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OBSTACLE DETECTION IN RAILWAY ENVIRONMENT

Filtering the output of an on-board detection system using railway maps

Master of Science Thesis
Faculty of Engineering and Natural Sciences
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March 2021

ABSTRACT

Eetu-Veikko Nisula: Obstacle Detection in Railway Environment
Master of Science Thesis
Tampere University
Automation Engineering
March 2021

The purpose of this thesis was to examine the differences in railways and roads as traffic environments in the context of obstacle detection, and to develop a prototype system that aims to satisfy the requirements of railway environment in varying weather conditions. There were three research questions that considered (1) improving obstacle detection on railways compared to the state of the art, (2) the differences between the aforementioned traffic environments, and (3) if it is possible to detect natural targets reliably from long distance with the developed system. The need for this research is backed by the fact that the upcoming unifying railway infrastructure safety systems European Rail Traffic Management System (ERTMS) and European Train Control System (ETCS) could be improved by using on-board detection systems for detecting various kinds of obstructions that may cause train derailments and other damages.

This thesis includes literature research of roads and railways as different traffic environments emphasizing the differences from obstacle an detection point of view. Additionally, various detection technologies as well as the state of the art were reviewed. On the side of empirical studies, a prototype of the detection system and a data processing algorithm were conceived. An experiment was carried out to get results by keeping eye on the third research question in particular: the system was mounted on the side of a road where detections could be obtained, allowing the evaluation of both the data processing algorithm and hardware performance.

The literature research results indicate that there is deficiency in current obstacle detection systems' reliability in all-weather conditions as well as the detection distance in railways that needs to be covered. Moreover, many automotive and sensor manufacturers along with research institutions have focused mainly on the road environment in the context of on-board obstacle detection systems, whereas railways have lacked the same interest. Because these traffic environments are very distinct, for example noticing the differences in braking distances and in the ability to dodge obstacles let alone vehicles' differences and the amount of traffic flow, there is a need for sensory equipment and data processing that is especially designed for railway traffic use. The experiments conducted showed that the system is capable of providing detections up to 200 meters, which is not enough to ensure adequate braking distance for an average running train. The results however can be used to guide the design of a more suitable detection system and to pinpoint critical areas regarding railway safety.

Keywords: railway, obstacle detection, railway map, filtering detections, radar

TIIVISTELMÄ

Eetu-Veikko Nisula: Esteiden havaitseminen rautatieympäristössä
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Maaliskuu 2021

Tutkimuksen tarkoitus oli tarkastella rautateiden ja maanteiden eroja liikenneympäristöinä esteiden havaitsemisen näkökulmasta sekä kehittää prototyyppi järjestelmästä, joka pystyy vastaamaan rautateiden vaatimuksiin erilaisissa sääolosuhteissa. Kolme tutkimuskysymystä käsittelivät (1) mahdollisuutta esteidenhavainnoinnin viimeisimpien ratkaisujen kehittämiseen, (2) eroja edellämainittujen liikenneympäristöjen välillä, sekä (3) kehitetyn järjestelmän kykyä havaita luonnollisia kohteita pitkästä matkasta. Tutkimuksen tarve syntyi parhaillaan kehitteillä olevasta eurooppalaisesta rautatieliikenteen hallintajärjestelmästä (ERTMS) ja eurooppalaisesta junien kulunvalvontajärjestelmästä (ETCS), joita voisi rautatieturvallisuuden puolesta parantaa käyttämällä junan keulaan kiinnitettävää esteiden havaitsemisjärjestelmää infrastruktuurimuutoksien lisänä. Esteiden aikaisella havaitsemisella pyritään vähentämään junien raiteilta suistumisia ja muita vahinkoja.

Tämä diplomityö koostui kirjallisuuskatsauksesta ja empiirisestä tutkimuksesta. Kirjallisuuskatsauksessa paneuduttiin maanteihin ja rautateihin liikenneympäristöinä, korostaen eroja esteiden havaitsemisen näkökulmasta. Lisäksi useita havaitsemiseen tarvittavia antureita ja menetelmiä vertailtiin, unohtamatta alan terävintä kärkeä edustavia ratkaisuja. Sen sijaan empiirisen tutkimuksen puolella kehitettiin prototyyppijäjestelmä ja datan prosessointialgoritmi, jotta ennen kaikkea kolmanteen tutkimuskysymykseen voitiin vastata tietoon perustuen. Havaitsemisjärjestelmä pystytettiin tien varteen, missä tehtiin mittauksia. Saaduilla tuloksilla voitiin arvioida sekä datan prosessointialgoritmia että laitteiston suorituskykyä.

Kirjallisuuskatsaus osoitti, että nykyisissä esteiden havaitsemisjärjestelmissä on puutteita niiden kantamassa joka tulisi saavuttaa rautatieympäristössä. Sen lisäksi järjestelmien tulisi toimia luotettavasti säällä kuin säällä. Useat auto- ja anturivalmistajat sekä tutkimuslaitokset ovat pitkälti keskittyneet maantieympäristöön tällaisia havaitsemisjärjestelmiä kehittäessään, kun rautatieympäristö on puolestaan ollut aliedustettuna. Koska nämä liikenneympäristöt poikkeavat toisistaan huomattavasti, esimerkiksi erot jarrutusmatkoissa ja mahdollisuudessa esteiden väistämiseen, puhumattakaan ajoneuvojen välisistä eroista tai liikenteen määrästä, tarvitaan antureita ja sovelluksia, jotka ovat nimenomaan suunniteltuja rautatiekäyttöön. Kokeet osoittivat, että kehitetty havaitsemisjärjestelmä kykenee antamaan havaintoja ulottuen noin 200 metriin saakka, mikä on ehdottomasti liian vähän taatakseen riittävän jarrutusmatkan keskivertojunalle. Tuloksia voi tosin hyödyntää sopivamman havaitsemisjärjestelmän suunnittelussa sekä rautateiden turvallisuutta koskevien ongelma-alueiden osoittamisessa.

Avainsanat: rautatie, esteentunnistus, rautatiekartta, havaintojen suodattaminen, tutka

PREFACE

First of all, I would like to thank all my teachers and professors, from those in the first grade to the last ones here at Tampere University. I'd also like to give thanks to the whole automated vehicles team at VTT, and the whole company for giving me the opportunity finalize my studies. Thanks to both Risto Ritala and Ari Virtanen for giving me invaluable guidance throughout the process that has culminated in this master of science thesis. I want to address my gratitude also to the second examiner of my work, Reza Ghabcheloo.

The persistent support from both friends and family has been more important than they probably realize. This all would have been a lot more difficult without it.

Thanks Mom.

Tampere, 26th March 2021

Eetu-Veikko Nisula

CONTENTS

LIST OF SYMBOLS AND ABBREVIATIONS

ACC	Adaptive Cruise Control
AFOV	Angular Field of View
API	Application Programming Interface
ARS	Advanced Radar Sensor
AV	Autonomous Vehicle
BSD	Blind Spot Detection
c	Speed of Light
CAN	Controller Area Network
CCD	Charge Coupled Device
CMOS	Complementary Metal Oxide Semiconductor
csv	Comma Separated Values
CW	Continuous Wave
Δf	Frequency shift
Δt	Delay, time interval
EBD	Emergency Braking Distance
ERTMS	European Rail Traffic Management System
ESRI	Environmental Systems Research Institute
ETCS	European Train Control System
f	Focal length
f_d	Doppler shift
FMCW	Frequency-Modulated Continuous Wave
FPS	Frames per second
FTIA	Finnish Transport Infrastructure Agency
GIS	Geographic Information System
GNSS	Global Navigation Satellite System)
GVSP	GigE Vision Streaming Protocol
IEEE	Institute of Electrical and Electronics Engineers

IR	Infrared
λ	Wavelength
LCA	Lane Change Assistant
LIDAR	Light Detection and Ranging
PoE	Power over Ethernet
ppm	Pixels per meter
RADAR	Radio Detection and Ranging
RCS	Radar Cross Section
RGB	Red Green Blue colour model
ROI	Region of Interest
RTSP	Real Time Streaming Protocol
SID	Survey and Inspection Device
SMART	Smart Automation and Rail Transport
SONAR	Sound Navigation and Ranging
τ_p	Pulse width
Tx/Rx	Transmitter/Receiver antennae
UGV	Unmanned Ground Vehicle
USB	Universal Serial Bus
WGS84	World Geodetic System 1984

1 INTRODUCTION

In Europe, the railway infrastructure is about to change in the context of safety. Despite the fact that significant accidents such as fatalities and serious injuries have decreased almost continuously since 1990 according to European Union Agency for Railways 2020 report [1], accidents such as collisions, derailments, and fires in rolling stock are stagnating. In addition, the progress has also been uneven across EU member states. As a result, unifying railway infrastructure safety systems are being developed in the EU. European Rail Traffic Management System (ERTMS) and the European Train Control System (ETCS) aim to unify transport policies between member states and increase both transport efficiency and safety. In other words, the main target is to promote the interoperability of trains within the single European railway area and remove issues arising from different railway signalling systems facing each other. According to [2], not only are ERTMS/ETCS railway signalling solutions are due to be deployed across Europe, but solutions developed in Europe are also to be sold worldwide. Also some non-European countries are already starting to deploy ERTMS/ECTS [3], including China, Saudi Arabia, India, Mexico, Brazil, and Australia.

Despite being a major improvement in the context of safety, the ERTMS/ETCS system does not seem to include obstacle detection components that are able to deal with a large boulder that has rolled on the tracks, for example. It is basically used for controlling trains and making sure that they do not crash into each other.

In this thesis, I will be addressing railway safety by dealing with an obstacle detection system that alarms the driver if there is an obstruction on the tracks. This kind of driver support system could be used for tackling dangerous situations caused by driver tiredness or aiding in bad weather conditions when visibility is inadequate. Because investing in railway infrastructure as a whole to make transport safer is an enormous task (considering for example rural vs. urban areas and differences in traffic density), I will be focusing on an on-board detection system.

The main constraints for the system are formed by bad weather conditions and long braking distance due to a train's velocity and weight. The main challenges are the long distance that needs to be considered when detecting obstructions (1000–1500 meters) and a narrow "corridor" that only needs to be unobstructed, so all the infrastructure near the tracks should not alarm the driver. In addition, a proper detection system should be able to handle track curvature to keep the distance constraint.

Hence, the research questions could be stated as:

1. How to improve obstacle detection in the railway context compared to the state of the art?
2. How do railways differ from roads in the context of obstacle detection?
3. Is it possible to detect natural targets reliably from this distance using the system depicted?

The detection instruments of the system are an automotive radar, a thermal camera, and an ordinary RGB-camera for detection. A radar is chosen (instead of lidar, for example) due to the fact that it seems to be the only sensor that is able to perform sufficiently considering dense fog, heavy rain, or snow. The cameras are mainly for visualization –– thermal camera assists RGB when the latter is useless (darkness, fog). A GNSS will be added to enable the use of railway maps to filter radar detections, which may also be useful for detecting obstacles when the track is curved. A local computer is needed in the train cockpit to read sensor data, which is in turn visualized for the driver on a display. Figure 1.1 represents the idea of how the components would be placed in the front of a train. It is important to note that the components are fixed in place, so for example the radar cannot rotate around its vertical axis.

Figure 1.1. *The radar is located on the bumper whereas the cameras as well as GNSS antenna are on the roof, above the windshield. The computer for data processing sits in the cockpit along with system's powering equipment. Photo: Courtesy of Pertti Peussa.*

The aim of this thesis is to combine the aforementioned sensors into a system via an interface created using Qt and C++. Afterwards the system's obstacle detection properties are examined, obviously highlighting the abilities of the radar, thus clarifying if the system would be suitable for use in a railway environment with an appropriate configuration.

A suitable system would extend the sensing capability of the train driver in bad weather. This means that relevant, natural objects such as people, vehicles, boulders, and other sufficiently large objects lying on the tracks should be detected from a distance that enables the driver to stop the train before collision, even if it is foggy or rainy, etc. In addition, a detection filter also needs to be applied so that only those objects on the tracks that pose a risk of collision need to be taken into account. The system must not alarm if there is a lump of grass or a mouse on the tracks.

Though there is some obvious similarities between railway and road environments in an automated vehicles framework, this thesis concentrates on detecting obstacles in a railway environment. This exclusion is set because there are many significant differences between the two environments, which would need a focus of their own. Due to environmental differences, trams are also excluded from the scope of this thesis.

The obstacle detection system this thesis covers is not connected to a train's braking system in any way. The system can be seen as an enhancement to the train driver's senses. The system aims to alarm the driver as it detects an obstacle, but the following operation is completely the driver's responsibility.

Finally, the thesis concentrates on detecting obstacles that are on the tracks. This means that there will be no special operations considering railway level crossings, e.g. examining cars or pedestrians that are outside the tracks but on the crossing, etc. This is clearly a weakness at this stage, but it is a conscious exclusion that may be fixed later if system development continues.

This thesis is structured as follows. Chapter 2 discusses the motivation for developing an on-board obstacle detection system for the railway environment, starting with a reference case in India and continuing to briefly address the problem of decreased visibility. The chapter ends with a comparison between roads and railways as distinct traffic environments. Chapters 3 and 4 cover various obstacle detection technologies and methods along with the current research in the field. Next, chapter 5 describes the detection system developed in more detail. Finally, chapters 6 and 7 present the results and discuss their significance, concluding with chapter 8 where everything is stitched together and possible future work is pondered on.

2 CHALLENGES

If an autonomous vehicle (AV) were to have a perfect perception, with the right algorithms it could plan its actions and act accordingly, thus achieving high reliability. Unlike human drivers, AVs never get tired or lose attention. In this situation, high-performing algorithms could quickly run multiple tasks, such as estimating, comparing, and executing the best action from among a number of different ones, taking into account objects it detects around it, the speed, and the utility of distinct outcomes.

Perception is a real challenge though. The driving environment of an AV includes lots of aspects to note [4]:

- other road users or obstacles that are on the road, such as vehicles, pedestrians, debris, and animals
- weather conditions that affect perception, such as fog, rain, snow, darkness, and glare
- dirt, shake, and damage that may reduce the performance of sensors used
- infrastructure conditions like roadworks.

This chapter addresses the problem of decreased visibility in a traffic environment, which may lead both to bodily injuries and material damages. First we will consider the decreased visibility in a non-optimal weather framework, supported by the case in India. Next we will turn to look into railways as one traffic environment and compare it to the road environment from the obstacle detection point of view.

2.1 Case in India

The idea behind the thesis comes from a need for this kind of detection system on Indian railways. Their specification for the system says that

> ... system shall enable the Locomotive Driver to visualize and warn about infringing objects from a reasonable far away distance so as to enable him/her to apply brakes sufficiently in advance to stop the train well short of the infringement in all-weather condition including day and night.

In India, the train operators basically rely only on the driver's own visuals (besides the aspect of signal posts) to look for obstructions on the track ahead to prevent collision or mishap. Because there may be extreme fog and heavy rain in the area and of course dark nights, this kind of detection system is needed to increase the safety of train operations.

The specification lays down minimum detection ranges for the system, which are shown in Figure 2.1. Emergency Braking Distance (EBD), which is considered to achieve these ranges, depends on the mass of the train as well as its velocity. In addition, the train type and its specifics are considered, but are not explained here.

Weather Condition	Train Speed	Normal Visibility	Human sized Object detection range (Visual through camera for real time video)	Human sized Object Detection range (Range finder device range for alert)
Clear	130 kmph	Horizon limited	1.1 Km	1.2 km
Mild Fog	130 kmph	300m	1.1 Km	1.2 km
Dense Fog	60 kmph	100m	550 m	900 m
Extreme Fog	10 kmph	5m	40 m (minimum)	200 m

Figure 2.1. *Detection range of human-sized object specified for the system to detect during day and night time, when the line of sight is uninterrupted.*

As the figure shows, normal visibility during extreme fog is so short, that the train would need to stop completely and wait for the fog to disappear before continuing.

2.2 Decreased visibility

Environmental influences on obstacle detection can be divided into lighting conditions and weather conditions. The effects of the conditions can also be seen as twofold: to decrease the ranges at which targets can be detected and to produce unwanted detections, false alarms. These both may cause a sensor to fail and thus become useless in that particular environment. As stated in [5], sensors such as a radar, lidar or camera may be covered in snow or dirt, which in turn can prevent reliable detections.

Both rain and fog consist of water droplets of varying size. Yu and Marinov [6] note that the droplets reflect the sensor's signals or block their vision, depending on the sensor used. Moreover, Trick et al. [7] suggest that collision risk increases in fog and rain as drivers feel that driving is stressful. This can be a consequence of the fact that both fog and rain impair distance perception. Fog can also make the driver underestimate the speed of other moving objects. According to [6], lidar performance deteriorates in thick fog, while in this situation vision sensors (cameras) become almost useless.

Falling snow poses the same issues as fog and rain to a large extent. In addition, the sensor can be easily covered by snow and ice. To prevent this, the sensor may be placed behind the windshield or some other proper casing. According to [6], vision sensors' and lidars' performances are considered especially vulnerable in snowy conditions. Snow banks also easily appear as "phantom obstacles", leading to false alarms as stated by

Radecki et al. [8].

Considering insufficient lighting conditions, sensors such as radars and lidars perform well because darkness does not deteriorate their signal, whereas it affects vision sensors crucially. Vision sensors, like regular RGB cameras struggle with dark conditions and even lighting variations in a single setting [8]. This is where thermal cameras come in, as their technology is based on thermal radiation which is present even when visible light is not. Some obstacle detection systems making use of computer vision algorithms may also perform poorly in darkness because of the lack of shadows. Yu et al. [6] describe a system that uses objects' shadows to distinguish them from a highly illuminated background. So even a slight darkness in the evening may make vision sensors' detections more blurry and unreliable.

2.3 Roads and railways as traffic environments

Both railways and roads have common features as traffic environments, but they are also different from each other in many respects. In this section the main differences between railway and road environments are laid out in the context of requirements for an obstacle detection system. Both [9] and [10] have discussed the topic. Roads will be covered first, after which the focus moves onto railways. These traffic environments are seen from the point of view of a car driver and a train driver. In which way do the other road/rail users need to be taken into account and how does this differ in these environments? How do the infrastructures differ when considering obstacle detection systems? As cars and trains are fundamentally different as drivable vehicles, how do they need to be controlled to avoid collisions and other accidents?

The road as a traffic environment is very diversified and it comprises many potential obstacles reflecting in the beam of the detecting sensor, such as a radar. According to [9] for example bridges, guardrails, road signs or other objects just on the edge of the road often send a stronger signal to the sensor than the vehicles or other obstacles located in front.

The road as a traffic environment is usually characterized by high traffic flow, compared to railways (comparing routes with the same characteristics, e.g. primary road and primary railway) [10]. Vehicles are more densely positioned and it is not uncommon for a large amount of vehicles to be speeding at the same time using both oncoming- and incoming lanes. Because of this, overtaking other vehicles and the possibility to dodge detected obstacles without coming to a total stop, on-board obstacle detection systems on road vehicles need to cover more than just the front of the vehicle. This clearly differs from the need for obstacle detection coverage in a railway context.

Obstacle detection on roads needs to take incoming traffic into account, whereas on railways this is supposed to not pose a problem. Railway marshalling systems are designed to prevent two trains from ever speeding toward each other. A car equipped with an obstacle detection system needs to consider incoming lanes in a case where an obstacle needs to be dodged in its current lane.

The fact that the traffic flow is much lower on railways than roads, as stated above, poses a problem for all thinking animals – both us people and wildlife. The problem is that railways are easily regarded as safe to cross because of the characteristic long traffic-free intervals [10], whereas in reality a train may shoot along the tracks any second.

From an obstacle detection point of view, the most crucial distinction between railway and road traffic environments is the ability to dodge obstacles and the difference between braking distances. When a fully functioning and accurate obstacle detection system detects a danger in front of the train, it may easily be already too late. A high-speed train carrying passengers needs a long way to come to a total stop. This is also the case for a slower, but by a magnitude heavier cargo train. One reason why there are relatively long traffic-free intervals on train tracks is because trains need a long headway between each other to compensate for the braking distance. This is the reason why on-board obstacle detection systems on railways need to cover a long distance ahead, whereas on roads a shorter distance is sufficient.

Because track corridors of railways are usually narrower than road lanes and there might be anything from infrastructure (signal poles, etc.) to vegetation and pedestrians, the detected obstacles that are no threat need to be filtered out more accurately than in the case of roads. It can be assumed that anything moving is not going to collide with the sides of the train. Here, obstacle detection needs to apply to the front and filter out everything that is outside the tracks, even slightly. This tight difference actualizes when detecting nearby infrastructure or when the train approaches a station. Figure 2.2 illustrates how close to the tracks both people and infrastructure can be in a real situation.

Figure 2.2. *Photo from Helsinki Central Railway Station shows how close to the tracks both people and railway infrastructure might be. This needs to be taken into account when designing detection filtering. Photo: Courtesy of Pertti Peussa.*

Such precision is challenging to achieve, especially when combined with long detection distances. However, at least in the case of high-speed railways, fencing the track corridors reduces pedestrian and wildlife traffic near the tracks. As [10] argues, this is not so common when considering highway roads.

3 OBSTACLE DETECTION TECHNOLOGIES

This chapter addresses obstacle detection technologies, mainly focusing on the ones that comprise the basis of this thesis: radars and cameras. First, various technologies are introduced briefly, after which radars are examined more closely.

3.1 General view

Detecting obstacles is an extensively researched field, particularly in the automotive industry, because it acts in such a key role when it comes to a vehicle navigating autonomously in various environments. For this reason, several distinct obstacle detection systems have been developed.

There seems to be an almost inexhaustible amount of papers, each depicting its own solutions for obstacle detection. In addition, there is literature [6][11][12][13] concerning the technologies used in obstacle detection that generally aims to offer a more comprehensive picture of this diverse collection. The gain from the aforementioned studies is the comparison between different obstacle detection technologies in various use cases and categorizing them accordingly.

According to [11] and [12], sensors can basically be divided into two classes according to:

- what they detect, and
- how they detect it.

This classification separates sensors between proprioceptive or exteroceptive as well as passive or active. The first category consists of proprioceptive sensors that measure an attribute regarding their own state, such as position, change of inclination, or speed. In the context of obstacle detection, these sensors monitor the vehicle itself. For example different accelerometers, tilt and position sensors, odometers as well as speed sensors are classified as proprioceptive. These are used for improving and sharpening the results of the detection algorithms, and not directly for detecting obstacles. Exteroceptive sensors measure attributes of external objects that are detected in a scene. These sensors include cameras (IR, RGB), sonars, laser scanners, radars, lidars, etc. Attributes measured can be the object size or shape, its distance from the sensor, or its color if that is needed for the application.

The passive sensors differ from active ones in the method or medium used for detection. Passive detection makes use of natural energy, such as light's visible wavelength. Naturally, this restricts the use of the aforementioned sensors. For example, a regular RGB camera is next to useless at nighttime, as there is no visible light, whereas thermal cameras and other IR sensors extend the detection capabilities at nighttime, assuming sufficient energy of IR radiation is available [12]. Sensors categorized as active produce energy to obtain detections on their own. For example, energy produced by a radar is reflected back from an object, which becomes the source of information about the situation in front of the radar.

Due to varying driving conditions from darkness to sunshine as well as from thick fog to regular rainfall, obstacle detection systems cannot rely on just one sensor's performance. Sensor fusion that joins data from several sensors is called for to attain a robust understanding of the environment.

Sensor fusion in the context of obstacle detection is a topic that has already been researched for some time. There are numerous papers, for example [14][15][16] that build on the fact that a single sensor cannot satisfy the demands of driving conditions discussed above, which leads to the conclusion that any practical detection system should make use of the joint benefits of multiple distinct sensor technologies. Besides just the sensors, sensor fusion solutions utilize various use-case-specific algorithms that create the actual fusion of data.

Both [14] and [16] aim to overcome the weaknesses of a camera with a radar sensor and vice versa. As it is hard to decide on the distance and relative speed of an object by using just a camera, a radar is used for it. On the other hand, a radar produces some false detections, which are corrected using images from the camera. In turn, [15] presents a solution in which a vision sensor and a lidar are used to detect obstacles in front of an unmanned ground vehicle (UGV). Here the deficit of the lidar is that it is unable to detect obstacles that are low because of its constant scanning height and angle. To overcome this, the vision sensor provides 2D information that includes the low objects. Since vision sensor distance data is relatively poor, this is in turn overcome with the lidar's excellent ability to measure an obstacle's distance precisely. Therefore, fusing data from sensors with different strengths is commonly used in obstacle detection systems to achieve higher accuracy and robustness.

3.2 Radars

A radar is an active, exteroceptive sensor for detecting and tracking objects based on electromagnetic waves in the radio-frequency spectrum, known as radio waves. Radar detection includes the object's distance, velocity, and angle of motion relative to the sensor itself. The radio-frequency spectrum extends from around 3 MHz to 300 GHz. In this frequency range, the waves hardly interact with dust, fog, rain, or snow [17], and even a small amount of vegetation at the lower end of the frequency range [18]. Thus radar is an ideal tool for detecting objects outdoors, under harsh weather conditions and from a long distance. Common applications listed in [17] include e.g. military air-defence systems, weather observation (meteorology), air and land traffic control as well as safety (adaptive cruise control, parking) and also remote imaging and mapping. For use as a visual sensor for autonomous vehicles' obstacle detection systems, the 22–29 GHz ("K-band") and 75–110 GHz ("W-band") ranges in the radio-frequency spectrum are used. It is pointed out in [19] that manufactured automotive radars are commonly operating in just the 76–81 GHz range of the W-band, as this is the IEEE-standard radar frequency band.

3.2.1 Radar measurement principle

Jain & Heydari [20] cover a significant amount of information on automotive radar technology, summarizing that basically every detection system utilizing a radar

- transmits electromagnetic energy to search for objects in a specific volume in space
- detects the reflected energy from objects in that volume
- measures the time between these two events, and
- provides estimates of range and velocity of the objects based on the detected energy and measured time.

These steps apply in principle to every radar system, despite the fact that there are for example multiple different transmitting technologies or tracking algorithms used. Nevertheless, the components are somewhat constant. According to [19] a typical radar system includes antennae for transmitting and receiving along with a duplexer. Figure 3.1 depicts a simple radar system with the aforementioned components. In addition, there is a display for presenting the detections. When in action, first the duplexer (which here basically works as a switch) connects the transmitter to the antenna, after which a signal is transmitted. If the signal hits one or more obstacles, it gets reflected back. This reflection, an echo signal, is received in the system as the duplexer has connected receiver to the antenna after the transmission. Finally, in Figure 3.1 the "Display" component gets both the received signal that is damped and the original transmitted signal.

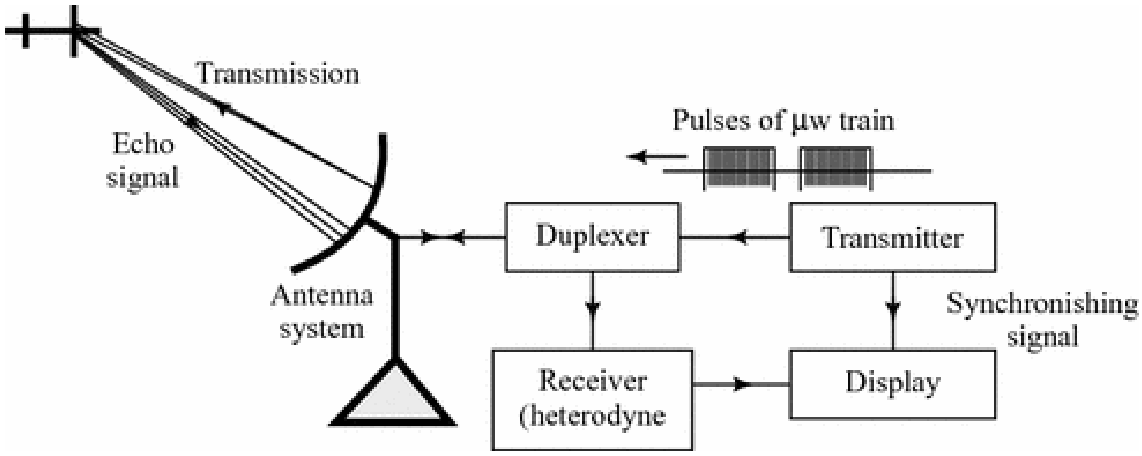

Figure 3.1. *A working principle of a radar system detecting an object. Note the arrows pointing the direction of information flow. [19]*

Considering radars that are relevant in the context of obstacle detection in traffic, the type of signal transmitted can be used to categorize radars roughly into two groups: pulsed radars and continuous-wave (CW) radars.

Pulsed radars transmit modulated pulse signals at fixed intervals of time. Object range is obtained by measuring the time interval between pulse transmission and reception. The direction of the object can be estimated according to the orientation of the radar. In turn, the velocity of an object can be extracted by calculating the change of range between detections. The operation principle of the transmitter and the receiver in a pulsed radar is time-duplexed as described above [20]. So as a pulsed radar receives a reflected signal, a comparison between transmitted and received signal takes place. The comparison of these two ultimately gives the delay Δt. The distance to the detected obstacle R at the time of detection can be calculated easily as the velocity of an electromagnetic wave c is known to be the speed of light.

$$R = \frac{c\Delta t}{2} \tag{3.1}$$

Radar range resolution (ΔR below) is the measure of a radar's ability to separate two objects that are in close proximity to one another. The principle is that these two objects need to reflect two distinct echoes, which is possible if they are physically separated by at least half of the sensor's pulse width $\tau_p/2$. Now the range resolution is

$$\Delta R = \frac{c\tau_p}{2} = \frac{c}{2B} \tag{3.2}$$

Here $B = 1/\tau_p$ is the radar signal bandwidth. For example, in the case of autonomous vehicles, where radar ranges are relatively short compared to radars that are used in detecting aircraft, for example, a high range resolution is preferred. For a Continental

ARS 408-21 SC automotive radar, the range resolution value is roughly 0.15 meters, with a bandwidth of 1 GHz (between 76–77 GHz).

CW radars, which transmit and receive continuous signals, are again grouped into two categories as these may use either an unmodulated or modulated frequency carrier as the radar signal. The difference between them is that unmodulated CW radars are able to detect an obstacle's relative velocity but not the distance, whereas modulated CW radars are able to do both [20]. Deciding if the obstacle is approaching or receding from the point of view of the sensor Doppler shift f_d between transmitted and received waves can be calculated as in Equation 3.3

$$f_d = \pm\frac{2v}{\lambda} = \pm\frac{2vf_0}{c} \tag{3.3}$$

where λ is the radar wavelength and v is the obstacle's relative velocity. The shift is positive for a target that is approaching the sensor and negative for a target that is departing [20]. Distance cannot be acquired in unmodulated cases, but from a frequency-modulated continuous-wave radar (FMCW) detection it can be obtained. In this case the obstacle distance from the sensor is

$$R = \frac{c\Delta t}{2} = \frac{c}{2}\frac{\Delta f}{df/dt} \tag{3.4}$$

where frequency shift Δf as well as corresponding delay Δt are known. Figure 3.2 shows the principle of FMCW radar as a "sawtooth pattern" frequency modulation is applied.

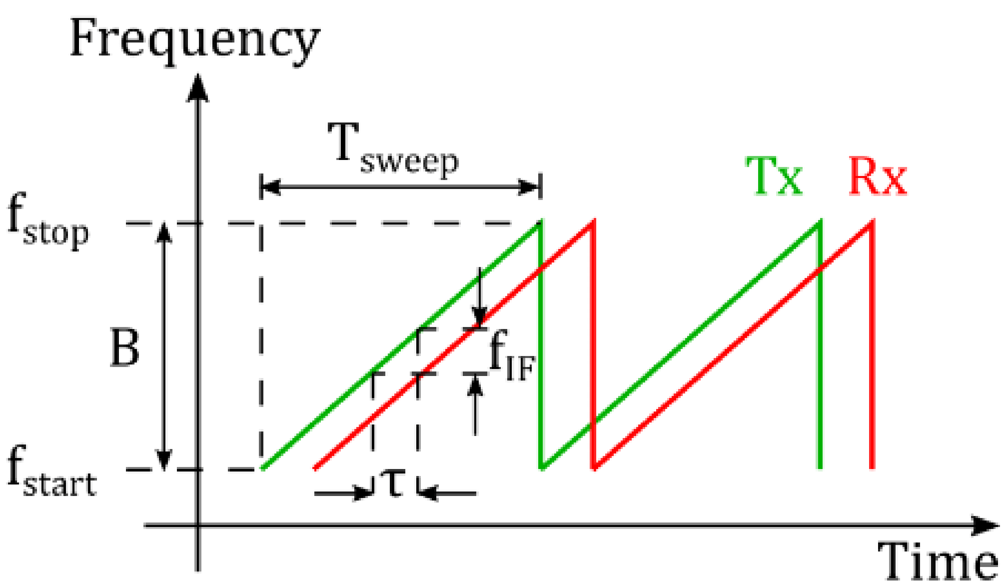

Figure 3.2. *In FMCW radar frequency shift and corresponding delay are known, which enables calculating the obstacle's distance from the sensor. Tx/Rx denote transmitter and receiver respectively. [21]*

Because of the lack of distance detection, unmodulated CW radars are not useful in an on-board obstacle detection system used in a vehicle, but can be used for example in traffic speed control. FMCW radars on the other hand are used in obstacle detection systems for autonomous vehicles. The radar used in the detection system described in this thesis likewise makes use of FMCW technology.

3.2.2 Radars in obstacle detection

Scherr et al. [22] consider radars as clearly advantageous compared to other distance measurement sensors. Compared to the often-used laser sensors, radar systems are able to measure distances despite harsh conditions like snow, dust, rain, fog, or even flying debris that may cause inconveniences if only lidar is used. Radar measurements can also be obtained during the day or night.

In practice, radars provide both accurate distance and relative speed measurements of the detected objects, whereas lidars provide a higher lateral resolution than the former. Moreover, lidars are also able to perceive the occupied area of an object and offer more detailed environment representation [16]. This is of course useful in road traffic, where vehicles may overtake each other and change lanes, etc. On the other hand, in a railway environment this is not so necessary, whereas being sure that there isn't anything blocking even far away is. Relative speed measurements become handy when one tries to decide if the blocking obstacle will still be blocking after a while. Radar's long distance, inferior lateral resolution, and the detection method itself produce a significant amount of clutter as a drawback [16], which needs to be dealt with intelligent data post-processing. This is one reason why radar manufacturers apply object tracking algorithms that estimate the probability of existence of a detected object.

The radar cross section (RCS) value represents the amount of energy reflected from a detected object. Each individual detected object (person, car, boulder) has its own RCS value that depends on the target's size, material, and relative angle [16]. Because metal surfaces are good radar reflectors [11], vehicles and roadside infrastructure such as poles and fencing have a much larger RCS (e.g. vehicle 10 m2) than people (0.2–2 m2), so detecting vehicles using radar technology is easier than human detection. In a complex environment like a city street with high traffic flow [11], the radar sensor itself has limited operability because it produces a lot of clutter. These false alarms from the surrounding objects reflect radar signals so efficiently that the actual objects to be detected may be harder to distinguish.

As Sugimoto et al. [23] noted in 2004, radar-based driver assistance systems such as ACCs (Adaptive Cruise Control) have been brought to the market by multiple car manufacturers, and the trend does not seem to be weakening. Most of the radar systems make use of millimeter-wave radar (the W-band) and the radars themselves are mounted on the front of a road vehicle. Deloof [24] notes that to cover a single lane on a road up to 100 meters, the radar sensor should have a directivity of about 2° horizontally and less than 5° vertically. In this case a lot of roadside objects cause false alarms, which is why post-processing takes place. Fixed interval objects such as streetlamps can be filtered out by their signature, but varying and unexpected obstacles need to be dealt with otherwise. To make such radar work efficiently in a railway environment, complex data post-processing is definitely needed. In this thesis, the filtering is performed using a railway map which the detected obstacle's approximate location is compared to.

3.3 Cameras

There are two main types of cameras [25] that are commonly used in obstacle detection: visible light and thermal cameras. As a sensor, a visible light camera (e.g. RGB camera) is able to provide a high spatial and temporal resolution image sequence of the environment in front of it, assuming sufficient illumination. This kind of camera is ideal for detecting even very small objects. On the other hand, thermal cameras are usually able to give a slightly lower spatial and temporal resolution image sequence in the IR spectrum than their visible light counterparts. Thermal cameras are able to detect objects that have a different temperature than their surroundings, especially at nighttime, and in low visible light conditions.

Cameras are probably the most common sensors that are used for obstacle detection, perhaps because they are relatively inexpensive compared to other sensors, they are somewhat intuitive to people or due to massively trending computer vision, in which cameras are utilized. In applications, image processing algorithms are commonly used to make sense of the acquired camera data. For example, in railway obstacle detection context, Karaduman [26] scanned camera images with predefined railway masks to detect obstacles laying on the tracks. Furthermore, Gibert et al. [27] used a computer vision- and pattern recognition-aided camera system to detect railway tracks defects.

3.3.1 Camera parameters

Because a camera image is divided into pixels, the resolution of the image is important when an object needs to be detected, recognized, or even identified. As Hollands et al. [28] suggest, there are multiple aspects affecting the resolution of the target (number of pixels that render e.g. an obstacle in the image), such as resolution of the camera sensor itself, zoom settings and the display resolution from which the image is viewed.

According to Rodin et al. [25], determining what a given camera system can detect may prove difficult beforehand, but as a theoretical basis for object detectability, Johnson's criteria [29] is still often used. In practice, it is based on the number of pixels from which an object is detectable in a camera image. The idea of differentiating detection, recognition, and identification comes from Johnson's criteria, which can be used to specify the resolution threshold that is needed to detect or identify different objects. The criteria stems from Johnson's research, in which he altered the object's range between easily detectable and barely detectable, or identifiable. This was done with multiple camera systems that had different magnification or brightness gain setups, for example. The threshold of detection or identification was determined by the use of parallel black and white lines that were placed in the same range as the object in question and the spatial frequency of these parallel lines was decreased until the lines could not be differentiated from each other. The threshold was the minimum number of line pairs in the minimum dimension of the object. Figure 3.3 clarifies the idea.

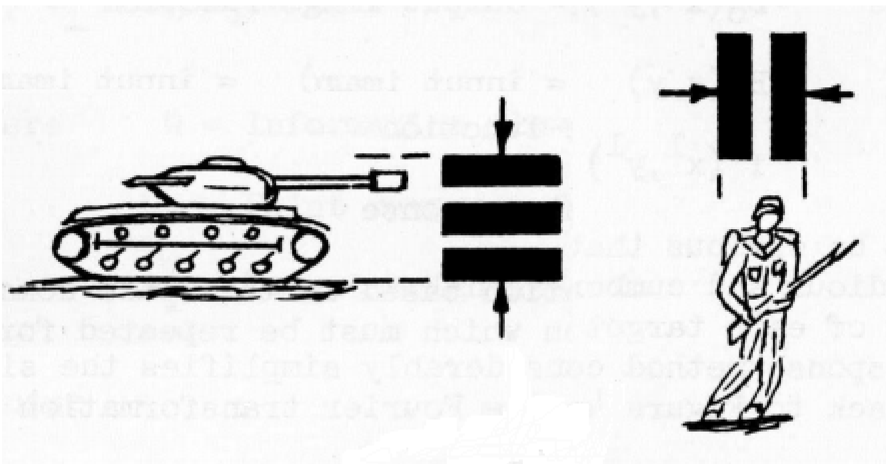

Figure 3.3. *As an army R&D engineer, Johnson used a soldier and a tank as objects, which can in the context of this thesis represent a car or a truck and any person. Here the minimum dimensions of a person is the width (approx. 0.5 meters), which is 1.5 pairs of lines or "cycles", as regarded by Johnson. [29]*

For example, to detect a standing person from an given image on a suitable display, the image would need to represent the person with at least 2 x 1.5 cycles = 3 horizontal pixels. Hollands et al. [28] note that with pixel per meter (ppm), the threshold for detecting a standing person would be 6 ppm (3 pixels for 0.5 meters). To successfully detect a person standing in the range of l = 100 meters in the scene, one would succeed in theory [30], for example with a sensor with a resolution of 2048 px x 1536 px (H x V) and a pixel size of 3.45 μm x 3.45 μm calculating

$$H_F = \frac{2048\ px}{6\ ppm} = \frac{1024}{3} m \tag{3.5}$$

as scene horizontal field of view H_F, when 6 ppm restriction is applied. This can be used along with accurate horizontal sensor dimension h acquired from

$$h = 0.00345\ mm * 2048\ (px) = 7.0656\ mm \tag{3.6}$$

to get the required focal length f for the camera lens

$$f = \frac{h * l}{H_F} = \frac{7.0656\ mm * 100000\ mm}{\frac{1024}{3} m * 1000} = 2.07\ mm \tag{3.7}$$

In this case the horizontal field of view is approximately 341 meters, which allows a great deal of the surroundings to be recorded by the camera. If for example only a train-wide area with a buffer zone of one meter on both sides is required to be recorded by the camera from the same range l, the needed focal length f for the same sensor would be

$$f = \frac{7.0656\ mm * 100000\ mm}{3250\ mm + 2000\ mm} = 134.58\ mm \tag{3.8}$$

in a situation where the train width is 3250 mm, the same as the one defined in the reference case in India that was discussed in chapter 2. Here the camera image would exceed the needed 6 ppm by a significant margin, as the image would consist of approximately 390 horizontal ppm. So the lens's longer focal length yields a smaller angular field of view (AFOV), which in turn translates into more pixels across the target object at a fixed range. This creates a compromise when choosing a camera lens (as well as a sensor) for detection: long lenses on a camera trade longer range detection for reduced AFOV. This means that target objects can be detected easily and even identified, but this requires knowing roughly where the target object lies in the scene.

Additionally, in the case of attaching the camera in front of a train or a car, there will be shake and tremor due to small bumps in the tracks or on the road. This causes the camera image to lose sharpness. Also as [11] and [28] both note, lighting changes and background movement affect the image quality and thus the reliability of obstacle detection. For example lighting changes can happen due to cloud movement, whereas background movement may come from wind in vegetation.

3.3.2 Cameras in obstacle detection

According to Debattisti [11], digital cameras are robust sensors for obstacle detection purposes. In obstacle detection two types of cameras are typically used: visible-light and infrared (IR) cameras. One of the most important features of a camera in obstacle detection is the ability to provide specific information about the target, such as colour.

Visible light cameras (or RGB cameras) are often used in autonomous vehicles' detection tasks because they are less expensive than for example lidar or radar systems, they provide high-quality colour information, as well as high resolution. Because cameras create a lot of data, various processing algorithms have been developed. Rosique et al. [31] list accident recording, blind spot detection (BSD), side view control, object identification, lane change assistant (LCA), and detection of traffic signs as the most common applications for camera detection systems in autonomous vehicles. According to [31], IR cameras are often used in autonomous vehicle applications to replace or complement RGB cameras. They are especially convenient in situations where scene illumination may change or in warm object detection, including for example pedestrians, other vehicles, or animals. In these cases IR images are simple to threshold, emphasizing the warm objects in the scene.

According to [11], using a single camera system is not suitable for obstacle detection and avoidance, because information of an obstacle's exact position is not accurate from a single image. For this reason stereo vision systems are more commonly used for obstacle detection – giving a complete 3D representation of the environment in front of the camera. So using a combination of two cameras with a known focal length and distance between the cameras, the baseline, provides depth information from the environment. To get reliable results, the baseline between stereo cameras needs to be fixed.

Comparing vision sensors to radars, the detection range is shorter, but the resolution is higher. This means that a camera is better at separating different objects from each other than a radar, even if the objects are positioned side by side. As [31] sees it, one reason why RGB cameras are especially useful in obstacle detection is the color perception ability, which a radar sensor does not have. Colour may be utilized when designing an image processing algorithm.

4 RAILWAY OBJECT DETECTION: THE STATE OF THE ART

The framework of object detection addressed in this thesis is largely based on autonomous vehicles (AVs) research, and especially in the railway context. In this chapter the main approaches of modern obstacle detection considering AVs is covered to obtain a general picture of the state of the art.

Research in the area has been carried out in collaboration between universities, companies and public organizations. Carnegie Mellon University in Pittsburgh [32], USA and the University of Parma in Italy [33] have been involved in the research of AVs in general for quite some time. Object detection in the traffic environment has also been heavily researched by many car manufacturing companies such as Volvo, Tesla, and Nissan [34][35][36], not to forget other big technology manufacturers from different perspectives, such as Google, Continental, and Bombardier Technologies [37][38][39]. Driverless metros and trains are utilizing object detection systems in Dubai, Vancouver and Singapore, for example.

Perhaps the most closely related state of the art project to the topic of this thesis is SMART (SMart Automation and Rail Transport), which has received funding from the Shift2Rail project ensemble, which is the European Union's Horizon 2020 research and innovation program. The project started in 2016 and finished in 2019. It was carried out by a consortium consisting of five universities from Bulgaria, Germany, and Serbia, featuring a Serbian company specializing in image intensifier technology. The project seemed to achieve its goals as the follow-up project (SMART2) is already ongoing and should finish in 2022.

The main goal of the SMART project was [40], to "increase the quality of rail freight, as well as its effectiveness and capacity, through the contribution to automation of railway cargo haul on European railways." The project consisted of a number of smaller objectives to achieve the main goal. To develop a "complete, safe and reliable prototype solution for obstacle detection and initiation of long distance forward-looking braking" is perhaps the most interesting one considering this thesis.

The obstacle detection system in the SMART project is a on-board multi-sensor system, combining a night vision sensor (a camera augmented with an image intensifier), a thermal camera, a multi stereo-vision system, and a laser scanner. The concept is shown in Figure 4.1.

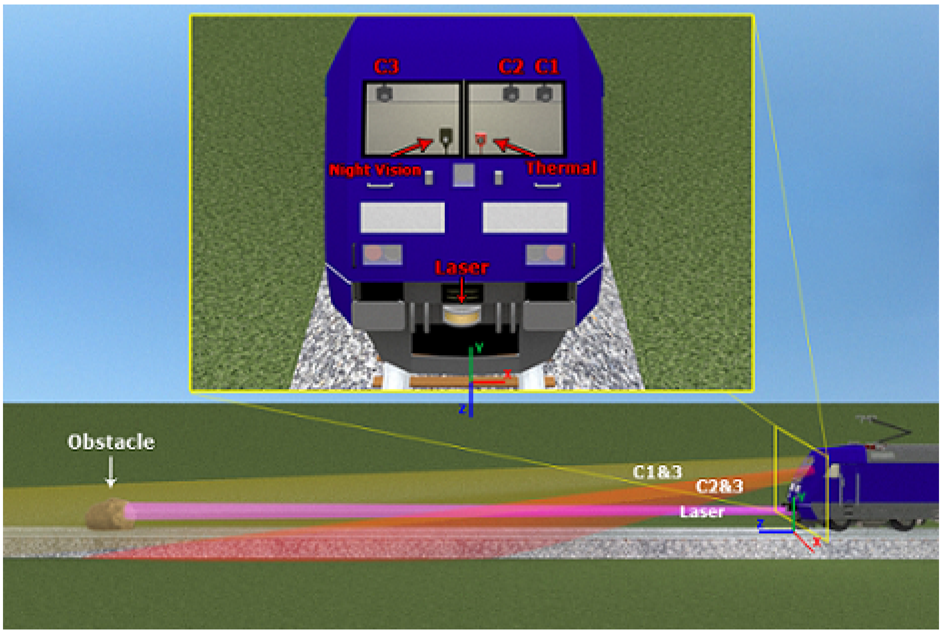

Figure 4.1. *SMART multi-sensor object detection system. The top part shows the sensors mounted in front of the locomotive. The bottom part represents an obstacle detection scene. C1&3 and C2&3 are stereo cameras with varying baselines. [41]*

According to Ristić-Durrant et al. [41], the system is designed for mid- (up to 200 meters) and long-range (up to 1000 meters) obstacle detection, which can operate in day and night conditions as well as in poor visibility conditions. Combining sensors for obstacle detection is not a novel idea as it has been done before [42], but only for short range (<100 meters) and for good lighting condition, as thermal camera has not been applied.

The idea behind a multi-sensor system is to fuse data from multiple sensors that perform differently, thus acquiring a more comprehensive view of the scene. The sensor fusion approach in the SMART object detection system was designed based on sensor data availability acknowledging that sensor data from a thermal camera and laser scanner is available all the time, whereas the stereo cameras cannot operate in poor lighting conditions, and the night vision sensor cannot produce data in daylight [40]. Distances from the locomotive to the detected obstacles are calculated from stereo cameras using a method called stereo triangulation. The distance acquired was fused with the distance received from the laser scanner so that they could extract a region of interest (ROI) including the rail tracks and important laser data points that are in the ROI. Figure 4.2 clarifies the SMART system architecture and the sensor fusion approach.

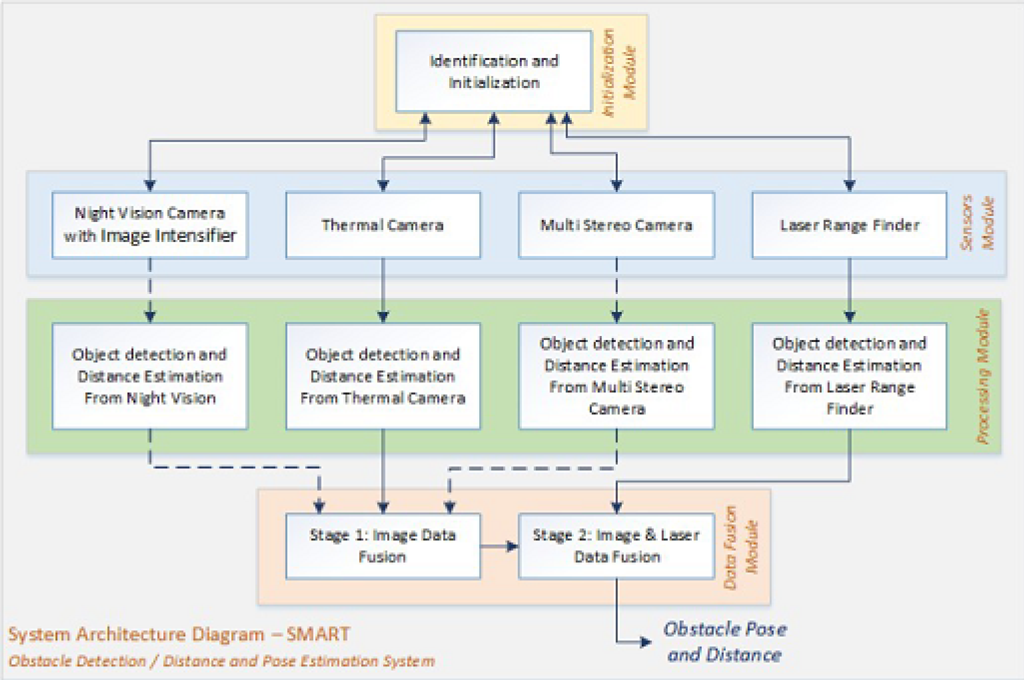

Figure 4.2. *SMART system architecture. Solid lines represent data that is available all the time. Dashed line for example in stereo camera states the fact that the camera will not provide data in poor illumination conditions. [41]*

The SMART object detection system was tested in approximately 1300 meters long, straight railway tracks. Despite the considerably longer theoretical range for the object detection system, both [40] and [41] report successful tests in the range of 50–100 meters.

Considering the state of the art of railway object detection systems, the solutions can be divided into two categories according to the main focus: sensor fusion or computer vision. The difference is that the former usually consists of a wider collection of sensors including cameras, whereas the latter ones rely solely on cameras and are more focused on computer vision techniques and deep learning.

SMART system is an example of sensor fusion based solution. As computer vision based solutions for example [43], [44] and [45] each use a camera system accompanied with intelligent video processing techniques. Train tracks are detected in the video feed and computer vision is used to deduce if there are obstacles in front of the train.

As a data fusion and interesting solution, SMART2 utilizes an airborne device that will be used to detect obstacles on the track is worth noting [46]. A system with a Survey and Inspection Device (SID) scouting the tracks as far as 2 kilometers in front of train has been studied [47]. The SID is basically a robotic device that travels on its own ahead of the train equipped with different types of sensors to detect obstacles and transmit detections to the locomotive.

5 DETECTION SYSTEM

This chapter describes in detail the on-board detection system depicted in the introduction chapter. At first the system will be examined from a more general view, after which the components will be covered one by one, which clarify their individual contributions to the system. Afterwards the algorithm utilizing the railway maps is covered. Finally the system's performance is considered.

5.1 Architecture

The detection system consists of a collection of sensors and a connected computer that runs a Qt-based software written in C++. The system architecture is shown in Figure 5.1 below.

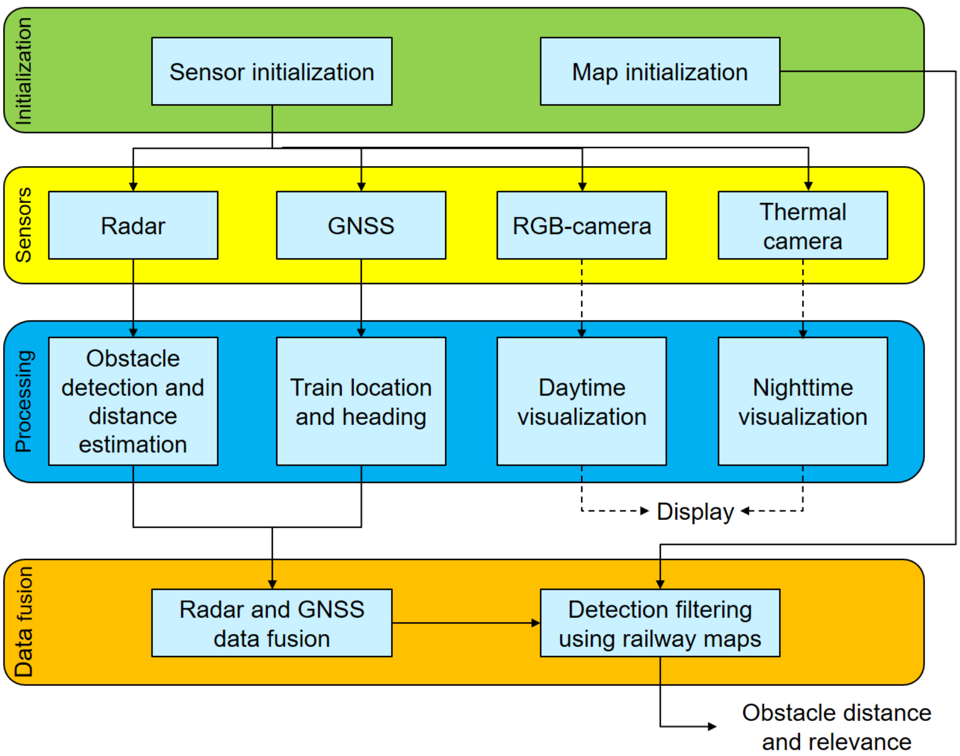

Figure 5.1. *Detection system architecture. Solid lines represent data that is available all the time and dashed ones for example in RGB-camera represents the camera's inability to provide data in poor illumination conditions. The system includes a simple display interface for camera image visualization purposes.*

At software initialization, the sensors are started and the railway map is read into computer's memory. The software includes drivers for all the sensors which execute the initialization of individual sensors. Reading the map into memory speeds up the later processing, as the map can be indexed without continuously opening and closing it.

Radar module outputs obstacle detections including velocity and distance information. The GNSS module provides current location and heading, which are combined with radar detections in data fusion phase. Here, the railway track's shape ahead is read from the map which is used as a filter to decide if a given radar detection is on the tracks or not. The area that is read from the map starts from the train's location and ideally ends to the far end of the radar range, thus covering the maximum distance possible. This "lookahead distance" can be adjusted in the software. The cameras output images to the display interface continuously while running the system. Finally the data fusion outputs obstacle detections as they are provided by the radar module, enriched with a Boolean value representing if a detection is considered as an obstacle. Figure 5.2 below illustrates the idea of the filter.

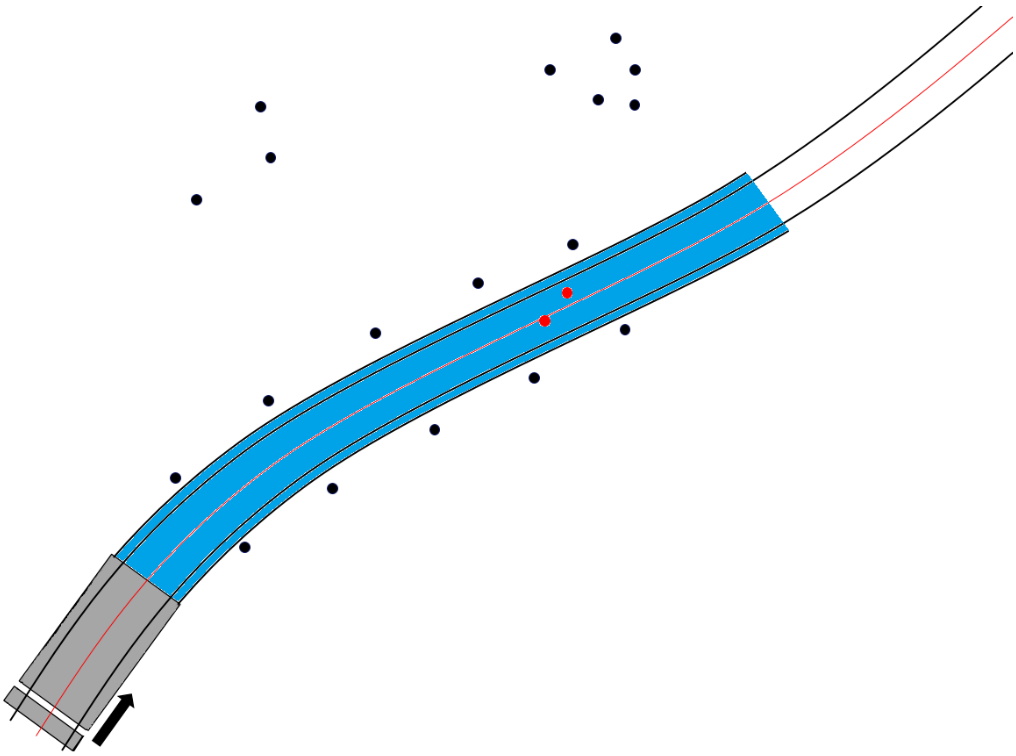

Figure 5.2. *The gray box represents the train which is heading towards the upper right corner of the image. The black circles are radar detections that are filtered as outliers, whereas the red circles are considered as obstacles. The red line is the center of the railway tracks, which is marked on the map. The blue area represents the filter, which is shaped like the tracks ahead of the train starting from the head of the train and ending to the lookahead distance.*

The software runs in a loop in which it creates a new filter every time GNSS module provides a new location after which the following radar detections are passed through this filter. The display interface shows relevant detections in red colour whereas the ones that are outside of tracks are indicated in black.

5.2 Sensors

The radar is a millimeter wave-length 77 GHz radar system manufactured by Continental, targeted for automotive applications. The ARS 408-21 SC1 (Figure 5.3) is a long-range model with measurement range extending up to 1200 meters for objects with high radar cross section (RCS) value.

Figure 5.3. *Continental ARS 408-21 SC1 radar and Basler acA2040-55uc RGB camera attached together to ensure same directivity.*

The radar operation is based on frequency-modulated continuous-wave (FMCW) modulations, realising the independent velocity and distance monitoring of objects in one measurement cycle, with a real time scanning at 17 Hz. The radar's detections are based on its proprietary algorithms. Figure 5.4 shows the coordinate system in which the detections are represented.

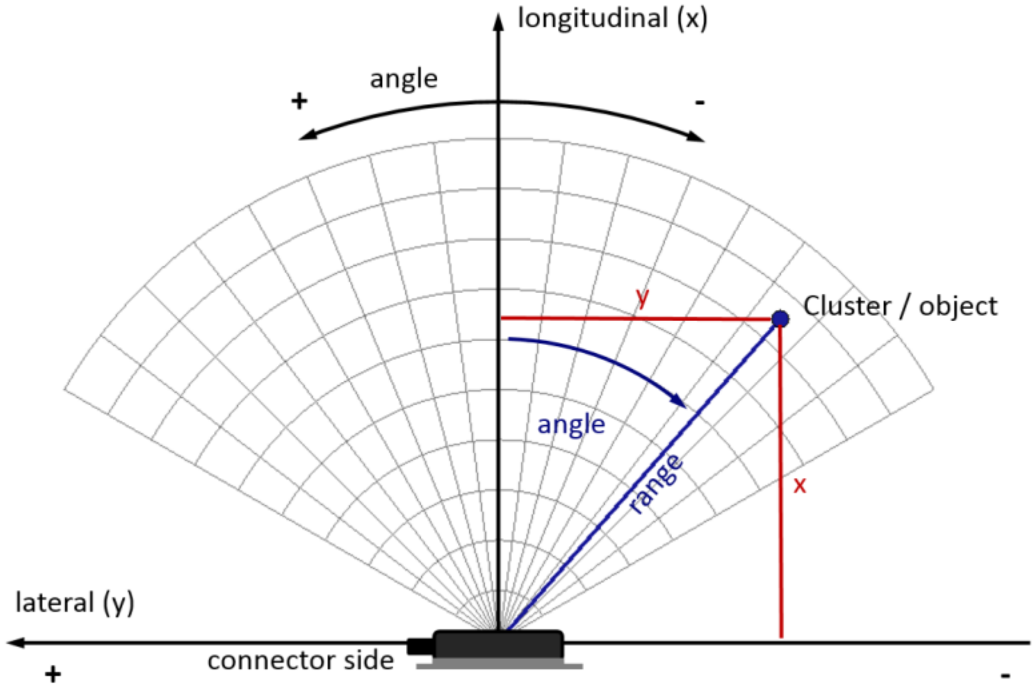

Figure 5.4. *The position of a detection is given in a Cartesian coordinate system relative to the sensor. [48]*

Clusters are radar reflections with information like position, velocity, and signal strength that are updated between radar pulses. Unlike cluster detections, objects include information about both history and the objects' dimensions. Objects consist of tracked clusters, that the tracking algorithm gathers together. The velocity of a detection is calculated relative to the vehicle, which is determined by using the speed and yaw rate information (commonly acquired from the inertial measurement unit) presuming that the sensor is fixed on the front bumper and the movement is in a longitudinal direction. In this application, the course parameters come from the GNSS module. Because the radar is developed for driver assistance applications, clustered object positions rather than raw measurements can be obtained. The ARS sensor can be switched between cluster and object modes by sending it specific CAN messages.

For obtaining train's location and heading, a high-precision GNSS module U-Blox ZED-F9P is used. The module is combined with an ANN-MB-00 antenna, also produced by U-Blox. Both the module and the antenna are shown in Figure 5.5

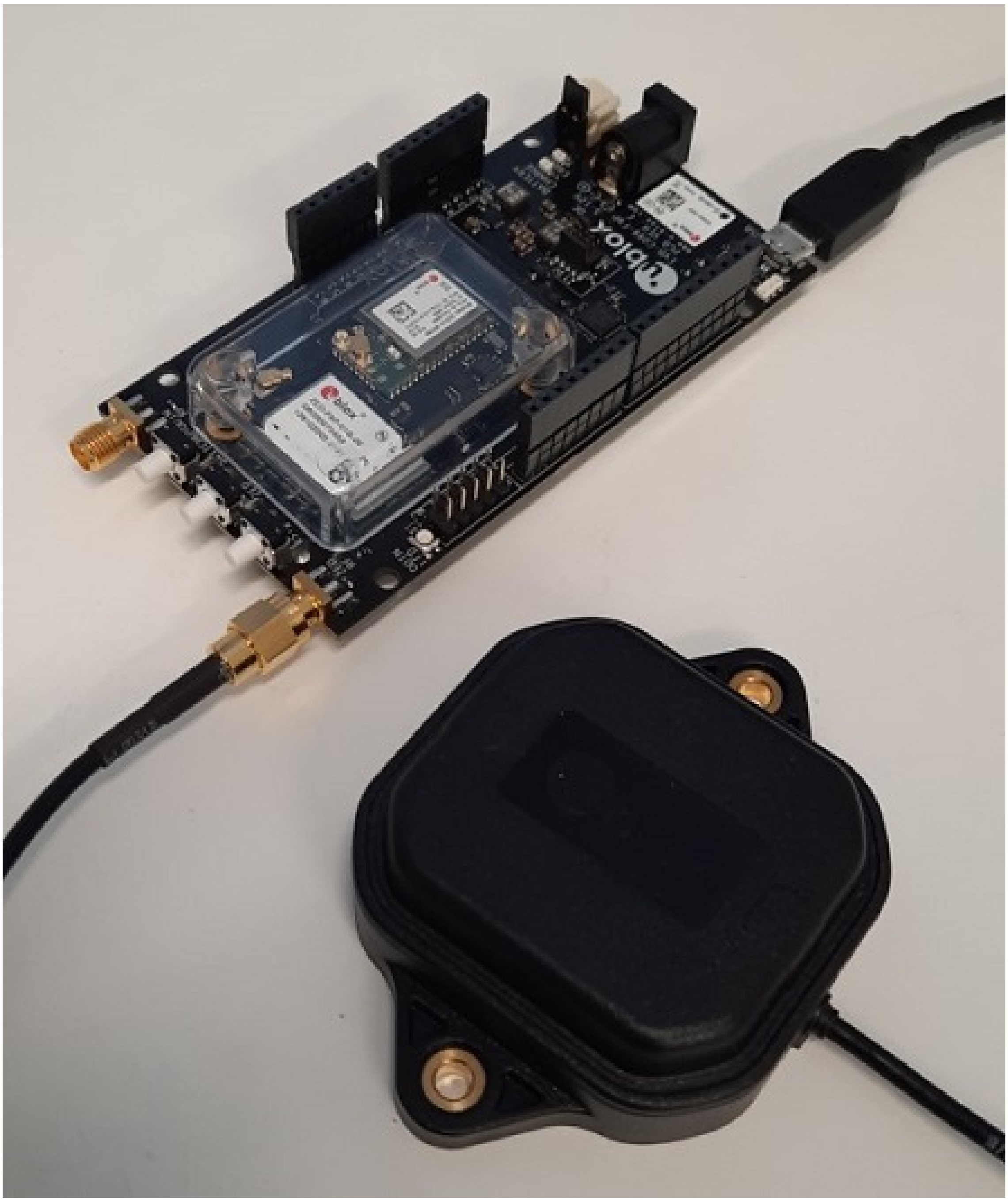

Figure 5.5. *U-Blox ZED-F9P GNSS module and the magnet- or screw-fixable antenna.*

The ZED-F9P GNSS module is able to deliver location at centimeter accuracy. The location acquisition rate is 0.5 Hz.

The thermal camera is a Flir A700 capable of utilizing both Real Time Streaming Protocol (RTSP) or GigE Vision Stream Protocol (GVSP) when recording either RGB- or radiometric video at 640 px x 480 px resolution. Image frequency is in both cases 30 Hz. For different scenes and applications, three IR lenses are provided with the camera, the focal lengths of which are 10 mm, 17 mm, and 29 mm whereas the AFOV of the lenses are, respectively, 42°, 24°, and 14°. Sensor accuracy is ± 2℃, for ambient temperature of

15℃ – 35℃ and target temperature above 0℃. The Flir camera is shown in Figure 5.6 below.

Figure 5.6. *Flir A700 thermal camera without lens cover.*

Flir A700 is connected to a computer via Ethernet, which is connected to a PoE (Power over Ethernet) injector both powering the camera and transmitting data. The camera can be configured using a simple web interface and the connection to the software is created using Flir's own Spinnaker SDK GenICam3 API library.

The RGB camera is a USB3.0 connected Basler acA2040-55uc, which is able to provide images at a 2048 px x 1536 px resolution (3.2 mpix) at 55 Hz. The attached zoom lens has a focal length of 8 to 48 mm, providing an AFOV of 47.65° when the zoom is adjusted to the minimum and 8.42° at the maximum zoom. The camera sensor is a Sony IMX265, utilizing CMOS technology. Connecting the camera to a computer is a webcam-like plug-and-play procedure. The camera is shown in Figure 5.7.

Figure 5.7. *Basler RGB camera with attached Canon zoom lens.*

The cameras are included in the detection system for visualization purposes. It is convenient to have a camera recording the detections that are made by the radar, because the camera images and radar detections that are saved with timestamps can be compared after experiments. One can see from the images if a detection is a false positive or not.

5.3 Map information

The railway maps are used to determine the shape of the railway tracks in front of the train, which in turn is used to determine if a given detection at a certain angle and distance is on the tracks. The maps are open data from Finnish Transport Infrastructure Agency (FTIA) which is accessible via FTIA's open APIs. Figure 5.8 below represents the railway map used.

Figure 5.8. *FTIA's railway map displayed on OpenStreetMap layer in QGIS.*

The railway map is exported in a more suitable format with QGIS, which is a open-source desktop geographic information system (GIS). Exporting is done because the ESRI (Environmental Systems Research Institute) Shapefile format is very fast to index, which makes it ideal for the map dataset that consists of nearly 7000 features which in turn build up from a large amount of coordinate points. Figure 5.9 illustrates a single feature near the center of Tampere.

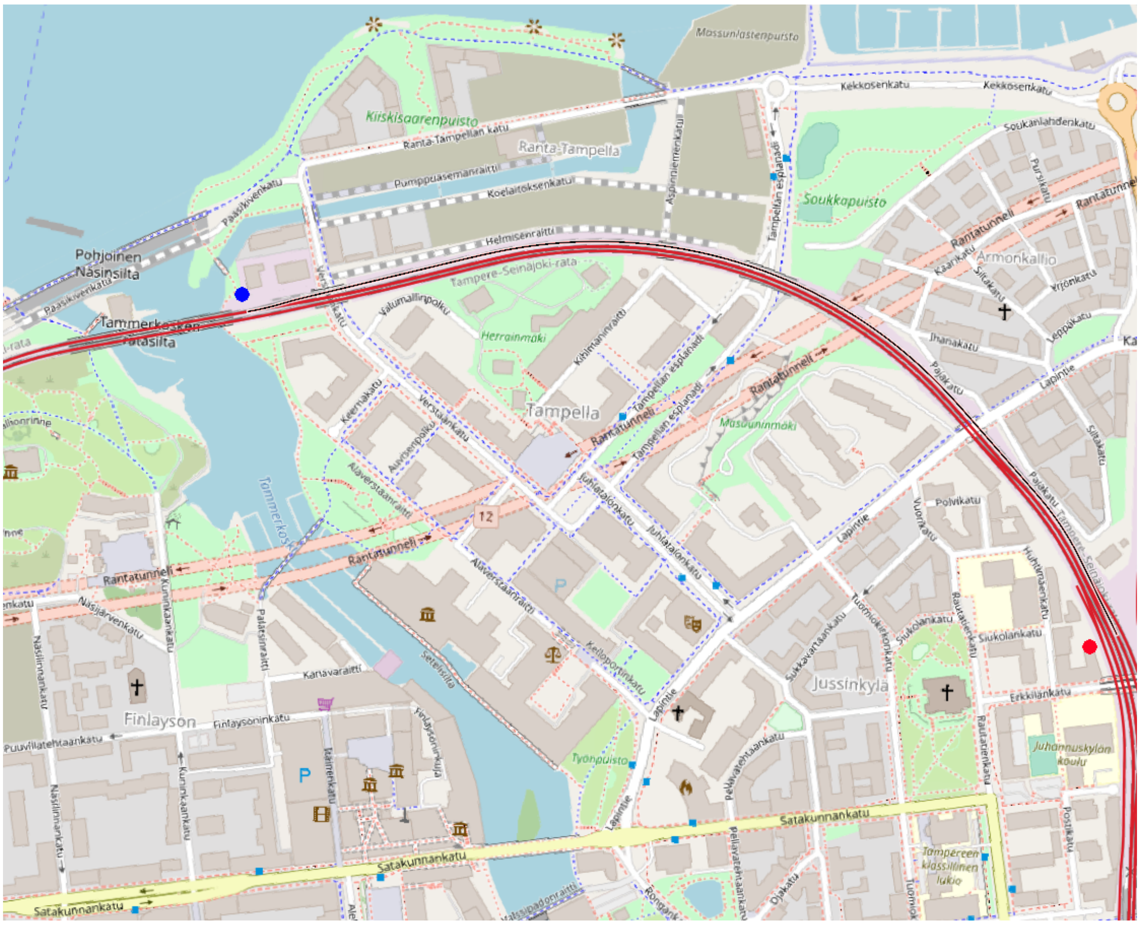

Figure 5.9. *A zoomed view into the map shown in Figure 5.8. A single feature, one pair of tracks, is marked by a black line, starting near the blue circle and ending near the red circle. Feature shown here is roughly 900 meters long, however, the features in the map vary from 30 meters to 1100 meters.*

A map feature contains information about its location in WGS84 (World Geodetic System) coordinate system. It also includes the distance between the first and the last point of the feature as well as its direction. A two-way part of railway tracks is thus represented by two features of the same length and location, but different direction. Also track numbers are included, so different parts of the railway tracks can be differentiated. In addition, a bounding box for a feature is also available in the map.

In principle, a map in ESRI Shapefile format consists of individual features, which in turn are built from more primitive shapes, polygons, that consist of coordinate points. When the map Shapefile is read by the software in the initialization (see Figure 5.1), two data structures are constructed: one containing the coordinate points of polygons and other containing feature attributes. The data structures are quick to use because the data records in them are indexed in the same manner and both data search and filtering can be done according to any attribute recorded.

Because the experiments with this detection system had to be carried out on a road instead of railway tracks due to restricted access on railways in Finland, the maps had to be handcrafted. The two handcrafted maps used in the experiments contain the same feature attributes for a single record as the FTIA's railway map. The difference between these is the data structure size. When FTIA's map contains nearly 7000 records, the two handcrafted maps including only one road contain 4 and 8 records. However, if further experiments would be carried out on railways, the FTIA's railway map could be used instead. In practice, if the data structure of a map is the same as it is in FTIA's railway map, the detection system's filtering algorithm works.

5.4 Data fusion

The problem with track curvature and static front-facing radar is addressed with railway maps. The algorithm is:

1. Get train's current location from GNSS
2. Correct the location to match a point on the railway track map
3. Examine the track shape that is in front of the train and create a track-shaped, train wide zone that is of interest
4. See if any radar detections are in the zone of interest

GNSS provides the train's location in coordinates (latitude/longitude), accompanied by its current heading. Coordinate values are used to find the corresponding part of the railway track map. First a suitable feature is searched from the map data structure using feature bounding boxes. The feature of interest is the one, which bounding box includes the location provided by the GNSS. Then to find the exact point on the track on the map, the GNSS location needs to be projected on the track. Figure 5.10 illustrates the location projection, which yields a point on the railway map that is closest to the location provided by GNSS.

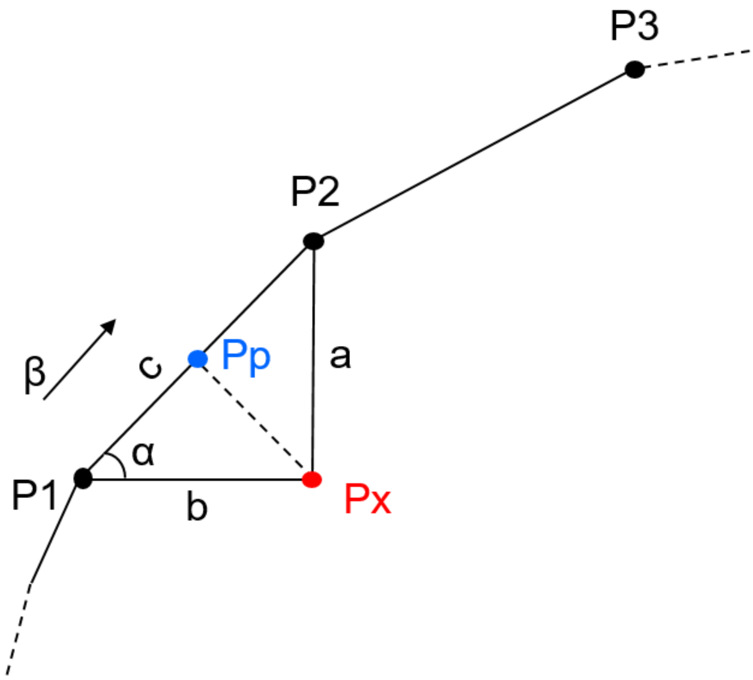

Figure 5.10. *Here a feature consists of three track coordinate points $P1$, $P2$, and $P3$. The projection distance between GNSS location P_x and projection point P_p is calculated for every point and the shortest is chosen.*

The projection location P_p is acquired from formula 5.1 below.

$$\begin{aligned} P_P x &= P1_x + [d * \cos\alpha] * \cos\beta \\ P_P y &= P1_y + [d * \cos\alpha] * \sin\beta \end{aligned} \tag{5.1}$$

Where $P_P x$ and $P_P y$ are the coordinates of the train's location projected on the map, and $P1_x$ and $P1_y$ are the coordinates of a given track point according to which the distance calculation is performed. Location provided by GNSS is Px, and α is the angle between a line from track points $P1$ to $P2$ and a line from point $P1$ to Px, whereas β is the train's current heading. The distance calculation is done for every point of the feature to derive the shortest distance and thus a very precise position on the tracks.

The distance d the formula 5.1 requires is calculated using great-circle distance between points, which is computed assuming flat-earth between two points indicated by coordinates. There are at least two known formulas to get the great-circle distance. First is the Haversine formula 5.2 [49]

$$d = 2r \arcsin\left(\sqrt{\sin^2(\frac{\varphi_2 - \varphi_1}{2}) + \cos\varphi_1 \cos\varphi_2 \sin^2(\frac{\lambda_2 - \lambda_1}{2})}\right) \tag{5.2}$$

where r is the radius of the earth, φ_1 and φ_2 are the latitudes of point 1 ($P1$) and point 2 ($P2$), and λ_1 as well as λ_1 are the longitudes of $P1$ and $P2$. The second option is Vincenty's formula [50]. In this application, the former is used, because it is computationally simpler and according to experience gained at VTT, the accuracy is not significantly increased by using Vicenty's formula. So the great-circle distance d between two points is acquired from Haversine formula 5.2 above. The angle α needed for equation 5.1 is acquired from the equation 5.3 known as the Law of Cosines:

$$\alpha = \arccos\left(\frac{a^2 + b^2 - c^2}{2ab}\right) \tag{5.3}$$

where a is distance from point 2 ($P2$) to train's current location Px, b is the distance from $P1$ to the train's current location Px and c is the distance from $P1$ to $P2$.

After obtaining the current location that is projected on the tracks, a "zone of interest" needs to be constructed. This is performed by reading the map to get the shape of the track ahead of the train for a suitable distance, here ideally 1200 meters. The map data structure is read starting from the train's projected location to the specified lookahead distance following the tracks to the same direction as the train is headed. This operation yields a path consisting of track points between train location and the far end of the lookahead distance. When this upcoming track shape has been acquired, it is "inflated" so that as an output of this track curvature examination we get a zone that can be used as a filter to the radar data. All the obstacles that are detected to lie in this zone must be considered as relevant objects. Figure 5.11 below clarifies this idea: red line from the train to the end of the lookahead distance is the path and the blue area is the zone of interest, which acts as the filter for detections.

As the train's location is acquired, it is projected on the map, and the detection filter is constructed, the algorithm starts filtering radar detections according to their position. As the target point from the radar comes in Cartesian coordinate system (see Figure 5.4) it first needs to be assigned with latitude/longitude coordinates so it can be affiliated with the map, which is achieved by inverse Haversine formula 5.4 [51] yielding target's coordinates in latitude/longitude.

$$\begin{aligned} \varphi &= \arcsin(\sin(\varphi_1) * \cos(d/r) + \cos(\varphi_1) * \sin(d/r) * \cos(\vartheta)) \\ \lambda &= \lambda_1 + \operatorname{atan2}(\sin(\vartheta) * \sin(d/r) * \cos(\varphi_1), \cos(d/r) - \sin(\varphi_1) * \sin(\varphi)) \end{aligned} \tag{5.4}$$

Where φ is the latitude component of the target's location and λ is the longitude component, whereas φ_1 and λ_1 are the coordinates of the starting point, which is here the location of the radar sensor. The radius of the earth is denoted by r, and the distance

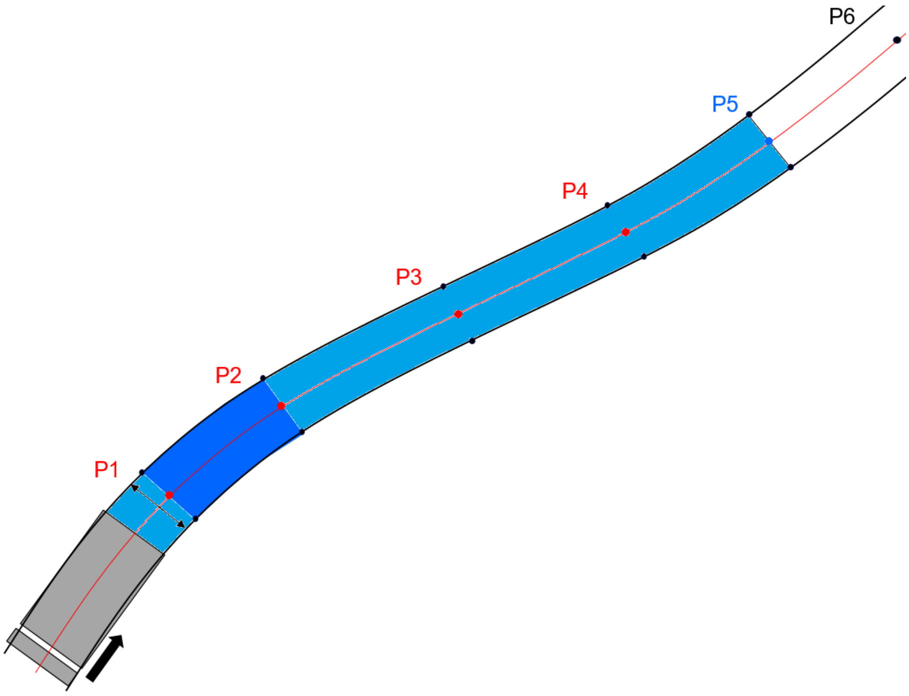

Figure 5.11. *Train (gray box) is heading toward the upper right corner, indicated by the black arrow. Points P1–P6 are track points from which map features consist of. Points P1–P5 belong to the path that is constructed for the filter. As the final point of the path, point P5 is at the lookahead distance. The two arrows from the path to the black lines on the sides represent the inflation. The width of the inflation is the area that needs to be clear for the train.*

and angle to the target are d and ϑ respectively. The distance and angle to the target are acquired from a radar detection.

Finally, the target's location is compared to the filter. The inflated path, "a corridor", consists of multiple subsequent polygons, one of which can be seen in Figure 5.11 between points $P1$ and $P2$. To decide if a given target is inside the zone of interest, the algorithm runs crossing number algorithm [52][53] for each of these polygons in the zone. Figure 5.12 shows the algorithm in C code.

```
int pnpoly(int nvert, float *vertx, float *verty, float testx, float testy)
{
  int i, j, c = 0;
  for (i = 0, j = nvert-1; i < nvert; j = i++) {
    if ( ((verty[i]>testy) != (verty[j]>testy)) &&
         (testx < (vertx[j]-vertx[i]) * (testy-verty[i]) / (verty[j]-verty[i]) + vertx[i]) )
       c = !c;
  }
  return c;
}
```

Figure 5.12. *The crossing number algorithm answers if a given point is inside a polygon. The first input argument for the function is $nvert$, which represents the number of vertices in the polygon. Second are $vertx$ and $verty$, which represent arrays containing coordinates of the polygon's vertices. Finally $testx$ and $testy$ are coordinates of the test point. The function returns 0 if the test point is outside the polygon and 1 if it is inside of it. [53]*

As the inverse Haversine formula and the crossing number test is ran for the detections, starting from the one with shortest distance to the sensor, the detection system's filtering algorithm is finished. The output is radar detections' distance and relevance according to map. Figure 5.13 illustrates the output of detection algorithm.

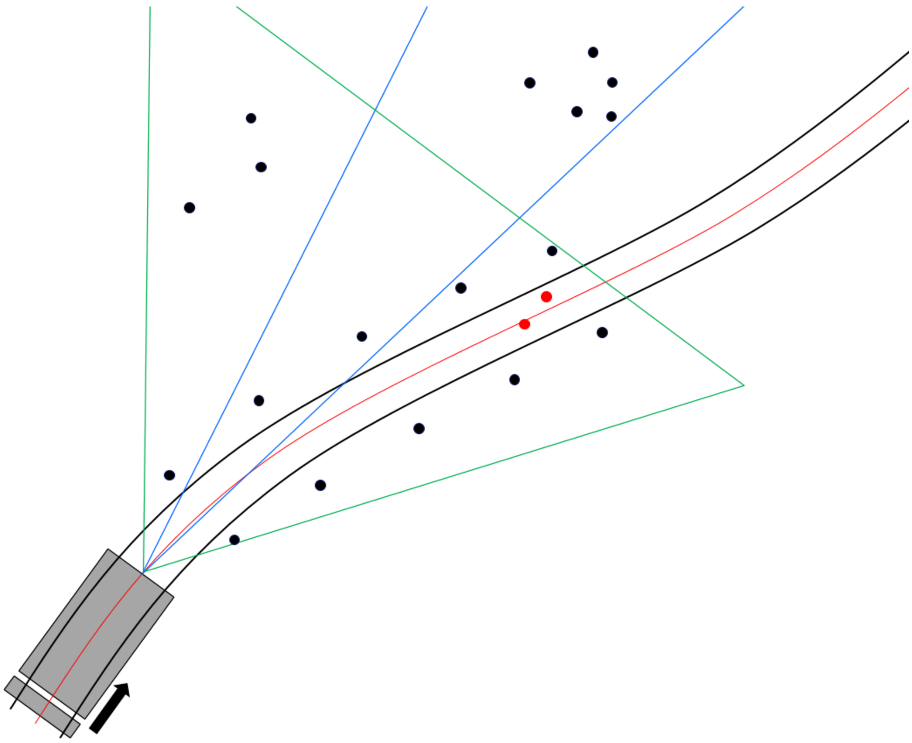

Figure 5.13. *Train (gray box) on tracks heading toward the upper right corner, indicated by the black arrow. Curved black lines represent the tracks and the red line between them the center of the tracks. The blue cone is the radar's far range sensing area (up to 1200m using extended range, 250m without) and the green cone is its near range sensing area (up to 100m). The black circles are detections filtered outside of the tracks whereas the red ones are detected on the tracks.*

The area from which relevant detections can be obtained diminishes if the tracks are very curved, because the radar's beam is narrow. In the railway environment the relevant areas for this detection method are larger and extend longer than in road environment, because commonly railways have less curves and they are more gentle. Still there is the limitation of insuperable obstructions, for example a cliff that is near the tracks that blocks the radar signal in a curve.

5.5 Detection system's performance criteria

To evaluate the performance of the detection system, at least its reliability and filtering capability should be taken into account when designing experiments. Because the filtering algorithm depends on the location provided by the GNSS module that updates the location in a cycle of every two seconds, its running time is not acting as a bottleneck.

The detection range that is filtered in the cycle is relatively long, so the system is able to run the filtering algorithm again before the train would be even near the far end of the filtered range. Thus, the running speed of the algorithm can be left outside of evaluation in this case.

In principle, here reliability refers to the radar's ability to detect and separate objects with different velocities, sizes, positions and radar cross-section (RCS) values as well as the filtering algorithm of the system. What is more, reliability also points to the radar's inbuilt tracking algorithm when it comes to moving objects. In an experiment, reliability could be tested in an environment where there are different kinds of objects present, both still and moving, with varying distances. If it is able to deliver steady measurements regardless of the object in question and the tracking algorithm ensures that a moving object is detected as one object and not multiple consecutive ones, it performs well. In addition, reliability refers to the detection quality of the system: the amount of false positives (the system alerts, but there is no obstacle present or there is, but it is not on the tracks) and the amount of false negatives (there is an obstacle on the tracks, but the system fails to detect it). Also the acquired location of a moving object needs to be accurate to prevent error accumulating in the filtering algorithm.

Evaluating the filtering algorithm performance is the main question considering the overall performance of the detection system, because the sensors used are designed by professionals and all data processing the system executes is associated to filtering. Do the detected objects that lie outside of the tracks get filtered out systematically? Do those on the tracks pass through the filter and thus get recognized as potential obstacles? Can this be done over a long range? Of course these questions are closely linked both to the accuracy of the radar (angular- and range resolution) and the accuracy of the calculations on which the filtering is based.

6 RESULTS

Running experiments on the detection system turned out to be more complicated than originally expected. This was due to the fact that in Finland only a very restricted set of operators are allowed to move on the tracks. What is more, the largest operator, VR, will not modify a train in its fleet because of strict railway standards. Attaching this kind of detection system onto one of their trains is thus not possible.

This chapter begins by describing the experiment plan, after which the acquired data from four measurement sessions is presented. Some possible defects are pointed out in between that may affect the results. Finally, general constraints for the application of the detection system are proposed.

6.1 Experiment plan

To be able to test the system, the environment had to be changed. The sensors were attached to a sturdy camera tripod, which was packed into a car together with a laptop. The car, equipped with a power inverter, acted as a power supply for the system. The first experiments took place at two locations, on the side of a road, at a standstill. Because the railway map does not apply in this situation, maps for these locations had to be handcrafted. The "tracks" are marked on Figures 6.1 and 6.2 in red, on top of the OpenStreetMap view. The measurement location is marked by a blue circle on top of the red line. The first measurement location is facing north at Niittyhaankatu, Tampere.

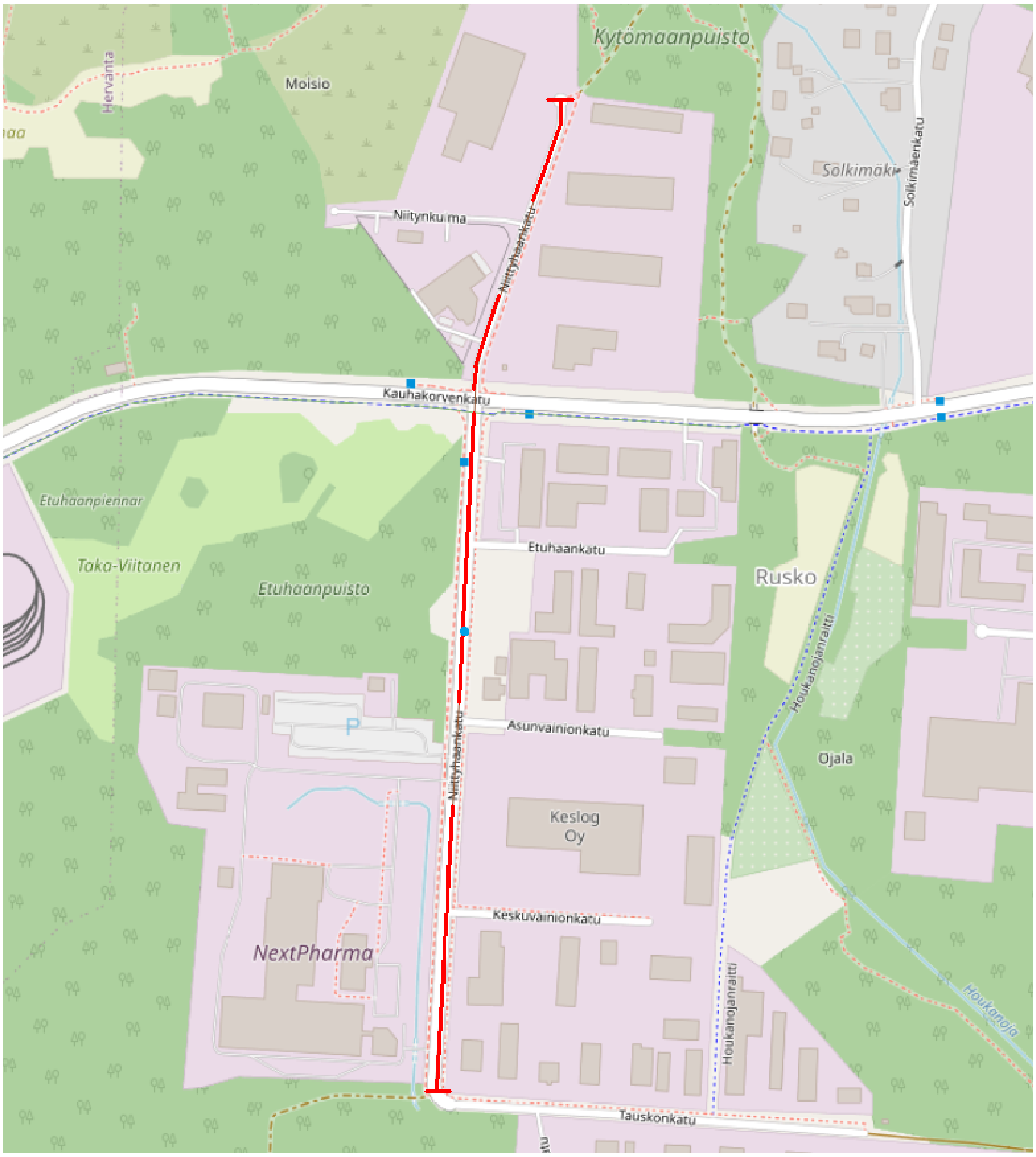

Figure 6.1. *The first measurement location. The red line represents the map, which was handcrafted using QGIS. The section in red is approximately 800 meters long.*

The second location is at Korkeakoulunkatu, Tampere. Here, the measurements were acquired facing roughly north-east. In both of these locations, the exact spot where to run the measurements was decided so that the traffic could flow through regardless.

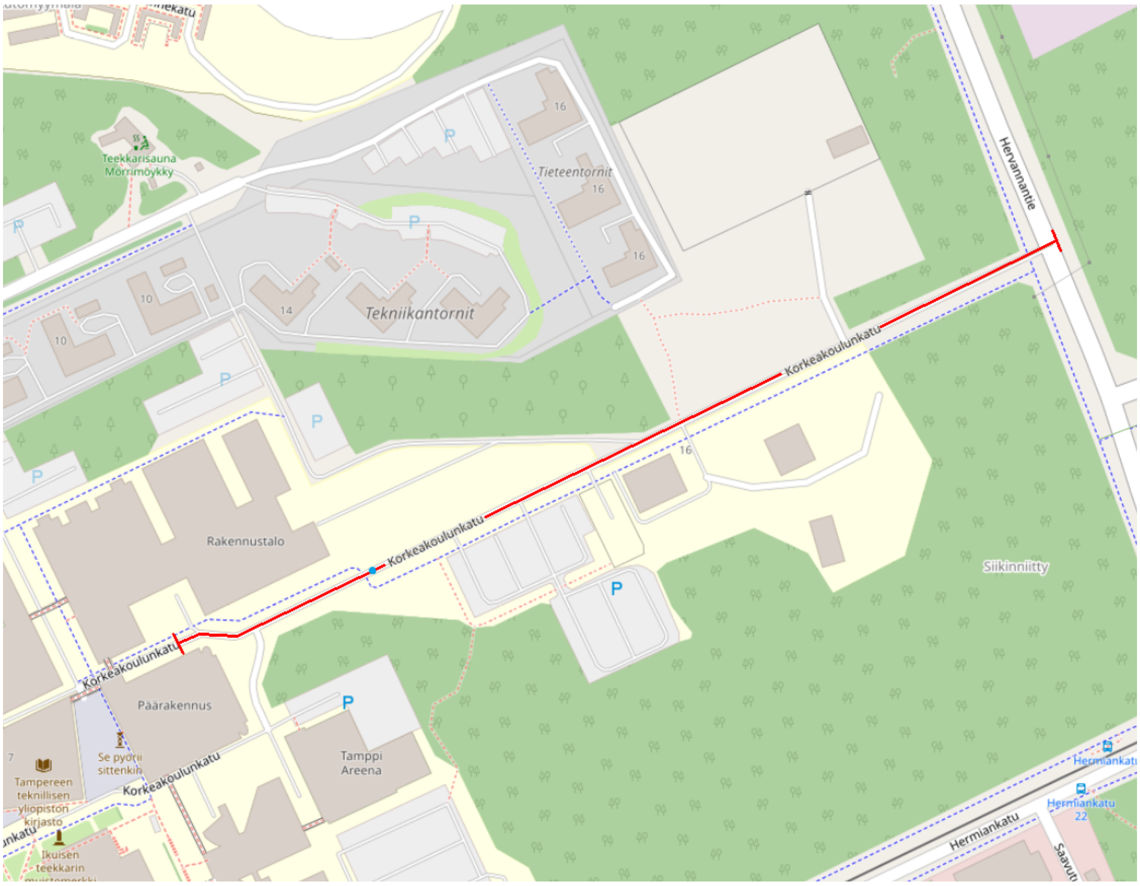

__Figure 6.2.__ The second measurement location. The section in red is approximately 500 meters long.

In both of the situations above, the measurement distance is far from the longest possible for the radar. It was relatively difficult to find road sections that were not too active considering traffic, were not clearly too curved, and were flat enough to get reasonable results. The main reason to choose these two locations was the possibility to park on the side of the road and mount the tripod as close to the center of the road as possible, thus simulating the situation where the system is attached on the head of a train.

6.2 Acquired data

The data collection of one measurement run consists of RGB camera images, thermal camera images, radar detections listed in a .csv-file and GNSS locations listed in a .csv-file. In addition, the interface of the software was recorded to examine the visualizations afterwards, as shown in Figure 6.3. A single radar detection consists of a detection ID, timestamp, its coordinates and relative distance, relative velocity, RCS value, and a Boolean value representing whether the detection lies on the "tracks" or not, according to the filtering algorithm.

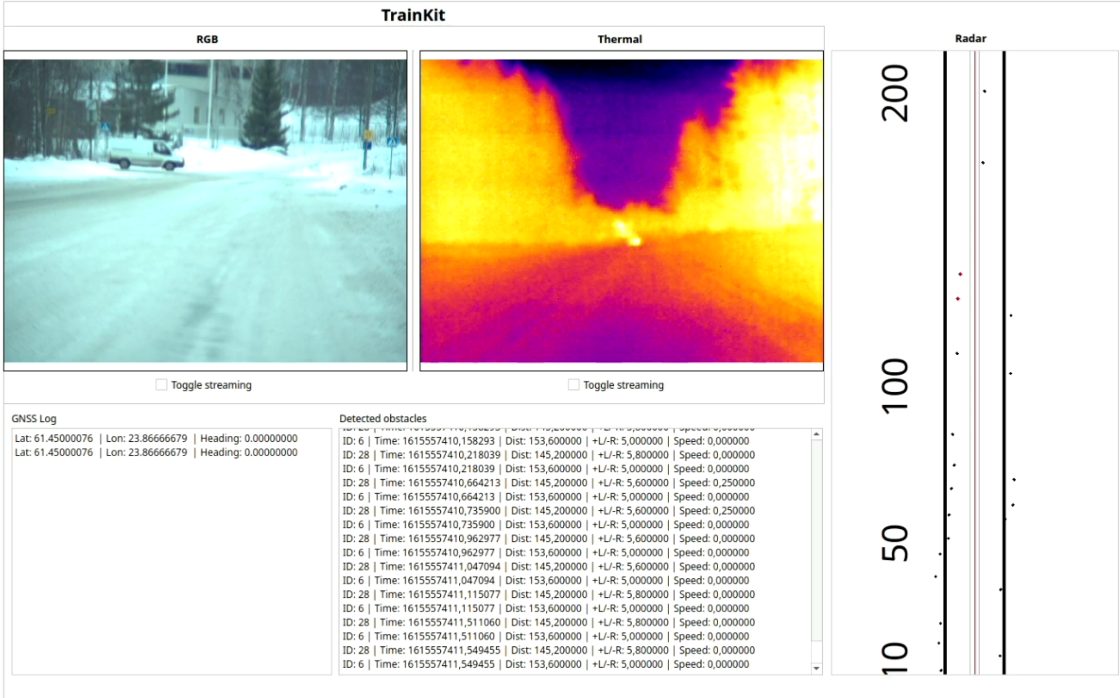

Figure 6.3. *The detection system interface. On the right, the black circles are detections that are outside the "tracks", whereas the red ones are on it. The latter ones are continuously listed in the "Detected obstacles" section in the center.*

The upper part of Figure 6.4 below shows a scene (from 6.1), where a vehicle overpasses the measuring point. Being at the center of the road at the moment, it is shown as a detected obstacle in the center of the radar display. When the vehicle moves forward, taking back the right lane, it is not detected as an obstacle anymore. This is shown in the lower part of the figure. So when an object moves away from the center of the road, it is not a relevant object anymore.

Figure 6.4. *In upper scene, the van is detected to be an obstacle 21.6 meters away, whereas in the lower scene where the van has moved slightly to the right, it is categorized to be outside of the tracks.*

In this scene, the system seems to work as planned. An obstacle is detected when it is near the center of the "tracks", and it is filtered out when it moves away from it. However, the distance is short and it seems that in the lower scene the algorithm probably picks up snow banks on the far side of the road. It is far from optimal to run measurements on the side of the road and not in the center of it.

A similar situation can be seen in Figure 6.5 below. Here two oncoming vehicles are in different lanes, and just the one on the left side is detected as an obstacle.

Figure 6.5. *Two oncoming vehicles in different lanes. The one on the left side is considered as an obstacle 46 meters away.*

Because both of these vehicles are considerably close to the center of the road, and just one is detected as an obstacle, it looks like the handcrafted map may lie closer to the left side of the road than the right. The accuracy of the categorization between obstacles on the track and outliers depends on the map accuracy, and how well it corresponds to the real world.

Next, in Figure 6.6 below, a detection from a longer distance is achieved. Here the other constant detections between 5 to 7 meters to the left are probably snow banks, but two underlined detections with ID 22 are clearly pointing to the vehicle speeding from right to left on the crossing road (Kauhakorvenkatu in Fig. 6.1).

Figure 6.6. *Moving vehicle detected at a distance of approximately 179 meters. Its velocity is measured in meters per second. Here the "Dist" is the distance from the sensor straight to the trajectory that the vehicle is running on, and "+L/-R" denotes how many meters left or right the detection is from this point. (x/y in Fig. 5.4)*

Again, the detection seems to be as it should, except it comes a bit late as the vehicle seems to have already passed the crossing, and it should not be considered as an obstacle anymore. However, this probably is again due to inaccuracies on the map. What is interesting is that the vehicle is detected behind a small snow bank, a couple of trees, and traffic signs. This is due to the tracking algorithm that keeps following the object.

At the second location (map in Figure 6.2), below in Figure 6.7 is a scene in which a person is detected as an obstacle in the center of the road, only 19 meters away. However two people walking in the distance, approximately 340 meters away are not detected at all.

Figure 6.7. *Nearby person is detected as an obstacle, but two people on the crossing sidewalk are not detected. The radar is showing constant detections 3.8 to 5.6 meters on the left, that are probably snow banks or light poles.*

Here there is a slight bump in the road, which can be seen in the above image by following the right hand snow bank lowering in the distance. The shape of the road surface cannot really be seen otherwise, as the snow reflects light so brightly to the camera. The bump may reflect the radar signals so that the objects behind it are difficult to detect. This may be the reason why the two people and multiple vehicles crossing the road did not get detected as obstacles.

In the next, final scene, there is a vehicle parked on the road and two people standing next to it. They are approximately 270 meters from the measuring point. Figure 6.8 shows the shape of the road as it forms a slight bump between the sensors and the car.

Figure 6.8. *A parked vehicle and two people on the road, at an approximate distance of 270 meters.*

Neither the vehicle nor the people were detected. There was also a large truck crossing the road approximately 340 meters from the measuring point, which was not detected. It seems the farthest detections, both on or off the "tracks", are around 150–250 meters from the sensors.

6.3 Application constraints

Generally, in a scene in which the radar's visibility is good, the system seems to operate as expected. This may not be the case in actual operation environment, in which for example the scene may take place on a downhill slope or might include a bump, such as the one in Figures 6.7 and 6.8. One aspect in the development of this system was to see if radar detections could be filtered in a meaningful way. The images in the previous section show that this can be done, but the reliability of the detections is dependent on the map in which the filtering is based, assuming that the GNSS provides the accurate location. Apart from the map, the radar seems to give a accurate position for its detections and the algorithm turns them into map coordinates, filtering detections that fall outside of the tracks successfully.

If, however, the map or the GNSS location is not accurate, the detections become more uncertain. Cloudiness may affect the GNSS module signal, which decreases its accuracy. If the location is not exceedingly off, the system provides detections because the location can be projected on the map. If no location is received from the GNSS, the system fails to provide reliable detections as it cannot read the map using appropriate location.

7 DISCUSSION

This chapter addresses the usefulness and functionality of the detection system. The performance of the system will be analysed, accompanied with challenges that indicate the system's possible faults. First the system will be compared to the state of the art, which in turn shows where the system sits considering the highest level of development in its field.

7.1 Relation to the state of the art

Comparing the developed system to the SMART obstacle detection system described in chapter 4, a clear difference can be seen between the level of completeness. SMART is a multi-sensor system that utilizes every attached sensor in obstacle detection to attain a more comprehensive view. This makes it more reliable in various environments, as it does not depend on any one module to perform. The obstacle detection system developed in this thesis does not make use of any computer vision techniques to detect obstacles from camera images. It focuses on the radar and filtering its detections using maps.

On the other hand, looking at the developed system as a potential component for a more complete obstacle detection system might be useful. In particular, the radar accompanied with the filtering algorithm could be coupled in a sensor fusion system as a component. Perhaps filtered radar detections could be verified with a computer vision system, which are largely utilized in object detection.

It is self-evident that the developed system would need to make use of other sensors in detecting obstacles. As the state of the art suggests, the other sensors would likely to be cameras. As the results in the previous chapter suggest, it is difficult to interpret radar data without the camera images from a detection scene. Even though both of the cameras are included in the system only for visualization purposes, they are important for the detection system as it is.

7.2 Performance

As mentioned in chapter 6, the system seems to fail to provide detections from further away than 250 meters. This is actually stated to be the far range of the radar in its documentation [48], but the manufacturer also adds that:

“With a special software version, the ARS 408 can extend its measurement range up to 1,200 meters (for objects with high RCS and an unobstructed field of view).”

The previous chapter showed a situation where the system could not detect the vehicle parked on the road. One would think that a vehicle like this should have been detected, but perhaps in that scene the object’s RCS was not high enough or the view was not unobstructed enough, featuring the bump in the road. All in all, detecting ground obstacles reliably from a distance of a kilometer and beyond using this kind of radar probably has to be done in a carefully chosen environment. Still, it might be unreliable considering the radar’s angular resolution and hence the tracking algorithm performance at distances of this magnitude.

Another issue that arose during experiments was the radar’s inbuilt tracking algorithm. It was common that an object that was constantly visible to the radar (e.g. the nearby person in Figure 6.7 in chapter 6) was suddenly lost and was caught up again after a while. This was noticed by looking at raw radar data output, which was not processed by the developed software at all. The tracking algorithm could potentially be improved and maybe even customized for use in a railway environment. In such cases, the radar beam could be narrower, which also would lessen the clutter caught by the radar.

On the performance of cameras, the laptop used seemed to suffer from too little memory, to be able to stream both cameras as well as other sensors at the same time. This observation was obvious in a case where the memory buffer increased rapidly, resulting in lowered FPS (frames per second). The RGB camera’s lens was also perhaps not ideal, at least in a snowy winter environment where the scene is highly illuminated.

The software itself performed well after configuring the sensors and filtering values, for example the corridor width. The detections it catches are accurate when comparing the system’s and a given detection’s coordinates in GIS software, even though the test material form the experiments is compact. Also, according to tests, the errors the obstacle detection software makes are mostly related to objects it completely fails to detect, which in turn might originate from inaccuracies on the map or from the radar failing to detect the object for example due to signal echoes from the ground or from other objects in the scene. The detections that the system catches well, which according to tests are those that are moving straight in front of it and are clearly under 250 meters from the sensor itself, are filtered as designed. The real challenge to overcome in developing this obstacle detection system is the one linked to inaccuracies in maps. As covered in chapter 2 considering different traffic environments, there are a lot of objects near the train tracks that are not obstacles. This poses a problem, as the map coordinates have to match the real world locations very accurately making the system able to deduce if an object is really too near the tracks or just far enough to be passed without colliding with it.

Lastly, in a real scenario where the system is attached to the front of a train and the driver would be unable to see far enough to control the train safely, the interface must not be this complex, including lots of text and numbers quickly running on the display. In the development stage the display is more of a visual aid to see the data flowing, and recording it made it easy to watch the experiment scenes again later on, and thus it was not put under scrutiny. The interface would need to be simplified to serve its real purpose – to assist drivers in a harsh environment.

8 CONCLUSION

A railway infrastructure safety system, such as the ERTMS/ETCS being developed currently in the EU, mainly concerns controlling traffic flow on railways. This disregards the fact that from the point of view of a train driver, there can be other obstacles on the tracks than another train, the exact location of which is known by the safety system. Colliding with these unexpected obstacles, such as cars, wildlife, boulders, or landslides may cost lives and material damages.

The obstacle detection system proposed in this thesis is a prototype of an independent on-board detection system that aims to support the driver in dangerous situations caused by the driver's tiredness or providing visual aid in bad weather conditions such as dense fog or a snowstorm.

How to improve obstacle detection in the railway context compared to the state of the art?

Considering the state of the art of obstacle detection in the railway context, the issues lie in reliability in all-weather conditions as well as the detection distance that needs to be covered. Improving the current level demands fusing sensors that are able to deliver a long range despite occluded view, e.g. radars. What is more, using railway maps to filter detections based on their location in the scene – a technique presented in this thesis – seems a valid way to approach the filtering accuracy that is needed in a railway environment.

How do railways differ from roads in the context of obstacle detection?

Mainly because changing tracks is not an available option for a train as changing lanes is for a car on a road, an on-board obstacle detection system needs to cover just the front of the train. Detecting obstacles in a road environment has to take incoming lanes into account in cases where an obstacle needs to be dodged in the vehicle's current lane. Additionally, railway tracks are a dangerous environment for all thinking animals, because the long headway that the trains require due to braking distance makes the railways' traffic flow seem much lower than on roads. For utilizing sensors, the railway environment is challenging because the railway corridors are usually narrower than on those of roads. Thus filtering sensor data into obstacles on the track and those outside of it must be performed with care.

Is it possible to detect natural targets reliably from long distance using the system depicted?

Detecting natural targets, such as cars or people, from a long distance using solely a radar sensor is definitely possible, but a reliable detection system should also consider utilizing cameras to detect object attributes such as lights on signal poles, for example. Nevertheless, the radar sensor used in the experiments of this thesis is one designed for the use of detecting targets in a road environment. The required detection range is significantly longer on railways, as dodging obstacles is practically impossible and the braking distance is on a completely different magnitude. The system caught reliable detections from a range of approximately 200 meters, whereas being able to perform so up to 1200 meters seems doubtful.

To further develop the detection system, more sensors and techniques to support the radar should be introduced. The most essential addition would probably be making use of computer vision for extracting the detections' features from camera images. This would allow the system to determine what kind of obstacle it is dealing with as well as getting support for the target's location that is also acquired from radar data.

What is more, a radar would possibly provide better detections if its orientation could be altered. As the radar's beam is quite narrow, it could be aimed straight in the potential obstacle's direction to catch its location accurately. To be able to get detections outside the radar's beam in the first place, perhaps precisely camera images could be analyzed accordingly. Instead of having the radar turning, multiple radars could be used in front of a train. The radars could have slightly different orientations, thus covering a wider area in unison.

Lastly, the radar's inbuilt tracking algorithm could be improved to better suit the railway environment, and the accuracy of the railway maps could be sharpened. The system performance could also be enhanced by adding level crossings to the map, for example, as these are probably the most risky areas on railways. Perhaps coupling the tracking algorithm with the railway maps would yield better results in a moving base scenario, where the tracking could be focused directly on the tracks, prioritizing the closest detections.

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