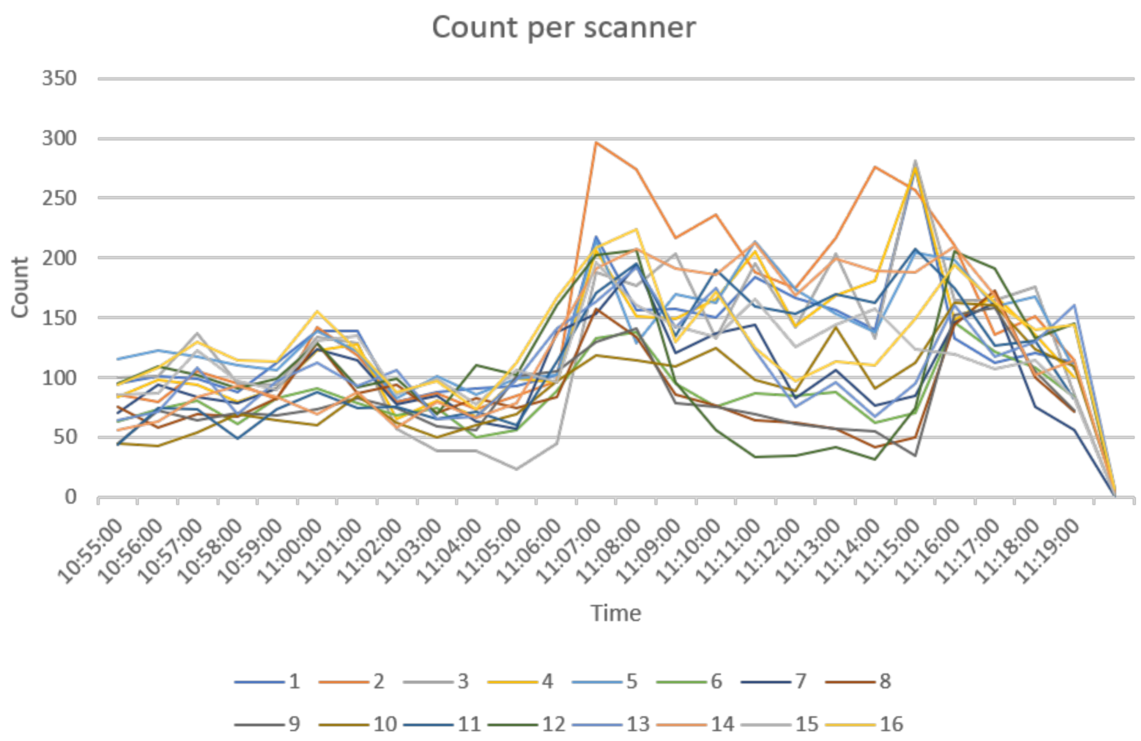


Figure 6.7: Count per scanner

6.4. Movement patterns

The date/time-sorted positions are converted to movement patterns. Figure shows a single movement pattern during the evacuation, that of an observer. Figure 6.9 shows the collection of movement patterns.

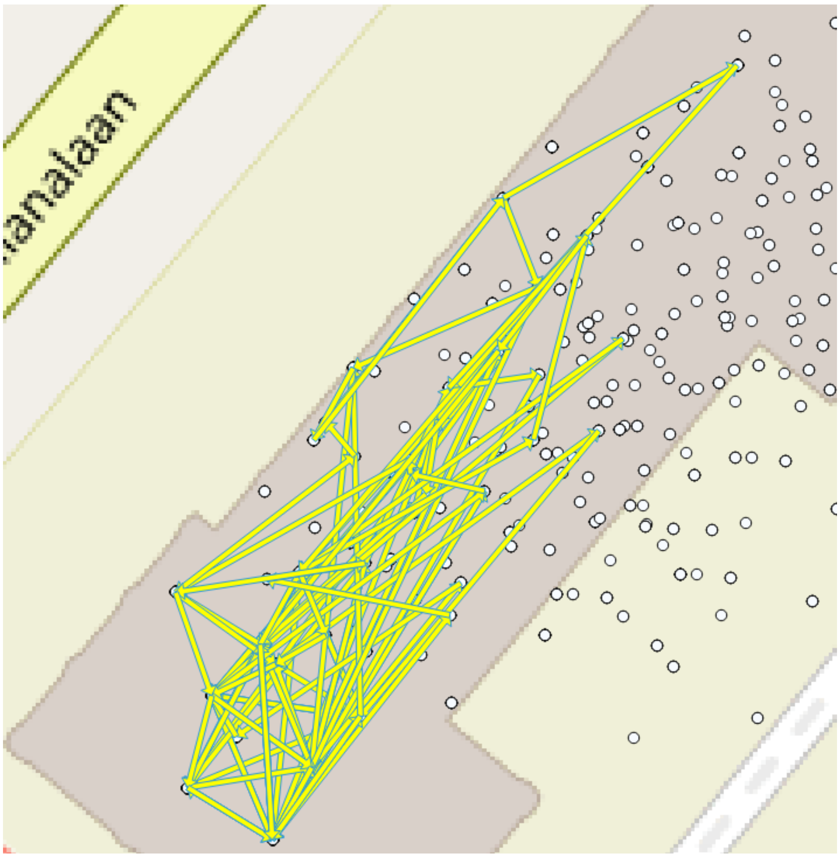


Figure 6.8: Sample movement pattern.

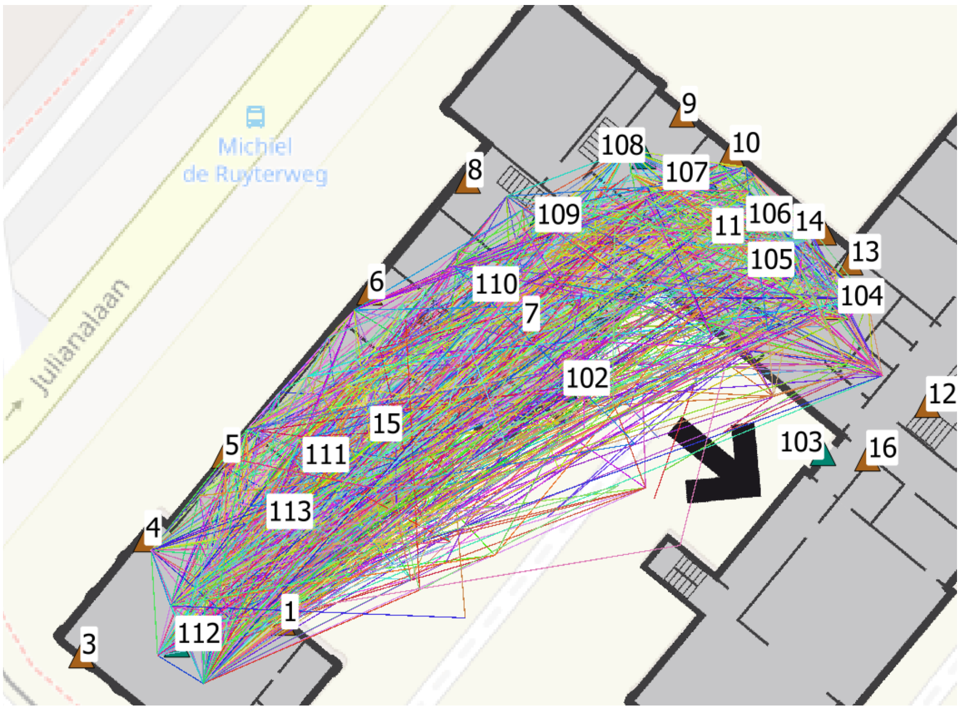


Figure 6.9: All movement patterns.

6.5. Data validation

During the fire drill data was gathered using Bluetooth bracelets. The Bluetooth bracelets were calibrated in an earlier experiment, see section 6.1.2. The Bluetooth bracelets were worn by all users in the test environment and tested beforehand. The localisation method used for the Bluetooth bracelets was a cell-based method with a high signal strength threshold. Figure 6.10 shows the comparison between the Wi-Fi data and the ground truth as collected with the use of Bluetooth bracelets. For 48% of the cases there is no deviation between the ground truth and the Wi-Fi location estimated, meaning that the occupancy is correctly measured. With 95% of the cases the maximum deviation is 4 users.

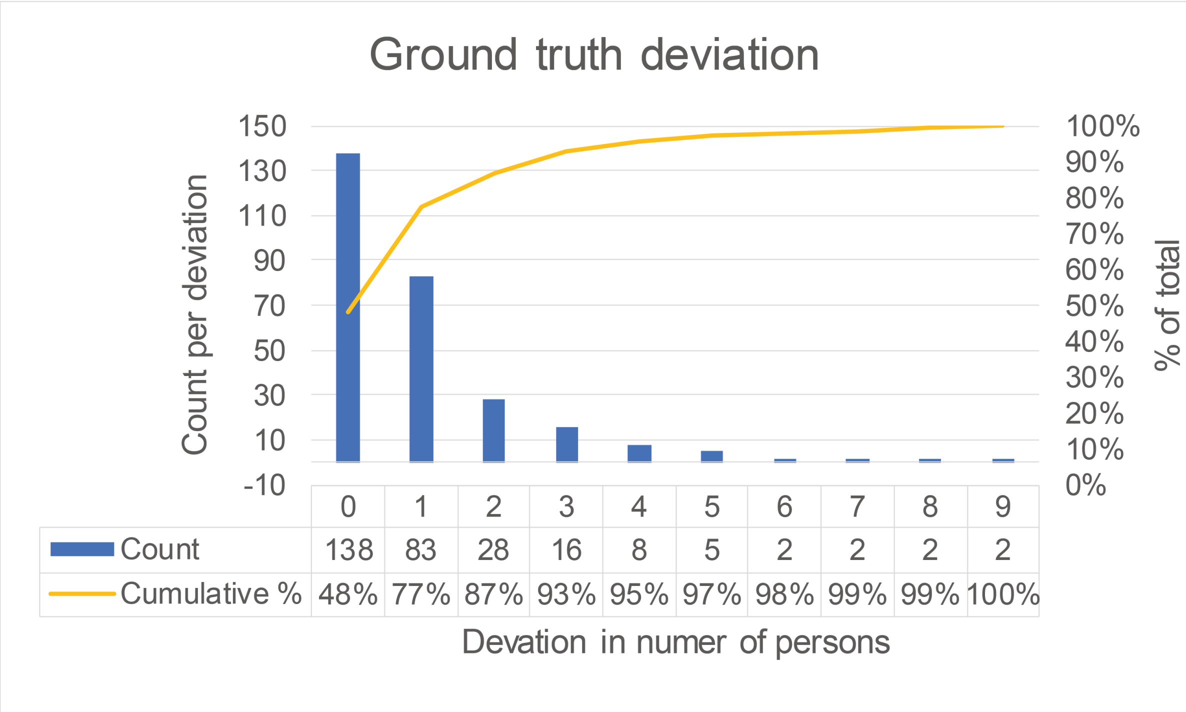


Figure 6.10: Comparison of measurement results with the ground truth in an uncontrolled test environment during a fire drill.

6.6. Client application

To visualize the obtained positions, and to relate the positions to places on a map, a program has been created as shown in figure 6.11.

Figure 6.12 gives the user of the program the ability to view the position of the building's users in real-time.

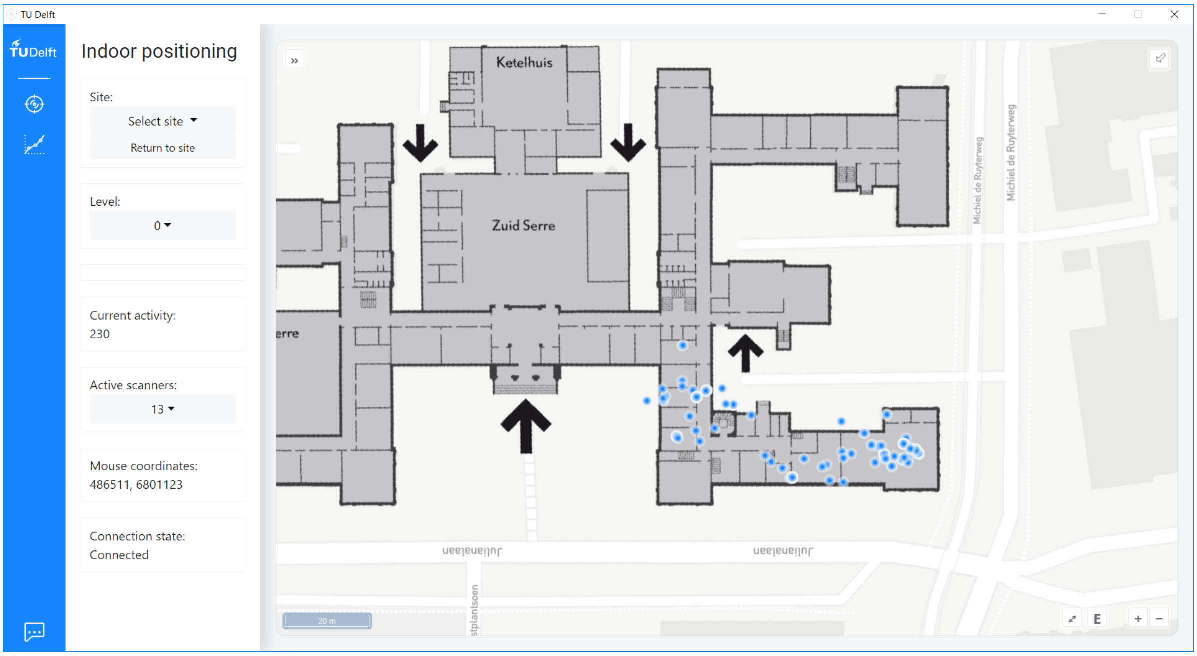


Figure 6.11: Overview of the management dashboard

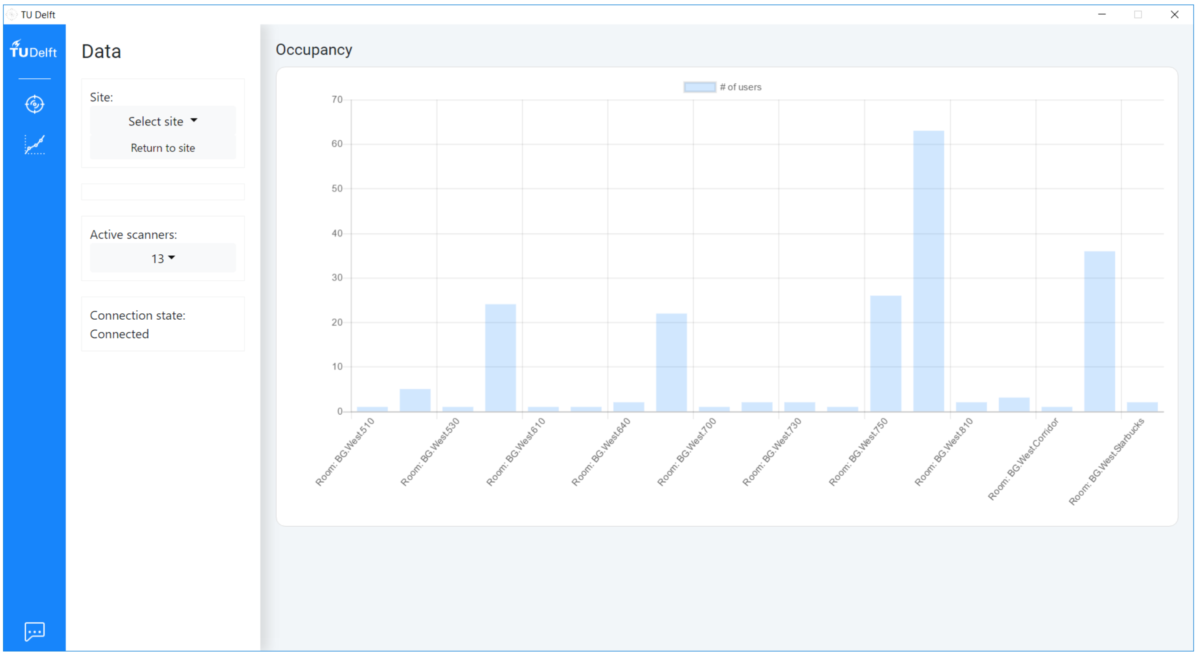


Figure 6.12: Occupancy in real-time

7

Conclusions and recommendations

This chapter will first go over the sub-questions in order to then come to an answer for the main research question.

7.1. Research questions

This section will address the research questions as stated in section 1.6. Together with the answers from the sub-questions the main research question will be answered at the end of the section.

7.1.1. Sub-questions

1. *How can information about occupancy rhythms and movement patterns support university campus management and what are the requirements of this information?*

   Occupancy and exploitation information is vital for campus management. This information is often missing during the decision-making process according to Den Heijer (2011). Occupancy information is also used to operationalise the performance of the building through various key performance indicators, such as measuring building efficiency or exploitation. Gaining insight in occupancy rhythms and user flows using a smart tool can give a much more realistic view of the actual situation than hand-counted information that is presently used. In addition smart tools can also provide the information in real-time so, that it can be used for monitoring evens and operational decisions. Occupancy information can be used to facilitate the user, e.g. in finding a suitable working place. The information can also be used in post analysis to reduce the footprint and cost of real-estate. For these tasks the requirements for horizontal accuracy are that the user can be localised within a specific room or area. Vertical accuracy should at least be sufficient to identify the floor of the user. Real-time information is necessary without delay for some applications, such as real-time occupancy and exploitation measurements.

2. *How can devices be linked to building users?*

   To match the number of devices to the number of users different techniques are used. Different devices can be identified through their unique MAC address, but this identifier is sometimes randomly generated. Randomisation takes place as long as the devices is not yet connected to the network. Therefore, for campus users randomisation usually does not apply as they make use of the network. In some cases where the user is not connected to a WLAN it is impossible to directly track the user. However, by using purge times for estimated user positions that are known to use randomised MAC address-addresses, the occupancy rate can still be correctly determined, avoiding double-counting in at least 48% of the cases.

   MAC address randomisation guarantees user privacy to some degree and still allows the calculation of the information such as occupancy and exploitation of rooms and areas. Users are defined as the persons behind devices. The devices belonging not belonging to users are filtered out based on their activity, the duration that they are seen and type of device (e.g. they are not sending out beacon frames like an AP).

3. *How can the sensors be calibrated to adapt to the indoor environment and its influences?*

   The indoor environment introduces 6 influences on the signal propagation that are less or not present in outdoor environments. By creating a network of interconnected Wi-Fi reference stations, aerial correction values can be computed and used in the calculation of distances. The correction parameters applied are locally valid to counter the local temporal variations in the RSSI. The devices are all synchronised through a central server which keep time and other critical parameters within suitable tolerances.

4. *How does base station distribution affect the indoor positioning accuracy?*

   During testing with different setups it has become apparent that the geometry of the Wi-Fi scanner network is decisive for an adequate accuracy. Namely the calculation of correction parameters and their validity depends on the distribution of reference stations throughout the area of interest. The optimal placement of reference stations therefore is one that allows for interpolation of correction parameters within the given area, so that from each user position at least 3 scanners nodes are in reach. Tests were also performed with base stations with low DOP and high DOP, with resulting accuracy differences between 2-5 meters, confirming that a spatial distribution should take into account the angle between the different stations.

5. *To what extent can a user be positioned or localised within a room or area as defined by the campus management?*

   The need for a differential system is clearly demonstrated when plotting the results of RSSI measurements taken over longer time spans. The signal strength fluctuates due to temporal variations in background noise and obstacles. Therefore the relationship between RSSI and distance can no longer be reliably determined without using up-to-date reference data. Using areal correction values in order to calculate user positions, the accuracy of the WPS is improved to a degree that is sufficient to position a user inside a room as defined by the campus management. Finally, accuracies between 2 and 10 meters are reported using a differential mutlilateration method using a base station in each room. In 48% of the cases the occupancy is correctly calculated. For 77% of the cases a difference of 1 users is estimated and in 95% of the cases there was a maximum deviation of 4 users.

6. *Which occupancy rhythms and movement patterns can be recognized and how to acquire them?*

   During the evacuation users were forced to move out of their rooms. From the results an occupancy rhythm can be identified over time. During the evacuation the rooms show a near-empty result. The rooms start to fill again after the evacuation. Occupancy rhythms were obtained by using the geometry of the rooms through maps provided by facility maps. The positions of that were obtained through the positioning system were then matches with the geometrical bounding polygons of the rooms in order to calculate the occupancy per room.

   Movement patterns were acquired by sorting the point geometry features based on time and MAC address-address. Subsequently the points were added to lists in order to create linestring features out of them.

7.1.2. Main research question

Following the answers of the sub-questions the main research question will now be answered.

> To what extent can indoor Wi-Fi monitoring be used for indoor localisation in order to determine occupancy rhythms and movement patterns within and between rooms to support campus management?

In this research the requirements for some of the tasks of campus management were used as a measure to benchmark and design a prototype for indoor localisation using a Wi-Fi positioning system.

In conclusion an indoor WPS can be used to capture, process and provide real-time and non-real-time occupancy and exploitation information. The devices can be fitted to users to a great extent and the devices can also be positioned within rooms to a fair degree with an accuracy of 2 to 10 meters. This research shows that it is not necessary to have an over-abundance of base stations, but that with the help of a differential system it is enough to have one scanner node per room as long as the scanner nodes are in range of each other. However, the probe frequency of the client device will be the limiting factor for real-time data access. Sometimes devices will only periodically transmit signals, limiting the amount of tracking possible. Tracking can also be limited by MAC address-address randomisation. When matching the system performance with the requirements and demands from campus management it can be concluded that Wi-Fi is a suitable technique for tasks that require a room-level accuracy such as real-time occupancy monitoring. However, other applications that require greater accuracy or an even lower latency would require additional arrangements such as specialised software on the devices of mobile users or the combination of Wi-Fi with another wireless positioning technique.

7.2. Recommendations and future work

The research conducted within this thesis has shown that an improved WPS is able to provide the required information for occupancy rhythms and real-time activity. To further reduce the positional error in the calculated position additional information sources such as network activity and also additional systems may be used in conjunction with the system. For navigational purposes the frequency of transmission could also be increased by listening to other types of traffic as well, but privacy concerns have to be carefully weighted.

Another aspect lowering the positional accuracy of the current WPS implementation is the difference of sent and received (perceived) signal strength between different devices, such as smartphones, tablets and other mobile devices. This different antennas produced by different manufacturers have different properties which allow the RSSI to variate based on manufacturer application alone. A way to better identify the different antenna types could aid diminishing unknown effects caused by the different antennas.

A future challenge could research the possibility to use the differential reference stations in conjunction with the existing Wi-Fi infrastructure to test methods such as fingerprinting with dynamic radio maps. However, more research needs to be done on the potential of such solutions.

A

Reflection

- The relationship between the methodical line of approach of the Master Geomatics and the method chosen by the student in this framework.

Within this thesis the Geomatics line of approach has been used as a guideline to identify and work out the different steps required for obtaining accurate indoor information. The building blocks of the Geomatics methodical approach are data acquisition, data storage, data analysis and data visualisation. This research presents a proof of concept that is built for indoor localisation based purely on Wi-Fi scanners and user devices. The research expands on the traditional methods of Wi-Fi positioning by adding extensive filtering and signal correction algorithms. The positioning and localisation system is deployed in a case study acting as a pilot to verify its capabilities in a real-world scenario. The starting point is the user that carries mobile devices. By using Wi-Fi signal strength measuring principles ranging is performed between the mobile device and Wi-Fi scanners. Together with building information and maps the Wi-Fi scanners are deployed in different constellations in order to capture the signals as sent by the mobile devices in the best way. After data acquisition and data storage the data is analysed and processed to best suit the case study. Finally the data is visualised in a way suited to the case study, thereby solving the problem of obtaining accurate and up-to-date information about the building usage on a room-level accuracy.

- The relationship between the conducted research and application of the field Geomatics.

Network-based indoor localisation with Wi-Fi devices as measuring principle presents certain challenges. While different research papers focus on one section of either positioning methods or measuring principles, certain Geomatics related aspects are lacking and this research tries to combine those aspects in a single research objective. An innovative positioning method has been proposed to overcome certain challenges regarding temporal fluctuations of signal strength due to temporal influences. Another key aspect to relate the conducted research to the application of the field of Geomatics is that the data from different sources are combined and enriched in order to solve real-world problems.

- The relationship between the project and the wider social context.

The research started from a problem statement identified in the context of campus management and smart tools based on Wi-Fi. Therefore the research is especially interesting for campus management, but its relevance can also be extended to different fields, e.g. hospitals, public buildings and public transport stations. The objective of this research is to provide information about occupancy and movement patterns inside buildings. This information can eventually lead to more efficient building management and cost savings, safer buildings and more environmentally friendly buildings etc. Ultimately the user also benefits in terms of lower costs, less waiting time and a safer building among other aspects.

B
Time planning

In the graduation process there are 5 official graduation moments:

- 24-04-2017 P1: Progress review
- 22-06-2017 P2: Formal assessment graduation plan
- 31-08-2017 P3: Colloquium midterm
- 11-12-2017 P4: Formal process assessment
- 29-01-2018 P5: Public presentation and formal assessment

Figure B.1 shows the milestones of the research project in relation to the methodology.

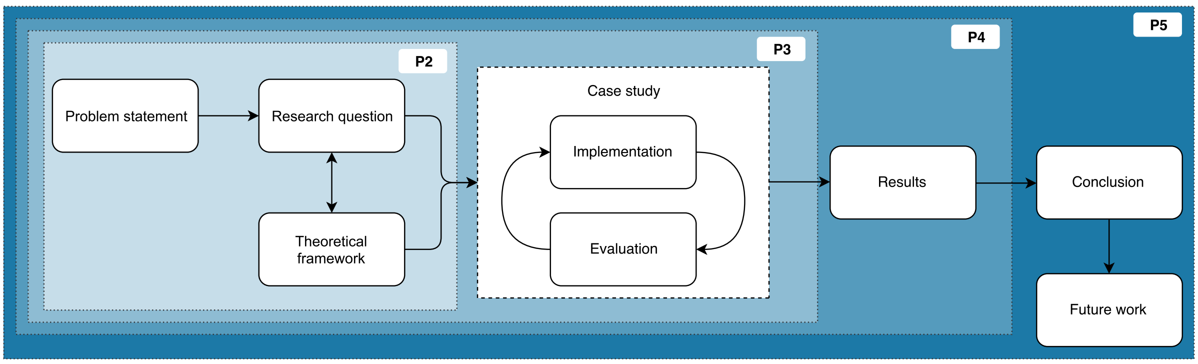


Figure B.1: Stages of the research process

C User notice

During the research users have been notified about the research in different ways.

Letter to users

Temporary research Wi-Fi tracking / tijdelijk onderzoek Wi-Fi tracking

Dear room user,

To improve our knowledge about sensor techniques to measure occupancy and movements within buildings, scientists from BK-Geomatics and EEMCS-Web information systems, are temporarily setting up Wi-Fi tracking devices in this part of the BK building, possibly also in your workspace. The devices do not emit waves, radiation, particles etc. Information gathered by the devices will be used for research purposes and for safety improvement such as evacuation protocols. You are kindly requested to cooperate in the research.

In case of questions you can contact me: d.hoeneveld@tudelft.nl Dick Hoeneveld, coordinator Delft Safety and Security Institute.

Website

Figure C.1: Notice on website

List of abbreviations

AOA Angle of Arrival 15

AP Access point xi, 4, 5, 13, 14, 20, 37, 52, 66

CORS Continuously Operating Reference Station 26

CREM Corporate Real Estate Management 29, 30

DOP Dilution of Precision 59, 66

DWi-Fi Differential Wi-Fi 13, 26

EM Electromagnetic xi, 14, 17

EU European Union 33

GNSS Global Navigation Satellite System 1

GPS Global Positioning System 1

IoT Internet of Things 28

ISM Industrial, Scientific and Medical 12

LBS Location-Based Services 1, 8, 25

LOS Line-of-Sight 16

LPPI Law for the Protection of Personal Information 34

MAC Media Access Control 72

NLOS Non-line-of-sight 16, 17

RF Radio Frequency 3, 5, 15

RSSI Received Signal Strength Indicator xi, xii, 4, 15, 16, 19–23, 25, 26, 33, 37, 40, 41, 43, 54, 55, 57, 66, 67

RTT Round trip time 15

SHA Secure Hash Algorithm 39, 54

SSID Service Set Identifier 13, 16

TDOA Time Difference of Arrival 15

TOA Time of Arrival 15

UHF Ultra High Frequency 12

WLAN Wireless Local Area Network 13, 15, 16, 65

WPS Wi-Fi Positioning System xi, 3–6, 36, 51, 66, 67

Glossary

exploitation Relative measure to indicate the relation between occupancy and the available floor space inside a specific room or area. A high exploitation indicates that the room is densely populated by people. 29

localisation Localisation is the process of determining the location of a user or object. The location is a physically restricted space, e.g. a room. 3, 5, 8, 23, 28

MAC address The Media Access Control (MAC)-Address uniquely identifies a network device on a network (Bluetooth, Wi-Fi, wired or other network) and is used to address the device during communication. 15, 16, 26, 34, 37, 39, 41, 54, 60, 65–67

monitoring The process of recording user activity and presence within a certain area, based on users' mobile devices. 10, 11

occupancy Number of users per room or area as designated by Campus Management, at a specific time. 28

positioning Positioning refers to the process of obtaining coordinates in an indoor local reference system. 3, 5, 8, 15, 26, 27

probe request A 802.11 management frame used to manage wireless network traffic. Used extensively as part of the Wi-Fi measuring technique in order to perform positioning and localisation. 13–16, 20, 23, 25, 38, 40, 41, 57

tracking The process of following Wi-Fi-enabled mobile devices through repeated positioning. Tracking yields a movement pattern or trajectory, whereas positioning only results in a single position/location. 10, 11

Wi-Fi Wireless local area network (WLAN) products that are based on the Institute of Electrical and Electronics Engineers' (IEEE) 802.11 standards Webopedia (2017). 2, 3, 8, 12, 14, 15, 26, 28, 40, 48, 52

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Colophon

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