Geographical Information Management and Applications

Secret room in the train?

A study about the use of indoor localization to measure real-time occupancy in the train per compartment

GIMA MASTER THESIS

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Summary

Passenger trains in the Netherlands and in other countries suffer from crowdedness. Crowdedness in public transport can be defined as the extent to which a vehicle is crowded or filled to excess. Crowdedness can cause lower customer satisfaction, longer perceived waiting times and stress. A problem that amplifies the crowdedness in the train is that passengers are often not equally distributed over the train. Some compartments tend to be fuller than others. This problem may be countered by informing passengers about the current crowdedness in each separate location compartment in the train, so they can anticipate and enter the train in a relatively less crowded compartment. This can for example be done by integrating this information in an existing mobile application about travel information or by using dynamic signs at the platforms of stations. To be able to provide this information to the train passenger it is needed to measure the occupancy of locations in the train in real time. Therefore the following main research question has been drafted in this research: *Which localization method is most suitable to monitor occupancy in the train in real time?*

To determine the most suitable method(s) it is first relevant to define which characteristics of a train environment are relevant with regards to indoor localization. The most important characteristics are described. Some trains already have Wi-Fi routers and/or security cameras installed which can be used for some methods of indoor localization. The location of the interior of a train compartment is known and static and the train compartment is thus a good fit for a local reference system that only functions for a small region. Due to this static infrastructure some assumption can also be made with regards to the locations of passengers, passengers are for example often located on chairs, and this can be used by indoor localization methods that are able to focus on a specific location. To evaluate the indoor localization methods they have been categorized per technology. Since this research is about monitoring train passengers technologies that require subjects to carry additional devices, such as tags, are disregarded as this is deemed too unpractical. An exception is made for Wi-Fi since many Dutch people carry a Wi-Fi device and have their Wi-Fi turned on most of the time. The technologies (that do not require tags) evaluated are: Wi-Fi/ WLAN, infrared, sound localization, ultra-wideband, camera and pressure sensors. The advantages and disadvantages of these methods are further assessed using a qualitative analysis of the literature. Based on this analysis and the characteristics of the train a combination of Wi-Fi and camera-based localization seems the most suitable. This is mainly because the infrastructure for these technologies is already available in the train and the costs of implementing these methods are therefore relatively low. The other technologies do not seem to have an edge in performance that can outweigh their relatively higher cost. The advantage of using two technologies seems that they can be used to verify and amplify each other and to mitigate each other's disadvantages. These two technologies are further researched and tested in environments similar to a train. The focus of the tests lies on one train to narrow down the scope of this research. The train chosen for this is the FLIRT, which is employed by the railway operator NS, because the FLIRT already has cameras and Wi-Fi.

A camera-based localization method is employed in this research by designing an algorithm that detects the difference between a frame of an empty train to the real-time frames of the footage from security cameras in a train by detecting differences in the color model of the pixels. In this algorithm the HSV color model is used and the focus lies on hue to avoid noise from differences in light. To determine the number

of taken seats this algorithm detects whether a relevant contour of pixels changed significantly on the headrest areas of the train. To determine the occupancy in the hallway of the train a ratio of changed pixels in the hallway is identified. This data of the hallway and the seat can be combined to estimate the occupancy in the whole compartment. To determine occupancy in the train compartment using Wi-Fi localization the number of unique Wi-Fi devices is measured. This is done by sniffing Wi-Fi probe requests, which are signals send out by Wi-Fi devices used to actively seek a Wi-Fi access point. Some probe requests contain a unique Media Access Control (MAC) address that belongs to the corresponding mobile devices. These MAC addresses are used to detect unique Wi-Fi devices.

The camera-based localization method has been tested in an office environment by using old train chairs and both of the methods have been tested in an old train in a railway museum. When interpreting the results of the tests it is important to take into account that testing in a real train may lead to different results, as the test setting are not a perfect description of reality. From the tests derived that the camera-based localization has an average false negative error of 5-9% and an average false positive error of 1-3% during a train journey when used to estimate the number of taken seats in relation to the total number of available seats. During a train stop a false negative error of 4-5% and a false positive error of 8-9% have been found. For the hallway it can be stated that it seems like camera-based localization can used to estimate its occupancy to some extent, but this estimation is most likely not as accurate as it is for the occupancy of the taken seats. The reason for this is that in the hallway the number of people per area can vary, whilst for the seats the number people is less variable (usually one person per chair). The occupancy of the seats is therefore easier to detect. In the railway museum test setting the number of Wi-Fi devices in a train compartment can be estimated using Wi-Fi localization with a false negative error of 10-15% and without a false positive error during a train journey of about three minutes. In the test setting the test subject were all instructed to bring one Wi-Fi device with its Wi-Fi enabled. Therefore the relation between the number of *Wi-Fi devices* and the number of *Wi-Fi probes* can be researched and not the relation to the number of passengers. It is therefore also hard to statistically determine the extent to which these two approaches can supplement each other based on the tests of this research. It seems however that camera-based localization is more accurate as it detects people instead of Wi-Fi devices.

Even though the camera-based localization appears more accurate, it seems likely that the systems can complement each other during a train journey by mitigating each other's disadvantages. The Wi-Fi localization is probably more accurate the more passengers there are in compartment. This is because it seems likely an expected ratio between Wi-Fi devices and passengers becomes more reliable the more passengers there are in a train. This is in contrast to the camera-based localization which may become less accurate when there are more passengers in a train compartment than the number of available seats. This because the number of passengers standing in the hallways is hard to detect using camera-based localization and because the camera view of train chairs may be blocked by passengers standing in the hallway. It can thus be stated that the Wi-Fi and camera-based localization may complement each other when used to measure occupancy in the train because they can be used to verify each other and they both thrive during different amounts of occupancy. Based on the test results is seems that a combination of Wi-Fi and camera-based localization is suitable to measure occupancy in the train, but the test results should be verified by testing the proposed methods in a real train environment.

Colophon

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Preface & Acknowledgements

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I wish you, the reader, all the best reading the document in front of you. If you need any additional information of clarification along the way feel free to contact me.

Contents

List of abbreviations

AoA	Angle of Arrival
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
ID	Identifier
IPS	Indoor Positioning System
ILS	Indoor Localization System
FLIRT	Flinker Leichter Innovativer Regionaltriebzug
LBS	Localization Based Services
MAC	Media Access Control
NS	Nederlandse Spoorwegen (Dutch Railways)
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
TDoA	Time Difference of Arrival
ToA	Time of Arrival
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local Area Network

1. Introduction & Context

In this paragraph the topic of this research is introduced. This is done by first describing the setting and problem of this research. Afterwards the societal and scientific relevance of this research are discussed.

1.1 Setting & Problem description

The Dutch newspaper the NRC had the following headline in 2016: 'The season of the bulging trains starts again' (Duursma, 2016). In the Netherlands the crowdedness in the train is a hot topic. Crowdedness in public transport can be defined as the extent to which a vehicle is crowded or filled to excess. The Dutch Railways (NS) also report that passengers may be inconvenienced by crowded trains during 2016 and 2017, especially during rush hour on specific routes (Nederlandse Spoorwegen, 2016). To partly mitigate this the NS employs 11 double-decker train cars from the 1980's starting 5 September 2016 (NU.nl, 2016). Additionally the NS tries to persuade train passengers to avoid the heaviest commuter traffic through their website. Furthermore the NS instructs its own personnel to avoid travelling during rush hours (NOS, 2016). To inform travelers about crowding an indicator of the expected level of crowdedness of each specific voyage is integrated in the smartphone application of the NS. This application is shown in Figure 1.1, the expected level of crowdedness is shown on the right and is highlighted with a red rectangle. The number of dark blue persons indicates the expected level of crowdedness of the journeys. The NS bases the data for this app on averages of crowdedness from the past months (Nederlandse Spoorwegen, 2016) which are gathered using data from the OV-Chipkaart (this is a personal card used to check in and out in public transport in the Netherlands).

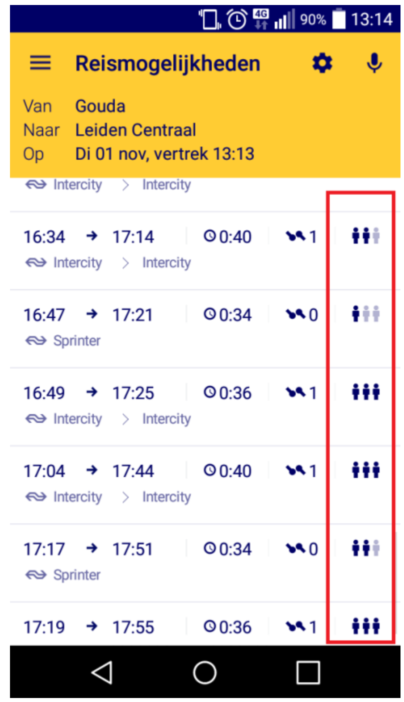


Figure 1.1: Crowdedness indicator in the NS app

An additional problem that amplifies this crowdedness is that passengers are not equally distributed over the train. According to the NS this is caused by the fact that travelers tend to board the train at the same entrance. Some compartments are thus busier than other compartments. The NS therefore advices passengers on their website to look for less crowded compartments in the train, to counter some of this inconvenience. Not all passengers seem to follow this advice and the problem of uneven distribution of passengers therefore remains (Nederlandse Spoorwegen, 2016). A solution to this problem can be to better inform passengers about the crowdedness in each separate compartment in the train so they can anticipate and enter the train in a relatively less crowded compartment. This should preferably be done in


Figure 1.2 Dynamic sign at 's Hertogenbosch

real time so passengers can be informed most effectively. Such real time crowdedness information can for instance be implemented in the current app or can be added to dynamic signs/displays at the platforms of the stations. Dynamic displays can already be found at the station of 's Hertogenbosch (shown in Figure 1.2). To get this information to such platform it is needed to measure the occupancy in the train in real time. To facilitate this, the suitability of indoor localization methods is studied in this research.

Localization Based Services (LBS) are popular nowadays; LBS accounted for an estimated revenue of 10.3 billion United States Dollar in 2014. This increase in use of LBS is related to the rise in popularity of the smartphone (Radaelli, Moses, & Jensen, 2014). Most of these devices employ GPS. Unfortunately GPS is inadequate in indoor environments (such as the train) due to multipath and signal blocking (Rothkrantz & Lefter, 2013). Indoor localization and mapping can therefore be seen as a distinct area of research. The research of indoor localization and mapping started more than 3 decades ago and in the last 20 years the use and demand for indoor localization and mapping by the public has also grown (Zlatanova, Sithole, Nakagawa, Zhu, & Gist, 2013). Various methods for indoor localization have been developed. The methods make for example use of technologies such as Bluetooth, WLAN, UWB, Infrared, Ultrasound and Cameras. None of these technologies, however, is as dominant for indoor localization as GNSS is for outdoor localization (Mautz, 2012). Therefore choosing to employ a suitable or a mix of suitable indoor localization technologies and methods should be done with a specific goal and environment in mind, since these methods and technologies have different performances (Pirzada, Nayan, Subhan, Hassan, & Khan, 2013).

Indoor navigation is one of the predominant purposes of indoor localization (van der Ham, Zlatanova, Verbree, & Voûte, 2016). Indoor location methods and technologies can however also be used to monitor humans or objects in buildings in real time (Kalogianni et al., 2015). These technologies may also work in the train and could therefore provide the necessary solution to provide passengers with real time information about the occupancy of the different compartments of a train. The occupancy of a compartment can be defined as the state or the extent to which a compartment is filled. This is thus very interrelated to crowdedness as this the extent to which a compartment is filled to excess. Occupancy is mostly used in this research in relation to the conducted tests when describing the extent of which a compartment is filled, because this term is not directly implies an excess. Crowdedness is used when an excess needs to be emphasized. The objective of this thesis is to research the most suitable indoor location methods to monitor the occupancy of passenger in the train per compartment in real time to foster a more even distribution of passengers in the train.

1.2 Societal relevance

One of the most widely recognized solutions with regards to traffic congestion and air pollution originating from urban transport is to encourage people to make use of mass public transit (Batarce et al., 2015). Comfort can be a significant factor in the decision making process of choosing a transport mode. Despite this the comfort of public transport is not always adequate enough to fit travel demand. It thus seems relevant to increase the comfort of public transportation modes (Batarce et al., 2015). Comfort also seems to be of importance for Dutch commuters when they choose a form of transportation. Of the half a million daily commuters that travel with NS transport, 50% indicates that one of the reasons they travel by train is to relax while travelling (Pel, Bel, & Pieters, 2014). Passenger density negative effects on the perception of travel time in public transport. Crowded journeys are generally perceived as longer by passengers (Batarce et al., 2015). The issues related to crowdedness are not limited to the Netherlands and occur in multiple countries (Leurent, 2009). According to Pel, Bel, & Pieters (2014) crowding related aspects such as the likelihood of a acquiring a seat are valued as one of the most important customer satisfaction factors. In a research about public transport in Paris the unit cost ‘standing time’ is evaluated as 1.6 times that of ‘seated time’, with an added 0.3 times if the public transportation mode is densely crowded (Leurent, 2009). An increased possibility of acquiring a seat is thus of added value to the usage of public transport.

Travelling in public transport can cause a significant amount of stress. The amount of stress can increase when a public transport mode is crowded. This stress can spill over to a person’s work and home time as well as affect the overall quality of this person’s life. This elevated stress can furthermore lead to health problems (Cantwell, Caulfield, & O’Mahony, 2009). It can therefore be stated that crowdedness in the train is a problem that negatively impacts society. Dziekan & Kottenhoff (2007) found that dynamic at-stop real-time information displays that show departure and arrival times have multiple positive effects on customers. These effects include reduced uncertainty, increased ease-of-use and a greater feeling of security, a higher customer satisfaction and a better image. It seems probable that some of these positive effects may also apply to systems that provide real time information about crowdedness in public transport. For the reason mentioned in this section it seems that research can be relevant to society.

1.3 Scientific relevance

In previous research a lot of indoor localization systems have been tested and evaluated (Van Haute et al., 2016). However they have not been tested in scientific research for the environment of the train. This environment of the train may influence the choice of the optimal technology especially since the train is a unique environment (the characteristics that make a train a unique environment can be found in chapter 4). Therefore an evaluation of indoor localization methods is imperative to be able to assess localization in practice. Furthermore the real time acquisition of dynamic environments, especially in environments with many moving objects, is one of the emerging problems in the research subject of indoor localization (Zlatanova et al., 2013). While the interior inside of train is static, the passengers (and their luggage) in the train are not. In the train is there is a relative larger density of people on average than in most indoor environments. Due to the relatively large density of people (and their luggage) located in the train, the train can be defined as a dynamic environment with many moving objects. The train thus seems a good addition to the current knowledge base of indoor localization in dynamic environments.

2. Research objectives

In this study the following main research question has been formulated:

Which localization method is most suitable to monitor occupancy in the train in real time?

The main research question is divided in the following sub-questions:

1. *Which characteristics distinguish the train environment from other indoor environments with regards to indoor localization?*

A train is unlike other indoor spaces and may therefore have unique characteristics that can influence the performance of indoor localization techniques. Characteristics of the train environment are defined in this research as a form of 'soft' factors that are not directly attached to a train. It is important to take these characteristics (as for example the fact that a train is moving) into account when choosing a suitable localization system. Therefore, the limitation and possibilities of the train regarding indoor localization are explained. This is researched by exploring the literature to find the features of an indoor location that influence localization, and relating these to the characteristics of a train found with empirical research.

2. *Which characteristics distinguish a train compartment from other indoor environments with regards to indoor localization?*

This sub-question is closely related to the previous sub-question. It differs however from the previous sub-question as it concerns the indoor situation at a different level. In this sub-question the train is studied per compartment instead of as a whole. Characteristics of a train compartment are defined as the 'hard' factors of a train; things/objects that are physically attached to a train compartment. This sub-question is also answered by studying the literature and comparing it to empirical research.

3. *What are the relevant characteristics of the indoor localization methods that can potentially be used in the train?*

Indoor localization systems have unique characteristics such as the performance parameters, these are researched using the literature. The second part of this sub-question: "*that can potentially be used in the train"* is used in this context to exclude active indoor localization methods that require passengers to carry devices other than their mobile phone. The potential localization methods are studied in a more in-depth manner and their characteristics are related to the characteristics of the train found in sub-question 1. Based on this study the most suitable system is selected and tested for the next sub-question.

4. *What is the performance of the most suitable indoor localization method(s) when used to monitor passengers in a train?*

This sub-question is answered by testing the most suitable method(s) in a test setting. The empirical results are assessed.

5. *How can the chosen method(s) be implemented in a working application to monitor occupancy per compartment in a train in real time?*

Using an indoor localization system a prototype of an application is created specifically to be used to monitor the location of passengers in the train.

To better define the scope of the research some issues that are not covered in this research are listed below:

1. This research does not cover an assessment of the user requirements of the stakeholders of the Dutch train. So for example no surveys amongst train passengers are used. The user requirements are therefore estimated.
2. Indoor localization methods that require tags or devices except a mobile phone are not tested, since these systems are probably too impractical to monitor train passengers.
3. In this research only systems that can continuously monitor the occupancy inside a train compartment are evaluated. This means that 'counting systems' at the doors of the train are excluded from this research.

The reason that counting systems are excluded is because this thesis is conducted as part of geographic information education and counting at the doors is not deemed geographic enough. Furthermore, a test has already been conducted by the NS with infrared counting systems at the doors, but this was deemed too expensive (Ladan, 2016; Voutê, 2016).

3. Methodological framework

In this chapter the methodological framework used in this research is described. This chapter explains the research strategy that describes the steps of how this research was undertaken. This research consists of four general main-stages. These stages can be subdivided in multiple smaller sequential stages. The aim of all the sub- and main-stages is to find an answer to the research questions, some of them do this directly and others do so indirectly. The paragraphs 3.1 - 3.4 elaborate on each main-stage and the sub-stages of each main-stage. In Figure 3.1 a schematic is shown of all the consequential stages and sub-stages of this research. This schematic suggests a very linear process, but in practice iterations and feedback loops are inherently part of this research and occur when they are needed in this research project. The research is thus better perceived as an ongoing process that uses these stages as a guideline.

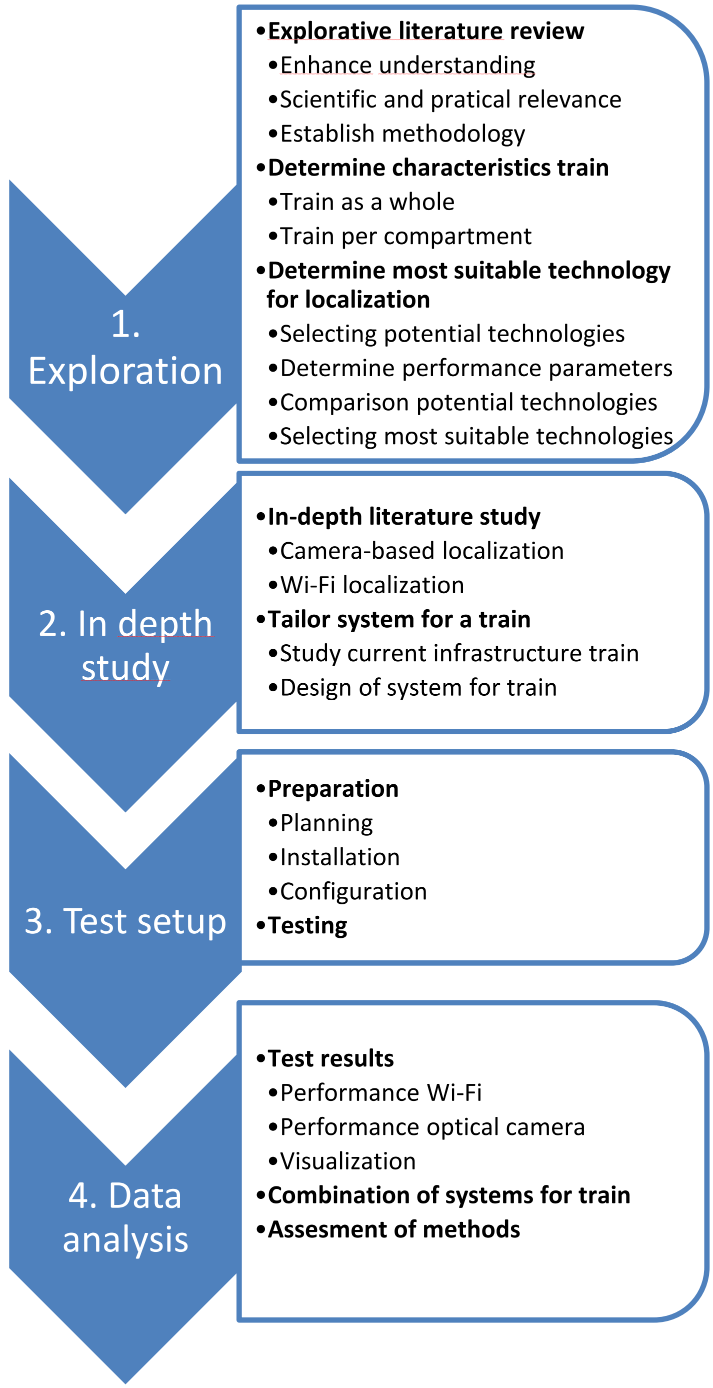


Figure 3.1 Schematic of the stages and sub-stages of this research

3.1 Stage 1: Exploration

This first stage of this research begins with a literature review to understand the context of the underlying problem of crowdedness in the train. This context also relates to the practical benefits of this research. Furthermore the relevant principles, concepts, construct and jargon related to indoor positioning/localization are studied in this stage. This explorative literature research is also used to explore the most recent relevant advances in the field of indoor positioning/localization to determine the scientific relevance of this research. This first exploration of the literature is not only done to be able to inform the reader but also to augment the relative lack of knowledge concerning indoor localization of the author of this research. Lastly the exploration of the research is used to establish the methodology.

The second part of the exploration stage is used to answer the first sub-question of this research. In this phase relevant characteristics of indoor environments with regards to indoor localization are researched using the literature and this knowledge is thereafter related to an empirical exploration of the indoor environment of the train. In this stage a distinction is made between the train as a whole and the train per compartment in accordance to the first and second research question. In the last part of stage 1 the localization methods are categorized per technology to determine the most suitable technologies to be used in the train. This is done by first making a selection of *potential methods* using certain preconditions. These potential technologies are then studied and described in more detail and their advantages and disadvantages are elaborated. Based on this and the relevant characteristics of the train and its compartment, the most suitable technologies are determined in accordance to the third research question. It is important to keep in mind that the last two parts of the exploration stage, about the characteristics of the train and the most suitable technology, are interrelated. Choosing potential localization technologies to monitor passengers in a train is a problematic process without knowing the relevant characteristics of the train environment. To determine, however, which characteristics of an indoor environment are of importance for indoor localization it seems needed to first explore the basic principles and features of potential localization methods and technologies. This segment of the first research stage was therefore performed using considerable amount iterations and feedback loops.

3.2 Stage 2: In-depth study

The second stage of this research starts with an in-depth literature study of the two chosen localization technologies: optical camera-based localization and Wi-Fi localization. This section elaborates on how these technologies have been used before to localize and monitor people and which architecture can be used. The architecture that can be necessary is the combination of sensors, processing units and software components (Gőzse, 2015). The second part of stage 2 is about matching these technologies to the train. First the current infrastructure of the train is studied in relation to Wi-Fi localization and optical camera-based localization. In this stage the locations of the Wi-Fi access points and cameras are for instance identified. Thereafter an indoor localization system (using Wi-Fi and Cameras) is designed that matches the corresponding infrastructure of the train. The focus in this part is embracing the needed software components.

3.3 Stage 3: Test setup

The third stage of this research concerns the testing of the chosen indoor localization systems. This stage consists of the preparation for the test. The phase consists subsequently of planning, installation and configuration. After this preparation is commenced with the testing itself. The testing is done in an office using old train chairs, and in the railway museum using an old non-operating train. In this testing data is gathered. This consists of recordings of simulated train journeys and Wi-Fi logs of simulated train journeys.

3.4 Stage 4: Data Analysis

The final stage of this research is data analysis. In this stage the data from the tests is analyzed and the performance of these results is assessed per technology (Wi-Fi and Camera). The results are visualized using tables and figures and videos. After that is attempted to assess to what extent the Wi-Fi and camera systems can be combined to monitor passengers in the train.

3.5 Model of methods and components

In this paragraph a model of the methods of components used is shown Figure 3.2. This model displays the interrelationships between the methods and components used in this research. It thus differs from Figure 3.1, because Figure 3.1 shows the sequence. The numbers between the brackets in this figure refer to the corresponding chapter, paragraph or section. The goal of this model is to help the understanding of these interrelationships by providing a simplified visual representation. The blue boxes show the components of this research. The funnel is used to emphasize the filtering of technologies to determine the most suitable one. The arrows show dependent relationships between components. The larger arrows can be seen as relationship that can be interpreted as “results in”.

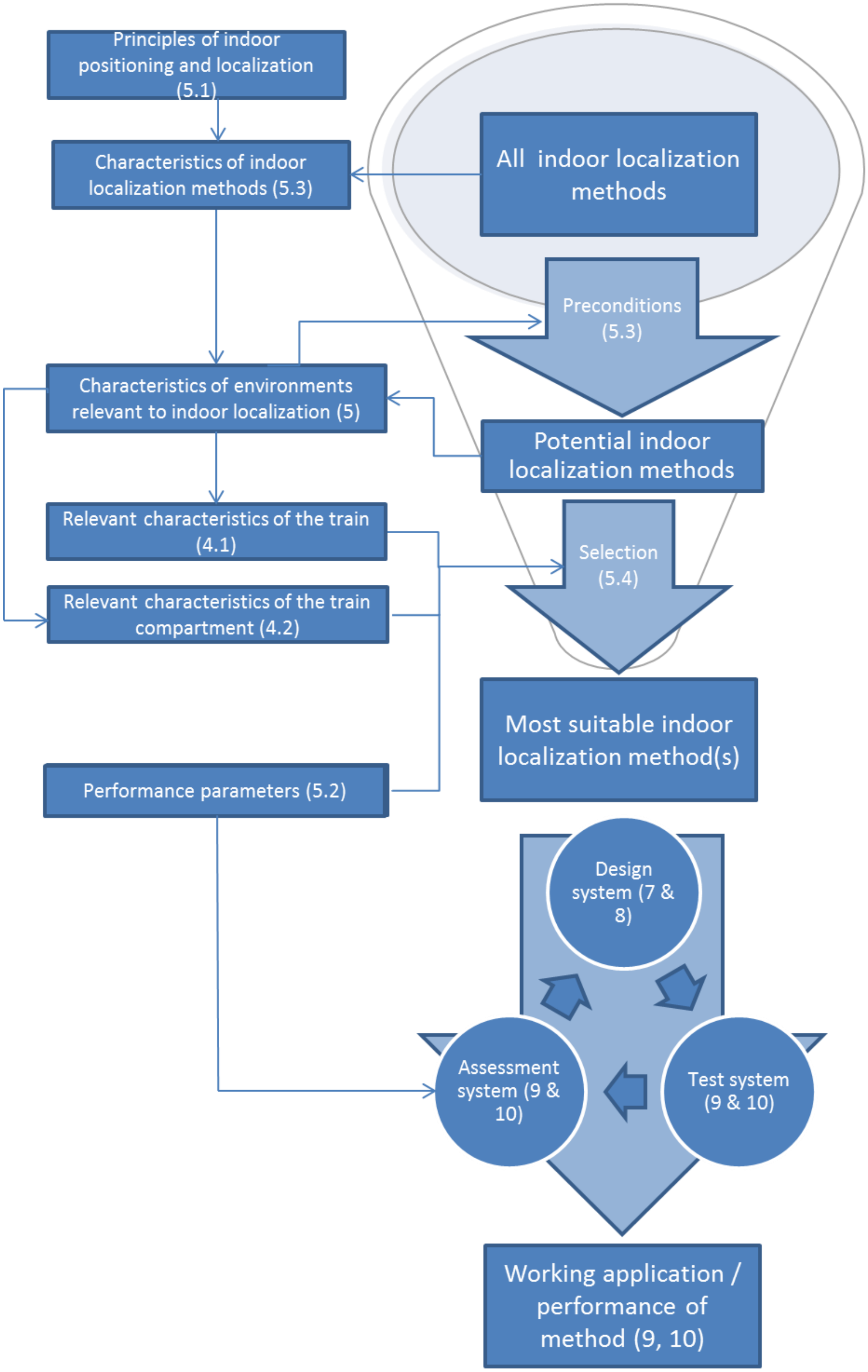


Figure 3.2 Model of relations between methods and components

4 The characteristics of the train relevant to localization

There are several factors of a structure that can influence the reason to select a specific localization system. In this chapter the characteristics of the structure “the train” that are relevant for choosing a localization method are described. This is subdivided in: 1) characteristics of the train environment and 2) characteristics of a train compartment. Characteristics of the train environment are defined in this research as a form of ‘soft’ factors that are not directly attached to a train. Characteristics of a train compartment are defined as the ‘hard’ factors of a train; things/objects that are physically attached to a train compartment.

4.1 Characteristics of the train environment

In this research a distinction is made between characteristics of the train environment that are perceived as a difficulty for localization and characteristics that provide an opportunity to increase the performance of localization. These are subsequently described in section 4.1.1 and 4.1.2.

4.1.1 Difficulties train environment

In this section the characteristics that are perceived as difficulty for indoor localization in the train are described. These factors are relevant to take into account when choosing the right localization methods.

- **Varying number of people.** In a passenger train a varying number of people are present. This has influence on the accuracy of methods that rely on signals, because people (which consist for approximately 70% from water) have different propagation properties than air. Therefore the travel time of signals and signal strength can vary depending on the amount of people it has to traverse. This especially influences fingerprinting methods because the presence of people may influence the predefined signal strength maps (Mautz, 2012). The train passengers may furthermore influence the performance of optical-based methods as the line of sight of cameras can be blocked by passengers.
- **Moving location:** Because the train is moving it is hard to indicate the location of occupancy using absolute coordinates as these constantly change. It is therefore necessary to choose a system that is able to measure the relative location. So a system that can for example indicate the location of the most forward compartment of this specific train that has as specific identification number. Relative localization at a compartment level is further elaborated in section 4.2.2 under the bullet point: Known and static interior.
- **Varying amounts of natural light:** Because the train is full of windows the amount of light coming into the train from outside can vary due to day and night, the shadow of clouds or objects such as trees and buildings and due to street lanterns in the night. This can decrease the performance of using localization methods that are affected by light, such as methods that employ cameras.

4.1.2 Opportunities train environment

In this section the characteristics of the environment of the train that are perceived as opportunities for localization in the train are described.

- **Predictable pattern of the number of passengers:** Passengers only enter and leave the train during train stop and between train stations passengers cannot leave the train (under normal circumstances). This provides the opportunity that once a person is identified by a system as being located on the train, it can be assumed that the person will not leave the train during the further duration of a train journey. This can be exploited by methods that make use of unique identifiers, such as Wi-Fi localization (Wi-Fi localization is further described in section 5.3.1). Because when a passengers has been identified and detected on the train it can be assumed that he will not leave the train during that journey. It furthermore provides opportunities to use a unique identifier measured from a passenger in one location in the train as a reference to detect this passenger if he/she moves to another location in the train. If a passenger is detected in another (new) compartment the assumption can also be made that he/she most likely left the old compartment.

- **Relative static location of passengers between stations:** Not only is number of people during a train journey static, the location of these people is also often static. When people enter the train it seems likely that they will look for a seat or spot to settle. When they are settled it can be assumed that most train passengers will remain in the same location. This knowledge might be used to increase the performance of the localization if it can be combined with knowledge of the time of departure and arrival at a station. The location of the people can be measured multiple times in the ride between stations and this multitude of measurements can be accumulated to create a more accurate estimation of their location.
- **Area with clearly defined boundaries:** When locating people in a train it is only possible for people to be inside a train. People outside of the train can thus be excluded as shown in Figure 4.1. This provides opportunities for signal-based localization methods as these methods may also measure people located outside the train. The relevant measuring principles used for signal-based localization are explained in section 5.1.4.

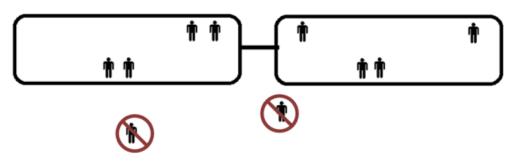


Figure 4.1: People inside and outside the train

- **People located on a platform often enter a train:** People that are located on the train platform where a train stops are likely to enter that train, especially people that are located on the corresponding side of the platform. This can provide an opportunity for signal based methods that use unique identifiers, such as Wi-Fi localization. As it may be possible to identify and detect people before they enter the train and then use the unique identifier as a reference to detect these people again during a train journey.
- **An empty train can be used as reference:** It can be an advantage that data can also be gathered from a train is empty, when it is for example located at a train yard. Data of an empty train can be used by some localization methods as reference to detect the difference between a (partly) occupied train and an empty train. Pressure sensor may use the amount of pressure from unoccupied chairs as a reference and cameras may use images from an empty train as a reference.

4.2 Characteristics of a train compartment

The inside of a train compartments can have multiple characteristics that are relevant for choosing a localization system. Here a distinction is also made between characteristics that are perceived as a difficulty for localization and characteristics that provide an opportunity for localization in the train. These are subsequently described in section 4.2.1 and 4.2.2.

4.2.1 Difficulties train compartment

- **Compartment size:** Train compartments in the Netherlands have an approximate length of 20m, an approximate width of 2.8m and an approximate height of 4m. This means that a system has to be chosen that functions on areas of that size.
- **Furniture:** Trains compartments contain furniture such as the chairs. The material of an area can have influence on the travel time of signals (see chapter 5), because this depends on the properties of the propagation medium. The furniture can also have negative effects on some methods that require LoS and can cause multipath errors (these are explained in section 5.1.5).
- **Metal objects:** The interior of the train is rich with metal objects. This can decrease the performance of signal-based methods due to the reflection of these signals (Alarifi et al., 2016; Farid et al., 2013). Figure 4.2 gives an impression of metal objects in the train. As can be seen in this picture most of the roof of this NS train consists of metal.

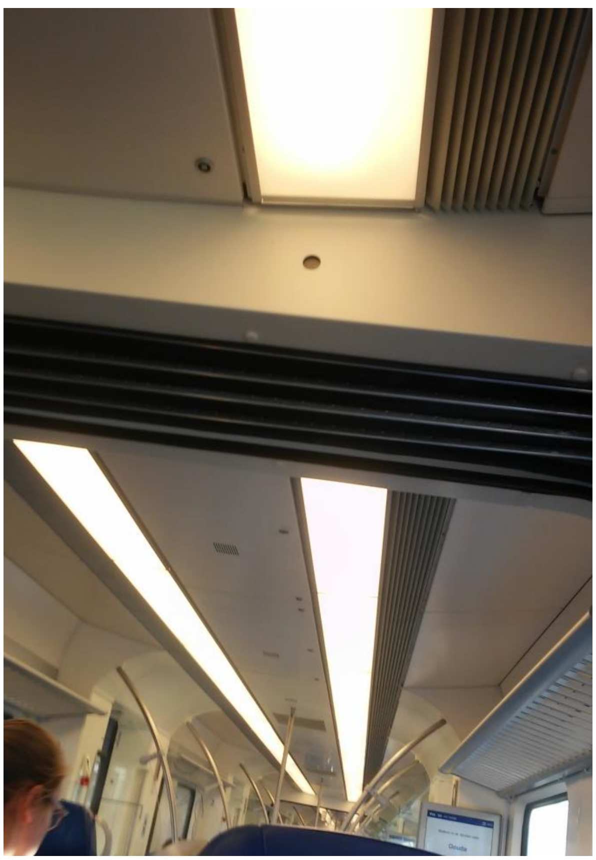


Figure 4.2: Metal in the train

4.2.2 Opportunities train compartment

- **Known and static interior:** The interior of the train is known and is static. The individual elements of each train compartment have a static location in relation to each other. It is furthermore not relevant to know occupancy in absolute terms such as latitude and longitude, because the localization of occupancy can be done per compartment. The train compartment is thus a good fit for a local reference system that only functions for a small region, so it is possible to choose a method that measures relative locations instead of absolute location. So in each train compartment of a train an individual local reference can be used to measure occupancy. The occupancy information of the local compartment reference systems can be combined to another local reference system of the whole train, which indicates the relative location of all the compartments to each other. This information can then eventually be distributed to train passengers using the identification numbers of the trains and their relative location, which can be determined using GPS. This research focusses on the first step of measuring occupancy in one compartment. The other two steps have been described to put the first step into perspective.

- **Format for common locations of passengers.** In a train compartment some assumptions can be made with regards to the locations of people. It is likely that people are only located in the chairs or the hallway and it is likely that only one person is seated in most chairs. It is furthermore impossible for people to be located in some locations such as a wall (Figure 4.3). These assumptions can be exploited by some indoor localization technologies that are able to focus on specific location, such as pressure sensors or cameras. Pressure sensors can for example be installed in chairs and not on the parts of the floor located under the chairs. Another opportunity is that the passengers located on the chair are likely to have a similar posture, and they are therefore easier recognizable and detectable for methods that employ cameras. The format in the train compartment is more rigid than in other indoor environments such as an office, because in an office chairs and other furniture can often be moved.

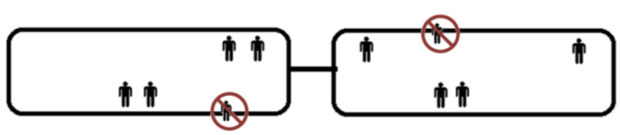


Figure 4.3: Nobody in the walls

- **Wi-Fi access points:** Most of the NS trains are already equipped with Wi-Fi access points in their infrastructure. The already available Wi-Fi access points can potentially make the use of Wi-Fi based location systems a relative cheaper option. Wi-Fi based localization can detect individual Wi-Fi devices that have their Wi-Fi enabled even if they are not connected to a Wi-Fi access point using a unique identifier called a MAC (Media Access Control) address (Wi-Fi localization is further explained in section 5.3.1). Detecting and identifying devices that are connected to a Wi-Fi access point is however more accurate. This is especially true for IOS devices that use random MAC-address, since their MAC address does not change anymore once they are connected to a Wi-Fi access point (Apple, 2016). This is further explained in the beginning of paragraph 10.3. It seems likely that a significant number of passengers are connected to the Wi-Fi access points in the train (NU.nl, 2016), so Wi-Fi localization may exploit this.
- **Security cameras:** Some NS trains that are deployed in the Netherlands are equipped with a security camera system. New trains, called FLIRT (Flinker Leichter Innovativer Regionaltriebzug),

that are deployed in in December 2016 by the NS are equipped with a security cameras system that according to Casper Mintjes (Coordinator CCTV, NS) can see 96% of the inside of a train. The availability of cameras in trains makes the use of cameras technology for indoor localization relatively cheaper.

- **Artificial lighting:** In contrast to the light coming from outside the train the light originating from inside the train hardly varies, because every Dutch train is equipped with artificial lighting. This thus (partly) mitigates the effects of the varying amount natural light described in section 4.1.1.
- **Availability of electricity:** In the train there are multiple objects that require electricity, such as the light, the engine, the heating and the automatic doors. This thus means that there are possibilities for connections to electricity available. This has the advantage that it is possible to use technology for indoor localization that requires electricity without having to rely on batteries. The costs required to connect to the electricity network may vary depending on the location and the number of connections needed.

5 Localization methods, principles and technologies

In this chapter the third research question *'What are the relevant characteristics of the indoor localization methods that can potentially be used in the train?'* is answered. First an introduction to localization and positioning is given, to clarify its concepts and principles. Thereafter the parameters that can be used to describe the performance of localization methods are elaborated. Afterwards the indoor localization technologies that can potentially be used in the train are described and out of these options the most suitable technologies are selected.

In this chapter the terms methods, principles and technologies are used in relation to localization. For these terms multiple definitions can be used. To avoid confusion the definitions used in this research are presented and clarified.

- **Principle:** A principle is defined as the basic idea or rule that explains or controls how something happens or works. In this research principle is mostly used in relations to measuring. A measuring principle in this context is the idea or rule used to measure something (for example a geographic position).
- **Technology:** Technology is defined as the purposeful application of information for practical means. To avoid confusion in this thesis, technology is only used to refer to the purposeful application of information for practical means in relation to sensors. Either the name of the sensor is used (for example a camera) or the name of phenomena that is measured (for example Wi-Fi or infrared) to refer to a sensor technology group, depending on what is standard practice in literature.
- **Method:** A method is defined as a particular form of procedure for accomplishing or approaching something. A method in this research can encompass both a principle and technology. A method can thus include both the principle measuring principle triangulation and the sensor technologies that measures Wi-Fi.

These distinctions are important to make sense of the large number of indoor positioning/localization methods that are available that employ different combinations of principles and technologies. The methods are categorized per sensor technology that they use to allow a clearer and more transparent evaluation (this is done in paragraph (5.3.) This categorization is based on the one used by Mautz (2012).

5.1 The concepts and principles of positioning and localization

Outdoors a rising trend of location-based services can be seen due to GNSS (mainly GPS). The use of GPS indoors is however limited due to walls, ceilings and other objects. Therefore different systems that do not require GPS are often used indoors. These systems are called indoor positioning systems (IPS) or indoor localizations systems (ILS) (Van Haute et al., 2016). In this paragraph the concepts related to the indoor methods are explained.

5.1.1 Positioning and localization

In the literature there are multiple definitions for positioning and localization. To clarify the use of these concepts in this research the definitions used are presented here:

- **Positioning** is the term used for the measuring process to determine the position of an object or a person in absolute coordinates. The measuring process can for example use angles or distance.
- **Localization** is a step further then positioning by adding semantics to the position of the object to be able to pin point it at a specific place and exclude all other places, is called localization. The location is determined relative and is related to an environment, such as specific room. Localization does not require coordinates.

These definitions can be explained by using an example of a car navigation system. Positioning is the determination of the approximate position of the car in coordinates using GPS, localization is then relating this position to a location on a road. These are the definitions that are also used in this research. Relating people to a specific place in a train such as is done in this research is thus localization.

5.1.2 Indoor tracking/monitoring

Indoor localization and positioning can be used for several different purposes. One can use it for example to provide navigation from one location to another. Another purpose can be tracking, which is the process of repeated positioning of a moving object in time. Contrary to navigation tracking is used to determine the location of an object, where the information about the location is not necessarily known at the object (Mautz, 2012 p. 26-27). The objects that need to be tracked in this case are people. To measure the occupancy of the train the information needed is the location of all people in the train. It is not needed for each individual in the train to know their own location and therefore the term tracking can be used to refer to the type of indoor localization used in this research. Verbree et al. (2013) and Kalogianni et al. (2015) used the definition Wi-Fi monitoring for a system that stores the signal strength of Wi-Fi devices on an external database to monitor the location of people. The term monitoring thus also seems applicable in this research. The terms indoor monitoring and indoor tracking are therefore also used in this research to refer to the specific form of indoor localization employed in this research

5.1.3 Active and passive systems

In positioning and localization systems a distinction can be made between an active system and a passive system. Mautz (2012) and Kivimäki, Vuorela, Peltola, & Vanhala (2014), Pirzada, Nayan, Subhan, Hassan, & Khan (2013) define the difference between the two systems, however their definitions have small differences. Therefore to prevent confusion the definition used in this research is stated below:

- An active system does not require users to perform any specific activities for the system to position them. It is depended on a tag or a device attached to the object(s) that is/are being located.
- A passive system merely uses self-reliant sensor data and can operate independently. Such a system does not require a tag or a device. (Kilic, 2015; Kivimäki et al., 2014).

For the measuring of the occupancy in the train passive systems seem like the best option, since people are generally unwilling to wear extra devices. Furthermore the distribution of tags or devices is very impractical and probably costly as well. The only active systems that may be usable are systems that make use of smart phones, since 81% of the people in the Netherlands own a smartphone (Bruyckere, 2015). Not everybody has a smartphone (or some may have multiple smartphones) and these systems require the phones to be turned on and have specific settings (as for example enabling Wi-Fi). Therefore the performance of such systems suffers and they can only give an estimation of the occupancy in the train.

5.1.4 Measuring principles

In this section several of the most basic measuring principles used in the most common indoor positioning/localization methods are described to give a better understanding of these methods.

Trilateration/ Triangulation

Triangulation it the collective name for the methods lateration and angulation. In lateration the position of an object is calculated based on its relative distance to several fixed known points in space. The relative distance is often calculated by measuring parameters with a direct relationship to distance (such as time of flight). Lateration is shown in Figure 5.1. In angulation the position of an object is calculated based on its angle of the arrival of the signal from several fixed known points in space (Mautz, 2012; Torres-Solis, H., & Chau, 2010). Angulation is shown in Figure 5.2.

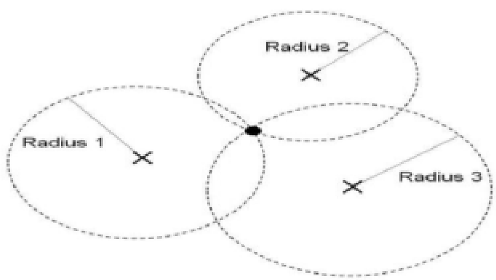


Figure 5.1: The principle of lateration

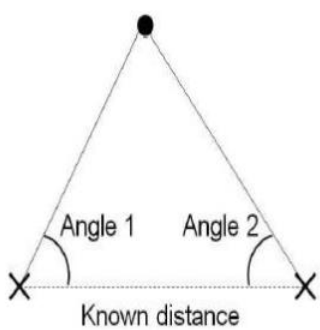


Figure 5.2: The principle of angulation (Disha, 2013)

Time of Arrival (ToA)

ToA is a principle in which the *absolute* travel time of a signal from a transmitter at unknown locations to receivers at known locations is measured. This is done by transmitting a timestamp with a signal. It is therefore of importance that the transmitter and the receivers are exactly synchronized. The sensitivity of the time measurement is in the order of nanoseconds (Mautz, 2012). The distance between these two entities can then be calculated using the travel time and the wave speed. The wave speed is depended on propagation medium. Different building materials result in different travel speeds (Farid et al., 2013; Mautz, 2012).

Time Difference of Arrival (TDoA)

TDoA also uses multiple receivers at known locations that measure a signal of a transmitter of an unknown location to determine the location of the transmitter. However,

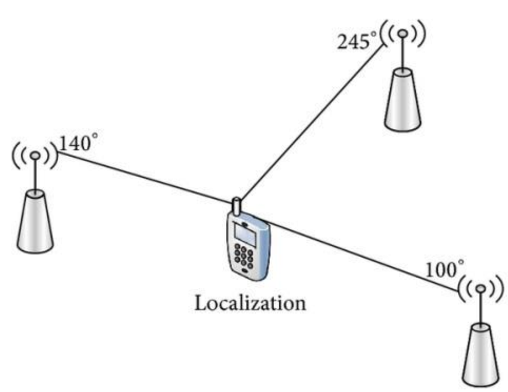


Figure 5.3 Angle of Arrival

TDoA relies on *relative* time measurements in contrary to absolute time differences (Mautz, 2012). With TDoA a timestamp is not attached to the signal sent by the transmitter and only the receivers require time synchronization. The differences between the arrival times yield a hyperbolic curve on which the location of the receiver is sited. The intersection of the numerous hyperbolic curves is the location of the transmitter device.

Angle of Arrival

This method determines the angle of which a signal from a device arrives at multiple beacons (angulation). To estimate the position of a mobile device in 2D two beacons are required. For a position in 3D at least three beacons are required. More than the minimum number of beacons can lead to a higher accuracy. The AoA method is shown in Figure 5.3.

Received Signal Strength Indication (RSSI)

RSSI values can be used for distance estimations. RSSI are the average Received Signal Strength (RSS) values over a certain period of time. The signal strength of radio waves can be used to measure distance because the signal strength gradually decreases with an increasing radius. This decrease is caused by the signal travelling through air or other materials. If this decrease is known RSSI can thus be used to estimate distance between a receiver and (multiple) transmitter(s). The performance of using RSSI to estimate distance can suffer from interference, multipath propagation and presence of obstacles and people (Mautz, 2012).

5.1.5 Common difficulties in indoor positioning and localization

In this section the two common difficulties in indoor localization and positioning are described that are of interest to the indoor localization methods described in this research.

Multipath propagation

This is the propagation phenomenon in which a receiver receives an electromagnetic signal by two or more paths. This is caused by the reflection of the signal from a surface before is arrives at the receiver. This is shown in Figure 5.4. This results in a received signal with a longer travel time which influences the accuracy of systems that use time based ranging methods (Mautz, 2012).

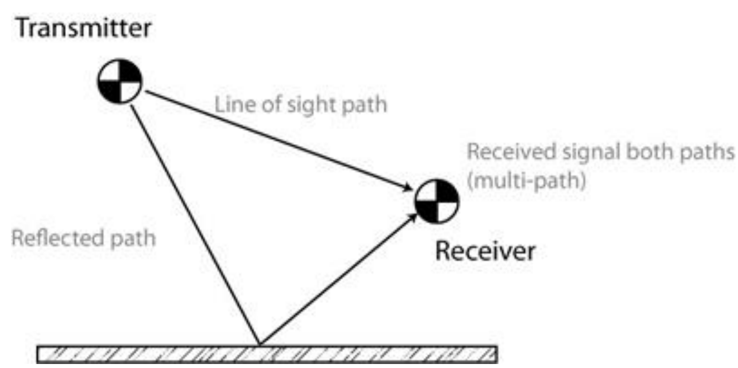


Figure 5.4: Multipath propagation (Ulmer, 2016)

Line of Sight (LoS) and Non Line of Sight (NLoS)

LoS is existent when a signal is able to travel in the shortest straight path from a transmitter to receiver. NLoS is the situation in which this is not possible. This can be due walls, people, furniture or other objects. These objects can thus influence the performance of methods that rely on LoS.

5.2 Performance parameters

To measure the performance of indoor positioning several factors can be compared. Mautz (2012, p. 16) suggests several parameters that can be used to identify the most ideal indoor localization/positioning system for each particular situation. These factors are shown in Figure 5.5.

Figure 5.5: Indoor positioning performance factors (Mautz, 2012)

The performance parameters are described shortly in the rest of this paragraph in Table 5.1. It is important to keep in mind that most of these factors cannot be measured with exact numbers. Furthermore, the importance of each individual factor can vary case-by-case due to the unique characteristics of each case. The weighing of the individual factors is therefore hard and cannot be done correctly in an objective manner. In practice these parameters are weighted largely subjectively (Mautz, 2012).

Accuracy	The performance of indoor positioning is quantified by most researchers, developers and vendors as positioning accuracy. Positioning accuracy is the degree of conformance of an estimated or measured position to the true position, expressed in for the vertical and horizontal components at a 95% confidence level. Accuracy is often seen as the key performance indicator. It should however be taken in perspective with the other performance parameters.
Coverage	Coverage defines the spatial area where the positioning system works properly according to standards of the system.
Costs	The costs of system. This can be costs to set-up the system, costs per user device, the costs per area or room and the maintenance costs.
Infrastructure	This is the additional hardware needed for the indoor positioning system. This can for example be markers, passive tags, and active beacons.
Market maturity	This is the level of development of the product. If there is for example a fully developed product available or only a prototype.
Output data	This is data produced by the system. This can have varying properties such as a relative or an absolute location, 2D or 3D.
Privacy	To what extent can privacy be assured using a system. More on privacy can be found in chapter 11.
Latency	This is the time difference between the position request and the position fix.
Interface	This relates to the user interface. The user interface can for example be text based or a graphical display
System integrity	This describes to what extent the system is able to provide a warning if it is malfunctioning.
Robustness	Robustness describes to what extent a system is vulnerable to damage or theft.
Availability	This factor is the percentage of time that the systems service is available since its start with the provided accuracy and integrity.
Scalability	To what extent and how can the area be scaled in which the area functions.
Number of users	Concerns the number of users can the system handle simultaneously.
Intrusiveness	Users can be disturbed by the localization system or the system can be imperceptible.
Approval	This concerns the legal aspects of the system.

Table 5.1: Indoor positioning performance factors (Mautz, 2012, p. 15-21)

5.3 Indoor localization sensor technologies

In this paragraph indoor localization methods have been categorized based on the type of sensor technology they employ. Most technologies can be employed using different methods for indoor localization. The technologies are therefore characterized at a high-level. This means that only their general advantages and disadvantages are given and that there may be outlying methods that are an exception to these advantages and disadvantages.

Not all technologies can be used in the train for indoor localization and some technologies are so impractical that they can be disregarded as an option. These are therefore not or shortly described. Technologies that can potentially be used in the train are described more in depth per technology (these are called potential localization technologies in this paragraph). The selection procedure of these potential technologies is done using certain preconditions that a technology must fulfill to be seen as a potential technology. A scheme of the selection procedure of the potential technologies is shown in Figure 5.6.

First it is important to make a distinction between active and passive localization (described in section 5.1.3). Passive localization methods seem usable in the train, since they do not require passengers to carry additional devices and are just depended on static infrastructure in the train. The most common technologies used in passive localization methods are therefore described further in this paragraph. For active localization a distinction has been made in this research between sensor technologies that only require a smartphone and sensor technologies that require additional devices (as for example tag). Technologies that require other devices are disregarded due to their impracticability and are therefore not described in depth. Technologies that require a smartphone are not disregarded, since 81% of the Dutch population between the age of 18 and 80 owns a smartphone (Marketingfacts, 2015). So the number of smartphones in a train can probably be used to estimate the number of passengers.

Another distinction that needs to be made is that it is important to differentiate between technologies in which the location is solely known at the location of the smartphone itself (client side) and technologies in which the location is determined at a server (server side) and its location is not necessarily known at the object. In this research the goal is to monitor/track people and therefore only technologies in which locations are known at the server are considered in this research. Technologies in which the location is only known client side, such as Inertial Navigation Systems and GNSS, are disregarded. From these *server side* technologies it is only useful to look into the methods of those technologies that do not require passengers to install additional software and enable additional uncommon settings. It is deemed unrealistic in this research that a high enough percentage of train passengers would enable additional settings to enhance an indoor monitoring system of the NS. According to a survey smartphone users have their Bluetooth turned on 43% of the time and their Wi-Fi turned on 75% of the time (John Kivit, 2015). Wi-Fi is therefore considered to be a common setting. This is in contrast to Bluetooth which is considered to be too uncommon to be a potential technology to monitor passengers in a train.

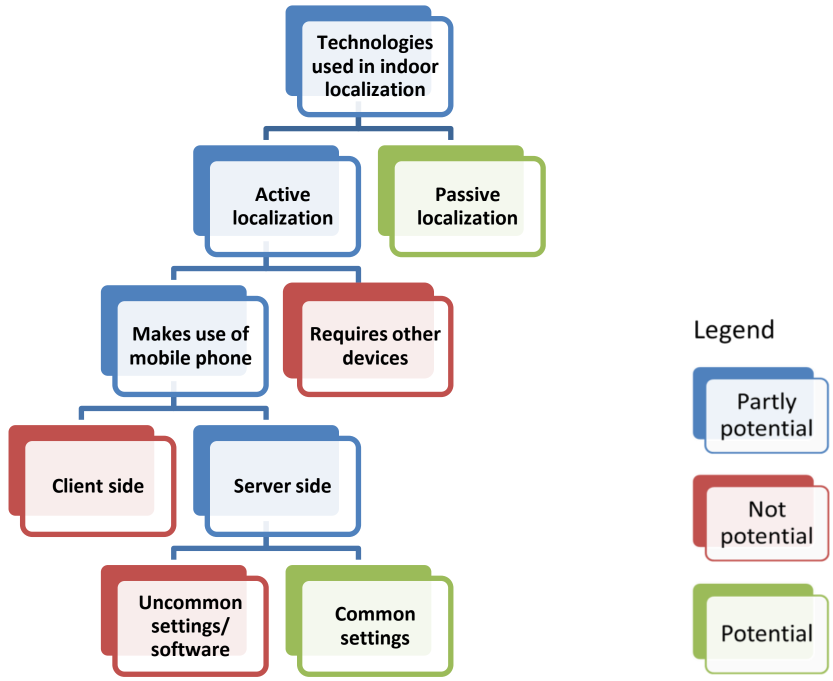


Figure 5.6: Selection process to select potential localization technology

The technologies used in indoor localization that satisfy the preconditions are described per technology:

- Active:
  - Wi-Fi/ WLAN
- Passive:
  - Infrared
  - Sound localization
  - Ultra-wideband
  - Cameras
  - Pressure sensor

From each technology only the sub-categories of methods are described that seem suitable for use in the train. For the potential localization technologies the general principles and the advantages and disadvantages are elaborated. In paragraph 5.4 the most suitable technologies from the potential technologies are chosen based on their characteristics and the characteristics of the train.

5.3.1 Wi-Fi / WLAN technology

WLAN is the network of devices that connects wirelessly with radio signals using standard IEEE 802.11 (IEEE, 2012). Wi-Fi is a brand name for the Wi-Fi Alliance that defines a subset of those protocols, tests and interoperability and it is often used interchangeable with standard IEEE 802.11 and is used in this research. WI-FI signals can be used to estimate the location of a mobile Wi-Fi device in an area. The range of WI-FI is 50m-100m. Wi-Fi technology is often used for indoor localization since Wi-Fi access points are often already available on locations. Furthermore, Wi-Fi is available on most standard smartphones

(Mautz, 2012). Wi-Fi based localization methods have varying amounts of accuracy; methods can have an accuracy ranging from 40 meter to sub-meter accuracy (Radaelli et al., 2014).

There are several different principles that can be used for localization with Wi-Fi. These have been classified in several categories and sub-categories (show in in Figure 5.7). This classification has been established using a classification of localization principles that make use of wireless technologies from Farid et al., (2013) supplemented with a classification of strategies concerning the use of WI-FI for indoor localization from Mautz (2012).

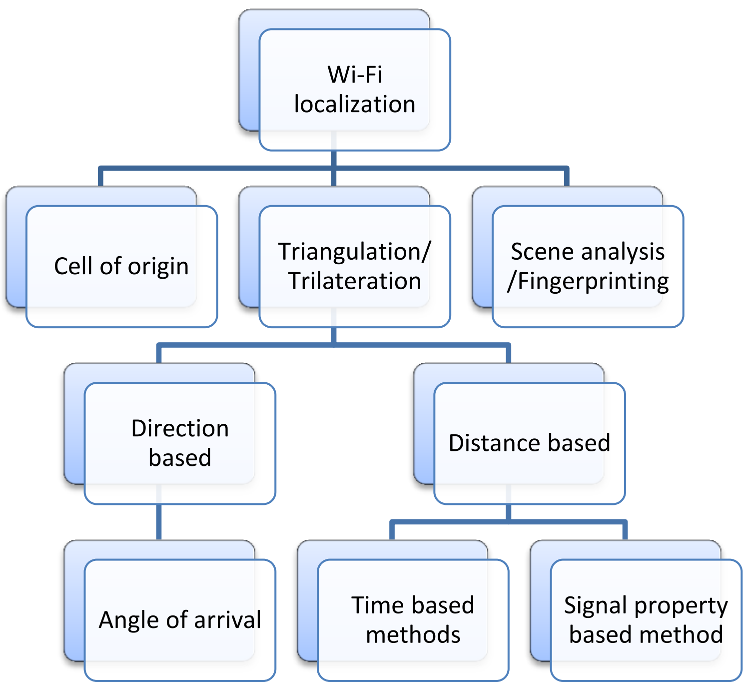


Figure 5.7: Classification of Wi-Fi localization

A mobile Wi-Fi device's location can be measured by the mobile device itself using the signals from WI-FI access points. Wi-Fi access points can however also be employed as Wi-Fi scanners to determine the location of a mobile device using Wi-Fi signals originating from a mobile device. The latter is of importance for this research as the location of the mobile devices needs to be known at the client's side to measure occupancy in the train. This can also be defined as Wi-Fi monitoring (Verbree et al., 2013), which can be seen as a sub-category of Wi-Fi localization. Wi-Fi probe requests are often used for Wi-Fi monitoring. Wi-Fi probe requests are signals send out by Wi-Fi devices used to actively seek a Wi-Fi access point. Some probe request contain a unique Media Access Control (MAC) address that belongs to the corresponding mobile devices, which can used to identify individual devices (Freudiger, 2015).

Cell of origin

In this method the location of a Wi-Fi device is related to the location of a Wi-Fi access point/scanner based on the strongest measured RSSI. The mobile device is then estimated to have the same location as the Wi-Fi scanner where the highest RSSI is measured. This can be done by the mobile device by measuring the RSSI of Wi-Fi access points or by the Wi-Fi scanners by measuring the RSSI of signals originating from a mobile device. The accuracy of this method is thus very depended on the density of the beacons in an area (Farid et al., 2013). This method is therefore often not very accurate, as the WI-FI beacon density is typically 50m (Mautz, 2012).

Triangulation/trilateration

These methods all use triangulation or trilateration to determine the location of an object. As described in section 5.1.4 these employ angulation (angle based) or lateration (distance based):

- Direction based methods:
  - *Wi-Fi Angle of Arrival (AoA) based methods.* These methods employ the angle of arrival measuring principle described in section 5.1.4. To measure the direction of a signal directional antenna or antennas arrays are needed, this has the disadvantages that this makes this method relative more costly than other Wi-Fi methods. Another disadvantage is that AoA methods are affected by multipath and NLOS propagation of signals, which influences the accuracy of these methods.
- Distance based methods:
  - *Wi-Fi Time based methods.* These methods measure a propagation time to estimate the distance between a mobile device and multiple beacons. These distances are then utilized to determine the location of the mobile device with lateration. To estimate the distances the ToA or TDoA methods described in section 5.1.4 are used. These methods have however the drawback that they require modifications to a Wi-Fi system, since probe requests normally do not contain a time stamp. These methods therefore seem too impractical to be used in the train.
  - *Signal property based method.* Like the time based methods the signal property based method also uses estimated distances and lateration to estimate the unknown location of a node. However, the distance between the unknown transmitter node and the receiver is estimated differently however; instead of time of flight, attenuation of emitted signal strength is used to estimate this distance. The property that is mostly used is the Received Signal Strength Indicator (RSSI). The RSSI received at the different known locations is used to estimate distance (a lower received RSSI generally means a longer distance). This received RSSI is however highly dependent on environmental interference and non-linear and therefore the accuracy suffers (Farid et al., 2013; Mautz, 2012; Palaskar, Palkar, & Tawari, 2014)

Fingerprinting/Scene analysis:

This method detects the RSSI of Wi-Fi signals and compares them with the values obtained in a previous (training) phase (Verbree et al., 2013). This can be done by measuring the RSSI of signals originating from Wi-Fi access points or by measuring the RSSI of signals originating from mobile devices. The latter one can be applicable in this research. In the training phase of this method the RSSI of Wi-Fi signals is observed at different locations in the indoor location and stored with ground-truth locations in a database called a radio map. This database is then used in the online phase to estimate the position of a mobile device by comparing its current RSSI measurements to those stored in the database (Mautz, 2012; Palaskar, Palkar, & Tawari, 2014).

Wi-Fi overview

In Table 5.2 the estimated advantages and disadvantages of using Wi-Fi technology for indoor localization in the train are shown.

Advantages	Disadvantages
• Inexpensive: infrastructure already available	• Not bound to train: may measure signals originates from outside the train • Low and varying accuracy: only one access point per train compartment • Depended on number of devices with Wi-Fi from passengers

Table 5.2: Advantages and disadvantages of Wi-Fi localization

5.3.2 Infrared technology

Infrared light is in the electromagnetic radiation spectrum, it has wavelengths between 750 nanometer to 1 millimeter (Kivimäki et al., 2014). It is outside of the visible spectrum, thus it cannot be seen by humans. It can however be used for indoor positioning/localization. Mautz (2012) distinguishes three general methods that use infrared light: 1) use of active beacons, 2) infrared imaging using thermal radiation and 3) artificial light sources. In this research the use of active beacons is not described, since active beacons requires train passengers to carry extra devices (which is too impractical). The use of artificial light sources is also not described since these have a coverage of only 3.5m which is too small for this research. Positioning systems employing infrared imaging from thermal radiation is also known as passive infrared localization (Mautz, 2012).

Infrared imaging with thermal radiation/Passive infrared

Thermal infrared has a wavelength of 8 to 15 micrometer so sensors that function in this spectrum are able to detect humans or objects without them wearing any infrared devices. Examples of thermal sensors are thermal cameras, broadband detectors, pyroelectric infrared sensors and thermocouples (Mautz, 2012). Humans can be detected by their body heat and the radiation they emit due to this. A persons head is often the warmest part of a body and is therefore often the easiest body part to detect with an infrared sensor. In the train this effect is most likely magnified, since people are often heavier clothed in trains than in other indoor locations.

A disadvantage of using thermal sensors is that their performance is influenced by strong radiation from the sun (Mautz, 2012). Furthermore the contrast in infrared light between a human and the background can change between day and night. Another disadvantage is that infrared light is influenced by metallic surfaces because these are good heat conductors and also reflect infrared light. This can be problematic in the train as there are quite a few metallic objects in the train. An additional drawback is that infrared sensors performance suffers when tracking multiple targets. It is therefore difficult to determine the exact number of people in a room. An advantage of using thermal cameras is that illumination is not necessary, this is in contrast to cameras that film the visible spectrum (Kivimäki et al., 2014). These advantages and disadvantages are shown in Table 5.3.

Advantages	Disadvantages
• Potential high accuracy*	• Performance suffers from tracking multiple targets • Expensive hardware: It requires additional infrastructure • Interference from sunlight, metallic surfaces and clothing

Table 5.3: Advantages and disadvantages of passive infrared localization

**The requirement for Illumination is defined as a disadvantage of (normal) camera-based localization instead of an advantage of infrared.*

5.3.3 Sound-based technology

Sound is not an electromagnetic wave but a mechanical wave that is transmitted through a medium (such as air). Localization systems either use audible sound or ultrasound (Mautz, 2012).

Audible sound

Audible sound localization has a big disadvantage that it suffers greatly from background noises, movement of sound sources and simultaneous sound sources (Kivimäki et al., 2014; Mautz, 2012). These disadvantages make audible sound localization unfit to monitor the occupation of people in the train and is therefore not described further.

Ultra sound

Ultrasound systems can be divided in *active systems*, *passive systems* and *echolocation*. *Active systems* require users to carry devices, this is too impractical for the train and therefore not further described. P*assive ultrasound systems* would not require passengers to carry devices. These are, however, typically used for small coverage areas (Mautz, 2012) and are therefore not feasible to use in the train. *Echolocation* can be used for larger coverage areas and does not require the use of tags. The method of echolocation is similar to the one used by animals such as bats. A transmitter/receiver sends out sound waves into an area and uses the echoes that return to determine the location and size of objects in that environment. This is shown in Figure 4.3. Jia, Jin, Chen, & Spanos (2015) propose for example an echolocation system (SoundLoc) that is a room level localization system and is supported by the internal microphone and speaker of a mobile phone or laptop, which would make it relatively cheap. The disadvantage of most echolocation systems is that they are still mostly in an experimental phase (Jia et al., 2015; Mautz, 2012). The advantages and disadvantages of echolocation are shown in Figure 5.8.

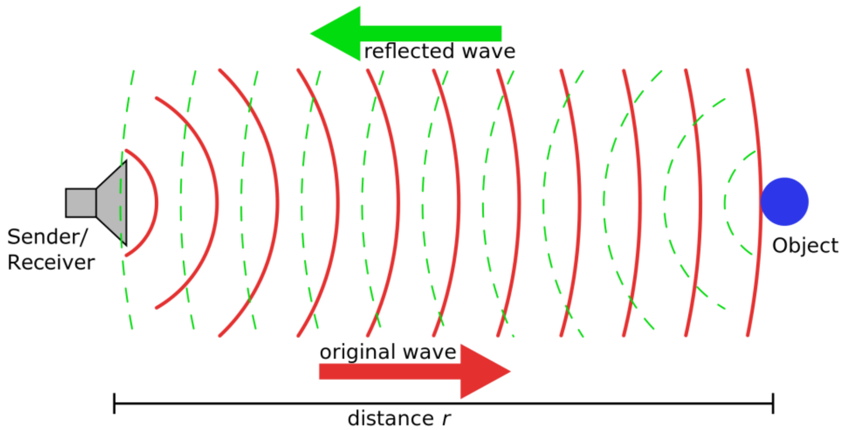


Figure 5.8: The principle of echolocation (Locke, 2014)

Advantages	Disadvantages
• Good accuracy: an expensive system can have an accuracy of 0.5m	• Technology is still in experimental phase • Performance suffers from noise

Table 5.4: Advantages and disadvantages of echolocation

5.3.4 Ultra-wideband technology

Ultra-WideBand (UWB) is a radio technology with a large frequency bandwidth of 500 MHz or higher. It has the distinctive characteristics of strong multipath resistance and penetrability of walls. UWB localization can be divided in an active and a passive form (Mautz, 2012). In this research only the passive form is described since the active form requires users to carry devices other than a smartphone.

Passive UWB detects people or objects using signal reflection through radar system. This means that (an) emitting antenna(s) produces electromagnetic waves and (a) receiving antenna(s), which can be the same antenna(s), captures the returning waves to determine the properties of an object/person. A schematic of this is shown in Figure 5.9. Because UWB has a fine time resolution multipath signal components from the environment can be discerned from the signal component from the target(s). The target, a person or an object, can therefore be identified (Kilic, 2015). When the target is identified its reflection can be used to finds its location using ToA or TDoA if the locations of the transmitting and receiving antennas are known (Kilic, 2015; Mautz, 2012).

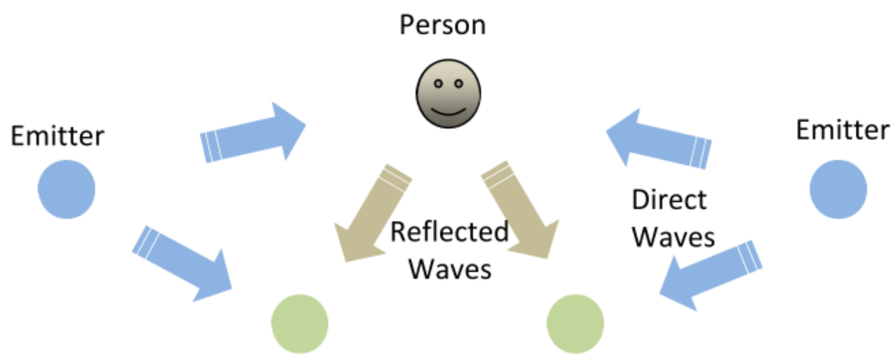


Figure 5.9: Passive UWB localization (Mautz, 2012)

A disadvantage of UWBs penetrating signal is that the object or person that is measured is also (partly) penetrated and therefore the returning signal consists of multiple returns besides the outer boundary reflection. This negatively affects the performance of UWB localization (Mautz, 2012). Another big disadvantage of using this method in the train is that the performance suffers when used to localize multiple people (Kilic, 2015). An overview of the advantages and disadvantages is show in Table 5.5.

Advantages	Disadvantages
• No LOS needed: ability to penetrate walls	• Performance suffers from tracking multiple targets • Requires additional expensive infrastructure

Table 5.5: Advantages and disadvantages of passive UWB localization

5.3.5 Camera-based technologies

Indoor localization systems that make use of cameras technology can be categorized in two systems: 1) systems in which the goal is to locate the whereabouts of a mobile camera, 2) systems where static cameras are used to locate objects or people (Mautz, 2012). This research focusses on the latter system, since the purpose of this research is to locate people. Another distinction that can be made is between camera systems that require users to carry a marker and marker-free solution (Braun, Dutz, Alekseew, Schillinger, & Marinc, 2013). For this research only the marker-free methods are of interest. The performance parameters (like accuracy and coverage area) of these existing systems can vary greatly. Some (expensive) system have an accuracy of about 0.03mm- 0.05mm (Mautz, 2012), to locate people in a train such accuracy seems an excess. Systems that are low-cost and with a large coverage area seem a better fit.

Tappero (2009) proposes a camera tracking system to monitor people in an indoor environment. In this system a camera is attached to a ceiling and is able to locate people and objects with an accuracy of decimeters. The camera relies on the detection of changes of succeeding frames and relies on cheap components. Sun, Di, Tao, & Xu (2010) suggest incorporating human detection with into multi camera video surveillance. They combine human detection with background subtraction by using convex optimization to increase the performance of both methods. Surveillance cameras have also been used in combination with Wi-Fi localization to reduce the training phase of Wi-Fi fingerprinting (Radaelli et al., 2014; Rothkrantz & Lefter, 2013).

An advantage of using cameras is that in some NS trains cameras are already installed and the NS plans to install cameras in all trains (Marloes Ladan, NS employee, 2016). Such a system would thus not require additional costs for new infrastructure. Another advantage is that the accuracy of these systems is relatively good. A disadvantage of these systems is that it relies on line of sight, so if a camera is blocked by an object or a person the system will not function. Another disadvantage is that cameras rely on light, the performance can therefore vary in different amounts of light (Gu, Lo, & Niemegeers, 2009; Mautz, 2012). This effect is mitigated by the artificial lighting that is installed in every NS train. Camera localization also had the drawback that it require high computing power, this is nowadays partly compensated by the exponential growth in computing power in the last decades (Mautz, 2012). The advantages and disadvantages of localization using cameras are shown in Table 5.6.

Advantages	Disadvantages
• Infrastructure already available in some trains • Relative high accuracy	• Prone to NLOS • Performance is depend on illumination • Requires relative high computing power

Table 5.6: Advantages and disadvantages of localization using cameras

5.3.6 Pressure sensor technology

Pressure sensor technology can also be used as an indoor localization system. Pressure sensors can be installed under a floor surface, but also under other surfaces like chairs. This installation requires flexible surfaces and abundant installation space beneath a surface (Kivimäki et al., 2014). When installed under floor tiles these system can reach an accuracy of 1 decimeter when detecting humans (Mautz, 2012). In the train it may be better to also install pressure sensors in chairs, to detect which seats are taken. The benefit of a pressure sensor system is that such it can be relatively accurate and it can focus on specific location, it may for example detect precisely which seats are taken in a train. Disadvantages of such a system are that the installation and maintenance of pressure sensors is laborious and therefore expensive (Kivimäki et al., 2014). Another disadvantage is the robustness parameter of the system; the NS has already conducted a test with pressure sensors in chairs, but the system was too often damaged by train passengers (personal communicaton with Robert Voutê, employee from the company CGI/Logica that implemented such a system for the NS, 2016). The advantages and disadvantages of pressure sensors are shown in Table 5.7.

Advantages	Disadvantages
• High accuracy: measurements per chair	• Expensive implementation • Prone to damage

Table 5.7: Advantages and disadvantages localization using pressure sensors

5.4 Selecting the most suitable technologies

To select the most suitable technologies a selection of the performance parameters from Mautz (2012) is used. The selected performance parameters are shown in the left column of Table 5.8. The performance parameters that are deemed most relevant and useful to localize people in a train have been selected. The selection of these performance parameters has been inspired by Van Haute et al., (2016) and meetings with NS personnel. In the selection procedure of this research the performance parameter accuracy is split in two parts:

1. **Accuracy of location:** This is defined as the degree of conformance of an estimated or measured location to the true location. So in this case this the extent to which an ILS is able to estimate the location of measured passengers.
2. **Accuracy of population:** This is defined as the degree of conformance of an estimated or measured population to the true population. In this case the population is the number of passengers. Wi-Fi is for example limited in this regard because it is dependent on the ratio of Wi-Fi enabled devices in relation to passengers. Cameras can be limited when the line of sight is blocked and the camera cannot be used to detect all the passengers.

The accuracy of location corresponds with the definition used by Mautz (2012). The accuracy of population is an addition to Mautz (2012). This addition is deemed necessary for this research, because this research uses the sub-category of indoor localization that can be defined as indoor monitoring (see section 5.1.2). For the indoor monitoring of this research is seems relevant to be able to estimate the number of passengers as well as their location.

For the other chosen performance parameters the definitions of Mautz (2012) are used (shown in paragraph 5.2). Cost is another of the chosen performance parameter, because the costs have to be taken into consideration when implementing such as system. The next performance parameter taken into account is the number of tracked users. This concerns the number of users the system can handle simultaneously. This thus relates to the capacity of the system with regards to the number of users and this differs from the accuracy of population which relates to the accuracy with which a population is measured. For Wi-Fi localization number of users can for example be the number of Wi-Fi devices a Wi-Fi scanner is able to measure simultaneously, while accuracy of population deals for example with differences in the ratio between the number of Wi-Fi enables devices and passengers. Another parameter taken into account is the market maturity. This is the level of development of the product. This seems important as this can give an indication of the extent at which methods that employ a technology have been developed enough to be applied in practice. It seems more suitable to use a technology for which mature localization methods are available then a technology for which only prototypes are available.

Since the performance parameters cannot be measured and compared with exact numbers (Mautz, 2012), qualitative units are used to compare the technologies with the performance parameters. The technologies are rated from negative to positive with -, **+/-**, or +. It is important to keep in mind that there are often multiple systems available on the market that employ the same technology (such as infrared) but have different performance. The ratings shown in Table 5.8 do not take into account every detail of every available system, but rate technologies on their general characteristics based on a review of scientific literature. It is important to realize the complexity of these rating as it is nearly impossible to take all possible factors into account. The rating system therefore only employs three intervals as more intervals would give a misleading impression of confidence. To rate the performance of each system with more accurate it would be better to test each system in the train. This is however not done in this research due to time and budget constraints.

	Accuracy of location	Accuracy of population	Costs	Number of tracked users	Market Maturity
Wi-Fi	-	-	+	+	+
Infrared	+	+/-	-	+/-	+/-
Echolocation	+	+	-	-	-
UWB	+/-	+	-	-	-
Cameras	+	+/-	+	+	+
Pressure sensors	+	+	-	+	+

Table 5.8: Performance parameter comparison of potential systems

When looking at Table 5.8 and paragraph 5.3 it can be stated that echolocation and UWB seem like the least best option of the potential technologies due to the low market maturity. Furthermore the performance of both technologies suffers from the number of users that need to be tracked. These methods are therefore disregarded. Pressure sensors seem like a technology that could potentially work well in a train. However, pressure sensor were tested in a train in 2012, and this system was not implemented in the complete fleet due to the high costs and due to the low robustness of the system (Voutê, 2016). This system is therefore not tested in this research. Infrared is also not tested in this research due to the following reasons: infrared and normal cameras almost have the same pros and cons, with the main advantage of infrared not being dependent on illumination. In the train, however, lights are continuously on and the requirement of illumination therefore is mitigates. Since cameras are already installed in some trains and will most likely be installed in future employed trains, there seems to be little reason to prefer infrared above (normal) cameras and therefore infrared is also disregarded.

In this research project cameras and Wi-Fi technology are designated as the most suitable technologies to use for indoor localization in the train. The main reason for this is that for both technologies the infrastructure is already available in some trains; the use of these technologies seems therefore relatively inexpensive. Cameras and Wi-Fi both have disadvantages with regards to the accuracy of population. For cameras the line of sight may be obstructed and Wi-Fi monitoring is dependent on the number of Wi-Fi enabled devices. The technologies may complement each other to mitigate these disadvantages. These technologies have been combined before for indoor localization and its incorporation can lead to an increased performance (Lassabe, Canalda, Chatonnay, & Spies, 2009). In this research a form of Wi-Fi cell of origin is used to be able to relate passengers to the location of a Wi-Fi scanner. This is done in combination with a form of Wi-Fi fingerprinting that makes use of RSSI to be able to exclude signals that derive from other compartments or from out of the train. Wi-Fi triangulation is not used because of the small number of Wi-Fi access points in the train (one per compartment).

Passenger trains have different characteristics. Trains can for example have a different size, color or can be made of different material. These characteristics may have influence on the performance of indoor localization methods. To narrow down the scope of this research the focus lies on one train. The development and testing of the methods that use Wi-Fi and camera-based technology is focused on the characteristics of the FLIRT, a train which is employed in the Netherlands by the NS. The general outlines of the methodology used in this research, however, should work for most trains. The FLIRT is thus used to develop and demonstrate an understanding of a real-life case. The motivations for choosing the FLIRT are elaborated in the next chapter, chapter 6 in which the FLIRT is introduced in more detail.

6 Study area

In this chapter the study area of this research is described. The proposed method developed in this research is tailored to the FLIRT (Flinker Leichter Innovativer Regionaltriebzug), which is employed in the Netherlands by the NS. The general outlines of this methodology, however, should work for any train that has a similar camera and Wi-Fi coverage and quality. The reason that the FLIRT is used as test subject in this research is because it has the most suitable camera and Wi-Fi coverage of the Dutch NS trains according to Casper Mintjes (Coordinator CCTV from the NS). It is furthermore the first train for which such a system will most likely be implemented. In the first paragraph of this chapter the general characteristics and interior of the FLIRT are described. In the second paragraph specification of consequently the security cameras are elaborated.

6.1 FLIRT train

The FLIRT is a single-decker regional train. The FLIRT trains that are active in the Netherland either have three cars and seating for 158 passengers or have four cars and seating for 214 passengers. The FLIRT trains have two entrances per car (Stadler, 2016). Maps of the two trains are shown in Figure 6.1. A photo of the inside of the train is shown in Figure 6.2. The first class seats have a different color (red) than the second class seats (blue). This difference is color can affect the performance of the camera-based localization employed in this research. Vehicle data about the length of the train and addition information is shown in Table 6.1. l

Figure 6.1 : Maps of the 3 and 4 cars FLIRT trains in the Netherlands (Stadler, 2016)

Figure 6.2: Photo of the interior of the FLIRT train (Stadler, 2016)

Vehicle data	**3-car**	**4-car**
Customer	NS	NS
Lines operated	The Netherlands	The Netherlands
Gauge	1435 mm	1435 mm
Axle arrangement	Bo'2'2'Bo'	Bo'2'2'2'Bo'
Supply voltage	1.5 kV DC	1.5 kV DC
Number of vehicles	33	25
Service start-up	2016	2016
Seating capacity 2nd Class	114	170
Seating capacity 1st Class	32	32
Fold-up seats	12	12
Floor height		
Low-floor	780 mm	780 mm
Low-floor PRM area	808 mm	808 mm
High-floor	1180 mm	1180 mm
Door width	1300 mm	1300 mm
Longitudinal strength	1500 kN	1500 kN
Overall length	63200 mm	80700 mm
Vehicle width	2820 mm	2820 mm
Vehicle height	4120 mm	4120 mm
Bogie wheelbase		
Motor bogie	2500 mm	2500 mm
Trailer bogie	2700 mm	2700 mm
Driving wheel diameter (new)	920 mm	920 mm
Trailer wheel diameter (new)	760 mm	760 mm
Maximum power at wheel	3000 kW	3000 kW
Starting tractive effort	200 kN	200 kN
Maximum speed	160 km/h	160 km/h

Table 6.1: Vehicle data of the FLIRT

6.2 Hardware

In the FLIRT multiple security cameras are installed. The specifications of these cameras are:

- 1280x1024 (1.3Megapixel) up to 10 frames per second
- VGA (sum of 4 pixels) up to 25 frames per second
- Lenses = 2.0 mm
- Sensor size 1/3 inch
- CMOS color sensors
- JPEG/MJPEG up to 1280x1024@ frames per second
- H264 up to VGA @25 frames per second

A relevant aspect of these specifications is the fact that the cameras record in color. This is of importance because the difference in color between a human and the train environment (as for example the chairs) is used to detect humans in the proposed camera-based method. Another aspect of importance is the position and angle of the cameras in the train. The angle of the cameras is probably not optimal for the hallways of the train, since downwards facing camera may be able to easier distinguish individual people when they are standing close together (Cohen, 2013; Tappero, 2009). According to Casper Mintjes, the coordinator camera surveillance from the NS (2016), the cameras have a 96% coverage in the train.

Multiple WI-FI routers are installed in the train (Stadler, 2016). According to Ladan (2016) the number of Wi-Fi access points in the Flirt is one per compartment. Another aspect of importance of the FLIRT is the computer system on this train. The images from the security cameras from the train are only stored locally and are not sent to a server. This thus means that the limitations of the computer system of the train have to be considered (Ladan, 2016, NS Employee). The method proposed in this research is not tested on the computer system of train and tests are only conducted on a PC. With the development of the proposed train localization method, however, it is taken into account that the computing power of the train is limited and the system is therefore kept as lightweight as possible.

7 Camera-based localization

This chapter starts by elaborating on the context related to using camera-based localization to monitor humans. Thereafter the software used for the camera-based localization is described and this chapter is concluded by explaining the camera-based localization approach.

7.1 Context

This paragraph is split in three sections. In the first section the literature with regards to human detection is studied. In the next section the literature is studied to elaborate how detected humans can be related to a location. In the third section the color spaces used in camera-based localization of this research are described.

7.1.1 Human detection

To be able to localize humans using cameras it is first required to detect the humans from a video using image processing. People detection in a real environment suffers from some difficulties such as non-rigid human poses, variant appearances, and occlusion due to clutter (Liu, Luo, Wu, Xie, & Li, 2016). According to Choi, Pantofaru, & Savarese (2011) detecting humans in an indoor environment is even more challenging than detecting humans in an outdoor environment. In outdoor environments people are more often observed in a standing position, this in contrast to indoor environments in which people are observed in a variety of positions such as sitting on chairs or lying down. The view of a camera is also more often blocked by objects. There are a multitude of methods to detect humans using "regular" cameras. Ghidary, Nakata, Takamori, & Hattori (2000) detected a human's head using motion detection, Hough transform and a statistical color model. Chowdhury, Gao, & Islam (2016) detected humans by using a fuzzy face detection algorithm. Tappero (2009) detected humans by identifying changes in different images. This approach is used to enhance computational efficiency. This is done using a static downwards facing camera. In this research it is tried to exploit the advantages of the known and relative static environment and format for common locations of passengers of the train compartment (as described in paragraph 4.2.2). Therefore the proposed method attempts to detect humans by finding changes between frames of a video. This method is similar to the method used by Tappero (2009). In a static environment (of furniture and cameras) it is easier to ascribe changes to humans, which seems to makes this method more suitable. An additional benefit of this method is the computational efficiency, which is particularly beneficial in this case study due to the limited computing power inside the train.

7.1.2 Localization

After detecting a human the person has to be related to a location. Similar to signal-based methods, camera-based methods can also use triangulation to estimate locations (Cohen, 2013). Another possible approach is cell of origin in which the detected person is assumed to be located at the location of the camera. In this study a method is used, that again exploits the advantages of the known and static environment of the train. The places where people are mainly located in the train are most likely the chairs. It is also very likely that in most chairs a maximum of one person is located. So when a significant change is detected when comparing the area of a chair from a video frame of an empty train to another video frame, it seems very likely that someone is seated on that chair. Since the location of all the chairs are known, this chair can then be related to the location of the chair in on a map. The number of passengers in the hallway is more difficult to estimate, as the number of people that can occupy an area is more flexible (most of the only a maximum of one person is located on a chair, while a varying number of people can be located in one square meter in a hallway). For the hallway a different approach is chosen to estimate a more general occupancy of the hallway (this is described in section 7.3.2). Since the location of the hallway is also known this can then be related to the specific hallway on a map.

7.1.3 Color spaces

Colors can be organized in multiple ways. A specific organization of colors is called a color space. Using different color spaces can lead to different results when employing computer vision (Rassem & Khoo, 2015). To give more insight in color spaces a few common ones are described in this section.

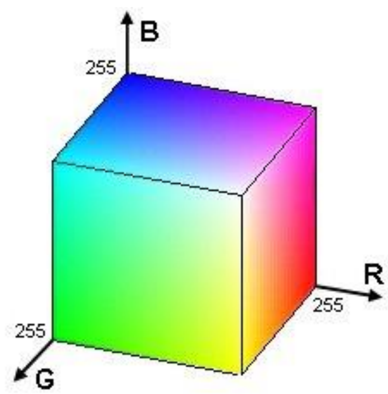


Figure 7.1: RGB color model

RGB (Red, Green and Blue)

RGB is one of the most common color spaces. It consists of three variables red, green and blue. It works similar to the human eye: the three variables can be compared to the three types of color receptors in the human eye. Each variable can vary from 0 to 255 (8 bits) and the higher each value the more intense the color is (as shown in Figure 7.1) (Vandevenne, 2004). Because RGB colors contain luminance information a disadvantage of it is that all three of the variables change when light changes (Rassem & Khoo, 2015)

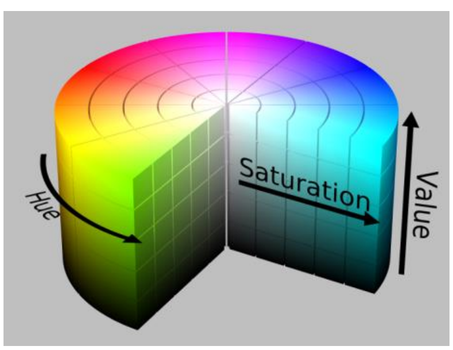


Figure 7.2: HSV color model

HSV (Hue, Saturation and Value)

HSV (shown in Figure 7.2) is one of the most used cylindrical color models and was developed in 1970 for computer graphic applications (López-Rubio, Domínguez, Palomo, López-Rubio, & Luque-Baena, 2016). An advantage of such a cylindrical model according to López-Rubio e.a. (2016) is that they feel more intuitive than the RGB (Red, Green and Blue) model. Hue of the HSV model refers to the color is resembles; all tins, tones and shades of for example blue have the same hue value. The saturation defines the whiteness of a color. The value of a color describes how dark a color is; a value of 0 means a black color (G.-W. Kim & Kang, 2015). According to van de Weijer, Gevers, & Bagdanov (2006) the Hue model of the HSV color space has invariance properties against light intensity shifts and changes. This is in contrast to value model from HSV which varies greatly due to light intensity shifts (Rassem & Khoo, 2015). The HSV model is therefore used in this research.

7.2 Software

The software used in this research is OpenCV (Open Source Computer Vision Library). This is an open source library that is created for computer vision and machine learning. OpenCV is supported by Windows, Linux, Android and Mac OS and has C++, C, Python, Java and MATLAB interfaces (OpenCV

Developers, 2016). In this research the Python interface is used, the main reason for this is that the researcher of this study is most experienced with this programming language. OpenCV has been used before to track people using an RGB-D camera (Choi et al., 2011), but also to track people using steerable cameras (Bernardin, van de Camp, & Stiefelhagen, 2007). OpenCV is open source software: an advantage of this is that it is freely available. Another advantage is that using open software allows for easier replication and corroboration of the empirical results of this research. A disadvantage of using open software is that support (especially long-term support) is often worse than for commercial software (Heron et al., 2013).

7.3 Approach/Design

As is stated in paragraph 7.1 the detection of humans in the camera-based localization part of this research is accomplished by finding differences between frames of the security camera recordings. A frame of an empty train is used as a reference frame. The recording of the camera is compared to the reference frame and the differences are detected. This system needs to be tailored to a specific train, since areas of interest of the video frames need to be supplied manually. Furthermore these areas of interest need to be manually related to their corresponding locations on a map of the train. In the tests in this research a reference frame is used that is created during day light. It may however also be possible to use multiple reference frames created during with different light condition during different times of the day for a better performance when implementing this method in an operating train.

Since the occupancy of the chairs in the train is less variable (most of the times this is one person per chair) than the occupancy of the hallways (varying numbers of people can be located at varying area sizes) a slightly different approach is used for both areas. This paragraph is consequently divided in two sections, the first section 7.3.1 describes the approach to measure the occupancy of the seats and the second section 7.3.2 describes the approach to measure occupancy in the hallways. The full versions of the created algorithms may be obtained by contacting the researcher of this thesis.

7.3.1 Seats approach

The process of ascertaining whether a seat is occupied consists of a number consecutive steps. To illustrate each step of this process relevant images are shown.

1. Selecting areas of interest

First the areas of interest of the video frames that can indicate whether a seat is occupied need to be determined per chair. For this the preference area is the headrest part of the chair. This preference area is chosen because this is the part of the chairs that is often in view of the security camera and not blocked by the surrounding chairs. Another reason is to avoid interference from luggage. A considerable number of train passengers put their luggage on the train chairs. Since the system detects change it will likely interpret a seat with luggage as a taken seat, which is an undesirable result. Luggage, however, seems not very likely to cover the headrest of a seat. Focusing on the headrest therefore most likely mitigates the interference effects of luggage. The areas of interest are selected in X and Y coordinates and each area is given a unique identifier and is related to the corresponding seat on the map. An example of such a selection is shown in Figure 7.3.

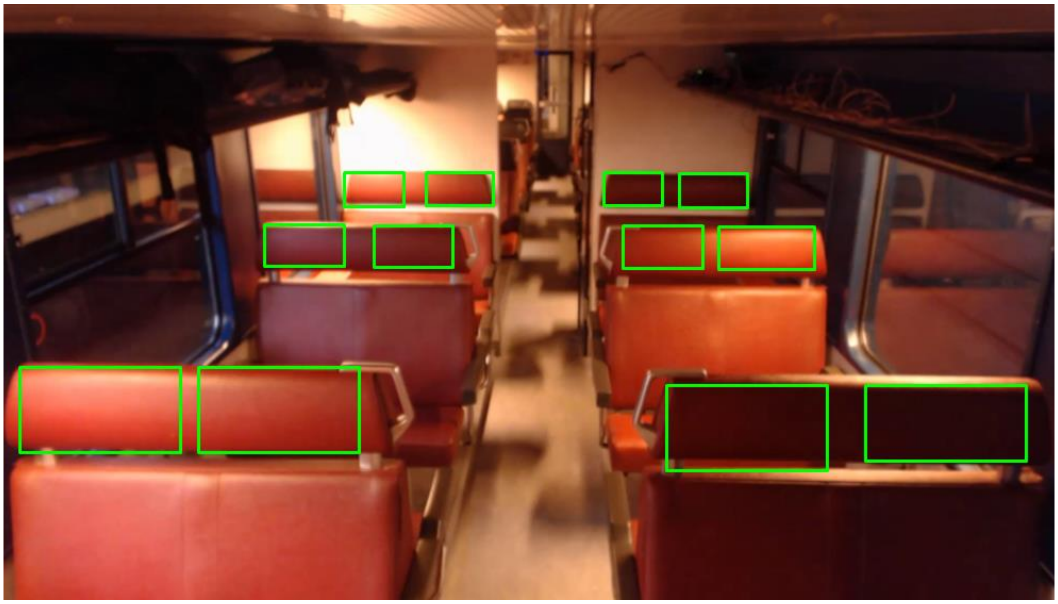


Figure 7.3: Selecting areas of interest

2. Comparing reference video frame to real time recording

The second step is to compare each area of interest (thus each headrest) of the reference frame to the recording. This step consists of two sub-steps (shown in Figure 7.4):

a. Find difference between two images

This process is shown in a flowchart in Figure 7.5. Both the reference frame and the recording are transformed to HSV (Hue, Saturation and Value) images. First the absolute *value* of every pixel of the recording is checked to see whether it has a certain minimum *value*. This threshold is applied to see if enough light is reflected from the object to do an accurate analysis. Cameras seem to have, much like our own eyes, difficulties with identifying colors if an environment is too dark. A camera may thus identify the *hue* of some pixels of a dark blue colored chair as dark green due to inaccuracies that can occur due to a lack of light. This *value* threshold thus prevents dark colored chairs in a badly lit environment from being identified as taken due to cameras inaccurately identifying the *hue*. The disadvantage of such a threshold is that the algorithm may have more trouble detecting people with darker hair, skin or headwear, because these people may also reflect too little *value*. If the pixel of the recording has a *value* lower than the *value* threshold a black pixel (binary 0) is returned. If the *value* is larger than the *value* threshold the process continues. The *hue* of every pixel of the recording is compared to the *hue* of every corresponding pixel from the reference frame. If the difference in *hue* is larger than the *hue* threshold, a relevant change in color is identified and a white pixel (binary 1) is returned. If the difference is smaller the process is repeated with a *saturation* threshold. If a difference in *saturation* is larger than the *saturation* threshold a relevant change is detected and a (binary 1) is returned. Else no change is detected and a black pixel binary (0) is returned. The output is thus a binary image that indicates whether pixels underwent a relevant change (white) or not (black). The reason *hue* and *saturation* are used for this thresholding is because these attributes are less influenced by differences in light than the *value* from HSV or images of the RGB color space. These thresholds are parameters that can be adjusted to customize this algorithm for a specific train.

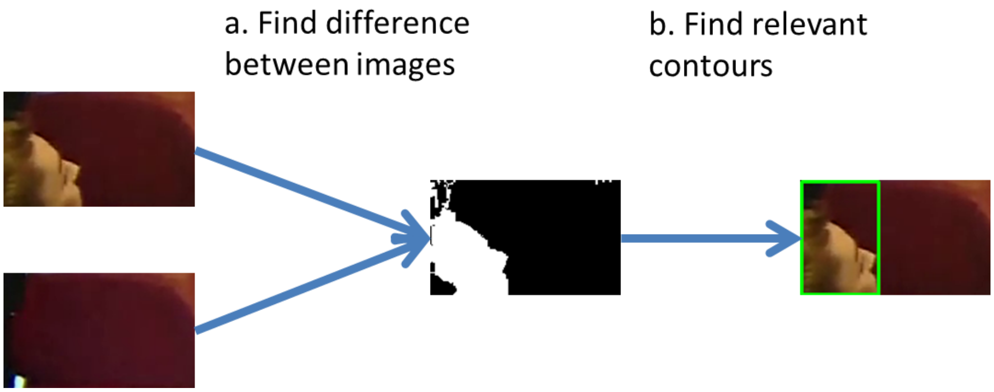


Figure 7.4: Comparing area of interest of reference video frame to real time recording

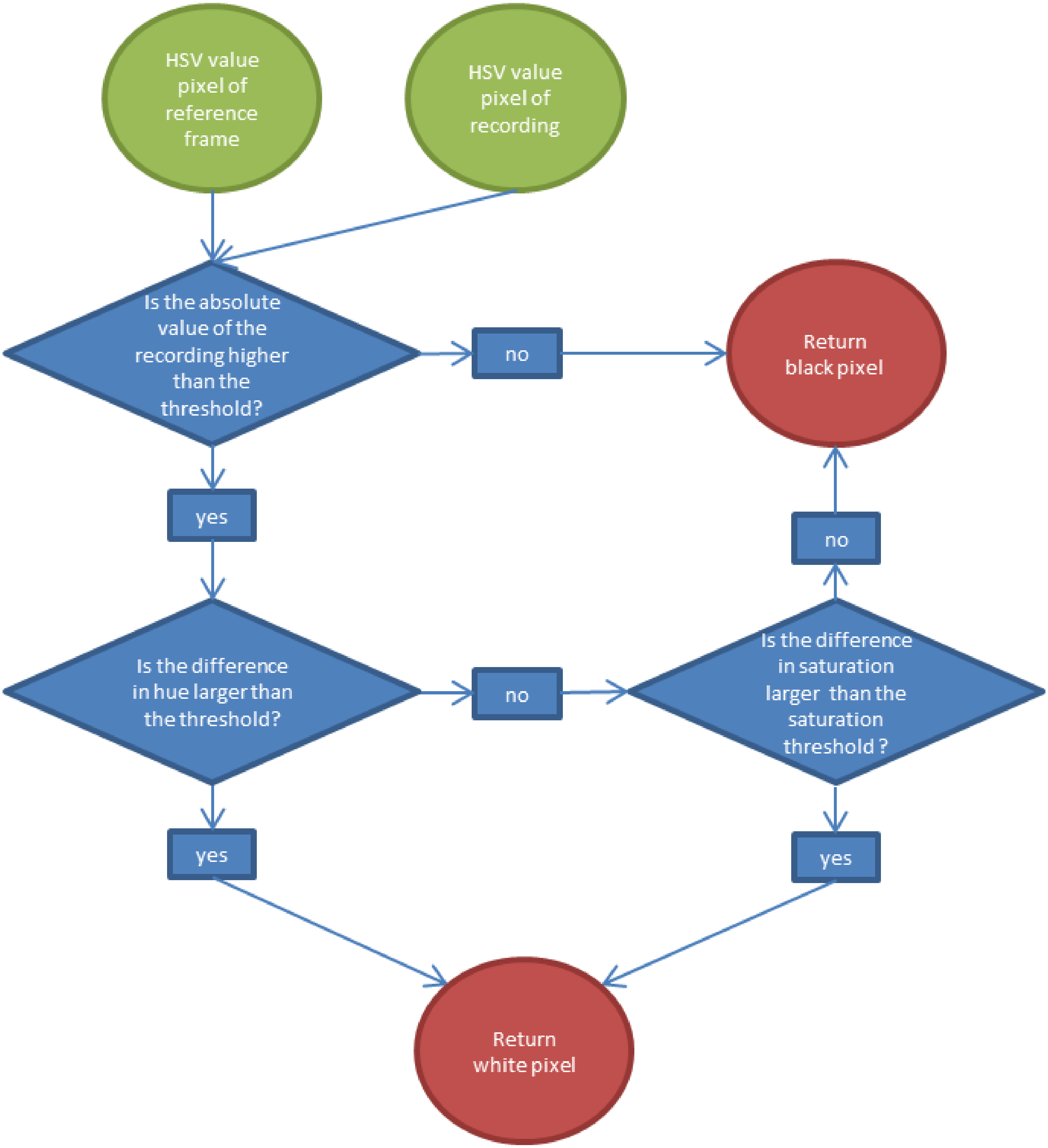


Figure 7.5: : Flowchart to identify changed pixel

b. Find relevant contours

The final sub-step is to find the relevant contours in the black and white output of the previous sub-step. Of these contours only the contours that are larger than a minimum contour size are deemed relevant. This minimum contour size is calculated per area of interest based on a percentage of the total size of this area of interest. This percentage is one of the parameters that can be adjusted in this algorithm. If an area of interest has a contour of a relevant size the corresponding seat is considered to be taken.

3. Storing the occupancy information per seat

The information about whether each seat is occupied or not is stored per seat in a database. This is shown with a visualization in Figure 7.6. In this image can be seen that the location of the passengers corresponds to the location of the people on the map, a red rectangle indicates a taken seat and a green rectangle indicates a free seat. In this Figure the recordings of 2 cameras are shown that film from a different angle. This visualization is also used as a tool to manually asses the accuracy of the measurement and to calibrate the parameters.

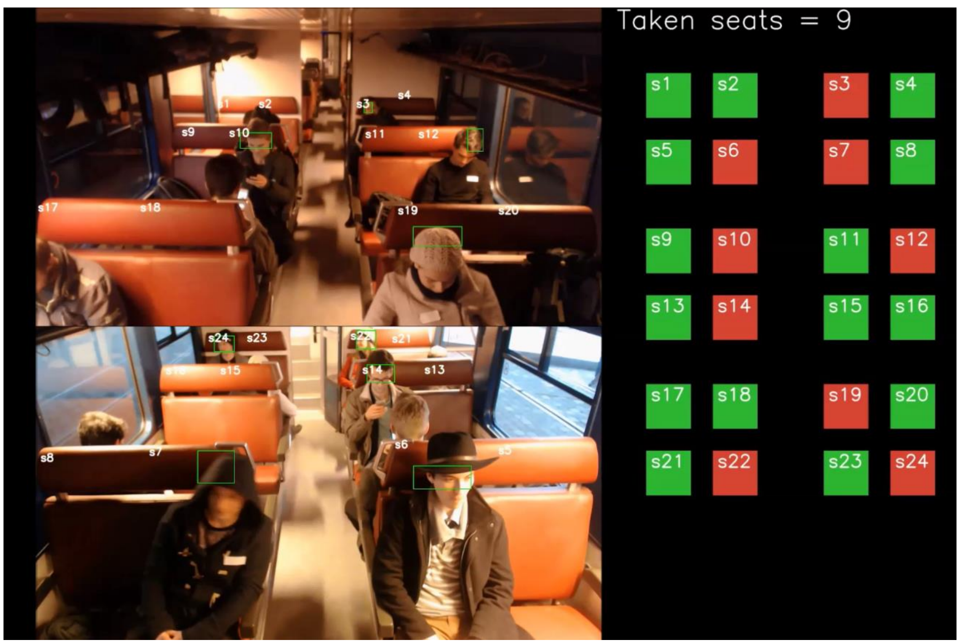


Figure 7.6: Relating seats to a map

7.3.2 Hallway approach

Some parts of the hallway approach that is used in this research are very similar to the approach used to detect empty seats. The steps used to detect the occupancy in the hallway are described in sequential order.

1. Selecting areas of interest

This approach is also started by selecting the areas of interest. The area of interest is in this case the hallway. The areas of interest are also selected in X and Y coordinates. An example of such a selection is shown in Figure 7.7. If two cameras are present that record the same hallway this is done for both cameras.

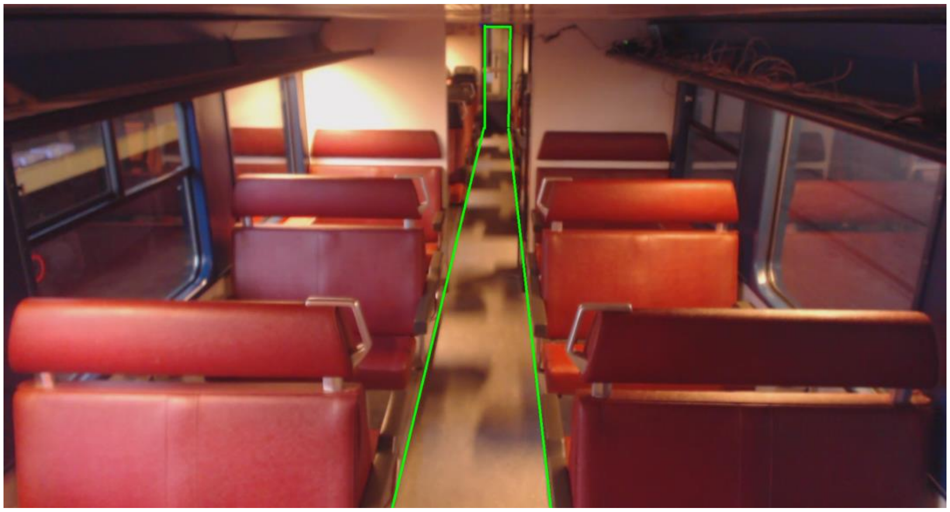


Figure 7.7: Selecting area of interest hallway

2. Comparing reference video frame to real time recording

The second step is to compare the area of interest (the hallway) of the reference frame to the recording. This step consists of several sub-steps.

a. Find differences between two images

The differences between the two hallways are identified using the same method as the one that is used to identify changes between the headrests. So an algorithm converts both images to HSV and detects pixel by pixel whether the color codes changed by a relevant amount. If a pixel is identified as changed a white a value is returned and else a black value is returned. The thresholds parameters that are used for this can be set to a different amount depending on the color of the hallway that is being analyzed.

b. Calculate percentage of changed pixels

In the hallway approach occupancy is not measured using the number of taken seats, but in a percentage of pixels that changed. This is calculated by dividing the total number of changed pixels by the total number of pixels located in the selected area of interest of the hallway. It is expected that there is a correlation between the changed number of pixels and the number of passengers located in the hallway. In the seats approach there can be made more use of the static environment of train, since it seems very likely that in most chairs only one person is seated. In the hallway such an assumption cannot be made, therefore estimating the occupancy in the hallway relies on the ratio of changed pixels.

3. Storing the percentage of changed pixels per hallway

The information of the percentage of changed pixels is stored per hallway in a database.

8 Wi-Fi Localization

The Wi-Fi localization used in this research is described in this chapter. The approach used for Wi-Fi localization in this research is more similar to approaches used in other research than the camera-based localization method used in other research. This method is therefore described less extensively than the camera-based localization method. Furthermore the Wi-Fi localization method is only employed in test setting 2 (chapter 10) of this research. It is therefore easier for the readability of this thesis to describe most of the used of approach in chapter 10 as it can therefore be more easily related to its context.

In this research a distinction is made between mobile phones that are on standby and mobile phones that are active. Standby is defined as the state of a phone when is in a low power mode in which the phone is able to turn itself on again during an event (receiving a call for example) and only some functions of the phone are still working. In standby a phone's screen is not lid. A phone is defined as active when the screen is lid and the functions of the phone are accessible. A distinction is made between these modes because the frequency in which phones send out a Wi-Fi probes is expected to differ between these modes. If a mobile phone is in stand-by it sends out a probe request every minute. When a mobile device is in active mode is sends out a request every 4-6 seconds (Cisco, 2013; Verbree et al., 2013).

The software used in this research to measure probes and their RSSI is Scapy. Scapy is an open source python library. Using an open source library for Wi-Fi localization leads to similar advantages as are described in paragraph 7.2 for camera-base localization. The hardware used in this research is a raspberry and a Wi-Fi TP Link USB adaptor. This hardware is employed as a Wi-Fi scanner. The approach used for Wi-Fi localization in this research uses the cell of origin method and RSSI. The Wi-Fi scanner measures probe requests. The MAC-addresses from the detected probe requests are analyzed using an algorithm to identify the number of unique MAC-addresses. The number of unique MAC-addresses is used to estimate the number of Wi-Fi devices in a train compartment (the tested approaches described in more detail in paragraph 10.3). The Python library Scapy measures the RSSI in arbitrary units and can give an indication of up to 8 bits (0-255). The higher the RSSI number, the stronger the signal.

9 Analysis test setting 1: Trains chairs in office environment

In this chapter the design of test setting 1: *trains chairs in office environment,* is described. Furthermore the analyses and results of test setting 1 are described and discussed. Test setting 1 is only used to test the performance of the camera-based localization, because it differs too much from a real train to be used as a test setting for the Wi-Fi localization.

9.1 The design of the test setting

To evaluate the performance of the camera-based localization method employed in the algorithm of this research a test is carried out in an office environment. To attain the most realistic results it has been tried to mimic the environment of the train, the FLIRT, as close as possible. The height of the camera is therefore 2.20m which is similar to the height of the cameras in the FLIRT, which are installed at a height of 2.10m and 2.40m). In the NS FLIRT trains the cameras are placed in the hallway and is has been tried to copy this position with the camera in the test setup. To further simulate a train environment old detached train chairs are used (shown in Figure 9.1), which have a very similar shape and size as the train chairs found in the current trains.

A lot of events and elements that take place in a real operating train can potentially influence the performance of the camera-based localization employed in this research. Therefore, multiple scenarios are tested that represent the most common circumstances in a train. These scenarios consist out of different combinations of three different variables. For each of these combinations a recording of 20 seconds is made. The algorithm is later on tested by comparing its measurements to the known reality to determine its performance. The variables and their options are described below.

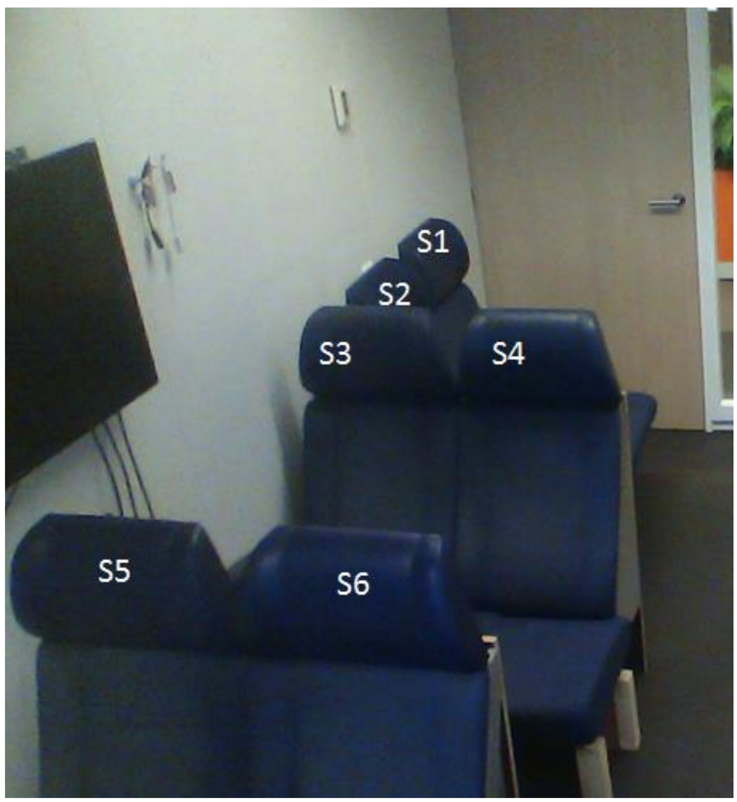


Figure 9.1: Office test setup from the perspective of the camera

State of person

Passengers of public transport can have different activities during their travel time and these activities can result in different postures. It is relevant to research these different postures since different postures can influence the extent to which the view of a headrest is blocked. Furthermore a different posture can result in a different color with which a headrest is blocked, one posture can for example result in a person blocking a headrest with his/her face while another posture results in a headrest being blocked more by the top of someone’s head. In order to closely simulate reality, the postures that seem most common are identified from literature. Russell et al., (2011) researched the activities of passengers in public transport. The most common activities are looking ahead/out of the window, reading, talking, texting. It is assumed in this research that reading results in a similar posture as texting and also that talking results in a similar posture as one would have when looking ahead/out of the window. Therefore two different postures are tested. The first is *staring out of the window/forward*, which is a more upwards facing pose in which the security camera will probably record a large part of a person's face. The second posture is *looking at a phone* which is a more downwards facing pose in which a security camera will most likely record a smaller part of a person's face and a larger part of a person's hair/headwear.

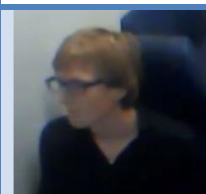
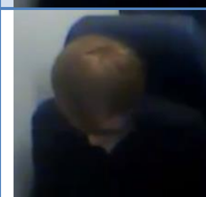
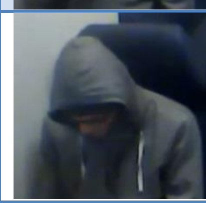
State of person	Example Image
Person staring out of the window/forward.	
Person watching their mobile phone.	
Person with headwear staring out of the window/forward.	
Person with headwear watching their mobile phone.	

Table 9.1: Clarification of the states of a person used in test setting 1 using images

The second option of the variable 'state of a person' has to do with headwear. Headwear can have a different hue than a person's hair. This may potentially influence the performance of the algorithm, especially if a person has a downwards facing posture. To take into account these differences the test is carried out with both a person wearing headwear and a person not wearing headwear with both of the earlier described postures. The headwear in this experiment consists out of a gray cap and hood. The described states are clarified using the images shown in Table 9.1. All of the described 'states of a person' are shown in Table 9.2 and Table 9.3.

Position of the chairs

The algorithm is tested with sideways facing chairs and forward facing chairs relative to the security camera. Both positions of the chairs can be found in the FLIRT, though forward facing chairs are more common; the four-car FLIRT train has 12 sideways chairs and 202 forward facing chairs (as can be seen in Figure 6.1). The chairs in the FLIRT are ordered in rows. For most seats of the FLIRT the view of the camera is therefore partly blocked. To imitate this situation seat 5 and seat 6 (S5 and S6) are used in this test setup to also partly block the view of the camera (as can be seen in Figure 9.1). The test subject only tests one forward facing chair (S3), the other forward facing seats are not tested due to their similarity to S3. The test subject tests both of the sideways facing seats (S1 and S2). The reason this is tested for both chairs is that the areas of interest of these chairs overlap. A person sitting in S2 that leans a bit forward can for example result in the algorithm identifying both S1 and S2 as taken. By testing both chairs the areas of interest that are estimated to be most optimal can be selected. The three selected options of chairs are tested for every different state of person. This is shown in Table 9.2 and Table 9.3.

Light

Since the algorithm looks for changes in color it may also identify a light intensity shifts between the reference frame and the frames of the recording as changed pixels. To examine whether the algorithm is affected by changes in light intensity the algorithm is tested during daylight and during nighttime. In both of these scenarios all the different states of a person are tested. In both of these scenarios artificial light is also present, since artificial light is also present in a train. Recordings are made both during daylight and nighttime for the earlier described options as shown in Table 9.2 and Table 9.3.

State of person during daylight	Seat 1	Seat 2	Seat 3
Person staring out of the window/forward	Test	Test	Test
Person watching their mobile phone	Test	Test	Test
Person with headwear staring out of the window/forward	Test	Test	Test
Person with headwear watching their mobile phone	Test	Test	Test

Table 9.2: Test scenario's during daylight

State of person during nighttime	Seat 1	Seat 2	Seat 3
Person staring out of the window/forward	Test	Test	Test
Person watching their mobile phone	Test	Test	Test
Person with headwear staring out of the window/forward	Test	Test	Test
Person with headwear watching their mobile phone	Test	Test	Test

Table 9.3: Test scenario's during nighttime

9.2 Camera-based localization in the office environment

In the first part of this paragraph the testing and calibration of the algorithm used for the camera-based localization in test setting 1 are described. Thereafter the results gained from test setting 1 are described and discussed.

9.2.1 Customizing and initial testing

To test the algorithm all of the 20 seconds lasting recordings of each test scenario (shown Table 9.2 and Table 9.3.) are combined in one video of 8 minutes (30 frames per second) for easier testing. The algorithm is set to analyze every tenth frame in the tests, which corresponds to 3 frames per second. To test the algorithm on the combined recording of the office environment it is first needed to customize the algorithm for this specific environment. This customizing consists of several actions. First the areas of interest need to be selected manually. These areas of interest are rectangle sets of coordinates of the location in which the heads of the passengers are most likely to be located. This has to be done manually since the position of the train chairs relative to the camera differs per environment. Afterwards several parameters need to be optimized for the specific environment. The reason that this customization has to be done is because different colored train chairs require different settings. The following parameters have to be customized:

- Hue threshold
- Saturation threshold
- Minimum contour size

The customizing of these settings is performed in a non-sequential matter. Each parameter is adjusted individually. After each change the algorithm is run and the researcher manually (with the naked eye) compares the recording of the train chairs to the computer generated map of the taken seats. He then estimates the performance and adjusts accordingly and then tests again. The process is repeated until a satisfying estimated performance is reached. The interface used for this process is shown in Figure 9.2 with one example frame.

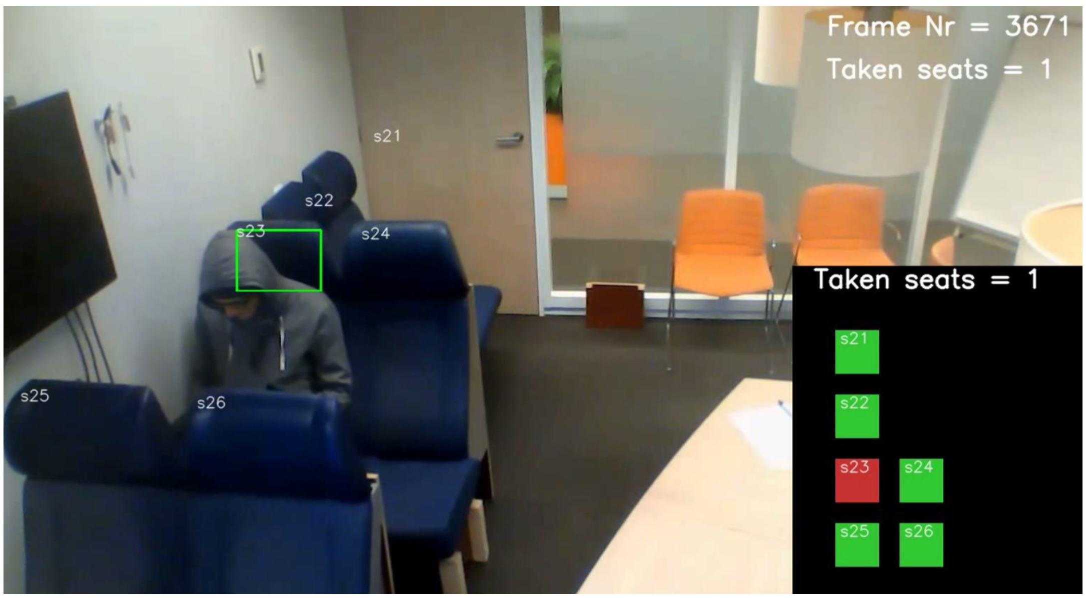


Figure 9.2: Example frame of the interface used to calibrate the camera-based localization algorithm

9.2.2 Automatic calibrating and adjustment

After the initial testing of the parameters of the algorithm they are further adjusted and calibrated in an automatic matter. This is done by running the algorithm multiple times with different parameters and calculating the performance for each run. The parameters are adjusted according to the calculated performance. The calculation of the performance is made, using an average weighted error of each tested seat. This is done by separately calculating an average weighted false negative error and an average weighed false positive error. False negative errors occur when the algorithm falsely detects a seat as free when it is in fact taken. False positive errors occur when the algorithm falsely detects a seat as free when it is in fact taken. These errors are calculated separately, to prevent the possibility of a false positive error compensating a false negative error. The calculation of the errors is done by using the algorithm to save whether it identifies a seat as taken or free per frame (the occupancy) in a database. A sample of the first 3 entries of the database is shown in Table 9.4, a 1 indicates a taken seat and a 0 indicates an available seat. A similar database is created by manually inserting whether each seat is taken or free per frame based on the known values. These two databases are compared to find the errors.

Frame number	Seat 1	Seat 2	Seat 3	Seat 4	Seat 5	Seat 6	Total taken seats
1	0	1	0	0	0	0	1
31	0	1	0	0	0	0	1
61	0	1	0	0	0	0	1

Table 9.4 Sample of database availability of chairs

For each of the seats that were tested (S1, S2 and S3) the average false negative error and the average false positive error are calculated per analyzed frame. The total number of analyzed frames in which a false negative error is found for a seat is divided by the number of frames in which the corresponding seat is known to be taken to find the average false negative of that seat. To find the average false positive error per seat, the total number of analyzed frames in which a false positive error is found for a seat is divided by the number of frames in which the corresponding seat is known to be empty. This is to compensate for the fact that there is only one test subject in this test setting for six chairs and this ratio between passengers and chairs is deemed unrealistic. The reason that an average error is calculated per seat is because the seats are weighted to calculate a weighted arithmetic mean of the average error to compensate for the fact that forward facing chairs are more common in the FLIRT than sideways facing chairs. The weights used in this research are based on the ratio between forward and sideways facing seats in the 4-car FLIRT. First the weights are explained for the false negative errors. The first weight is calculated with the formula shown in equitation 9.1 in which *wf* is the weight for the FLIRT chairs, *ff* is the total of forward facing chairs in the FLIRT (202) and *sf* is the total of sideways facing chairs of the FLIRT (12).

$$wf = \frac{ff}{sf} \tag{9.1}$$

Another weight has to be calculated to compensate for the number of forward and sideways facing chairs for which is tested in the office setup. This is calculated using equitation 9.2 in which *wo* is the weight for the office chairs, *fo* is the number of forward facing chairs in the office for which is tested (S3) and *so* is the number of sideways facing chairs in the office for which is tested (S1 and S2). The weight for the office chairs is thus 2 divided by 1 which is 2.

$$wo = \frac{so}{fo} \tag{9.2}$$

These weights are then used to calculate a weighted average error (*e*) of false negatives of all seats. The summation of the average errors per seat of the set of sideways facing seats(*SE*), seat 1 and seat 2, is added to the summation the set of average error per seat from the forward facing seats (*FE)* seat 3 multiplied by the earlier described weights. This is then divided by the number of sideways facing chairs in the office setting plus the number of forward facing seats included in this test (only S3 in this case) multiplied by the two weights (as shown in equitation 9.3).

$$e = \frac{\sum SE + (\sum FE * wf * wo)}{so + (fo * wf * wo)} \tag{9.3}$$

The average false positive error of all seats combined is calculated in a similar fashion using the same equations, only using different weights and input. The weight for the office chairs is in this case different, because false positive error can occur at all six seats. So the weight for the office chairs (*wo)* in this case is 2 divided by 4 which is 0.5. Equitation 9.3 also has different input when calculating false positive errors, since *FE* includes the sets of average errors of 4 seats (S3-S6) instead of only S1. Furthermore the input of *fo* is therefore also 4. The average weighted false positive error of all seats (*EP*) and the average weighted false negative error of all seats (*EN*) are both subtracted from 1 to gain an estimated performance (p) of the algorithm (shown in equitation 9.4). This performance is an arbitrary rating that is used for the calibration of this algorithm.

$$p = 1 - EN - EP \tag{9.4}$$

The adjustment of the parameters is done based on this performance. This adjustment is done in a sequential manner in the following order: hue threshold, minimum contour size, saturation threshold. For each of these parameters an initial input is chosen using the method described in section 9.2.1. After the initial run of the algorithm the first parameter (hue threshold) is increased with a certain value (the large adjustment value). For each parameter the corresponding adjustment value is shown in Table 9.5. After this adjustment the algorithm is run again with the newly adjusted parameter and the performance is calculated again. This performance is then compared with the performance of the previous run. If the performance has increased the parameter is increased again with the large adjustment value and the algorithm is rerun. This process is then repeated until the performance does not increase anymore. If the performance however decreased after the initial run the large adjustment value is subtracted from the parameter and the algorithm is rerun. This subtraction process is then repeated until the performance does not increase anymore. The parameter setting with the highest performance is in the end selected and returned for the next optimization process. This process is shown in Figure 9.3. After completing this process with the large adjustment value its final parameter setting is used to repeat this process using the small adjustment value, to come even closer to optimum parameter settings. This whole process is then repeated for the second parameter (minimum contour size) while using the earlier found optimum parameter (hue threshold). This process is continued for the final parameter (saturation threshold).

Parameter	Large adjustment value	Small adjustment value
Hue threshold	5	1
Minimum contour size	0.01	0.001
Saturation threshold	5	1

Table 9.5: Adjustment values of the parameters

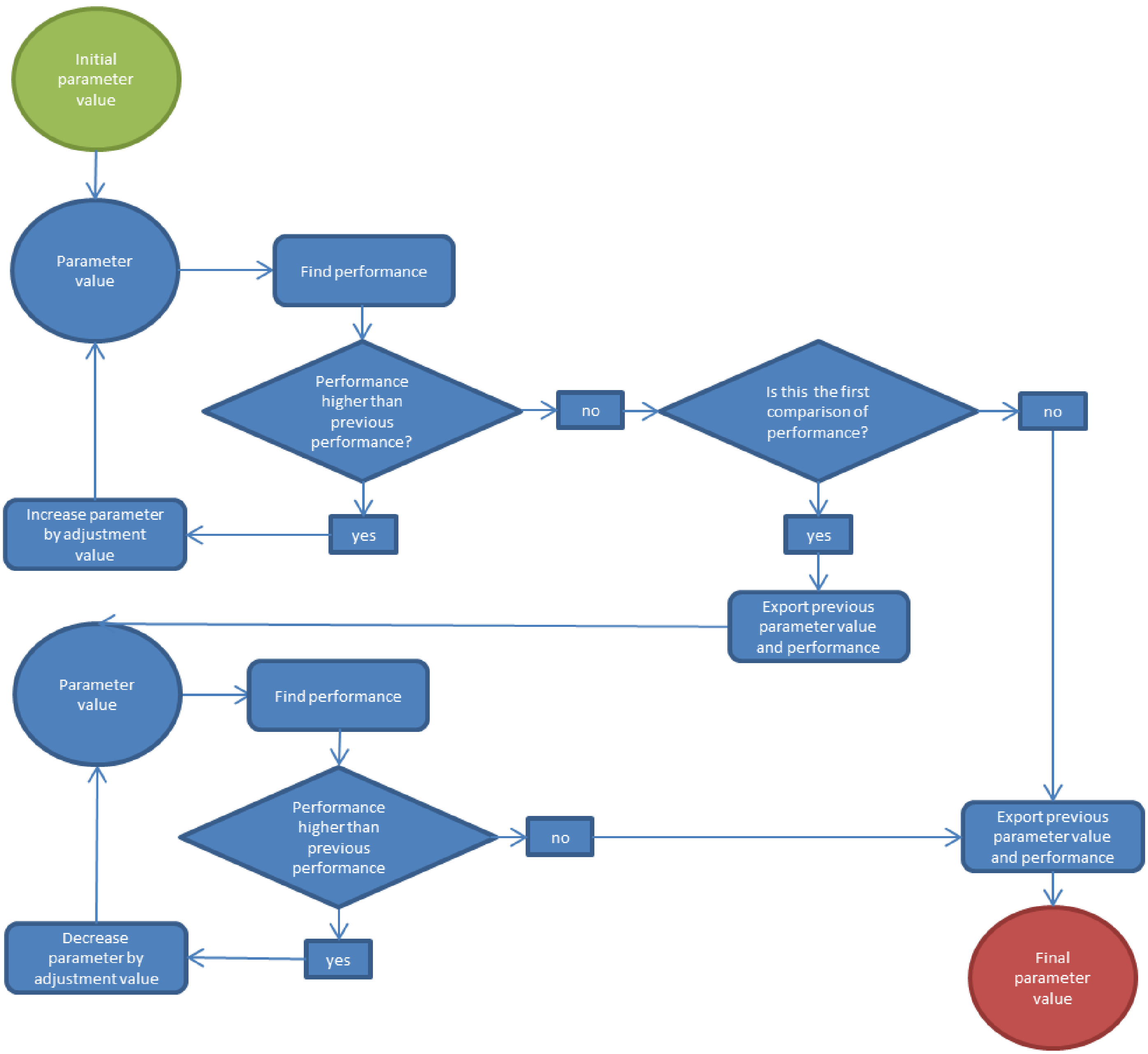


Figure 9.3: Process of finding the optimum parameters

9.2.3 Results

In Table 9.6 the results of the optimization process are shown. Using these optimized settings the algorithm has been used to find the average false positive error and false negative error. These errors are calculated per seat and a total weighted average is calculated (Table 9.7). As can be seen in the table there are no errors for the forward facing seats (S3-S6). Some errors however have been found for sideways facing seat (S1- S2). The false positive error mostly occur when the test subject's head or shoulder partly cross the area of interest of the seat which he is not occupying. An example of such a false positive error is shown in Figure 9.4. In this example the test subject's body is found to be occupying S1 as well as S2. This error however only occurs approximately 1% of the time for S2 and 5% of the time for S1. The false negative errors occur mostly on seat 1. The reason why these errors occur on this specific seat is due to color of the background of the area of interest. The background of the area of interest of S1 has a hue which is very close to the hue of the skin and hair of the test subject. Therefore the algorithm has trouble detecting the test subject in the scenarios when he is not wearing headwear. The average weighted errors are average errors calculated using the weights for the FLIRT train described in section 9.2.3 in equations 9.1 and 9.2. Based on this test scenario it thus seems that the method employed in this research has a relative good performance. There are however some limitation and constrains to this test scenario which are discussed in section 9.2.4

Parameter	Optimized setting
Hue Threshold	54
Minimum contour size	0.023
Saturation Threshold	74

Table 9.6: Optimized setting per parameter office

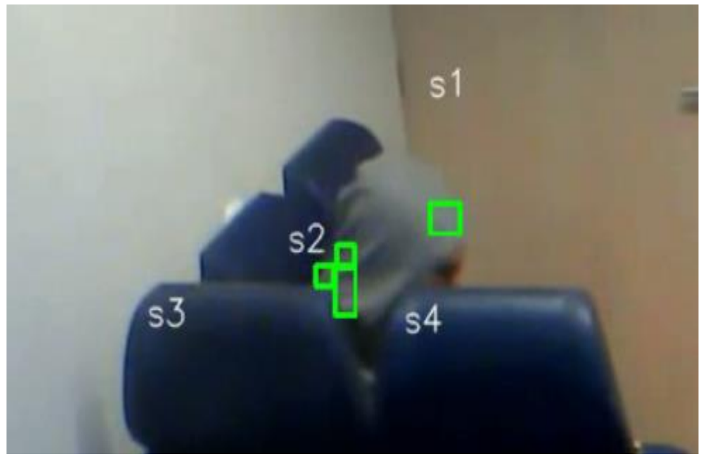


Figure 9.4: Example of a false positive error

Seat	False negative error	False positive error
S1	0.299	0.048
S2	0.135	0.005
S3	0.000	0.000
S4	N/A	0.000
S5	N/A	0.000
S6	N/A	0.000
Weighted average	0.026	0.002

Table 9.7: Average error per seat office

9.2.4 Discussion

In this section the expected limitations of 'Test setting 1: Trains chairs in office environment' are described. With the test setup it has been tried to simulate the train environment of the FLIRT as close as possible, there are however several limitation to this model. The limitations of the test setup that could result in the algorithm having a different performance than it would have in a real train are listed in Table 9.8.

Inadequacy of test setup	Description of expected influence
Color of the chairs do not comply with reality	In the algorithm the chairs are often selected as the area of interest. In these areas the algorithm than detects if the color changed. If the color of a chair is for example more similar to the color of the average person's head or headwear it may be harder to detect. A different color can thus result in a different performance of the algorithm. Furthermore lighter colored chairs reflect more light and the hue and saturation of these chairs can therefore more accurately detected. It is expected that using the blue chairs of the FLIRT can result in a fewer errors, because these chairs have a lighter color and therefore reflect more light. This makes it easier to accurately identify the color (hue) of the chairs. The red chairs of the FLIRT may result in lower performance because the hue of these chairs may be closer to the average hue of people's heads.
Relative location of the chairs are not the same as in reality	Chairs in the actual train can have different locations relative to the cameras. The occupancy of chairs that are located further from the camera may be harder to assess, since their headrest areas are smaller.
Different light conditions	The office has different lights that have a different intensity and a different angle compared to the train. The chairs and the passenger(s) may therefore reflect light differently than they would in a train. Furthermore due to the fact that the train is moving the amount of natural light (from the sun) can have great variance in a short amount of time due to objects such as trees and tunnels. This can also negatively affect the performance of the algorithm.
Different background environment	For the sideways facing chairs (such as seat 1 in this test setting), not only the color of the chairs is of importance, but also the color of the object which is behind the headrest area of the chair (which is the door) in this scenario. If this object has a different color this can lead to a different performance.
Only one test subject (train	In a real train journey, there are multiple train passengers, who can

passenger)	have a different height, skin color or headwear. In this test scenario only one type of headwear is tested. If a train passenger wears headwear that has a more similar color to the train chair he/she may be harder to detect. Furthermore it may be harder to detect passengers that are shorter that the test subject, who is relatively tall (1.94 meters). Another limitation of using one test subject is that there is only tested for one skin color. Passengers with a darker skin color may be harder to detect, especially when they are sitting on a darker colored chair.
Behavior of the test subject	In a real train journey there are many forms of behavior that a passenger can have. In this test scenario only the two most common ones are tested. Furthermore in this research the test subject knows that he is being filmed and what the purpose is of the test. He may therefore (unconsciously) have acted differently.
No noise images	In this controlled environment there is no noise in the images of the recording from people or objects that are located between the camera and the area of interest. In a real train it is possible that people put objects like jackets over the areas of interest, which could result in more false positive errors. Furthermore is may be possible that people stand between a camera and a headrest area, which could potentially result in more false positive errors.

Table 9.8: Limitations to test setup 1

10 Analysis test setting 2: Railway museum

In this chapter the analysis of test setting 2 is described. Test setting is an old train that currently in use as a museum piece in the Spoorwegmuseum located in Utrecht in the Netherland. This test setting is used to further evaluate the potential of using camera-based localization and to evaluate the potential of using Wi-Fi localization. In the first paragraph of this chapter the context of the test setting is described. Thereafter the analysis using camera-based localization is described followed by an explanation of the analysis conducted using Wi-Fi localization.

10.1 The design of the test setting

In this paragraph the design of the test setting is described. In the first section the location in which the test is conducted is described. In the second section the test simulations used in the test setting are described.

10.1.1 The location of the test setting

The environment in which this test is carried out is an old train which is currently used as a museum piece. In Figure 10.1 the interior of the train is shown. The train that is used is a double decker train. In the test a compartment is used on the lower deck, this compartment has half of the length of a complete wagon. This compartment contains 24 red chairs. At the beginning and end of the compartment two cameras are attached to the ceiling. These cameras are both aimed at chairs of the compartment. Furthermore a Wi-Fi scanner is located near the end of the compartment in the baggage space. The positioning of the cameras and the Wi-Fi scanner is shown in Figure 10.2 on a map. During the conducted tests the cameras were recording and the Wi-Fi scanner was monitoring Wi-Fi probes. The recorded data is analyzed after the tests were conducted.

Figure 10.1: Interior of the train used in test setting 2

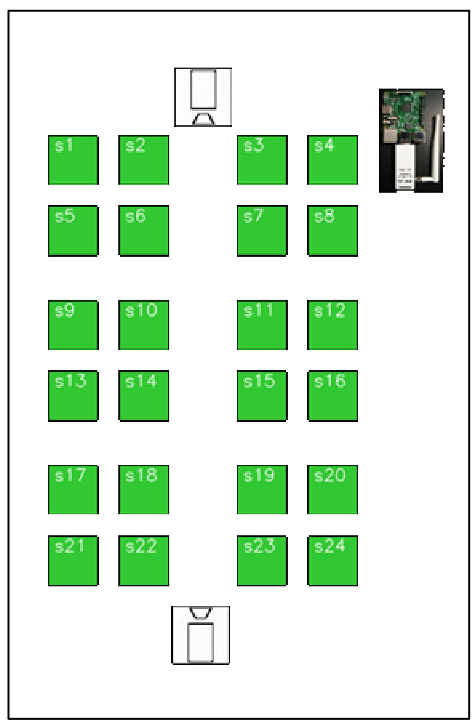


Figure 10.2: Schematic map of the train compartment used in test setting 2

This old train differs in some aspects from the FLIRT train. These differences should be taken into account when interpreting the results of the conducted test. First of all the train in the museum is stationary. Furthermore the outside doors are always open, which may influence the signal propagation. Another difference between this train and the

FLIRT train is that most of the chairs of the FLIRT are blue and the chairs of this train are red. This can influence the performance of the camera-based localization as this relies on differences in color (hue). Furthermore the ceiling of this train is lower than the ceiling of the FLIRT and since the cameras are installed at the ceiling this results in a different angle from which is being filmed. In this test setup passengers standing in the halfway are more likely to block the view of the cameras.

10.1.2 The test simulations

The test simulations in this research have been designed to resemble a train journey as closely as possible. They have also been designed to test to what extent the system can measure occupancy during two different main events in the train. These two events are:

- **During a train stop**: This is defined as the time period in which people are standing up to leave the train or when people are still searching for a seat.
- **During a train journey:** This is defined as the time period when a train is travelling between two stations and in which most people are seated.

A distinction between these two events has been made for multiple reasons. The main reason is that measuring occupancy during a train stop is more difficult than during a train journey, from a technological perspective. Measuring occupancy during a train stop is more difficult because people are more likely to stand in front of a camera. Furthermore, during a train journey the occupancy is not constantly changing and it is therefore easier to aggregate data from measurements to determine an average occupancy than during a train stop. The occupancy information measured during these two events can also be used differently for the goal of informing passengers waiting at the train platform about the occupancy in each separate compartment in the train, so they can anticipate and enter the train in a relatively less crowded compartment. If an accurate estimation can be made of occupancy in the train compartments and delivered to the passengers just before it arrives at a station they can then anticipate on the occupancy and locate themselves accordingly on the train platform before the train arrives. However if an accurate estimation of occupancy can be made continuously in real time during a train stop and delivered to the passengers, they can also continuously anticipate and decide to enter a different train compartment while people are getting in or out. It may furthermore even be possible to estimate the number of people that will leave the train before a train arrives at a train station, because some people start leaving their seat before a train arrives at a train station. In the analysis described in paragraph 10.2 and 10.3 a distinction is also made between these two events. In this research the distinction between these two events when applying the algorithm is supplied manually by the researcher. In a real train it may be possible to detect these events by using GPS or the Wi-Fi signals of static Wi-Fi devices located at the train station.

The test simulations in the railway museum are all conducted using the same 15 test subjects. The test subjects in this research are all adults, so children are not taken into account in these test simulation. All test subjects that participated knew the purpose of the test and knew to some extent how the tested methods worked. This may have influenced their behavior which can have affected the results of this test. This has to be taken into account when interpreting the results of this test. In this paragraph the script of each test simulation is shown. The test subjects have also received the general instructions and for each instruction a short motivations is also given:

- **Eight people are instructed to watch their mobile phone and seven people to stare out of the window/forward:** The reason for this distinction is twofold in this test setting. The first reason is the one also given in section 9.1 that watching a mobile phone can lead to a more crouched position which is harder to detect using camera-based localization. The other reason is related to Wi-Fi localization. Mobile phones in standby are expected to send out less Wi-Fi probes than mobile phones that are active. By making this distinction the performance of the system can be tested for both active phones and phones in standby.

- **Every test subject is instructed to have one phone (of which the MAC-address is known) on them with Wi-Fi enabled**: The motivation for this instruction is to make it easy to relate each MAC-address and Wi-Fi probe to the location of the test subject in time and space. It can be argued that not instructing the test subjects with regards to their Wi-Fi settings and Wi-Fi devices can be more beneficial for this research. The reason for this is that it may then be possible to study a relation between the number of Wi-Fi devices that have Wi-Fi enabled and the number of passengers in this test. However since the method of Wi-Fi detection was already known to the test subjects they are deemed unsuitable to be used as a sample of the general population with regards to the relation between the number of Wi-Fi devices with Wi-Fi enabled and the number of train passengers. Therefore all test subjects are instructed to enable their Wi-Fi to gather as much data as possible.

- **Every test subject is instructed to act as they normally would in a train:** This instruction is given, because it is tried to mimic a normal train as close as possible. It has to be taken into account that it is possible that test subjects have unconsciously behaved differently despite this instruction.

ID	Team	Mobile watcher (M)/ Forward watcher (F)
1	1	M
2	2	F
3	3	M
4	1	F
5	2	M
6	3	F
7	1	M
8	2	F
9	3	M
10	1	F
11	2	M
12	3	F
13	1	M
14	2	F
15	3	M

Table 10.1: Overview of test subjects of test setting 2

The test subjects are divided into three teams of five members (shown in Table 10.1). The teams are divided in such a way that the mobile phone users and the people that stare out of the window/forward are equally divided amongst the teams. The test subjects have been divided into teams, to make it possible to give each team separate instructions. All test subjects have also been given a separate identification number (ID) so they can be more easily referred to. The script used for test simulation 1 is shown in Table 10.2. The main purpose of test simulation 1 is to resemble a typical train route as closely as possible, to be able to test the performance of the proposed system under normal conditions. In this simulation two teams start in train and every 3 minutes one teams is instructed to first leave a train after which another team enters the train. This cycle repeats itself two times after which all test subjects leave the train.

Relative time	Activity
0:00	- Team 2 and 3 are sitting in the train
3:00	- Team 2 leaves the train - Team 1 enters the train - Team 1 and 3 are sitting in the train
6:00	- Team 3 leaves the train - Team 2 enters the train - Team 1 and 2 are sitting in the train
9:00	- All teams leave the train

Table 10.2: The script of simulation 1: Regular train ride

The main purpose of test scenario 2 (shown in Table 10.3) is to test the performance of the system for all locations (chairs and hallway) in the train. First all test subjects are instructed to sit on the chairs next to the windows and then to sit on the chairs next to the hallway. This is done to ensure that the camera-based localization system can be tested for all chairs in the train. In the second part of the simulation the test subjects are instructed to stand in the hallway. The test subjects are instructed to lounge in the hallway as they normally would in a train if all seats are taken. Each team is then instructed to leave the train per team with an interval of approximately one minute. This is done to assess whether the proposed method is able to detect differences in occupancy in the hallway. This can furthermore be used to test whether people standing in the hallway influences the received RSSI.

Relative time	Activity
0:00	- Everyone sits next to the windows
1:30	- Everyone sits next to the hallway
3:00	- Everyone stands in the hallway
3:30	- Everyone moves to stand in the hallway at a different place
4:00	- Team 1 leaves the train
4:30	- Team 2 leaves the train
5:00	- Team 3 leaves the train

Table 10.3: The script of simulation 2: All location in the train

Test simulation 3 is used to test the performance of the system when under difficult circumstances. In this test scenario all test subjects are instructed to sit on the chairs except for one person (ID 9). She is instructed to pretend to be a ticket inspector who inspects all tickets. Afterwards all the test subjects are instructed to assume poses that are less common in the train. These poses should however not be poses that would never occur in a train. The script for this test scenario is shown in Table 10.4.

Relative time	Activity
0:00	- All teams are sitting in the train
0:30	- The tickets inspector pretends to check all tickets
3:00	- Everyone assumes an uncommon train pose
4:00	- Everyone assumes a different uncommon train pose
5:00	- All teams leave the train

Table 10.4: The script of simulation 3: Difficult situations

Test simulation 4 is used to assess to what extent the proposed Wi-Fi localization method can be used to discriminate between Wi-Fi devices that are located on the train platform and Wi-Fi devices that are located in the train. Simulation 2 already contains a sample of all devices located in the train. Simulation 4 is therefore only used to gather data from Wi-Fi devices located next to the train. In simulation 4 all passengers are instructed to locate themselves near the entrance of the train as if they are planning to board the train. As this seems like a common situation to occur on an actual train platform. The script of simulation 4 is shown in Table 10.5.

Relative time	Activity
0:00	- All test subjects are located next to the train near the entrance
2:00	- All test subjects leave

Table 10.5: The script of test simulation 4: Wi-Fi noise on the platform

10.2 Camera-based localization in the railway museum

The algorithm used for camera-based localization is tested and calibrated for test setting 2 in a similar way as for test setting 1. There is therefore often referred to 9 in this chapter. Changes to the procedure are clarified in this chapter.

10.2.1 Customizing and initial testing

This section is divided in a part that describes the method that is used to estimate the occupancy of the seats in the train and a part that describes the method used to estimate the occupancy in the hallway.

Seats approach

For explorative testing of the seats approach the camera footage from simulation 1 is used as this simulation is intended to resemble the train environment as close as possible. The algorithm is set to analyze every 30th frame; this is one analysis per second. In the initial testing phase the areas of interest, located at the headrest areas, are manually selected. In test setting 2 this has to be done for both cameras. Each of the cameras monitors one half of the chairs, which are the chairs that are facing the camera. The parameters of the camera-based localization system are manually optimized by testing the system and estimating its performance. The interface used for this is shown in Figure 10.3. Figure 10.3: An example frame of the interface used to estimate the performance of the camera-based localization system in the railway museum.In this figure the red squares corresponds with the taken seats and the green chairs with the available seats. The performance is estimated by manually comparing the recordings with these rectangles to see whether these are accurate.

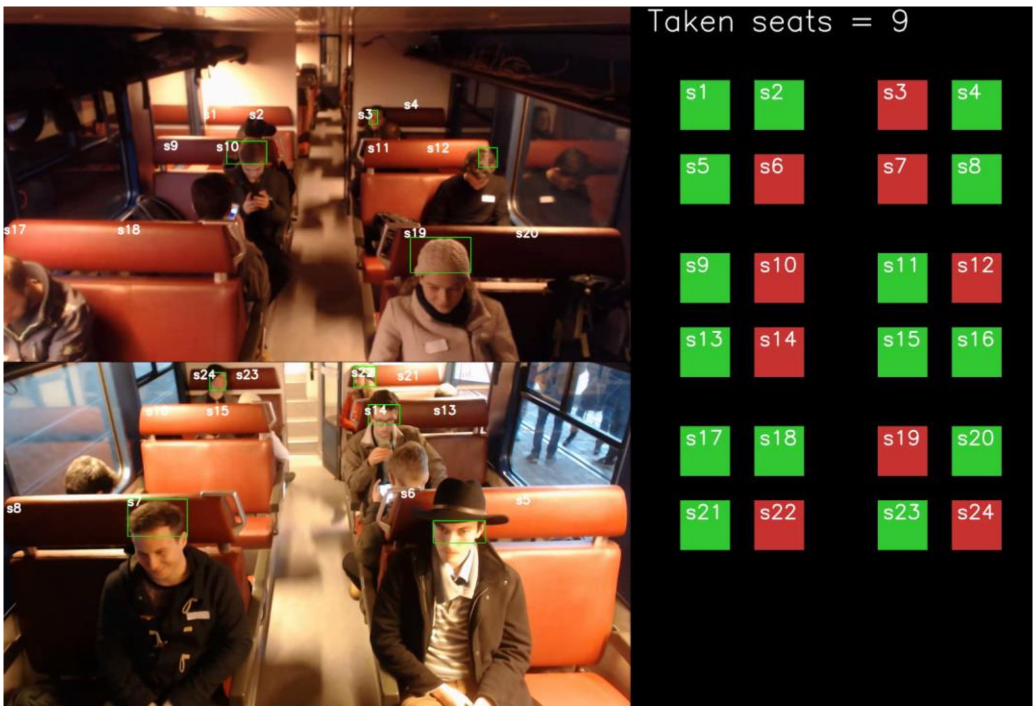


Figure 10.3: An example frame of the interface used to estimate the performance of the camera-based localization system in the railway museum.

During this phase it was noticed that a much more sensitive hue threshold was needed to enable the system to detect head and hair of the test subjects as was needed for test setting 1. The reason for this is the difference in chair color. The red chairs that are used in the railway museum have a hue that is much closer to the heads and hair of people than the blue chairs used in the office environment. Using a more sensitive hue threshold however leads to more false positive errors. To mitigate the lower performance caused by the difference in chair color some changes are made to the algorithm:

- **When a pixel is overexposed the hue and saturation thresholds are adjusted**: If a chair is in direct sunlight the hue and saturation often change more than they normally would. The hue tends to become more yellow and the saturation tends to be higher. This can result in false positive errors. These effects are more noticeable in this test setting because the parameters are set to a more sensitive level. To mitigate the effect of overexposure, the hue and saturation thresholds are increased if the value of a pixel affected to overexposure. Overexposure is detected by using the value component from HSV.

- **A pixel is also defined as changed by a combination of hue and saturation:** Due to the sensitivity of the hue threshold the system more often has extra false negative errors. To mitigate this effect another threshold is created. This threshold is constructed using a combination of the hue and saturation thresholds. It classifies a pixel as changed if the hue **and** the saturation have changed a certain amount. These amounts are calculated using a ratio of the other hue and saturation thresholds. This threshold is referred to as the combined threshold in this research.

These changes are shown in Figure 10.4. These adjustments seem to increase the performance of the camera-based localization system to detect the occupancy of the seats of the train.

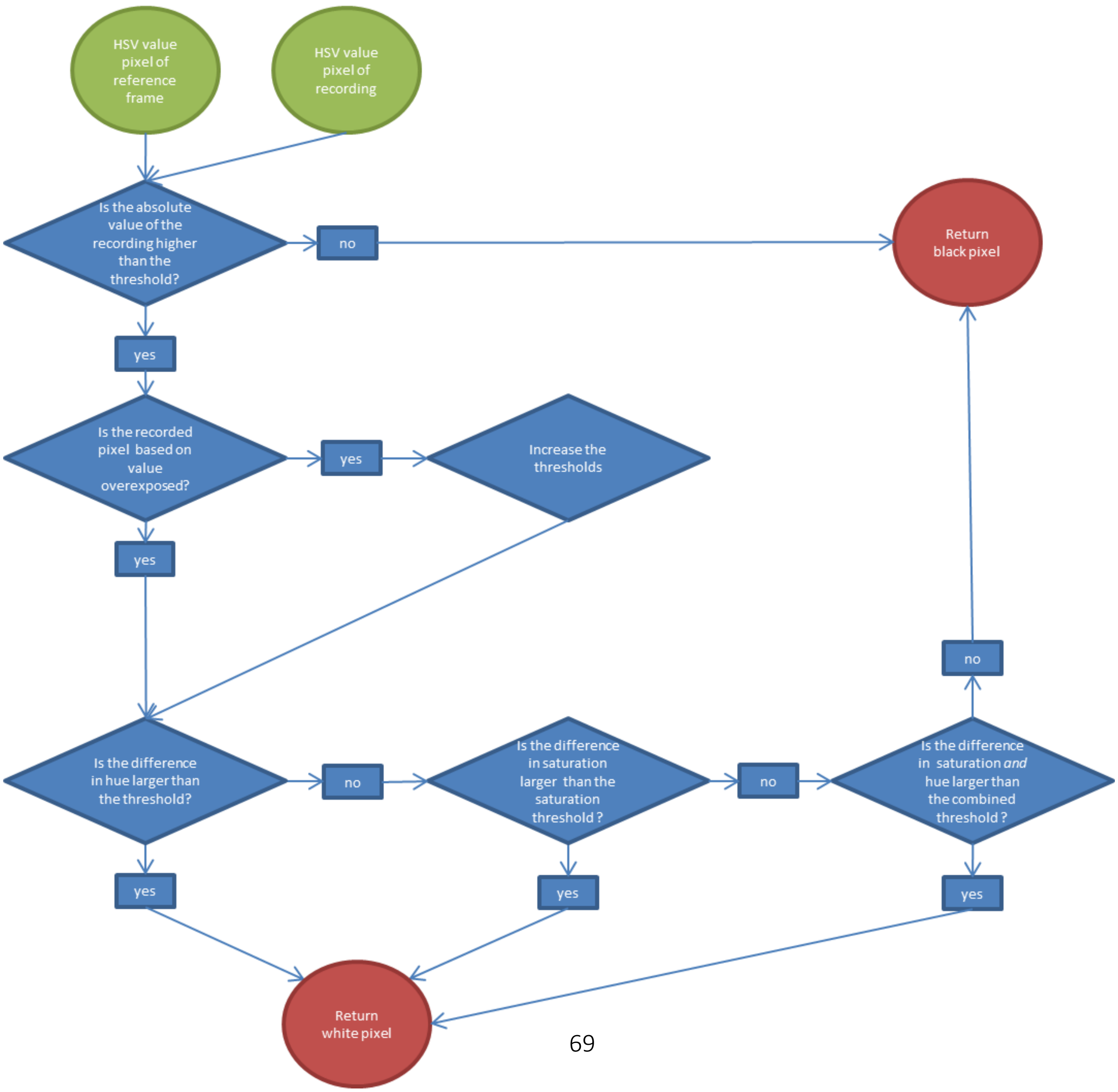


Figure 10.4: Adjusted flowchart to identify changed pixels

Hallway approach

For the explorative testing of the hallway approach simulation 2 is used. The reason for using this simulation is that in this simulation the test subject are asked to stand in the hallway. In the initial testing phase the area of interest the hallway, is selected for both of the cameras. The parameters of the camera-based localization system are manually optimized by testing the system and estimating its performance.

The difficulties that occur in test setting 2 for the seats approach do not occur in the hallway. Since the floor of the hallway is located lower than the seats it is less prone to overexposure from sunlight as direct sunlight does not seem to reach the floor. The color of the floor of the hallway does not seem as similar to the color of the train passengers as headrests of the train chairs are to the heads of the train passengers. Therefore the adjustment of the combined threshold and the methods to counter overexposure described in Figure 10.4 are not used and the original approach to find change shown in Figure 7.5 is used.

10.2.2 Automatic calibration and adjustment

After the initial testing the parameters of the algorithm for the seats approach are further adjusted and calibrated in an automatic matter. The parameters for the hallway approach are not adjusted and calibrated in an automatic matter. This is due to the difference in output of the two approaches. The output of the seats approach is an estimated number of taken seats, which can be compared to the actual taken seats. The output of the hallway approach is a percentage of change in the pixels recorded in the hallway, and this cannot be directly compared the actual number of passengers located in the hallway. The calibration of the parameters of the algorithm of hallway approach is therefore only done manually.

The calibration of the parameters of the seats approach is done using a similar method for the test conducted in the railway museum as the method that is used for the test in the office. A difference is that for test setting 2 of the railway museum no weights are used for the calculation of the performance since there are no sideways facing chairs in this test. Another difference is that in test setting 2 the average false positive/negative errors per seat are calculated by using all analyzed frames, it is calculated by dividing the amount analyzed frames in which such an error occurred by the *total number of analyzed frames*. This differs from test setting 1 in which only the analyzed frames are taken into account for each seat in which the corresponding seat was known to be taken, to compensate for the fact that there was only 1 test subject for 6 seats. For this test setting this is deemed unnecessary, because the ratio between people and seats seems more realistic (15 test subject for 24 seats). Using the average false positive and false negative errors per seat a total average false positive and false negative error is calculated for all seats. The logic of not calculating the errors by using the total measured occupancy of all seats (so the total number of passengers measured by the system) and comparing it to the actual number of passengers observed by the researcher is because that method would lead to false positive errors compensating false negative errors. The parameters in this test setting are also optimized by running the algorithm multiple times with different parameters. The output of each run is compared to a database for which the data has been manually supplied by watching the records. The performance used in the automatic calibration is again calculated using equitation 9.4.

The adjustment of the parameters after each run is done based on the calculated performance, using the same method as is used for the test in the office environment (shown in Figure 9.3). The adjustment is done for the following parameter in the following sequential order:

- Hue threshold
- Minimum contour size
- Saturation threshold
- Hue ratio
- Saturation ratio

For test setting 2 additional parameters are calibrated. These are the hue and saturation ratio which are used to determine the hue and saturation for the combined threshold. The adjustment of the parameters is done using the adjustment values shown in Table 10.6. The final parameters of this process are used to assess the system in the next sections.

Parameter	Large adjustment value	Small adjustment value
Hue threshold	5	1
Minimum contour size	0,01	0,001
Saturation threshold	5	1
Hue ratio	0,1	0,01
Saturation ratio	0,1	0,01

Table 10.6: Adjustment values of the parameters

10.2.3 Results

In Table 10.7 the resulting parameters of the optimization process for the seats approach are shown. These optimized parameters are used to generate the results of the seats approach shown in this section.

Parameter	Optimized setting
Hue Threshold	8
Minimum contour size	0,026
Saturation Threshold	78
Hue ratio	0,62
Saturation Ratio	0,72

Table 10.7: Optimized parameter for test setting 2.

Results seats approach during train journey

The algorithm is first tested for test simulation 1 to assess its general performance during a train journey. In test simulation 1 it has been tried to simulate a real train journey as close as possible. As is stated in section 10.1.2 there is differentiated in the results between a train stop and a train journey. The first part of test simulation 2 is tested to examine how the system performs on all seats. It is also used as a validation to see whether the system works as accurate on another recording as the parameters are optimized using only test simulation 1. The system is tested for test simulation 3, to see whether the performance is affected by the difficult situations presented in this simulation. Test simulation 3 is split in two parts for this. In the first part the ticket inspector pretends to check the tickets. In the second part all passengers take an uncommon train pose. Simulation 3 has been split in two parts because the performance is estimated to greatly differ between these parts. A visualization of this analysis of test simulation 1 can be found through https://youtu.be/bB0UpRj8sZ8 or by contacting the researcher of this study. This visualization only shows the parts of the train journey and does not show the train stops.

	Test simulation 1: Regular train ride	Test simulation 2: All location in the train	Test simulation 3: Difficult situations, ticket inspector	Test simulation 3: Difficult situations, uncommon train poses
Average false negative error of all seats	5,2%	7,2%	8,8%	31,3%
Average false positive error of all seats	2,2%	1,4%	1,7%	10,3%
Total error of all seats	7,4%	8,7%	10,5%	41,6%

Table 10.8: Performance of the camera-based localization system during the train journeys of different simulations

As can be seen in results (Table 10.8) the system has a 7-11% error when estimating occupancy during most simulations. Only the uncommon poses of simulation 3 are the exception. However this simulation can be perceived as a very uncommon situation to occur in a train. It seems likely that the fact the test subjects know how the camera-based localization works has had influence on the results of simulation 3. As can be in Figure 10.5 quite some of the test subjects have removed their heads from the areas of interest. The errors during simulation 2 and the first part of simulation 3 are slightly higher than the error during simulation 1. This can be caused by the fact that the calibration of the parameters is done using simulation 1. This however does not seem to have a very large impact on the measured errors. The overall performance of the system during the train journeys can be seen as fairly good.

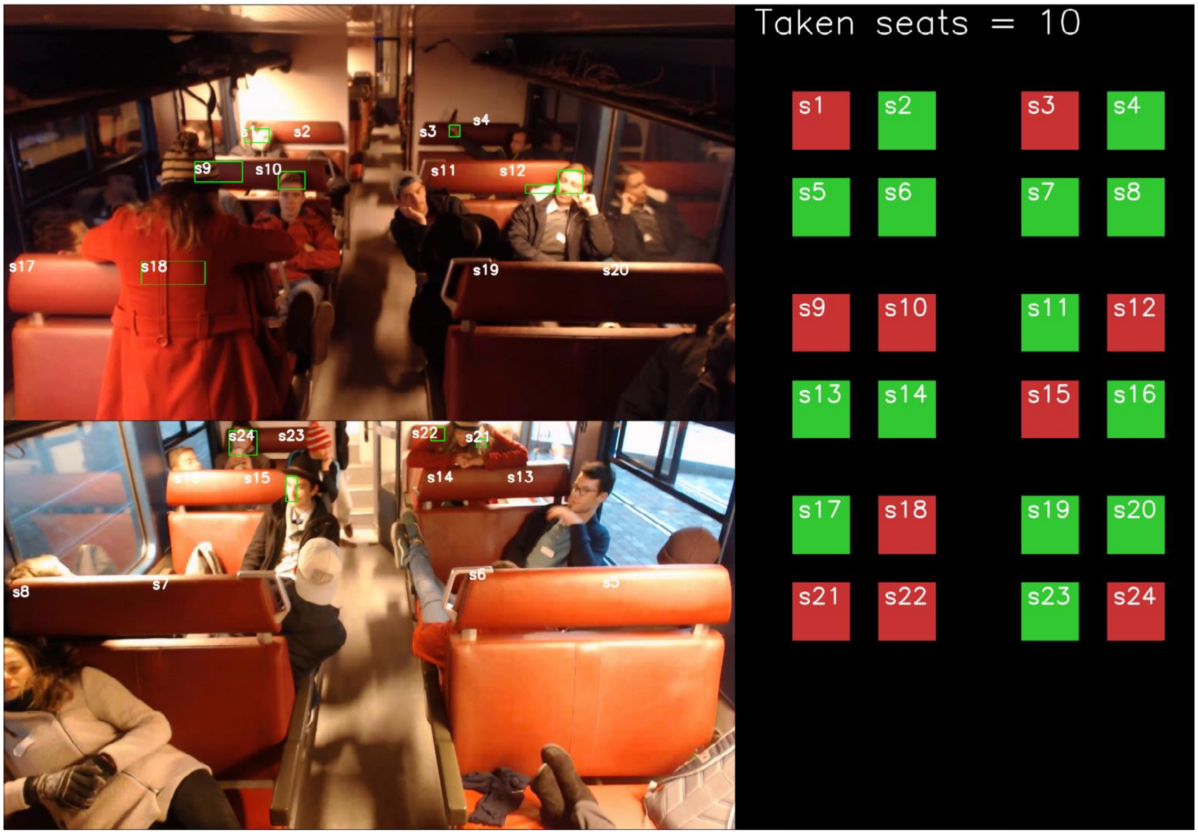


Figure 10.5: An example frame of simulation 3: Difficult situations, uncommon train poses

Results during a train stop

As is described in section 10.1.2 a distinction is made in this research between a train journey and a train stop. The results of the camera-based localization during a train stop are shown in this section. During this time period it seems likely that the occupancy of the chairs is the most important indicator of occupancy in the whole compartment during a train stop in a real situation. If a train is not overcrowded, and the number of passenger is for example ¾ of the number of total seats, it seems likely that shortly before a train arrives at a station some passengers may start standing up. The system may then already detect free seats and this information can then be passed on to passengers waiting on the train platform, that can than move on the platform to the compartments that have the most available seats. During the train stop when the doors of the train are opened some additional passengers may leave their seats to leave the train and after this new passenger can enter the train and start to take seats. The resulting detected occupancy information can continuously be passed on to passengers that are still on the platform so they can choose a suitable compartment based on this information. If a compartment is overcrowded and all seats are taken and passengers are waiting in the hallway the situation becomes different. In this situation it seems likely that when travelers stand up from their seats to leave, the train passengers that are waiting in the hallway will almost immediately take their spots. When a busy train, in which more people were standing in the hallway during the journey than the number of seats that will become available during a stop, arrives at a station it seems probable that almost all seats in the train will almost continuously be taken. It thus seems most useful to estimate the number of taken seats shortly before a train arrives at a station.

The occupancy in the hallway during a train stop has to be considered differently than the occupancy of the seats. If a train is not overcrowded (if the number of passenger is ¾ of the number of total seats) it seems likely that during a train journey the hallway is almost not occupied. However just before a train arrives at a station it is expected that the hallway will to some extend be occupied by people leaving the train. If a train is overcrowded and it is arriving at a station it seems likely that the number of people standing in the hallway will be relative stable, because the people that were seated will replace the people that are waiting in the hallway. When a train arrived at the station and the doors of the train are open it seems likely that the number of people standing in the hallway will vary, as these people will leave the train and will be replaced by new people waiting on the train platform. It can be stated that the occupancy of the hallway during a train stop must be considered in relation to the occupancy of the seats during a train stop, or it must be considered in relation to an average measured occupancy in the train journey that preceded the train stop.

Simulation 1 is chosen to test the performance of camera-based localization method for the seats during a train stop of a train that is not overcrowded. Simulation 1 seems suitable because there is a maximum of 10 passengers inside the train compartment, while there are 24 seats inside that compartment. The compartment thus not seems overcrowded. The occupancy of the seats therefore seems the most relevant indicator during this time period for simulation 1 and is thus analyzed. The occupancy of the hallway in the train stop is analyzed for simulation 2, in which an overcrowded train is simulated and the test subjects pretended that all seats were taken. Simulation 2 is also more suitable for analysis of the hallway since the number of people in the hallway varies in this simulation from 1-15 and for simulation 1 this amount varies from 1-5. The analysis of the seats approach for simulation 1 during a train stop is described first.

For the analysis of the occupancy of the seats of simulation 1 during a train stop, the same parameter settings are chosen as the ones that are used for the seats approach during a train journey (shown in Table 10.7). The analysis is run starting from the moment the first test subject stands up and the last test subject sits down. The results are shown in Table 10.9. A visualization of this analysis can be found through https://youtu.be/nH1BOIhymiM or by contacting the researcher of this study. This visualization only contains the train stops and does not show the train journeys.

	Test simulation 1: Train stops
Average false negative error of all seats	4,3%
Average false positive error of all seats	8,7%
Total error of all seats	13,1%

Table 10.9: Performance of the camera-based localization system during the train stop

As can be seen in Table 10.9 the false negative errors measured during the train stop are fairly similar as the false negative errors measured during the train journeys (as shown in Table 10.8). The measured false positive errors are however higher than the ones measured during the train journey. The false positive errors seem to occur more often during a train stop, because people than frequently block the view of the camera by standing between the camera and a headrest. An example of this is shown in Figure 10.6 in which the person that is getting seated blocks the headrests of seat 9 and seat 1. When considering this results it has to be taken into account that they are calculated by comparing the output of the computer system to a database for which the data has been manually supplied by the researcher. In this manual database a seat is considered empty as soon as the person sitting on it has completely stood up. Some people stand up in a different way than other people so the exact moment that this occurs is a bit of a gray area. The manual database can thus be prone to human error. It also has to be taken into consideration that manual database may have been prone to an unconscious confirmation bias from the researcher.

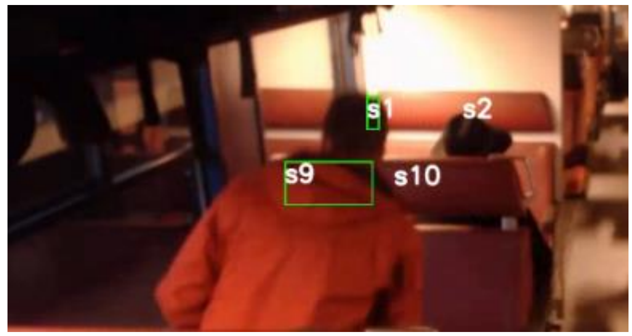


Figure 10.6: Common false positive error that occurs during train stops

Results hallway approach

For the hallway approach it is attempted to research a relation between the number of people standing in the hallway and the percentage of change detected by the system. To find this relation simulation 2 is used. Because in this simulation the test subjects were instructed to pretend to wait in the hallway as if all seats are taken by other passengers during a train journey. In the other simulation test subject are only located in the hallway when getting in or out of the train during a train stop. From simulation 2 the number of people standing in the hallway is manually observed and compared to the average ratio of changed pixels from both cameras. These two variables are shown in a graph Figure 10.7. As this required more manual labor only 3 frames per 10 seconds are analyzed. A visualization of this analysis can be found through https://youtu.be/b_HGf9W8P_E or by contacting the researcher of this study.

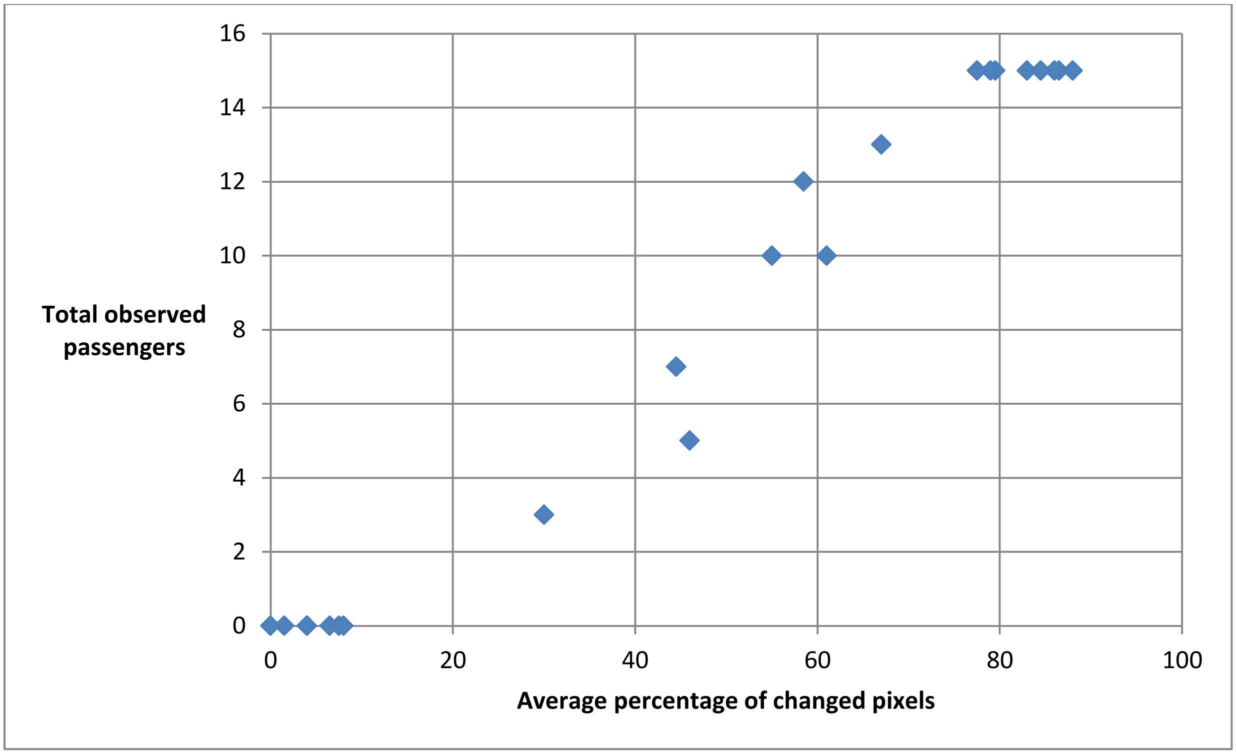


Figure 10.7: Number of observed passengers vs the average percentage of changed pixels

From this figure it seems like there is a positive correlation between these two variables. During the analysis however an error can be observed that may have influenced the results significantly. This error is caused by two of the test subjects that wear clothing that has a similar color as the floor of the hallway. These two persons were located very close to one of the cameras during the time period that 8 – 10 people were located in the hallway. Therefore the number of measured change pixels is significantly lower during that time period. This is illustrated in Figure 10.8. In this figure a video frame of the hallway is shown on the left and on the right corresponding pixels that are measured as change by the system. If there would have been other persons standing in that area the measured number of changed pixels during the time period could have been significantly different. The error may have played a role in the correlation shown in Figure 10.7. It therefore seems that more data is needed to properly model a relation between the number of people standing in a hallway and the percentage of changed pixels.

Figure 10.8: Error caused by people with the same colored clothing as the floor

10.2.4 Discussion

In this section the limitations of the camera-based localization used in 'Test setting 2: Railway museum' are described. In this test it has been tried to simulate a real train journey as close as possible, there are however some limitations to the test. The limitations are discussed in Table 10.10. Some limitations are similar to the ones in test setting 1 that are discussed in Table 9.8, these are therefore discussed briefly.

Inadequacy of test setup	Description of expected influence
Color of the chairs do not comply with reality	The red color of the chairs in this test setting differs from the blue ones in the FLIRT. The red colored chairs of this test setting have a hue that is very similar to the hue of the skin and this is expected to have decreased the performance of the camera-based localization method.
No sideways facing chair	In test setting 2 there are no sideways facing chairs in contrast to the FLIRT. Since people are harder to detect on sideways facing chairs than forward facing chairs. It seems likely that this has a positive effect on the measured performance.
Height of the ceiling and cameras	The ceiling of the train in the railway museum is lower than the ceiling of the FLIRT. This is expected to have had a negative influence on the performance of the system in the test setting as the cameras are also lower. This is expected to lead to more false positive errors as it is more probable that train passengers will block the view of the camera. These errors mainly occur when people are standing in the train.
Different light conditions	• In the train used in the railway museum three out of the six lamps are non-functional. In a normal train it is expected that most lamps work. This bad lighting can have negatively influenced the results of this research. • In a normal train the amount of natural light (from the sun) can have great variance in a short amount of time due to objects such as trees and tunnels. Since the train from the railway museum is static this is not taken into account in this test setting.
Limited number of test subjects	In a real train, there can be a multitude of train passengers which can have a different height, skin color or headwear. In this test setup only 15 test subjects are present. All of the test subject have light skin tone and all of the test subjects are grown-ups. This can have had influence on the performance of the system as these characteristics can have influence on the accuracy of the detection system. Due to the limited number of test subjects it is also harder simulate a train journey in which the train compartment is overcrowded.
Behavior of the test subjects	The test subjects in this test setting know that they are being filmed

	and they may have therefore (unconsciously) acted differently.
Limited amount of data	In this test setting only three simulations of approximately 5-12 minutes are used to test the system. The performance of the system can be better validated if more test data is available.

Table 10.10: Limitations to test setup 2 with regards to camera-based localization

There are also some aspects that have to be taken into account with regards to the used algorithm for camera-based localization in this research. The algorithm mostly uses universal parameters for all areas of interest. Currently only the relevant contour size differs per area of interest since it is calculated relative to the size of the area of interest. For the rest of the parameters (such as the hue threshold) the same setting is used for each area of interest. Using a different setting of each parameter for each area of interest could results in more accurate detection. This is however not applied in this research because this method is relatively time intensive. Because this method is more time-consuming it also seems less feasible to apply this when implementing the proposed methods of this research in practice. Than unique parameters would have to be chosen for every different seat in the train, which would cost relatively more time. This may however be beneficial if it results in a significant increase in performance, it is therefore recommended to test this in future research.

Another point of discussion is related to the automatic calibration and adjustment of the algorithm. The current method relies on running the model multiple times while each time slightly increasing or decreasing one parameter based on the increase or decrease of the performance. If the optimal setting of one parameter has been estimated the process continues with the next parameter. The disadvantage of this method is that it could lead to sub-optimal results if the relation between the performance and the parameter is not a hyperbolic function. However, it seems likely that the relationship between each parameter and the performance is a hyperbolic function or close to a hyperbolic function. Another disadvantage of the applied method is the sequential way of optimizing the parameters. In this method each parameter is locally optimized, while a global solution may lead to a better performance. A better fitting solution to optimize the parameters can be a genetic algorithm. This is however more time consuming than the currently used method, since it requires running the model relatively more times. Since one run of the model takes about 1-5 minutes and the current calibration method seems to generate sufficiently good results a genetic algorithm has not been applied in this research. It may however be useful to test such a method in future research.

Some improvement may also be made to the algorithm that is used for the hallway approach in this research. This approach currently detects the number of changed pixels in the hallway when comparing each frame from the video feed to a frame from an empty hallway. In this approach people that stand closer to the camera have more influence on the number of changed pixels. It may yield more accurate results to apply a filter that weights pixels on their relative distance to the camera. It may also be useful to test another camera-based localization approach in the hallway. Background subtraction using a mixture of Gaussian may be used to detect movement of the passengers entering the train (Kim, Chalidabhongse, Harwood, & Davis, 2005). This approach seems most suitable to use during a train stop in the hallway when people are entering the train. It is recommended to test such an approach in future research.

10.3 Wi-Fi localization in the railway museum

In this paragraph the measured Wi-Fi probes are used to estimate the number of Wi-Fi devices in the train. In the test setting the test subjects knew the purpose of the test and were all instructed to bring one Wi-Fi device with its Wi-Fi enabled. Therefore no conclusions can be drawn with regards to a relation between the number of *passengers* and the number of Wi-Fi probes with a unique MAC-address in this test. In this paragraph is therefore only attempted to estimate the location and number of *Wi-Fi devices* based on information of the measured Wi-Fi probes. The MAC-addresses from the Wi-Fi probes can be related to the Wi-Fi device, because the Wi-Fi devices' MAC-addresses were collected prior to the test. A relation between the location and number of Wi-Fi devices and the measured Wi-Fi probes can be researched, because the actual location of the Wi-Fi devices in time is recorded during the tests. Unfortunately not all test subjects can be related to a MAC-address. Of the test subjects 5 people have a phone with IOS installed. It appears that this program uses random MAC-addresses when sending out Wi-Fi probes. This theory is supported by the security guide of Apple (Apple, 2016), which states that for newer devices than the IPhone 4s the MAC address now changes when it is not connected to a Wi-Fi network. This thus means that it may be possible to detect people with an IPhone that connect to the Wi-Fi in the train. This is however not tested in this research. In this research the measurements with a random MAC address are therefore not used since they are difficult to relate to a device. In Table 10. is indicated by ID which test subjects have an IOS device with MAC-address randomization (red) or a device without MAC-address randomization (green). In this table is also shown whether the test subjects were actively using their phone or had it on standby and in which team they were grouped.

ID	Team	Mobile on standby or Active
1	1	A
2	2	S
3	3	A
4	1	S
5	2	A
6	3	S
7	1	A
8	2	S
9	3	A
10	1	S
11	2	A
12	3	S
13	1	A
14	2	S
15	3	A

Table 10.12: Test subject with MAC-address randomization (red) or without MAC-address randomization (green) of test subject

To use the measured data some preprocessing has to be done. In the measurements it often occurs that within a short period of time (of less than one second) the same MAC-address is measured multiple times with a slightly varying RSSI. An example of this is shown in Table 10.11. In this table the RSSI values are shown in arbitrary units the higher the RSSI number, the stronger the signal. In which 255 is the strongest signal and 0 the lowest signal. Active mobile devices typically send out a probe request every 4-6 seconds. A possible explanation for the multitude of probe request that are received in an instant is that one probe request is measured 5 times due to multipath errors. Multipath would also explain the variations measured in RSSI. Another explanation for the multitude of received Wi-Fi probes within an instant is that some Wi-Fi devices occasionally send multiple probes at nearly the same time for specified access points instead of for all access points. The variations of RSSI may then be explained by a mixture of slight measurement errors and multipath errors. This theory can be clarified using an example and Table 10.11. The multitude of measurements with one MAC address in an instant in this table may be caused by the system that searches for specified access points. The relative small variations in RSSI between ID 1-4 may be caused by measurement errors. The relative large variations of ID 5 may be explained by the possibility that one Wi-Fi probe (for a specified access points) was influenced by multipath errors.

In both of the described possible causes duplicate measurements with the same MAC address that arrived in the same instant can be seen as superfluous, since they do not contain extra relevant information. The duplicates are therefore discarded and only the measurement with the highest RSSI is taken into account, since this measurement is probably least influenced by multipath and the information of the other measurements can be seen as redundant. This reasoning is illustrated using Table 10.11. The RSSI of measurement ID 5 in this table may indicate that the mobile device is located outside while the RSSI of ID 1-4 indicate that the mobile device is located in the train. In this situation it seems likely that RSSI of ID 5 is lower due to multipath propagation. It seems therefore most accurate to only take the measurement with the highest RSSI into account, since this measurement is probably least influenced by multipath. To enforce this selection in this research a filter is applied to the measurements using Python. If multiple measurements of the same MAC-address occur within two seconds only the measurement with highest RSSI is selected. In this example only the measurement with ID 2 is selected, the rest is discarded as duplicates. The applied python filter is visualized in Figure 10.9. A disadvantage of this filtering can be that it requires a small delay to take into account probes that arrive later.

ID	Timestamp	Anonymized MAC-address	RSSI (0-255)
1	1485180773	02:1b:14:94:47:67	213
2	1485180773	02:1b:14:94:47:67	215
3	1485180773	02:1b:14:94:47:67	214
4	1485180773	02:1b:14:94:47:67	213
5	1485180773	02:1b:14:94:47:67	198

Table 10.113 : Example of multiple measurement of the same MAC-address

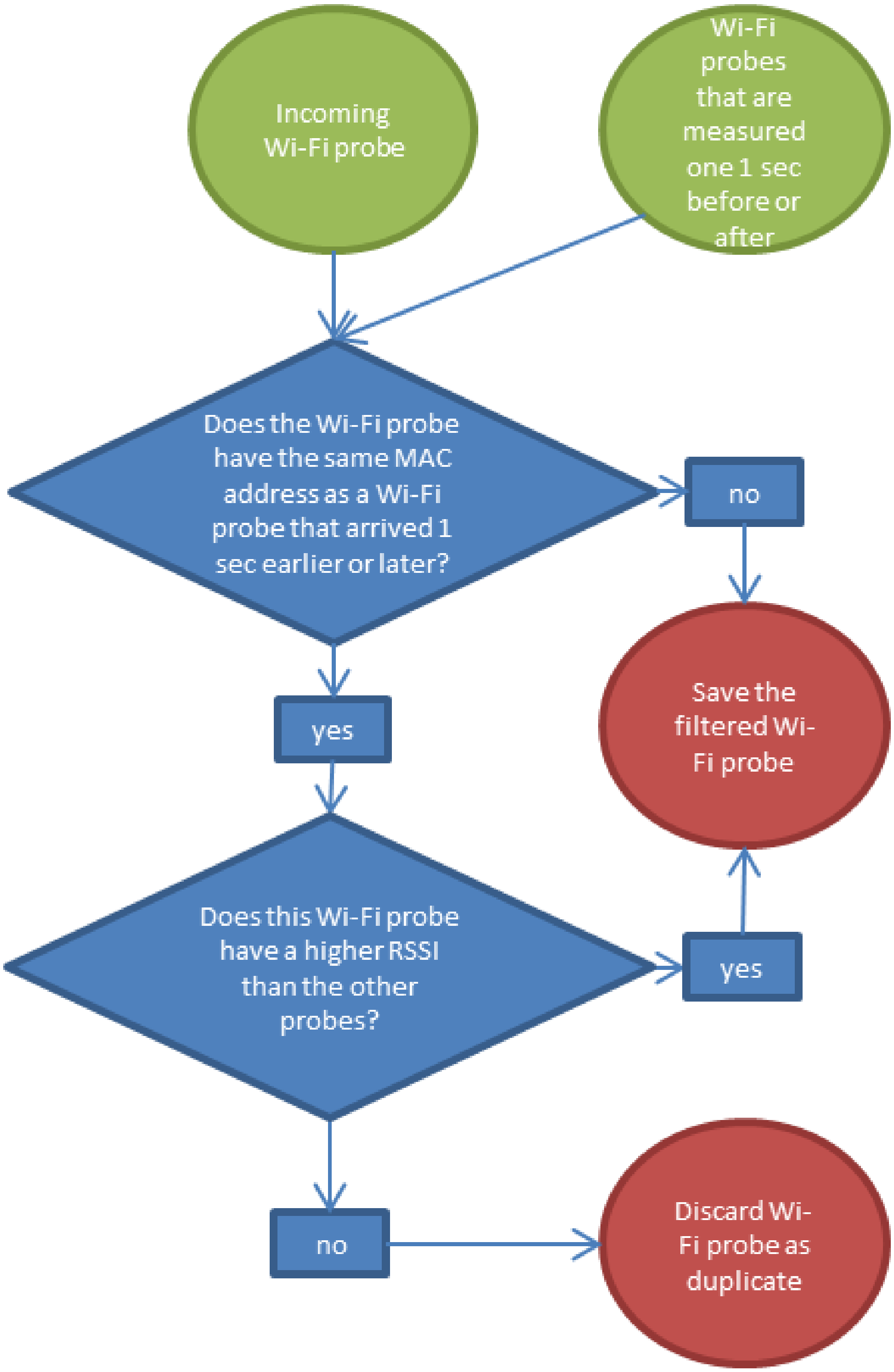


Figure 10.9: Flowchart of filtering incoming Wi-Fi probes for duplicates

10.3.1 Customizing and initial testing

To test whether occupancy can be estimated for the journey between two train stations test simulation 2 is used. The reason for choosing test simulation 2 is that in this simulation all test subjects were in the train so more date can be used. Furthermore half of the test subjects were instructed to watch their mobile phone during simulation 2. This simulation thus includes phones in standby mode and active phones, which according to the literature has influence on the frequency of the Wi-Fi probes. This seems similar to a real train journey in which it seems likely that some people are using their phones actively while others have their phone on stand-by. The time period for which is measured is three minutes. This corresponds to the shortest trip durations that are common in the Netherlands. In this test simulation the train did not actually leave the station. This means that Wi-Fi devices that are near the train are still measured during the simulated train journey in this test. In a real situation this does not happen since the train then actually leaves the station, so after a certain amount of time the Wi-Fi probes from devices on the train platforms will not be measured anymore. To counter this only the probes for which the MAC-address is known to correspond to one of the phones of test subjects are selected in this analysis. This means that the MAC-addresses from other devices that may be close to the test train are not taken into account. For these devices however it seems unlikely that two or more probes will be received in a real train during a journey between two stations. Especially when considering the applied filter that filters duplicate probes in a small time frame (shown in Figure 10.9) and the fact that a train travels approximately 25m per second. The number of measured probes per static MAC-address, while applying the filter for duplicate probes, is shown per mobile device in Table 10.12.

Device number	Phone active/stand-by	Number of measured probes
1	Active	7
2	Stand-by	22
3	Active	9
4	Stand-by	10
5	Active	12
9	Active	3
10	Stand-By	14
12	Stand-By	18
13	Active	12
15	Active	0

Table 10.12: Number of measured probes per Wi-Fi device

From the results shown in Table 10.12 it seems that there is no obvious correlation between the number of measured probes and whether the phones are active or on stand-by. The average number of measured Wi-Fi probes per device per minute is 3,5. The number of Wi-Fi devices in a train between stations is estimated by an algorithm that counts the MAC-addresses that are measured *twice* in the filtered Wi-Fi probes. The main reason for applying a minimum number of two probes is to counter the MAC-address randomization of some devices (such as IOS and Windows 10). If the assumption is made that each unique MAC-address is a unique device a device that employs IOS would be counted multiple times. It therefore seems reasonable to only count MAC-addresses which are measured at least twice during a train journey. The selection process is shown in Figure 10.10. For this test it is possible to detect every device except for device ID 15. This thus means that there is a false negative error of 10% when measuring the Wi-Fi devices with a static MAC address in this test. There is no false positive error, since only devices are measured of which the MAC-address is known. It is however important to take into account that the train journeys between most stations are longer than 3 minutes. So it may be possible that more Wi-Fi devices can be identified during longer train journeys. This test gives a good indication that it seems possible to measure the number of Wi-Fi devices without MAC-address randomization relatively accurately with Wi-Fi localization during a short train journey.

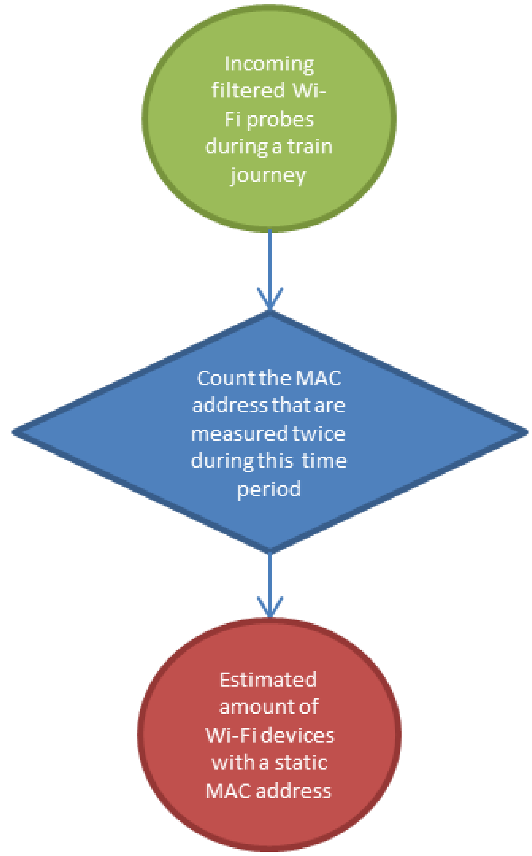


Figure 10.10: Flowchart of estimating number of Wi-Fi devices with a static MAC-address during a train journey

10.3.2 Localizing using RSSI

To determine whether it is possible to measure changes in occupation of the train during a train stop at a station using Wi-Fi probes, it seems necessary to be able to distinguish Wi-Fi probes originating from devices located inside the train from those located outside the train. The RSSI of Wi-Fi probes is used to make this distinction of location. In this research the RSSI measurements in relation to the known location of the test subjects during test simulation 1 are used to create a reference of RSSI that is common for devices located in the train. This reference is verified using data from simulation 2 and 4.

The measured RSSI of phones that are located in the train is first compared to the measured RSSI of phones located outside the train during test simulation 1. The people located outside the train were standing in a proximity of under 10m from the train and the outer door of the train was open during the test simulation 1. To determine whether there is a significant difference between RSSI value from probes coming from devices inside the train in contrast to devices outside the train the dependent t-test for paired samples is used. This is done by grouping all measured probes of the first test simulation in two groups based on whether they came from a device inside the train or a device outside the train. The t-test for paired samples resulted in a p-value very close to 0. It can therefore be concluded that there is a significant difference between RSSI measured from devices inside the train compared to devices outside the train.

The Z-test is used to create a reference of RSSI for when it is more likely that a probe comes from a device that is located inside the train or outside the train. Two Z-scores are calculated for each group of RSSI measurements for which the location of the device is unknown:

- One using the average and standard deviation of the RSSI of the reference group of Wi-Fi probes originating from devices *inside* the train.
- Another one using the average and standard deviation of the RSSI of the reference group of Wi-Fi probes originating from devices *outside* the train.

The *z*- scores are calculated using the equitation 10.1 in which *x* is the average RSSI of one of the groups, *s* the standard deviation of that group and *i* the RSSI of the probe for which the location is unknown.

$$z = \frac{i - x}{s} \tag{10.1}$$

The z-scores that are calculated for both groups are then compared to each other, the group for which the z-score is closer to zero is deemed as a more likely fit for that measurement. The location of the measurement with the unknown location is assumed to correspond with the location of the group for which it has a better fit. A threshold can be found by finding an *i* value for which the *z* of both groups is the same. In this situation this occurs for an *i* of 199,6. RSSI in this research is only measured in integers. Therefore if the measured RSSI of probe is 200 or higher it probably originates from inside the train and if it is 199 or lower it probably originates from outside the train.

To test the accuracy of the threshold simulation 2 and 4 are used. From simulation 2 different time frames are used:

1. A time frame in which all test subjects are sitting in the train
2. A time frame in which all test subject are standing in the train

These different time frames are used to test whether the position of people has influence on the RSSI. As described in section 5.1.4, people can influence the accuracy of Wi-Fi localization methods that rely on RSSI due to the fact that humans have different propagation properties than air. For each individual RSSI measurement of these time frames is estimated whether they originate from the train or from outside the train using the threshold from the z-scores. These estimated locations are then compared to the true locations (in these two cases the true locations are all inside the train) to determine the relative accuracy of this localization. These results are shown in Table 10.13. The relative accuracy of the estimated locations is for sitting and standing respectively 80% and 78%. There does not seem to be a significant difference in accuracy between a situation in which people are standing and a situation in which people are sitting. To test this method for Wi-Fi devices located outside the train, simulation 4 is used. In test simulation 4 all test subject were standing close to the train as if they were standing at a train platform with the intention of boarding the train. For this simulation the location of the test subject is also estimated using the RSSI of the measured Wi-Fi devices for which the MAC-address is known. This resulted in a relative accuracy of 93%.

Situation	Total measured number of unique probes	Probes estimated inside the train	Probes estimated outside the train	Relative accuracy
Sitting	55	44	11	80%
Standing	41	32	9	78%
Platform	107	8	99	93%

Table 10.13: Accuracy of localization using RSSI

Based on the results shown in table 10.3.4 it seems that RSSI can to some extent be used to distinguish between passengers inside the train and passengers standing on the platform outside the train. Wi-Fi localization may therefore possibly be used to monitor changes in occupancy in real time during a train stop to some extent. The performance of such a system however also heavily depends on the number of Wi-Fi probes received during this time. This is tested in the next section (10.3.3).

10.3.3 Testing the performance

As described in paragraph 10.1 it has been tried to simulate a real train journey in test simulation 1. To test the potential of using Wi-Fi localization in the train an algorithm is applied using Python on the measured Wi-Fi probes during this test simulation. It is of importance to note this algorithm is only used to estimate the number of Wi-Fi devices (that have a static MAC-address) and not the number of passengers.

This algorithm distinguishes between two situations:

- The train travelling between two stations
- The train stopped at a station

In this research the time frames of the two situations are selected manually. When applying this method in a real operational train it may be possible to do this automatically by using GPS or by identifying Wi-Fi probes that originate from static devices on the train station (such as a Wi-Fi router from a kiosk). The algorithm functions differently during the two situations and the performance is also described differently for the situations. The algorithm is elaborated for both situations below

Estimating Wi-Fi devices located in the train when it is travelling between two station

The Wi-Fi probes that are measured during these time periods are first filtered using the duplication filter (shown in Figure 10.9). The number of Wi-Fi devices with a static MAC-address is estimated from these filtered probes using the method described shown in Figure 10.10. The algorithm thus counts the number of MAC-addresses of which at least *two* Wi-Fi probes are measured during the train journey. During these time periods only the Wi-Fi probes with a MAC-address known to correspond to a phone of the test subjects are selected. This is done to counter for the noise of Wi-Fi devices near the train that would not occur in a real situation since a train than actually leaves the station. In simulation 1 there is even more noise from Wi-Fi devices close to the train than in simulation 2, since in this simulation a third of the test subjects is located on the platform. At the end of the simulated train journey between train stations a total number of Wi-Fi devices is estimated. The time slot that is defined as train journey in this test simulation is defined as 10 seconds before people are beginning to stand up and 10 seconds after all people have been seated. The results of the algorithm are shown in Table 10.14. In this table the actual test subjects that were located in the train are shown by ID and are compared to the measured test subjects also shown by ID to determine the error. In this analysis there are only false negative errors, since only devices are measured of which the MAC-address is known. The ID's of the test subject can be found in Table 10..

The train journey	Duration in seconds	Measured device ID's	Actual device ID's	False negative error
Journey 1	220	2, 3, 5, 9, 12	2, 3, 5, 9, 12, 15	17%
Journey 2	182	1, 3, 4, 9, 12, 13	1, 3, 4, 9, 10, 12, 13, 15	25%
Journey 3	147	1, 2, 4, 5, 10, 13	1, 2, 4, 5, 10, 13	0%
Total	549		Average error	14%

Table 10.14: Performance during train journey

The average error that is found here (14%) is similar to the earlier found error of the algorithm for simulation 2 in section 10.3.1 (10%). It seems thus possible to make a reasonable estimation of the number of Wi-Fi devices located in the train during a train journey. The output of this part of the algorithm is used for the next part of the algorithm.

Wi-Fi devices leaving during a train stop

During this timeframe the algorithm estimates whether the Wi-F devices that are detected during the train journey exit the train during the train stop. So the algorithm tests whether earlier found unique MAC-addresses are leaving the train. The algorithm tests this by detecting if one of these earlier found devices sends out a Wi-Fi probe with a lower RSSI, that indicates that it is probably located out of the train. This threshold is created by using the reference frame described in section 10.3.2. The flowchart of this algorithm is show in Figure 10.11. For this algorithm it is not needed to detect at least two probes with the same MAC-address, since the Wi-Fi devices with a static MAC-address are already identified during the train journey. The results of this algorithm applied during the train stops are shown in Table 10.15.

In this analysis a false positive error is when a device is falsely detected to leave the train during a train stop when it in fact remained in the train. As can be seen in Table 10.15 no false positive errors are found. A false negative error is when the system does not detect a device leaving the train when it is in fact leaving the train. False negative errors do occur in this analysis. The false negative errors vary from 0% - 75% per stop. Based on these test results it seems as if some indication of the number of people leaving the train can be given but that the method is not very accurate. The main reason for this is that Wi-Fi probes per device are not measured frequently enough. In the simulations an average of about 3,5 Wi-Fi probe per minute per device is measured and these numbers differ greatly per device (as is shown in Table 10.12). The duration of the train stops is about 45 seconds. During this time not enough Wi-Fi probes are measured to give a good indication if Wi-Fi devices are leaving the train, especially if such an indication needs to be given in real time, or with only a small delay.

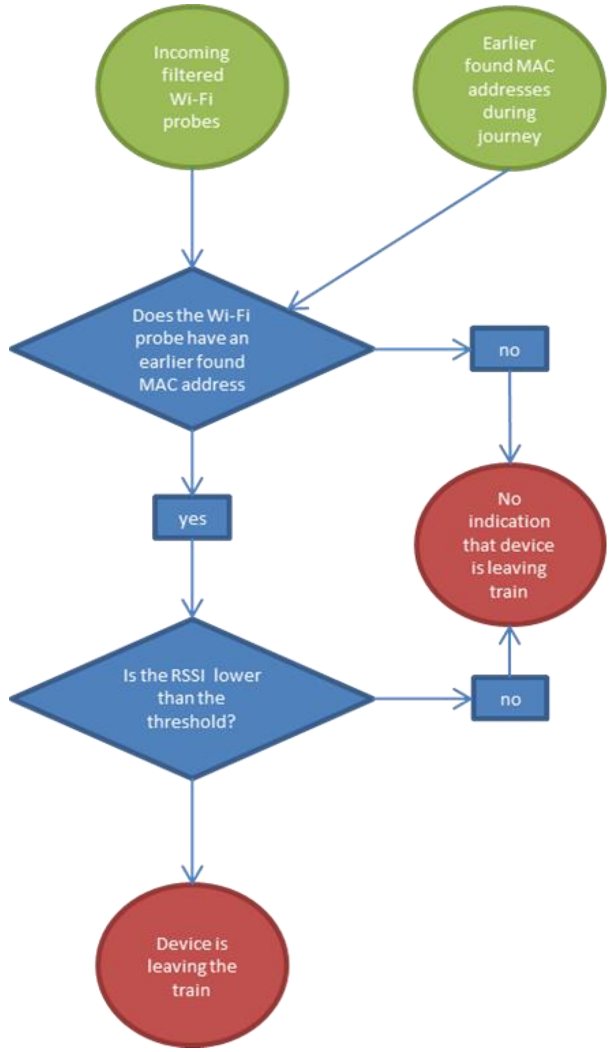


Figure 10.11 : Flowchart of detecting device leaving the train during a train stop

Train stopping at a station	Duration in seconds	Device ID's measured leaving the train	Actual device ID's leaving the train	False negative error	False positive error
Stop 1	48	2, 5	2, 5,	0%	0%
Stop 2	57	3	3, 9, 12, 15	75%	0%
Stop 3	30	2, 5, 10, 13	1, 2, 4, 5, 10, 13	33%	0%
Total	135		Average errors	36%	0%

Table 10.15: Performance of measuring device leaving the train during train stop

Wi-Fi devices entering the train during a train stop

The algorithm also tries to identify the number of Wi-Fi devices entering the train during a train stop. It does this by examining all incoming Wi-Fi probes during a train stop to detect whether they have a MAC-address that was not found during the prior train journey. To make sure that devices with MAC-address randomization are not counted as multiple devices at least two probes with the same MAC-address need to be measured. Furthermore the RSSI of the last probe needs to be high enough to indicate that the device is located in the train. The flowchart of this process is shown in **Error! Reference source not found.**. In this test the probes are also filtered for duplicates with the process shown in Figure 10.9. However, in this test the incoming Wi-Fi probes are not filtered to select only the probes of which the MAC-address is known to belong to one of the phones of the test subjects. This filtering is not applied since the proposed system can also be prone to noise from Wi-Fi devices located at a station when applied during a real train stop. The probes with a MAC-address corresponding to one of the devices from the researcher are however filtered. The results of this process are shown in Table 10.16

In this analysis, a false negative error occurs when a device is in reality entering the train but this is not measured. A false positive error occurs when a device is falsely measured as entering the train when it did in fact not enter the train. As can be seen in Table 10.16 the algorithm is not able to give any indication of whether Wi-Fi devices are entering the train during the train stops. During stop 1 and 2 no devices are detected entering the train, while in reality respectively two and four Wi-Fi devices (without MAC-address randomization) entered the train. During stop number 3 one device with an unknown MAC-address is detected to have entered the train, while in reality all devices left the train during that time period. The reason why an unknown MAC-address is detected is unclear. A possibility is that there was a device near the train that sends out probes with high signal strength.

Figure 10.12: Flowchart of detecting devices entering the train during a train stop

Another possibility is that one test subject unknowingly carries an extra Wi-Fi device. Regardless of the unknown package it seems that the system is unfit to measure the number of Wi-Fi devices entering the train during a train stop in real time based on this test.

Train stopping at a station	Duration in seconds	Device ID's measured entering the train	Actual device ID's entering the train	False negative error	False positive error
Stop 1	48	none	1, 4, 10, 13	100%	0%
Stop 2	57	none	2, 5	100%	0%
Stop 3	30	1 unknown ID	None	0%	100%

Table 10.16: Performance of measuring device entering the train during train stop

10.3.4 Discussion

Based on the results of paragraph 10.3 it seems possible to give a good indication of the number of Wi-Fi devices located in the train during a train journey. During stops however it seems that the proposed system is not accurate enough to indicate how many Wi-Fi devices are exiting or entering the train. The current system only detect the amount Wi-Fi devices. An extra step in the proposed system is needed to use the estimated number of Wi-Fi devices to give a good indication of the occupancy in the train during a train journey. For this extra step a lot of factors need to be taken into account. These factors are:

- The average number of Wi-Fi devices that people have with them in the train. People can have a varying number of Wi-Fi devices, some people may have no Wi-Fi devices while others carry multiple such as phones, tablets and laptops.
- The percentage of people that have their Wi-Fi turned on in the train.
- The percentage of Wi-Fi devices that have a static MAC-address, since the current system only takes static MAC-addresses into account.
- The average ratio of Wi-Fi devices that sent out more than two probes during a train journey. As is stated in section 10.3.1 it is possible that no Wi-Fi probes are measured from a Wi-Fi device that has its Wi-Fi enabled and does not have MAC-address randomization.

It seems difficult to take into account all these factors in a test setting. For future research it is therefore recommended to research Wi-Fi localization in a train that is in operation to determine a relation between the number of estimated Wi-Fi devices and the number of passengers. It is recommended to implement Wi-Fi scanners to estimate the number of Wi-Fi devices and monitor the number of passengers using another method for verification to find a correlation. It is recommended to conduct this testing during an extended periods of time during different hours of the day, since the ratio between Wi-Fi devices and passenger may differ between different time frames such as rush hours and weekends.

Another recommendation for future research is to test the proposed system in a test setting in which multiple compartments are occupied to test to what extent can be discriminated between probes that originate from different compartments. It seems likely that a Wi-Fi device is located in the compartment in which the (average) RSSI of the Wi-Fi probes is the highest. This however has to be tested in practice. Another recommendation for future research is to use RSSI to create a radio map of a compartment in the train. This way is may be possible to relate the measured Wi-Fi devices to locations in the compartment (such as the train chairs). With such an approach it may be more feasible to combine the data of the Wi-Fi localization to the data of the camera-based localization. The camera-based localization method can than detect a seat as taken and this measurement can then be verified by the Wi-Fi localization method using the radio map.

A disadvantage of this proposed method may be future technological developments that need to be taken into account. Currently IOS and Windows devices have easy options for MAC-address randomization; it is therefore plausible that Android may also employ easy MAC-address randomization in the future. Such a scenario will make the proposed method less accurate, since the proposed system relies on static MAC-addresses. In such a scenario is may be possible to employ a system that measures the absolute number of Wi-Fi probes of a certain RSSI threshold per time unit. Such a system is however probably less accurate than a system that can use MAC-addresses as a unique identifier.

10.4 Integration of approaches

In this paragraph is elaborated about how the Wi-Fi localization and the camera-based localization can be combined. Some problems are encountered when trying to combine the two approaches using the tests conducted in this research. The main problem in this research is that only the relation between the number of Wi-Fi devices (with a static MAC-address) and the Wi-Fi probes can be studied. The relationship between the Wi-F probes and the number of passengers cannot be determined based on the data gathered for this research. The camera-based localization does not measure the number of Wi-Fi devices, but focusses on the number of passengers. Because the two approaches measure different things it seems hard to objectively measure to what extent these approaches can supplement each other.

In simulation 3 it has been attempted to simulate a crowded train by instructing the test subjects to stand in the hallway. This instruction is useful to estimate the performance of the camera-based localization system in a crowded train compartment. It has however less influence on the Wi-Fi localization system as the number of Wi-Fi probes is not affected. It is therefore very hard to use this test to give a good estimation of the performance of the Wi-Fi localization system for when a train compartment is actually crowded (when all seats are occupied and people are standing in the hallway). Making such an estimation would require an assumption about the ratio between the number of train passengers and Wi-Fi devices and also an assumption about the Wi-Fi probes that may have been measured from the passengers sitting on chairs that do not exist in this test simulation. There is furthermore too little data available to properly estimate the occupation of a hallway using the camera-based localization system. Due to these limitations it cannot statistically be tested to what extent Wi-Fi- with camera-based localization can be integrated. This is there not done in this research

Some expectations regarding a possible combination of the two methods are however described. The Wi-Fi localization during a train stop seems too inaccurate to use, it seems therefore better to rely on the camera-based localization during a train stop if an estimation of occupancy has to be made during this time period. During a train journey it may be possible that the two methods can complement each other to some extent by mitigating each other's disadvantages. The Wi-Fi localization is probably more accurate the more passengers there are in located in a compartment. This is because it seems likely that an expected ratio between Wi-Fi devices and passengers becomes more reliable the more passengers there are in a train. This is because a larger sample more reliably reflects a population mean. This is in contrast to the camera-based localization. The camera-based localization may become less accurate when there are more passengers located in a train, especially if there are more passengers in a train compartment than the number of available seats. This is because the camera-based localization is less accurate in the hallway. The people in the hallway may also block the view of the camera(s) of the train's seats and can therefore also decrease the performance of the localization at the seats of the train compartment. It can thus be seems that the Wi-Fi and camera-based localization may complement each other when used to measure occupancy in the train because they can be used to verify each other and they both thrive during different amounts of occupancy.

11 Privacy

In this paragraph is elaborated about how the proposed methods of this research are related to privacy. The reason the privacy aspect is highlighted at the end of this thesis is because it is first necessary to thoroughly understand the proposed method of indoor localization before comprehending the relation between privacy and the proposed method. Furthermore privacy is not the focus of this research, and it seems therefore more appropriate to describe it in in a section at the end of this research so it can be focused and tailored on the methods used in this research, instead of a broader description of privacy. In this section is furthermore concentrated mostly on Dutch and EU privacy legislation as this research studies train in the Netherlands.

The protection of personal data is regulated in article 8 of the Charter of Fundamental Rights of the European Union (EU, 2000). This article is further elaborated in the Data Protection Directive of the EU, which in the Netherlands is enforced with the Dutch law: "Wet Bescherming Persoonsgegevens" (European Union, 1995; Kulk & van Loenen, 2012; Wet bescherming persoonsgegevens, 2000). According to the directive and law personal data should be processed fairly, lawfully and for specified, explicit and legitimate purposes. Furthermore, the data should only be stored until the point that the information does not serve its purpose anymore (Verbree et al., 2013; Wet bescherming persoonsgegevens, 2000). The concept personal data is also defined by the Data Protection Directive. The directive states that: *"personal data is data that can be related to an identified or identifiable person"*. An identifiable is a person who can be identified, directly or indirectly, in particular with a reference to an identification number, or to one or more factors specific to his or her physical, physiological, mental, economic, cultural or social identity (EU, 2000). Characteristic examples of personal data are names, IP addresses and telephone numbers (Kulk & van Loenen, 2012). To evaluate whether data can be related to an identifiable person it is import to taken into account technological development. Data that is not considered personal data may be considered personal data a few years later because technological developments have made it possible to identify a person using that data.

The information that the proposed methods of this research (Wi-Fi and Camera-based localization) produce, is data about an estimated occupancy of different sections in a train in real time. This information about the occupancy does not seem to be personal data, since it cannot be related to an identified or identifiable person. The occupancy information just gives an estimate about the (relative) number of persons and does not indicate the names, id numbers or any other information about these individual persons. Since this information is most likely not personal it can probably be freely shared with the public or stored for future analysis.

The data that is used to produce the information about the occupancy in the train, the surveillance camera footage and Wi-Fi log data can be seen as personal data. MAC-addresses can be used to relate data to a person and camera footage can possibly be related to people when for example analyzing it with facial recognition software. Therefore this data should be, according to the EU, processed fairly, lawfully and for specified, explicit and legitimate purposes. The processing of the data done in this research does not seem to be in conflict with the law and seems to be in good faith and it is therefore probably lawful, legitimate and fair. To decide whether the processing has a specified and explicit purpose the processing objectives of the NS are taken into account. The processing objectives are amongst other the following:

- “Continuity of service and growth - for example, hiring temporary personnel or in order to offer you promotions.
- Company efficiency - for example, by analyzing logistical information about train capacity and the flow of passengers, for which individuals remain anonymous.” (Nederlands Spoorwegen, 2016)

The processing of the personal information in this research could be seen to fall in line with either of these two objectives. For the aforementioned reasons in this paragraph is seems likely that the proposed method when applied in the Dutch train does seem to be in conflict with privacy legislation. Privacy legislation however seems to be open for some level of interpretation and it is therefore hard to make a definite claim about this. One could for example argue that the objectives of the use of personal data given by the NS are not specified and explicit enough. It is furthermore important to take into account that different countries have different laws, rules and regulations regarding privacy.

12 Conclusion and Discussion

In this chapter the findings of this thesis are elaborated. There is explained what the most important findings are what they might mean, how valuable they are and why. This chapter is subdivided in a conclusion, a reflection and recommendations for future research.

12.1 Conclusion

The main question in this research is: *Which localization method is most suitable to monitor occupancy in the train in real time?* To answer the main question this study has been structured around several sub-questions. The first sub-question is: *Which characteristics distinguish the train environment from other indoor environments with regards to indoor localization?* In this research several characteristics of the train environment have been identified and the following are deemed the most relevant:

- **Predictable pattern of the number of passengers:** Train passengers only leave the train at stations, and the number of passengers remains the same between stations. It is thus likely that if someone is detected and identified as in the train they will remain in the train in the rest of the train journey. This thus provides an opportunity for Wi-Fi localization which uses unique identifiers.
- **Relative static location of passengers between stations:** When people enter the train it seems likely that they will find and occupy a location in which they will often remain during the whole train journey. Their location can thus be measured multiple times in the ride between stations and this multitude of measurements can be accumulated for more accuracy.

The second sub-question is: *Which characteristics distinguish a train compartment from other indoor environments with regards to indoor localization?* The characteristics of a train compartment that are deemed most relevant are:

- **Wi-Fi access points and security cameras:** Some trains have Wi-Fi access points and/or security cameras installed which can be used for some indoor localization methods.
- **Known and static interior:** The individual elements of each train compartment have a static location in relation to each other and the localization of occupancy can be done per compartment. The train compartment is thus a good fit for a local reference system that only functions for a small region, so it is possible to choose a method that measures relative locations instead of absolute locations (often expressed in longitude and latitude).
- **Format for common locations of passengers.** In a train compartment some assumptions can be made with regards to the locations of people: it is very likely that people are only located in the chairs or the hallway and it is likely that only one person is seated in most chairs. These assumptions can be exploited by some indoor localization technologies that are able to focus on specific location, such as pressure sensors or cameras. Especially since measurements from an empty compartment can be compared to a compartment that is (partly) occupied.

The third sub-question in this research is: *What are the relevant characteristics of the indoor localization methods that can potentially be used in the train?* The indoor localization methods have been categorized and evaluated per technology.

- For **sound-** and **UWB** –based technology the market maturity was deemed too low as only prototypes are available.
- **Pressure sensor** technology was deemed too expensive and too fragile (based on earlier tests conducted in the train).
- The technologies **infrared cameras** and visible spectrum (normal) **cameras** both have the main disadvantage that they require a line of sight. Normal cameras have the disadvantage that they require light, this is however mitigated by the artificial light present in the train. Normal cameras do have the advantage that they are more economical since they are already present in some trains.
- **Wi-Fi** technology has the main disadvantage that it is dependent on the number of Wi-Fi devices train passengers have on them. The main advantage of Wi-Fi technology is that the infrastructure for Wi-Fi localization is already present in most trains which makes it relatively economical.

Mainly due to their low costs, Wi-Fi and cameras have been selected to be tested. Combining two technologies can have the advantages that they may be used to verify and amplify each other. Wi-Fi localization can for example mitigate the effect of a camera which is blocked and Camera localization can mitigate the fact that not all train passengers have one Wi-Fi enabled device.

The fourth and fifth research questions are: *"What is the performance of the most suitable indoor localization method(s) when used to monitor passengers in a train?*" and "*How can the chosen method(s) be implemented in a working application to monitor occupancy per compartment in a train in real time?*". These two research questions are interwoven and are therefore elaborated simultaneously. For camera-based localization an algorithm has been designed to detect passengers using security camera footage. This algorithm has been tested in an office, using train chairs, and in an old static train in a museum. The algorithm detects the difference between a frame of an empty train to the frames of the camera footage by comparing the recorded pixels. The HSV color model is used and the focus lies on hue to avoid noise from differences in light. This algorithm has a different approach to detect occupation at the seats then for the hallway of a train. The seats approach consists of the following steps:

1. **Areas of interest are selected.** The focus lies on the headrest to avoid noise from objects such a bags or jackets.
2. **Recording is compared to the reference frame.** The pixels of areas of interest from the recording are compared to the pixels of the corresponding areas of the reference frame to identify pixels that changed significantly.
3. **Relevant contours are selected.** If a contour of pixels that are identified as changed is large enough to be deemed relevant the corresponding seat is considered taken.

From the conducted tests can be concluded that the camera-based localization has an average false negative error of 5-9% during a train journey and an average false positive error of 1-3% when used to estimate the number of taken seats. During a train stop a false negative error of 4-5% and a false positive error of 8-9% have been found. The hallway approach works differently; in this approach a percentage of changed pixels that are detected in the hallway is used to estimate the occupancy of hallway. Based on the tests conducted in this research it seems that there is a relationship between these two variables, however more testing is needed to model this relationship.

The Wi-Fi localization system estimates the number of Wi-Fi devices in a train compartment by measuring Wi-Fi probes requests and identifying and counting the number of unique MAC-addresses. In the test setting (an old static train in a museum) the test subject were all instructed to bring one Wi-Fi device with its Wi-Fi enabled. Therefore only the relation between the number of *Wi-Fi devices* (with a static MAC-address) and the number of Wi-Fi probes can be researched and not the relation between these variables and the number of passengers (which can be used to determine the occupancy). From tests derived that the number of Wi-Fi devices in a train compartment can be estimated with a false negative error of 10-15% and without a false positive error during a train journey of about three minutes. The system seems too inaccurate to be used during a train stop due to the low number of measured probes.

Because the Wi-Fi localization system in this research cannot be related to number of passengers using the tests conducted in this research, it is difficult to statistically test to what extent Wi-Fi- and camera-based localization can be integrated. It does however seem that the two systems can complement each other to some extent during a train journey by mitigating each other's disadvantages. The Wi-Fi localization is probably more accurate the more passengers there are in compartment. This is because it seems likely that an expected ratio between Wi-Fi devices and passengers becomes more reliable the more passengers there are in a train as a larger sample usually more reliably reflects a population mean. This is in contrast to the camera-based localization which may become less accurate when there are more passengers in a train compartment than the number of available seats. This because the number of passengers standing in the hallways is hard to detect using camera-based localization and the camera view of the train chairs may be blocked by passengers standing in the hallway. It can thus be concluded that the Wi-Fi and camera-based localization may complement each other when used to measure occupancy in the train because they can be used to verify each other and they both thrive during different amounts of occupancy. Based on the test results is seems that a combination or integration of Wi-Fi and camera-based localization is suitable to measure occupancy in the train, but these test results should be verified by testing the proposed methods in the real train environment of an operating train.

12.2 Reflections

The goal of this research is to find the most suitable methods to measure occupancy in the train. There are a multitude of technologies that can be used for indoor localization, but only methods that use camera- and Wi-Fi technology were tested in this research. The rest of the methods and technologies have only been researched using the literature. Testing all of these in the train or a test setting similar to train can lead to new insights and a more accurate assessment of their performance for specifically the train. It can therefore be argued that testing all the potential technologies in a test setting would have led to more accurate results in this research. This was however not done due to time constraints. For the selection of the most suitable technologies performance parameters are used. Only performance parameters that are deemed most relevant, based on characteristics of the train and previous research are used in this selection procedure. The selection of the used performance parameter is therefore not completely objective. Furthermore the performance parameters cannot be compared using exact numbers. It therefore seems that both the selection and the use of the performance parameter is not an objective procedure and if different considerations were made during this selection it could have led to the selection of a different method.

The proposed methods of this research have been tested in an office, using train chairs, and in an old static train in a museum. These test settings have several limitations with regards to camera-based localization. Both of the test settings have the limitation that physical characteristics such as the color and location of the chairs and the background do not comply completely with those of the actual train the FLIRT. Another limitation is that the lighting in both test setting is different than those in the FLIRT and that the ceiling and therefore the angle of the cameras used in this research is different than in the FLIRT. The measured errors and performance in this test may therefore be different than they would be in a real operating train. It may be also be better to perform a test in which the participants are not informed of the goal of the test. Knowing the goal of the test may cause them to behave differently than they normally would.

There are also some limitations to the applied algorithm of camera-based localization. The algorithm is currently written in the programming language Python. Using a lower-level programming language (such as C++) may have led to the algorithm being faster. Another limitation to the algorithm is the method of automatic adjustment and calibration of the parameters (minimum contour size and the hue and saturation thresholds). Each parameter is locally optimized while a global solution, such as a genetic algorithm, may result in a better performance. If the algorithm was faster, due to for example using a low-level programming language, it may have been less time consuming and therefore more feasible to apply a genetic algorithm. Another limitation is that algorithm currently applies universal parameters for all areas of interest. It may lead to better result to customize local parameters for each area of interest. This was estimated to be too time consuming for this research, it can however be relevant to test whether this has influence on the performance of the algorithm.

The test setting of the railway museum employed in this research has several limitations with regards to the testing of Wi-Fi localization. Limitations are that the system is not tested in a moving location and that the differences in RSSI were not researched for different compartments. The main limitation with regards to Wi-Fi localization is that only the relationship between the number of Wi-Fi devices and Wi-Fi probes could be studied and that no conclusions can be drawn with regards to the number of passengers. These limitations leads to another limitation of this research. The localization methods tested in this research measure different things; the camera-based localization measures the number of taken seats and gives a rough estimation of the occupancy of the hallway, while the Wi-Fi localization measures the number of Wi-Fi devices. It is therefore hard to statistically determine to what extent these methods can supplement each other.

12.3 Recommendations

In the first part of this paragraph recommendations are given for the further research into potential methods to measure occupancy in the train. In the second part recommendations are given for the use of the developed method of this research for other research, methods and applications.

In this research several test settings are used to examine the performance of the developed method. These test settings however have several limitations. It is therefore recommended to conduct a test in a train that is currently operating. In this test both Wi-Fi localization and camera-based localization should be tested, to assess to what extent these two methods complement each other. Conducting such a test would result in more accurate outcomes and can be used to improve the method even further. For such tests it is however needed that the data can be verified. This may be done by manually counting the people per compartment in the train or by using security camera footage. It may also be possible to partly verify this data using the historic data of the OV-Chipkaart, which is a card used to check in and out in public transport.

Other recommendations are concerned with the technology tested in this research. In this research only camera-based and Wi-Fi technology is tested, it may however be useful to also conduct tests with other technologies such as infrared, UWB and echo localization to assess their performance. It may also be possible to improve the algorithm employed for camera-based localization in this research. As is described in section 10.2.4, it may be relevant for future research to use a lower-level programming language to create the algorithm. It may also be relevant to test the use of genetic algorithms to improve the calibration of the parameters. Furthermore it can be relevant to test the use of local parameters per area of interest. Another improvement can be to make more use of the relative static location of passengers between stations with the camera-based localization. It may be feasible to aggregate all measurements of the camera-based localization of one seat, to make an estimation of whether that seat was taken during a whole train journey. With regards to the Wi-Fi localization it is recommended for future research to create a radio map of a train compartment. This way is may be possible to relate measured Wi-Fi devices to locations in the compartment (such as the train chairs). Such an approach may make it easier to combine the Wi-Fi and camera-based methods, as the camera-based method can also measure occupancy per chair.

The main motivation of the research question of this project was to research a method to measure occupancy in the train to inform train passengers of real time occupancy in the train per compartment. By informing train passengers it is assumed, that they are able to better anticipate on the occupancy per compartment, which can lead to a more even distribution of passengers in the train. Therefore, it seems relevant for future research to study what the effects of applying this method in operating trains and informing train passenger of the occupancy per compartment are. This way it can be researched whether it leads to a more even distribution of passengers and if that leads to more traveler satisfaction and less stress.

Apart from the main motivation of informing passengers, the developed method can also be used for other purposes. It may for example be used to save the occupancy in the train and create an historic database. This database can then be used by a passenger railway operator (such as the NS), to compare the occupancy per train and per location and determine when and where more or less train capacity is needed. Another potential application of the developed method can be to combine the measurements of occupancy with navigation in the train and at the railway platforms. In this manner train passengers can more efficiently use the information about the occupancy as they can more easily locate a crowded or empty compartment relative to their own location. Navigation and localization of the personal locations of train passengers in the train or at the platform can for example also be done using Wi-Fi localization. At the platforms GNSS also seems a suitable method. It may be relevant for future research to investigate the possibilities of combining navigation with localization in the train.

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