Analysing the effects of sensor fusion, maps and trust models on autonomous vehicle satellite navigation positioning

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This thesis analyzes the effects of maps, sensor fusion and trust models on autonomous vehicle satellite positioning. The aim is to analyze the localization improvements that commonly used sensors, technologies and techniques provide to autonomous vehicle positioning. This thesis includes both survey of localization techniques used by other research and their localization accuracy results as well as experimentation where the effects of different technologies and techniques on lateral position accuracy are reviewed. The requirements for safe autonomous driving are strict and while the performance of the average global navigation satellite system (GNSS) receiver alone may not prove to be adequate enough for accurate positioning, it may still provide valuable position data to an autonomous vehicle. For the vehicle, this position data may provide valuable information about the absolute position on the globe, it may improve localization accuracy through sensor fusion and it may act as an independent data source for sensor trust evaluation.
Through empirical experimentation, the effects of sensor fusion and trust functions with an inertial measurement unit (IMU) on GNSS lateral position accuracy are measured and analyzed. The experimentation includes the measurements from both consumer-grade devices mounted on a traditional automobile and high-end devices of a truck that is capable of autonomous driving in a monitored environment. The maps and LIDAR measurements used in the experiments are prone to errors and are taken into account in the analysis of the data.

Keywords: GNSS, autonomous vehicle, localization, IMU, LIDAR, trust, trust models, maps, Digiroad, sensor fusion, Extended Kalman Filter, Cyber security

Contents

1 Introduction

It is said that autonomous vehicles are the next big step in technological advancement. The benefits of autonomous driving range from safer travel to reduced traffic congestion [1]. 90% of all traffic accidents happen because of human error [2]. The amount of road accidents could be greatly reduced if human error could be removed from traffic by using autonomous vehicles.

Unfortunately, autonomous driving has various technological challenges that it has to overcome in order to reach the safety and reliability requirements for public use. These challenges are in the fields of sensing, computing, security, localization and decision making [3]. Autonomous vehicles need to process a lot of data really fast in real time and there is very little room for error. The autonomous vehicle needs to know where it is, where it is going, and what is around it at all times using the information provided by its sensors or it risks the safety of its passengers and its environment. Safety is the most important part of autonomous driving, which is why focus on the trust and accuracy of its key systems and sensors should have high priority.

High positional accuracy with high reliability is necessary for safe autonomous driving. There is little room for error because in the worst case scenario, errors may lead to human fatalities. In fact, autonomous vehicles have already caused a fatal accident. In 2018, an autonomous vehicle tested by Uber made a fatal collision with a pedestrian [4]. If autonomous vehicles are to be trusted with human lives, they should be able to know when to trust the data given by their sensors and when to recognize faulty sensor data.

This thesis will focus on the global navigation satellite systems (GNSS) in autonomous vehicles, the localization of autonomous vehicles and the reliability of sensors in autonomous driving. Requirements for autonomous driving are strict and while a GNSS receiver can perform well enough in optimal scenarios, it still has many challenges to overcome. By using many different techniques and technologies the positioning results from GNSS can be improved. One of such techniques is sensor fusion which combines the measurements of multiple sensors to produce a more reliable and accurate measurement result. Because of sensor fusion, this thesis will also overview other sensors and their relationship to autonomous vehicle positioning. The goal of this work is to provide insight into the the accuracy and reliability of GNSS in autonomous driving and the experiment with methods that can be used to improve them. This work will address the some of the challenges of GNSS positioning in terms of its accuracy and reliability evaluation as well as its use for localization in autonomous driving.

Satellite navigation systems have the reputation of being too inaccurate for localization and are often only used for navigation in autonomous vehicles. However, there is much research that proves otherwise. GNSS receivers can be quite useful even for accurate localization. To gain positional accuracies below the meter level GNSS receiver often has to be complemented with other sensors, unless it is a particularly high-end receiver. [1]

The accuracy and reliability of GNSS and inertial measurement unit (IMU) sensors in this thesis are measured empirically and the results are compared to the results of other similar research. The empirical tests in this thesis are divided into two sections. The first section is an experiment on the performance consumer-grade GNSS and an inertial measurement unit of a smartphone mounted on an ordinary automobile. The second section is an experiment on the performance of light detection and ranging system (LIDAR), GNSS and IMU of an autonomously driving truck in its testing phase.

A well performing GNSS can help in many aspects of autonomous driving and other sensors are not really of capable of replacing GNSS in those aspects. Satellite positioning is one of the only ways to get the absolute position on the globe consistently and accurately [1]. There are many advantages of global positioning that relative positioning cannot provide. Navigation for example is one thing that is nearly impossible to do without a proper map and a satellite navigation system. It is also difficult to detect errors in those maps without accurate global positioning that does not rely on known positions of objects in that map [5]. In addition to all of these advantages, even a consumer grade GNSS can be used to improve the localization accuracy of autonomous vehicles through techniques such as sensor fusion [6] or map-matching [7].

This thesis is organized as follows: The second chapter looks at the properties of autonomous vehicles, autonomous vehicle localization and the role of positioning sensors in them, especially the role of GNSS sensor. The third chapter seeks to address the goals and requirements of GNSS positioning in autonomous driving. The fourth chapter reviews the research methodology of the experiments. The fifth chapter shows the results of the experiments done for this thesis. The sixth chapter compares the results obtained from the experiments in this thesis to those of other research. The seventh chapter presents the contributions of this thesis.

2 Localization of autonomous vehicles

2.1 Autonomous vehicles and autonomous driving

Autonomous driving is when the system of a vehicle controls some or all functions of the maneuvering and navigation of the vehicle. As detailed by liu et al. [3], autonomous driving is not one technology but rather an integration of many technologies. Autonomous driving requires that the car knows where it is in relation to its environment and what it should do next to reach its destination safely. To accomplish this task, autonomous vehicles use various different sensors, algorithms and maps. Autonomous driving can be divided into different levels based on how much control, and therefore responsibility the driving system has over the vehicle [8].

The society of automotive engineers (SAE) has defined 6 levels of autonomous driving. The levels range from assisted driving to fully autonomous driving. Level 1 (Driver assistance) describes a vehicle that assists the driver in basic functions of the car such as breaking and includes currently common technologies such as cruise control and anti-lock braking system (ABS). Level 2 (Partial driving automation) includes advanced driver assistance systems where the car can be in control of both acceleration and steering, however a human has to constantly monitor the driving and be ready to intervene at all times. At level 3 (Conditional driving automation) the car is capable of decision making and is aware of its environment, but like in level 2, the driver has to remain alert and be able to take over the autonomous driving system in the case of errors in the system. At level 4 (High driving automation) the vehicle rarely requires human assistance, but can be overridden by a human if necessary. At level 5 the vehicle (Full driving automation) does not require any human attention or assistance for autonomous driving and therefore also requires the highest reliability, accuracy and security for safe travel. At level 0 the system has no control over the vehicle but may still give information to the driver. The levels of autonomy are summarized in table 2.1. [8]

The higher the level of autonomy, the more precise and secure data the autonomous driving system requires [8]. Although accurate GNSS positioning is also useful for lower levels of automation, the focus of this thesis' experiments are on autonomous systems of level 3 and up where constant human assistance is not necessary for maneuvering and monitoring of the driving environment.

2.1.1 Autonomous vehicle sensors and their role in localization

Autonomous vehicles need sensors to drive safely. Sensors provide important information of the vehicle's condition and the environment that the vehicle uses for driving and decision making. Every type of sensor has its own strengths and limitations. The most commonly used sensors in autonomous vehicles are radar, LIDAR, camera, inertial measurement systems and satellite navigation systems. Sensors used in autonomous vehicles have gotten both better and cheaper over time and will continue to do so. [3] [9]

Sensors used in autonomous vehicles can be split into two separate groups: proprioceptive sensors that measure the internal state of the vehicle and exteroceptive

Table 2.1: SAE levels of autonomy

Level	Definition
	Human driver monitors environment
Level 0	Driver completely in control of the vehicle.
Level 1	Individual tasks may be performed by the vehicle.
Level 2	The vehicle may perform several of the tasks of driving, the driver performs the rest.
	Automated driving system monitors the driving environment
Level 3	The vehicle performs all driving tasks, the driver is expected to take over if requested.
Level 4	The vehicle performs all driving tasks, the driver is allowed to take control of the vehicle.
Level 5	The vehicle performs all driving tasks in all conditions.

sensors that measure the properties of the environment of the vehicle. IMU, wheel odometry and GNSS are examples of proprioceptive sensors. Exteroceptive sensors include sensors such as LIDAR, ultrasonics, camera and radar. [2]

The automotive radar's role is to detect and range objects in the environment, based on a point representation. Radar works by bouncing radio waves off of objects and measuring the distance to the object by calculating the time it takes for the waves to arrive back to the sensor as well as measuring the speed of the object via the Doppler effect. Traditionally automotive's radar is used for blind spot detection and pre-crash systems but as radar technology improves, so do its uses in autonomous driving. Radar sensors are great at performing in poor conditions where the weather or time of day may affect other sensors. Radar sensors are mostly limited by their resolution, their capability to measure height and their imaging performance at low speeds. [9] [10]

The light detection and ranging system's (LiDAR) role in autonomous vehicles is perception and localization. A LIDAR can be used to perceive the shape, pose, velocity of objects as well as geometry of the environment. The LIDAR measures the distance to objects in the environment by shooting precise lasers at reflective surfaces and processing the reflections of those lasers. The LIDAR's biggest advantages are its high accuracy, resolution and speed. Since LIDAR uses light, it is limited by weather conditions (fog, rain etc.) and poor surface textures of objects as well as the texture of the road. [11] [5] Another weakness of the LIDAR is that dynamic objects in the environment can make localization difficult if they obstruct the key elements in maps used with the LIDAR [12]. The accuracy of modern spinning/mechanical LIDARs are in the centimeter range and their detection range is from 1 meter to 100 meters [2].

Inertial measurement units (IMUs) in autonomous vehicles are used to measure the acceleration and orientation of the vehicle using accelometers and gyroscopes. Sometimes a magnetometer is included with an IMU to measure the sensor's orientation in relation to the magnetic field of the Earth. IMUs weakness are the difficulty of its calibration and its accuracy over long time periods. The strengths of the IMU are its measurement speed and availability in difficult environments such as in tunnels and poor weather conditions. IMU is commonly used for a dead reckoning, a positioning technique where measurements of the IMU are used to calculate a vehicle's position when satellite navigation becomes unavailable and only the previous location of the vehicle is known. The inertial measurement unit's biases and the effect of sideslip make it hard to use it for dead reckoning positioning over long periods of time. [12] [13]

Cameras are often used for object recognition, object tracking and vehicle localization. They can be used to detect objects such as lane markings, traffic lights and pedestrians. Cameras are great at generating lots of data of the environment quickly, especially if multiple cameras are used. The camera is limited by the effects of weather, effects of lighting and computing requirements of image processing. Additionally, the image recognition algorithms used in autonomous vehicles play a big role in the effectiveness of the camera as a sensor because misclassification in images can lead to large errors. [3] [9] [14]

The role of GNSS in autonomous driving is to provide global positional data to the vehicle. The primary strength of GNSS is its ability to provide absolute position on the globe for the vehicle. The biggest limitation of GNSS is the general accuracy of the positioning. In addition to that weakness, the accuracy is even more limited in environments where physical obstructions make satellite positioning more difficult. Some techniques to greatly improve the satellite positioning accuracy exist. [1]

2.1.2 Autonomous vehicle sensor fusion

The outputs of a vehicle's sensors can be combined with sensor fusion in order to increase their accuracy and reliability. Since some of the sensors' output data overlaps with each other, the reliability of that data improves because it is less likely that multiple independent sensors will have the same error for the same spot. For example, if location data given by GNSS matches with the location data extrapolated with an inertial measurement unit, the vehicle can be more certain of its location than it could be if it only had to rely on GNSS or IMU alone. The limitations of some sensors can be offset with the strengths of others by using sensor fusion. It has been shown that the more sensors are included in sensor fusion, the better the performance and reliability of the system becomes. [2] [6] [9]

There are many types of sensor fusion methods, but they can be boiled down to classical sensor fusion algorithms and deep learning sensor fusion algorithms. Classical sensor fusion algorithms use inaccuracies and uncertainties to fuse the measurement data of the sensors. A good example of a classical sensor fusion algorithm would be the error-state Kalman filter used by, for example, Wan et al. [15] to improve autonomous vehicle localization. Deep learning fusion algorithms use neural networks to fuse sensor data. For example, deep learning sensor fusion can be used to fuse data from LIDAR point-clouds and camera images for object detection and recognition. [2]

It should be noted that while classical sensor fusion methods that are used for localization such as Kalman filters are able to detect measurements that do not sufficiently match the current pose of the vehicle, they are not able to detect biased drifts in measurements that are common with GNSS and IMU. Extended Kalman filter (EKF) is a popular sensor fusion method used with GNSS and IMU that is less subject to biases, but is more subject to estimation errors. Particle filters can also be used for sensor fusion and are also less subject to biases, but are considered too computationally heavy for use in autonomous vehicle applications. However, many improvements to current sensor fusion methods that are used with GNSS sensors are still under research. [7] [16]

Extended Kalman filters are non-linear versions of Kalman filters. Kalman filters estimate the optimal state of a system from noisy or erroneous observations of linear systems. Extended Kalman filters use Taylor series expansions to linearize non-linear systems. However, Kalman filters and extended Kalman filters require proper initialization values for optimal performance. These initialization values are the state vector and the covariance matrix. A good estimation of these values will improve the performance of the filter. The state vector is the estimation of the initial properties of the system. In autonomous vehicles this would be the initial position, velocity and orientation of the vehicle. The covariance matrix represents the confidence the system has in its variables. In autonomous vehicles these would be the different noise and bias values of the used sensors. [17] [18]

2.2 Autonomous vehicle positioning

The precise knowledge of position and orientation is paramount for autonomous vehicle path planning, perception, control and safety. For localization the car needs information about its local environment from its sensors. This information is often combined with a data set such as a map. Knowledge about the car dimensions and sensor locations is also necessary to estimate car pose. [19]

By using a suitable map, cameras or range measuring sensors such as LIDARs can be used for localization by measuring distances from the vehicle to known landmarks in the environment and estimating vehicle pose in relation to those landmarks. The map used for this kind of localization can be either generated during the driving or provided to the vehicle by systems other than the vehicle. Sensor fusion with proprioceptive sensor such as a GNSS or IMU can then be used to improve this estimation and reduce errors in localization. [6]

Unfortunately, localization is always prone to errors but autonomous vehicle applications can estimate their probable maximum error horizontally and vertically. These maximum errors can be used as buffers known as protection levels. To ensure that a vehicle knows that it is within its lane, near decimeter-level accuracy is a requirement. In such scenarios the protection level has to stay within this decimeter-level limit, so that the vehicle knows that its localization error is definitely below this level. The decimeter limit here is known as the alert limit. If the protection level of the vehicle's system goes above this alert limit, then it becomes probable that the system encounters a localization error that risks unsafe maneuvering of the vehicle. Alert limits for an autonomous vehicle are defined by the required precision for safe operation in its operation environment. [19] [20]

Protection levels and alert limits also apply to orientational errors of the vehicle's pose. If the orientational protection level of the system exceeds the orientational alert limit, the system risks a localization error that is too big for safe autonomous driving [1]. For safe autonomous driving, the error in the pose estimation of the vehicle should stay below the degree level [19]. Protection levels and alert limits are visualized on Figure 2.1.

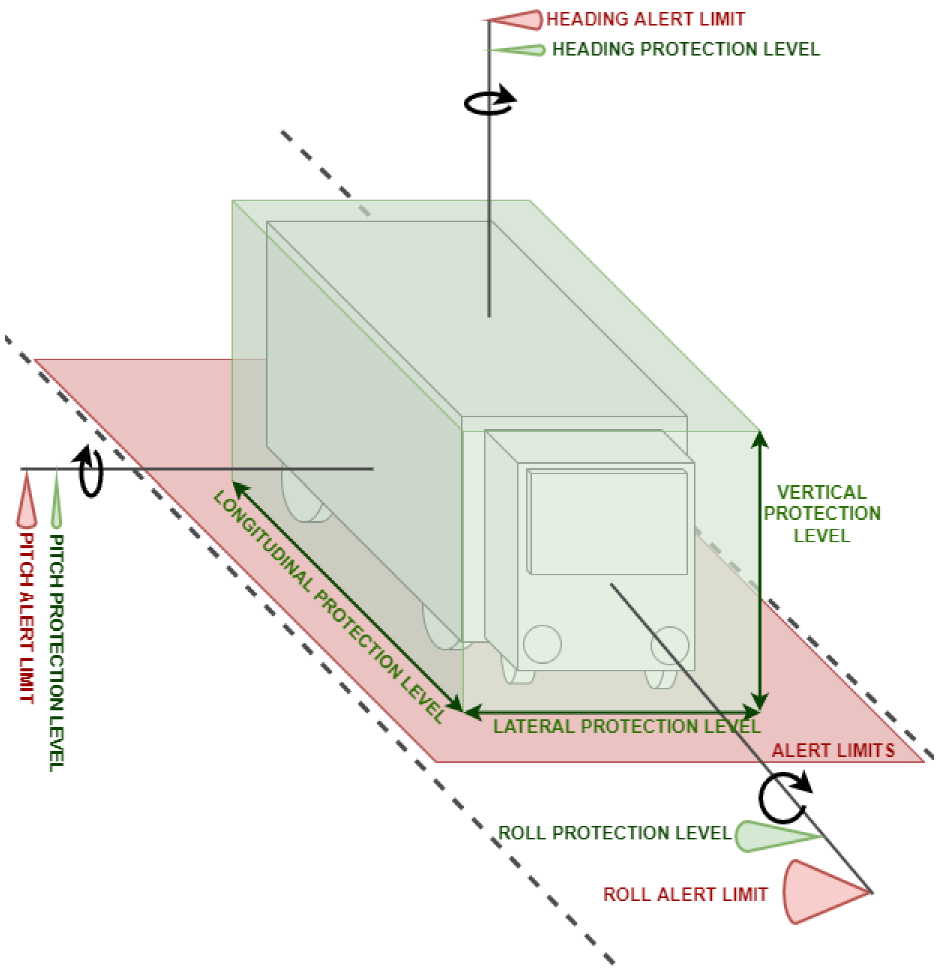

Figure 2.1: Definition of protection levels

There are many algorithms that improve upon the positional data given by the vehicle's sensors and reduce the maximum error of the data. Particle filtering, map-matching, resampling and particle cloning are a few examples [20]. Connected vehicle applications that use vehicle-to-everything (v2x) or Vehicle-to-vehicle (v2v) communication technologies for localization are also proven to be able to improve the positional accuracy of the localization of the vehicle [21].

Machine learning and deep learning algorithms can also be used to improve the localization accuracy of autonomous vehicles. For instance, Akail et al. [22] showed how machine learning can be used to detect LIDAR localization failures by evaluating the reliability of its measurements.

2.2.1 Role of maps in autonomous vehicles

Maps tell key information about the environment for autonomous vehicles. Maps can be used to localize the car position both globally (Vehicle absolute position on earth) and locally (Vehicle position relative to road elements in environment) [23]. There are two types of maps: priori maps and SLAM (Simultaneous localization and mapping) maps. Priori maps are maps that are generated from prior records of the environment. SLAM maps are virtual maps that are generated by the vehicle at the same time as it is localizing itself. [24]

Priori map accuracy varies a lot and for autonomous driving a "lane-level accurate" priori map is often enough for partially automated driving outside of cities. However, research in [23] suggests that a high-definition map (HD map) is necessary for safe highly automated driving in urban environments. HD maps contain not only information about lane positions of the road, but also about complex environmental details such as bicycle lanes, sidewalks, road markings and traffic signs. Only up-to-date HD maps that are accurate to a few centimeters are good enough to be used for safe highly automated driving in any environment [23]. High-quality HD maps are often stored in the cloud due to data storage limits of vehicles [25]. Priori maps have an absolute and a relative accuracy. The former defines how accurate the map is on a global level and the latter defines how accurate the map elements are relative to each other [26].

Most commonly used priori maps that are used for autonomous driving can be split into 2 types: Planar maps and point-cloud maps. Planar maps are maps that use the layers or planes of Geographic Information System (GIS) to represent points of interest and geometric elements on the map. Point-cloud maps are 3 dimensional maps where the information of the environment is stored as a cluster of points with specific locations in 3 dimensions. Point-cloud maps take up a lot of storage and are often computationally intensive to use. One weakness of priori maps is that large changes to the road environment can make the map obsolete. One solution to this is to use probabilistic maps which are used to compare GNSS positioning to map-based localization to spot errors in outdated maps and errors introduced by dynamic elements. One example of a probabilistic map is the Gaussian mixture map demonstrated by Wolcott et al [5]. In addition to reducing effects of dynamic elements, the Gaussian mixture map also reduces the computing and storage requirements of a point-cloud based map [12].

For global positioning autonomous vehicles use a GNSS receiver together with a global map. Matching GNSS position with roads on a map is called Map-matching. However, the level where map-matching is done only for road level is only useful for navigation and is not enough for localization. Lane-level map matching has benefits for accurate autonomous vehicle localization, but it requires an accurate lane-level map structure of the vehicle's environment as well as precise GNSS positioning. This is especially true in urban environments where there is less room for error due to smaller roads. [20]

For relative positioning during driving without a priori map, autonomous cars use their exteroceptive sensors to create a local virtual map for themselves. This virtual map is a SLAM map where the vehicle simultaneously estimates its position in relation to its environment as well as the position of key features in the environment [27]. Commonly a LIDAR, radar, and/or a camera with image recognition is used for this purpose. Local virtual maps are necessary for decision making and maneuvering. Most modern SLAM applications of autonomous vehicles do not use GNSS at all due to its apparent lack of availability and precision. Instead mainly LIDAR and camera are used. However, there are some proposals of using modified version of SLAM with GNSS where even a low-cost GNSS receiver improves the localization accuracy when used together with LIDAR. [6] [24] [28] [29]

Using maps introduce its own errors to car localization due to their inaccuracies. Depending on the map, the key information of the roads in a map may be off their true location by tens of centimeters or even many meters. By using just code-phased GNSS, it is possible to make horizontally sub 50-cm accuracy digital maps of urban environments [29]. However, for the more accurate and detailed HD maps (High-definition maps) data from multiple high-quality sensors together with high-end GNSS receiver is required. HD maps and point-cloud maps are considered accurate enough for map-matching localization with high resolution sensors such as LIDAR. A HD map generated with high-quality IMU, GNSS and LIDAR sensor fusion can reach absolute localization accuracies in the centimeter level. [30]

However, even maps with inaccuracies above one meter can be useful for autonomous vehicle localization and navigation. A study in 2018 [31] used an inaccurate topological map that has inaccuracies of multiple meters in a rural environment in combination with LIDAR SLAM to predict the future vehicle position to be within the road boarders >99% of the time despite the road not having markings or a predictable geometry of curbs. Inaccurate maps can also be useful when using collaborative v2v. Maps with inaccuracies up to a few meters can be useful for precise exchange of vehicle position, velocity and intent in collaborative v2v autonomous driving [29]. The relative and absolute accuracies of different kinds of maps used in autonomous driving are listed on Table 2.2.

OpenStreetMap is a large collection of geospatial data that is mostly created with data collected by ordinary citizens. Its quality is largely dependent on the GPS capabilities of those citizens. Because of this, there are large deviations in its data accuracy. One study in 2015 measured that 95% of open street map data

Table 2.2: Accuracy of maps

Map	Absolute accuracy	Relative accuracy
OpenStreetMap [32] - 2018	4 meters	-
Digiroad [33]	3 meters	-
Tomtom HD map [34] - 2016	$<$ 1 meters	0.1 meters
Sanborn HD map [35] - 2021	$<$ 0.1 meters	-
Lidar + GNSS + IMU generated HD map [30] - 2020	$<$ 0.1 meters	-
Gaussian mixture map [5] - 2017	$<$ 0.3 meters	-
LIDAR + GPS + IMU SLAM [36] - 2020	-	$<$ 5 cm

points lie within 4.2 meters of their true location but in the worst case errors may reach almost 6 meters. [32]

Digiroad is a national open data database of the Finnish road network. Digiroad provides a large scale road map of Finland. Road geometry of many of Finland's public roads is provided with a maximum absolute error of 3 meters. However, some sections of the map provide absolute accuracy in the decimeter range. Additionally, locations of other road elements such as traffic lights and road signs are provided in the map. [33]

Tomtom HD maps provide a decimeter level relative accuracy and a sub-meter level absolute accuracy of 3D map attributes such as lane geometry. Their map is claimed to be accurate enough for automotive localization accuracy of 50 cm longitudinal and 20 cm lateral [34].

2.3 Global navigation satellite system

A system that uses satellite constellations for absolute global positioning is called a satellite navigation system. Satellite navigation works by calculating latitude, longitude and altitude of a system by using the precise time information contained in the signals that are transmitted by satellites in orbit and the known satellite positions by using a process called trilateration. This process requires the signals of at least three satellites, but often more satellites are used to improve the accuracy of positioning. [1]

A GNSS (global navigation satellite system) uses multiple different satellite constellations simultaneously to achieve high precision positioning. Currently there are 4 primary fully operational GNSS satellite constellations: GPS, GLONASS, BeiDou and Galieo. Additionally, QZSS and IRNSS constellations can be used for improved accuracy. GPS (Global Positioning System) is the United States' satellite-based positioning system. At the moment, there are 31 GPS satellites in orbit and 5 of them are part of the GPS III block [37]. The GPS III block is the newest GPS satellite block which aims to provide sub-meter level positional accuracy for civilian use by 2030 [37]. GLONASS is the Russian Federation's satellite-based positioning system. GLONASS has 24 satellites in orbit. GLONASS aims to improve the accuracy of the positioning system by launching GLONASS-K2 satellites to orbit in 2022 [38]. BeiDou is the chinese satellite positioning system. The current BeiDou-3 system has 30 satellites in orbit [39]. Galileo is the European Union's satellite positioning system. Galileo has 24 satellites in orbit and is claimed to provide sub-meter level accuracy for general use [40]. Each satellite constellation broadcasts encrypted codes that increase their positioning accuracy for military use. [1]

There are 2 generations of GNSS: GNSS-1 and GNSS-2. The second generation GNSS (GNSS-2) provides better accuracy and lessens the problems with signal reflections when compared to the first generation GNSS. Also modern L5 band satellite frequencies offer ten times the bandwidth of legacy L1 frequencies reducing errors in multi-path environments and increasing speed of signal acquisition. These legacy L1 frequencies should not be confused with L1C frequencies which is the newest civil

GPS signal designed to improve signal reception in challenging environments such as cities [41]. GNSS receiver's performance is affected by the used frequency band [42].

In good conditions a modern GNSS can provide decimeter-level accuracy with 95% availability. The accuracy and availability of positioning are dependent on noise, signal interference, biases in clocks, biases in satellite orbits, hardware, physical obstructions, atmospheric conditions and even the movement of the earth's crust and tidal forces. Fortunately, some of these errors are greatly reduced with modern technologies, techniques, coordinate systems and services. For example, the biases in clocks that result from GNSS receiver having a deviation in system time in relation to the time in the clocks of the satellites can be reduced by gaining correction information updates about satellite time more frequently. Unfortunately, most of these errors still affect the positioning accuracy of GNSS to this day and cannot be completely eliminated. [1] [42]

Physical obstructions may reduce satellite visibility for the GNSS receiver which affects position fix availability and forces the receiver to use satellites that have worse satellite geometry. The closer the used satellites are to each other, the worse the satellite geometry. Physical obstructions may also lead to multipath error. Multipath is when satellite signals reflect off of physical obstacles before reaching the receiver. This leads to problems where the extra distance and delay caused by the signal reflection reduce the positioning accuracy. Many techniques to reduce the effect of multipath exist, but multipath still continues to be a problem in well obstructed environments. [43]

GNSS may also be used to calculate the velocity of the vehicle up to a 5 cm/s accuracy with basic receivers, improved to 1 cm/s accuracy by higher cost GNSS devices. Heading can also be measured using multiple GNSS sensors using the ambiguity resolution function. By using ambiguity resolution function, two GNSS antennas can reach an accuracy in heading that can be as accurate as 0.1 degrees horizontally and 0.4 degrees vertically. [1]

A GNSS system also has quality indicators that estimate the reliability of its positioning estimate. For example, the geometry of the used satellites can affect the precision of positioning. The satellite geometry refers to how the used satellites are positioned in relation to each other. The effects of satellite constellation geometry on positioning are referred to as "dilution of precision". Dilution of precision can be calculated for geometric dilution, horizontal dilution, vertical dilution, position dilution and time dilution. [44]

Machine learning has also been used to improve the positional data given by GNSS receivers in many different contexts. Hsu [45] showed that machine learning can be used to detect multipath error in received satellite positioning signals where there was no direct line of sight to satellites from the receiver. Since traditional multipath error detection and mitigation techniques do not work in contexts where there is no line of sight to the used satellites, the machine learning proved to be valuable improvement to positioning in physically obstructed environments.

2.3.1 Precise forms of GNSS positioning

In order to reduce GNSS error given by noise, biases and other significantly accuracy-reducing effects, some error correction and fault detection methods have to be used for decimeter level accuracy. By using techniques that measure the amount of carrier cycles between the satellite and the receiver, a centimeter-level accuracy is possible. Receivers that use this technique for positioning are called carrier-phase based differential global navigation satellite systems (CDGNSS). [42] [46]

Using satellite-based augmentation systems (SBAS) is a technique that can improve positioning of a GNSS system. In SBAS, monitoring stations relay correction information about orbits and clocks to SBAS satellites which broadcast the information from orbit to GNSS receivers. Most commonly used satellite-based augmentation systems are WAAS (United states), EGNOS (Europe) and MSAS (Japan). [1]

Code-based differential global navigation satellite systems use the correction information given by various services such as SBAS or a nearby reference station. The positioning accuracy of code-based GNSS navigation depends on the source of the correction information, though typically it is 1 to 2 meters. [1]

Precise point positioning (PPP) is a technique that corrects the errors of the GNSS system by using orbit and clock corrections that are estimated from global reference receivers. However, navigation systems may require many minutes for PPP convergence and are normally limited to decimeter level accuracy for automotive positioning. [42]

Real time kinematics (RTK) is a form of CDGNSS that improves positional accuracy by differencing signals of accurately known reference station and signals given by satellites. RTK is very limited since it requires a reference station to be within a few dozen kilometers. Network RTK or N-RTK uses multiple reference stations improving positioning in dynamic environments where the receiver is moving quickly. [1] [42]

Modern GNSS may also use a hybrid RT-PPP method that combines both PPP and RTK. RT-PPP works as long as a GNSS base station is within a couple of hundred kilometers. RT-PPP can provide positioning accuracy of 10 cm with a convergence time of less than half a minute. [1] [42]

3 Reliability, requirements and goals of GNSS systems for autonomous driving

3.1 Requirements for autonomous driving

According to Matthei et al. [47], a SAE-level 5 autonomous vehicle has at least 8 requirements that it must be able to handle in order to function properly: Operating, Mission accomplishment, Map data, Localization, Environmental perception, Cooperation, Safety and Self-perception. Operating means that the vehicle must be able to follow instructions given by a human such as go to a destination or stop immediately. Mission accomplishment means that the vehicle must be able to accomplish a mission such as a navigation task. Map data means that the car must have a map for route planning. Localization means that the car must be able to know its pose. Environmental perception means that the car must be able perceive the obstacles and actors in its environment. Cooperation means that vehicle car has to be able to react to the intentions of actors in the environment as well as communicate its own intentions to other actors. Safety means that the vehicle must not be of any danger to its environment. Self-perception means that the vehicle needs to be aware of its current state such as the capabilities of its components such as brakes or the engine and its current velocity.

GNSS is important for satisfying to many of these functional requirements and can be used together with other sensors to improve other functional requirements. GNSS is the only sensor that relatively easily provides absolute global positioning and as such it is paramount for navigational tasks. For localization, environmental perception, safety and self-perception GNSS can be useful when used together with other sensors and an accurate map. [47]

3.1.1 Localization requirements for safety

One common safety requirement of fully autonomous vehicle localization is one localization failure per one billion miles [42] or 10 localization failures per one billion hours [19]. There is much research that outlines the positional requirements for this level of safety. Research [19] about localization requirements for autonomous vehicles outlines an alert limit of 0.57 m laterally, 1.4 m longitudinally, 1.3m vertically and 1.5 degrees orientation for localization of passenger vehicles on highways. On local streets these alert limits need to be even tighter at 0.29 m longitudinally and laterally with 0.5 degree orientation alert limit for target level of safety at 10 localization failures per billion hours. This requires that the vehicles system knows lateral and longitudinal position with 0.1 meter accuracy, vertical position 0.43 m accuracy and orientation 0.17 degree accuracy 95% of the time. Stephenson [1] outlined the vehicle positioning requirements for autonomous vehicle active control to a position requirement of 0.05 meter lateral and longitudinal positional accuracy with an update rate of 500 Hz. Stephenson argued that high-quality GNSS can be enough for the required accuracy in the right circumstances if used together with a good inertial measurement unit with high update frequency. The positional error of the vehicle can be reduced further by using more sensors in conjunction with GNSS and IMU.

Reid et al. [19] defined the orientational alert limit on highways as 1.5 degrees in each direction to guarantee a 0.5 degree orientational accuracy 95% of the time. On local streets, the alert limit would have to be 0.5 degrees to guarantee a 0.17 degree orientational accuracy 95% of the time. An autonomous vehicle whose attitude error would exceed alert limits ten times or less in a billion hours of driving, would satisfy the orientational localization requirements for autonomous driving.

Used maps affect localization accuracy so the used maps should also be as accurate as possible for minimal positioning errors. Total localization of vehicle position can be calculated with $e_p^2 + e_m^2 = e_t^2$), where e_p is the positioning inaccuracy of the vehicle's sensors and e_m is the inaccuracy of the map used for localization. e_t is the total localization error. While a map with errors in centimeter level accurate would minimize the effect map inaccuracy has on localization errors, more inaccurate maps have also been proven useful for accurate localization. [42]

3.2 Evaluating positional data accuracy, reliability and availability

Accuracy is the deviation from true value. To know the accuracy of a positional estimate, one must also know the true position, or at least know the true position with more precision than the estimate. This is referred to as the ground truth. Most commonly accuracy is described with how large the deviation from true value is on average with standard deviations or root mean square error (RMSE) [1].

In the Cambridge University dictionary, reliability is defined as "how accurate or able to be trusted someone or something is considered to be" [48]. The reliability of sensors is a big part of how autonomous vehicles make decisions. A vehicle has to be able to know when it can or cannot rely on a sensor in order to make failure diagnoses and switch to backup mode. This requires that the vehicle can detect inaccurate or misleading data given by a sensor for one reason or another. [49]

Reliability of sensors is dependent on internal and external factors. Most sensors can provide some error/inaccuracy information of their data themselves using quality indicators, but sometimes it is necessary to compare the outputs of one sensor with other sensors in order to see if the data is faulty in some way [50]. For an autonomous vehicle's GNSS this means that the vehicle must be able to know when the positioning information is too inaccurate to be reliable and it should instead rely more on other types of positioning information. Reliability in GNSS systems is also sometimes referred as continuity which is defined as the probability that the GNSS will not provide a measurement of position over a certain time period. This also includes situations where an integrity monitor of the receiver discards good positional measurements as if they were inaccurate. [1]

Availability is the quality of being able to be used or obtained [51]. If data from a sensor is too inaccurate to be used or nonexistent, it cannot help an autonomous vehicle in its decision making process. GNSS is commonly known to have poor availability in obstructed places such as tunnels due to weak signal strength. Autonomous vehicles have to be able to rely on other sensors for positioning when one becomes unavailable, with dead reckoning for example. [6] Accuracy of 0.15m with availability of 95% means that 95% of the time, the error is less than 15 centimeters.

3.2.1 Trust and reliability evaluation

There are several methods of evaluating sensor reliability. One such method is to create a reliability evaluation function such as in [50] that takes into account the various factors that affect the "mistrust", "distrust", and "trust" of the sensor. These factors are then used to calculate the "trustworthiness" of the sensor using a model based on Dempster-Shafer theory. Some of the factors that affect the sensors trustworthiness are the operational factors, environmental factors, technical limitations of the sensor and security related factors.

There are many things that would affect the reliability of GNSS in the trust evaluation model proposed by Halla-aho et al. [50]. Many of those factors should be taken into account when calculating the reliability of the positional data. In terms of environmental factors, the ionospheric effects, the weather and multi-path errors caused by environmental objects would have to be taken into account. In terms of operational factors for GNSS positioning, the following should be evaluated: the continuity of positional data, supporting positional measurements of other sensors and the GNSS antenna wear. Security related factors would be the detection of GNSS spoofing and jamming. The technical limitations of the sensor would be dependent on the sensors capability to use advanced GNSS positional technologies such as differential GNSS. Once these factors are taken into account, the malfunctions and disturbances in the positional data of the sensor can be estimated and therefore used for safer decision-making in autonomous driving.

Trust evaluation of sensor data should be done before sensor fusion since it can affect the decision-making process of the vehicle [50]. The reliability of sensor data can also be used in sensor fusion, giving more reliable measurements more weight in the data fusion process. For example in map areas with few key environmental elements for LIDAR object recognition, GNSS measurements should be given more weight in localization sensor fusion such as with the experiments done by Miguel et al. [28].

3.3 Cybersecurity of autonomous vehicles

Cybersecurity should be a great concern in autonomous driving since if the integrity of the data and the system cannot be ensured, neither can safety of the vehicle. Threats to autonomous aspects of modern vehicles already exist. V2v and v2x systems can be hacked, GNSS can be vulnerable to jamming, spoofing and injection, and sensors are vulnerable to manipulation and interference. As the vehicles' systems gain more control of the movement of the vehicle, the more dangerous the attacks against those systems become. [52]

It is critical that the vehicle can detect attacks against its systems and is capable of informing the driver in case the autonomous driving is compromised. For example, the auto-landing systems of civilian aircraft monitor the vital parts of transmissions and if any significant deviation in transmission is detected, the auto-landing systems are disabled and the pilot is notified to take control. Safety measures such as these could benefit autonomous driving. [53]

Like all computers, the computer of the autonomous vehicle is susceptible to not only bugs in software/hardware but also to malware installed in components by malicious actors. Basic information security should not be overlooked anywhere, but especially not in places where human lives are at stake. Network connections should be protected by a firewall and received data, such as map data, should be authenticated and encrypted. [54]

Many modern cars use the controller area network (CAN) standard for in-car communication. CAN is a dated protocol and its vulnerabilities are well proven if an adversary gets an access to the network. It has been demonstrated that brakes can be disabled, doors locked or engine turned off all while the driver's input has been completely shut off [53]. Since CAN is very vulnerable to security threats, it should be well protected against all incoming connections. CAN bus message encryption is one way to make the system more secure [3].

There are some privacy concerns regarding autonomous vehicles data collection. Autonomous vehicles may use connected networks and share geographical location data with v2v and v2x communication networks. It is not exactly clear what sort of data may need to be collected and shared in the name of safety of autonomous driving. Additionally, passive attacks that do not modify or add data to vehicles systems are hard to detect and may become a privacy problem for autonomous vehicles that store a large amount of personal data of their users. [52]

3.3.1 Cybersecurity of sensors

It has been demonstrated that modern GNSS receivers are vulnerable to various different attacks. Even sophisticated GNSS receivers can be spoofed with advanced attacks despite many defence strategies. There is also concern about unintentional signal interference and jamming of GNSS signals. Manipulating GNSS may affect the decision making of autonomous vehicles badly enough to make them do unsafe or even dangerous maneuvers. Many different countermeasures against GPS spoofing have been proposed such as encryption-based carrier phase measurements and using signal processing to find misleading signals. [1] [54] [55]

Petit and Shladover [54] defined various potential attacks on the sensors of autonomous vehicles. The LIDAR of a vehicle can be jammed. The camera is vulnerable to blinding by IR lasers and errors in machine vision such as fake images or mislabeling actors. Sensors such as radar can be jammed or even made to believe the existence of a "ghost vehicle" that is just noise created by a digital radio frequency memory repeater. Maps can be "poisoned" with erronous data, leading to potentially large problems in navigation and localization [56]. Even inertial measurement units that are relatively isolated systems can be vulnerable to remote attacks via strong magnetic fields [3].

Systems can be equipped to detect many of these attacks on vehicle sensors, but some of these attacks on sensors are best mitigated by compensating erroneous sensor data with data from other sensors since it is much more difficult to attack multiple independent data sources simultaneously; Even multiple units of a same kind such as multiple cameras are more resistant to errors and attacks. In cooperative autonomous driving, the information provided by other actors can be treated as another data source but should be less trusted due to the fact that the source of data is outside the vehicle [54]. If there is suspicion of a potential attack on a sensor of an autonomous vehicle, its measurements should be trusted much less than the measurements of other sensors [50].

Physical access to vehicles gives malicious actors even possibilities to sabotage autonomous vehicle systems that are resistant to remote attacks. Even if direct mechanical tampering is not included, there still is the possibility of malware being installed, sensors being manipulated or tracking devices attached to the vehicle. [54]

4 Research methodology

4.1 Data collection process

There were two sets of empirical experiments done for this thesis that evaluated and improved the positioning accuracy of a vehicle. The first one was an experiment done with a consumer-grade GNSS sensor mounted on the door of an automobile that was driven multiple times on multiple occasions over a particularly well measured road segment where the absolute position of the road was on the decimeter level. The second experiment was done with a truck that was equipped with a GNSS, an IMU and a LIDAR. While the truck was was capable of autonomous driving, it was driven by a human during the experiment. In both experiments a digital priori map was used for road geometry.

In the first experiment the automobile was driven accurately over the road lane boundary in such a way that the GNSS device was just above the lane's edge. The accuracy of the road lane width in the digital map was confirmed to be on the centimeter level by measurements done on site with standard measuring tape. In the first experiment the error of the driver over the boundary was constantly an order of magnitude below the error of the measuring sensors. The first experiment contained drives at different speeds at different times of day as well as in different weather conditions. Inertial measurement sensors of a smartphone were also used during some of the drives. Inertial measurements included data from an accelometer, a gyroscope and in the case of the first experiment, a magnetometer. The vehicle used for the first experiments was a stock Volvo automobile. The data for the first experiment was collected in December 2021 and January 2022.

For the second experiment a LIDAR sensor was used alongside a GNSS device and inertial measurement unit. The truck was driven normally along the center of a lane on a highway and the distance to the nearest road curb was measured using the LIDAR. The data for the second experiment was collected in February 2022.

Figure 4.1: The vehicle used for the first experiment

Figure 4.2: The GNSS used for the first experiment

The testing environment for the first experiment was a road called Tuulissuontie in Turku, Finland. The road has very few buildings nearby, but it does have a small forest and a hill nearby which may cause some multipath errors. The length of the road segment used in the experiments was approximately 1 and a half kilometers long with gentle curves and slopes. The lane width of the road segment was 350 cm. The total distance traveled during the recorded drives was approximately 30 kilometers with standalone GNSS sensor and approximately 5 kilometers was driven with both GNSS and IMU sensors.

Figure 4.3: The truck and its LIDAR sensors used for the second experiment

The testing environment for the second experiment was the route from Rajamäki to Hyvinkää in Finland. The width of the road from curb to curb was between 7 and 9 meters, depending on the location. The route provided both a highway environment and an urban environment. The total distance travelled during the second experiment was approximately 15 kilometers. GNSS, IMU and LIDAR were used for the whole length of the drive.

4.1.1 Processing the gathered data

The empirical experiments primarily focused on the lateral accuracy of vehicle positioning. For the first experiment, by using the painted lane boundary as ground truth vehicle trajectory, the lateral error of system positioning could be calculated. For the second experiment, a LIDAR was used to measure distance to the road curb and the distance of GNSS positioning to the curb in the map were combined to estimate lateral error of the positioning. In points of high curvature, the longitudinal error of positioning also played a role in the calculated lateral positioning error. Maps used for experiments provided lane widths, road geometry and road locations necessary for empirical testing. Two different priori maps were used for measurements. First one had road absolute position error below one meter and the second one had road absolute position error above one meter. In addition to horizontal and vertical position data, data of the GNSS receiver's velocity and angle was collected. Various quality indicators present in the receiver's collected data were also used for algorithms and analysis. All GNSS data used in the experiments were parsed from the recorded NMEA 0183 messages provided by the devices. NMEA 0183 is a standard protocol commonly used by satellite navigation devices to log position, altitude and speed information of the receiver [57].

First the accuracy of raw GNSS measurements in both experiments was evaluated using both maps. The Digiroad map provided a more accurate map and the OpenStreetMap map provided a more inaccurate map. Road geometry of the map data in both instances comprised of geographic information system (GIS) polyline geometry. In polyline geometry, nodes are connected form a line that represents a road in a map. Both maps used the WGS84 coordinate system which is an ellipsoid representation of the earth where the center of the ellipsioid is within a few centimeters of earth's center of mass [1]. The GNSS of the experiment also used the WGS84 coordinate system for latitude, longitude and altitude fix. Lateral error of the localization was calculated by measuring the distance of the position fix to the right lane boundary of the road.

Next the accuracy of measurements with sensor fusion of the IMU and the GNSS of both experiments were tested by using extended Kalman filter. The initial state vector and the covariance matrix of the extended Kalman filter were approximated using the initial measurements of the sensors as well as trial-and-error to achieve the best results. The tuned covariance matrix parameters were magnetometer bias, magnetometer noise, accelometer bias, accelometer noise, gyroscope bias, gyroscope noise, GNSS position noise and GNSS motion noise. The angle of motion of GNSS for the filter was calculated from the difference of two consecutive positions and the velocity of motion which was provided by the GNSS velocity measurements.

After that, a trust algorithm was used to evaluate the trustworthiness of sensor readings based on sensor data continuity, quality indicators of sensors, disagreements of sensors' measurements and previous trustworthiness values. The extended Kalman filter was fed sensor data with different covariance values based on the "trustworthiness" of the sensor data. Sensor data with high trust value was considered more robust and sensor data with low trust value was considered less accurate and in the worst case, the data was discarded. In an ideal world, the trust algorithm would always be able to tell if the sensor data was reliable enough to be accurate and use only the accurate data for localization. However, in the real world, that is not possible and sometimes even unreliable measurements are accurate by pure chance. Additionally, if all data deemed inaccurate was discarded, the vehicle could be left without any localization data for long periods of time and this would decrease the availability of positioning. In this experiment, the calculated sensor measurement trustworthiness is a value that gives different weights to kalman filter sensor reading covariance values.

The unreliable sensor measurements were more likely to be inaccurate so they had higher high noise values. Reliable sensor measurements were given lower noise values in the Kalman filter. The used algorithm for trust calculation was simple total value from 0-100 based on the average value of each calculated trust parameter. There were 4 trust parameters for GNSS measurements and 3 trust parameters for IMU measurements. First trust parameter for GNSS is the continuity trust measurement. This was calculated by evaluating the velocity of GNSS and the distance between two consecutive GNSS measurement positions. If the distance between the two points is greater or lower than the distance that would be traversed with the measured velocity, the continuity trust parameter would get a low value. The second trust parameter of the GNSS is the environmental trust measurement. The environmental trust is affected by the satellite geometry, amount of used satellites, used satellite constellations, type of fix, SNR of used satellites and weather. A trust parameter which affects both IMU and GNSS is the effect of previous trust values. A measurement that is deemed unreliable is more likely to be followed by another unreliable measurement than a reliable one. Another trust parameter which affects the trust values of both GNSS and IMU measurements is independent supporting measurement trust. If the vehicle heading change of two consecutive GNSS measurements matches the yaw rate of the gyroscope and if the accelometer measurements match the change in GNSS measured velocity of the vehicle, the sensor measurement of both sensors are deemed more reliable. Last trust parameter is the supporting measurement trust of the IMU's rotation based on the change in orientation measured by the magnetometer and the change in orientation measured by gyroscope. These trust parameters are summarized in table 4.1.

Results of the effects of positioning improvement techniques are detailed in sixth chapter.

Trust parameter	Affected sensors	description
Continuity	GNSS	Evaluate how much the position diverts from measured velocity.
Environment	GNSS	Evaluate how much poor satellite conditions affect position accuracy.
Previous trust	GNSS / IMU	Measurements with poor trust values are more likely to be followed by unreliable measurements.
Supporting independent measurements	GNSS / IMU	Independent measurements that agree with each other are more likely to be accurate.
Supporting measurements	IMU	Rotation rate in both gyroscope and magnetometer indicate reliable measurement of vehicle rotation.

Table 4.1: Trust evaluation parameters

4.1.2 Capabilities and limitations of the experiments

There are some limitations to the accuracy of the results of the experiments. In the first experiment, the accuracy of the driving on the road lane can only be guaranteed to be within two decimeters of the ground truth. In the second experiment, the accuracy of the LIDAR was highly dependent on the method of detecting the road curbs and during intersections, it became difficult to estimate the lateral error of the vehicle. In both experiments the inaccuracies of the digital map could have also distorted the accuracy of the results. Additionally, selected Kalman filter covariance values may not be the optimal and better results are possible with more optimal covariance values.

The trust algorithm used in the experiments only evaluated the reliability of IMU and GNSS sensors and assumes that the used map and LIDAR data is accurate. However, the errors introduced by momentary inaccuracies in both the map and the LIDAR could introduce significant errors in the measurements. An autonomous vehicle should be able to detect if the used map was inaccurate and maybe even evaluate the reliability of the used map. There also was snow on the road during the second experiment. The snow that piled on the edge of the road helped detecting road curbs, but it also may have increased the inaccuracy of the LIDAR distance measurement to the curb.

In addition to these limitations, the experiments were limited by the amount of measurements and data. While the results provide a certain level of positioning accuracy for the used systems and techniques used seem to improve the lateral accuracy of the positioning, the amount of data is not enough to guarantee that those levels of positioning accuracy could be consistently achieved by the system or that the techniques used would generally improve the positioning of the system.

4.2 Used resources

For the first experiments an NL-8004U GNSS receiver was used for satellite positioning measurements. The GNSS receiver was able to use GPS, Glonass, Galileo and QZSS satellite constellations for satellite positioning. SBAS (EGNOS system) integrity information was used as well as differential GNSS whenever a differential GNSS fix was possible. The update rate for the receiver was 5 Hz. The GNSS receiver was capable of receiving L1C (GPS), E1 (GALILEO) and L10F (GLONASS) frequencies from the satellite constellations. Receiver used on NAV5 "automotive" dynamic model during the experiments which is a setting on the used GNSS device that improves the position measurement while moving. The IMU used for the first experiments was an ICM-20690 model chip of a Huawei P20 EML-L29 smartphone. The smartphone was attached to the approximate center of the vehicle with tape. The gyroscope, accelometer and magnetometer data from the phone was gathered with a GNSS/IMU logger application.

For the second experiment a u-blox GNSS receiver, a Murata SCHA600 (gyroscope and accelometer) and Ouster OS-1 LIDAR were used. Accuracy of the LIDAR is advertised to be on the centimeter level [58]. The gyroscope is reported to have an root mean square (RMS) noise below 0.007 °/s and the accelometer is reported to have RMS noise below 0.0029 m/s^2 [59]. The GNSS ran on 1 Hz, IMU ran on 100 Hz and the LIDAR ran on 10 Hz.

Matlab was used for the analysis of the collected data. In addition to the code written specifically for the experiments various Matlab toolboxes were used to assist in data analysis. Sensor fusion and tracking toolbox, Satellite communications toolbox, Navigation toolbox, Mapping toolbox, Statistics and machine learning toolbox and Automated driving toolbox were used.

The QGIS mapping software was used to parse the Digiroad map data into an esri shapefile format that was compatible with Matlab as well as to calculate the altitude values of the road used for experiments. U-center v.8.23 software was used for the configuration of the GNSS receiver and the recording of satellite positioning data for the first experiments.

4.2.1 Used maps

The Finnish free access road database Digiroad was used for the locations and sizes of roads in the environment. The coordinate system of the geometric elements was transformed into WGS84 format with QGIS. Digiroad provides maximum absolute position error values for its road locations. It also provides the widths of the lanes, the altitude of the road and the width of the road. The Digiroad map is based on the layered GIS mapping model. [60] [61]

The OpenStreetMap open data map was used to compare the effects of map accuracy on the localization of the system. Global position errors of road geometry in OpenStreetMap can reach multiple meters [32]. OpenStreetMap road positions and geometry are measured by using aerial imagery and satellite navigation receiver tracklogs. [62]

5 Results of experiments

5.1 Resulting localization accuracy and results of improvements of the first experiment

The raw positioning data of the first empirical experiments resulted in GNSS lateral localization accuracy of 1.30 meters root mean square error (RMSE) and 95% of measured values had lateral error less than 2.37 meters. Positioning fixes where the velocity was below the median speed (10 m/s) were laterally 36% more accurate than positioning fixes where the velocity was over 10 m/s. Positioning accuracy improved by 9% if the amount of satellites used for the position fix (13 satellites) was above the median. Positioning accuracy improved by 5% if the mean signal-to-noise ratio (30.07 dB-Hz) of used satellites was below the median. Figures 5.1, 5.2, 5.3 and 5.4 provide information about the lateral error of the GNSS positioning of the vehicle during the drives of the first experiment.

By using sensor fusion with extended Kalman filter, the lateral error in the position fix was reduced by 23%. In the drives where sensor fusion was used, the RMSE lateral accuracy was reduced from 2.06 m to 1.84 m.

By using trust based sensor fusion weighting, the average lateral error in the position fix was reduced by 5%. The greatest localization improvements were seen in positions where the vehicle was turning in a curve, so the heading change rate of GNSS positioning and IMU were different enough to warrant lower trust value for

GNSS. With trust based sensor fusion weighting the RMSE error was reduced to 1.79 meters from 2.06 meters. In certain moments, the trust function worsened the positioning result either by misevaluating reliable measurement as unreliable or by

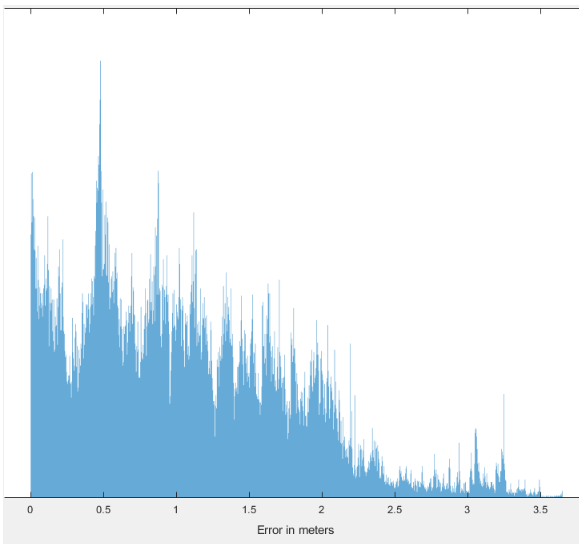

Figure 5.1: The lateral error of GNSS of the first experiments

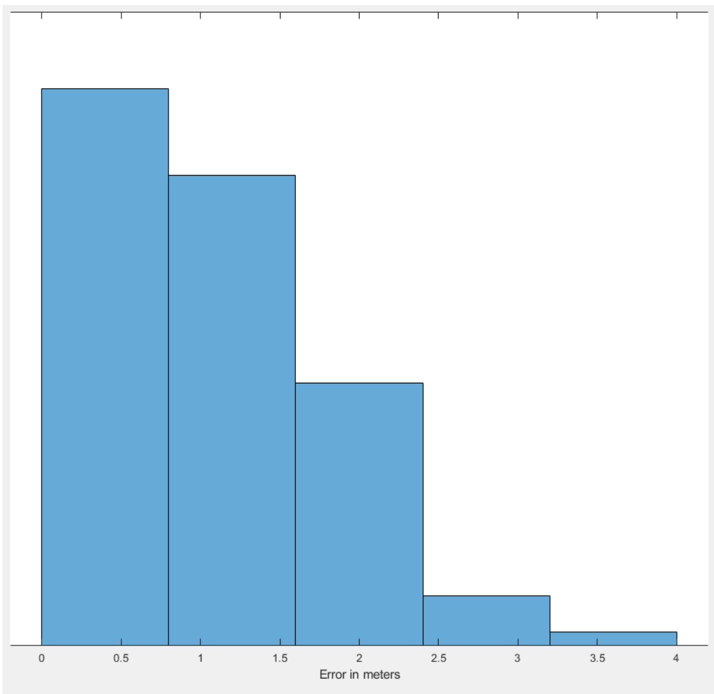

Figure 5.2: The lateral error of GNSS dived into sections of the first experiments

chance where unreliable measurement turned out to be accurate. Figures 5.5 and 5.6 provide information about the lateral error of the GNSS when sensor fusion with and without trust function was used.

By using the more likely to be inaccurate map data of OpenStreetMap instead

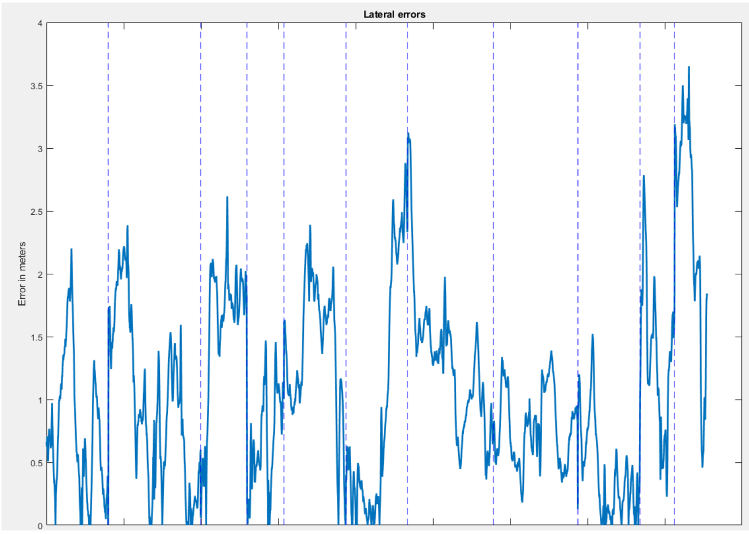

Figure 5.3: The absolute lateral error of GNSS for each drive of the first experiments. Each drive is separated by a line.

Figure 5.4: Drives of the first experiments as lines on a map.

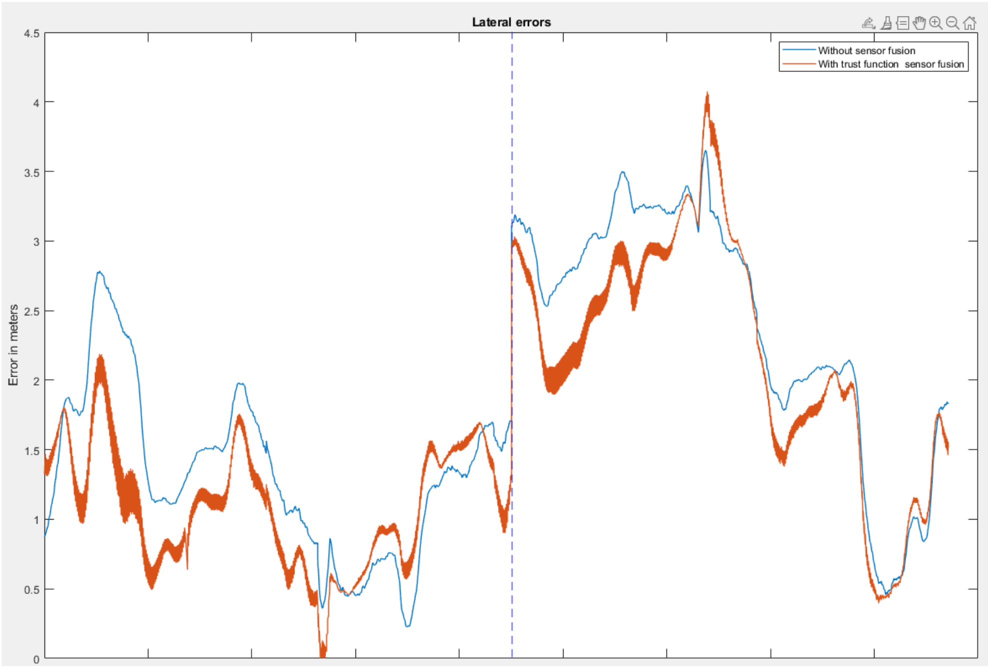

Figure 5.5: The lateral error of GNSS of the first experiments with and without IMU EKF sensor fusion.

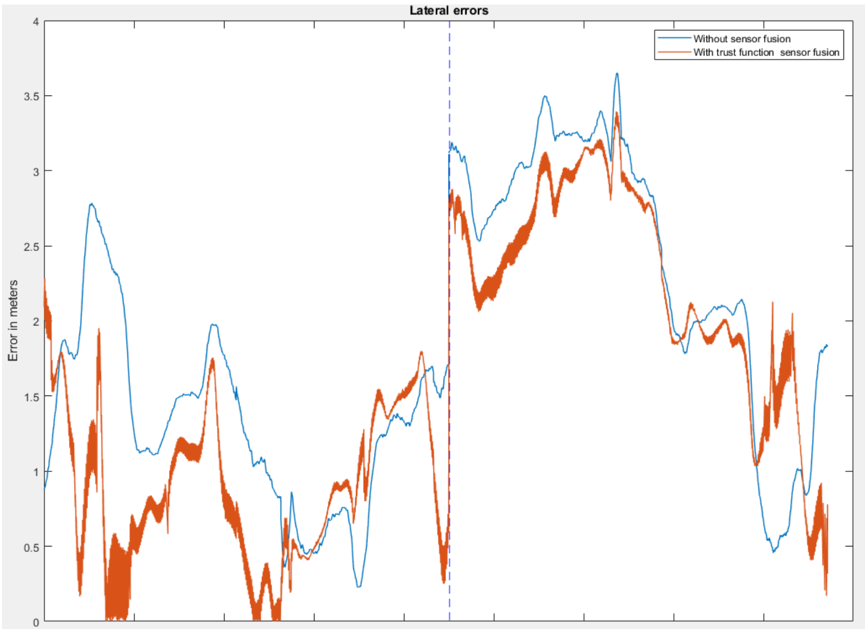

Figure 5.6: The lateral error of GNSS of the first experiments with and without IMU sensor fusion when using trust based EKF covariance weighing.

of the more accurate Digiroad, the inaccuracies of lateral positioning increased by 62% in the first experiments. At their worst, the lateral errors in positioning could reach above 5 meters by using OpenStreetMap.

5.1.1 Implications of results in regards to autonomous driving

The alert limit in the environment of the first empirical experiment should be 0.29 m laterally with 0.5 degree orientation accuracy as per chapter three. For safe autonomous driving, this alert limit should only be exceeded once in a billion miles. Raw GNSS measurements achieved this level of lateral positioning accuracy with 14% availability.

However, for lane-level localization, error below one and a half meters is enough. This level of lateral accuracy was achieved with raw GNSS measurements with 72.4% availability in the first experiment. The maximum lateral error measured was 3.65 m which does satisfy the requirement for basic navigation, but is not enough for lane-level autonomous driving [1]. During the drives in which sensor fusion was used, the lane level fix availability of the system increased from 40.5% to 50.03% by using extended Kalman filter sensor fusion with IMU. Using trust based sensor fusion weighting did not improve the lane level availability of the positioning.

While the results of consumer grade GNSS and IMU positioning alone does not prove to be accurate enough for high level autonomous vehicle applications, They do provide some level of usefulness in autonomous vehicles where the localization relies less on those sensors. Lane level determination is useful for level 2 autonomous vehicle architectures and independent sensor output proves useful to improve autonomous system robustness especially during moments where other sensors are compromised [42]. Reliability evaluation of sensor measurements may prove important in autonomous vehicle decision making in addition to the localization accuracy improvement it seems to provide.

5.2 Resulting localization accuracy and results of improvements of the second experiment

If errors given by inaccurate LIDAR road curb detection and large map inaccuracies are not ignored, the Raw GNSS positioning provided a lateral positioning accuracy of 1.39 meters. 95% of those values were below 1.42 meters. By combining the GNSS with IMU by using EKF sensor fusion, the RMSE was reduced to 1.28 meters and 95% of lateral error values were below 1.19 meters.

If the inaccuracies in measurements caused by LIDAR road curb detection caused by intersections, bus stops, road widening and other roadside objects are ignored as well as measurements in those positions where the digital map's road was clearly over a meter off the ground truth road position, the RMSE of raw GNSS was reduced to 0.82 meters. In this scenario, the EKF sensor fusion reduced lateral error RMSE to 0.67 meters. Figures 5.7, 5.8 and 5.9 provide information about the lateral error of the GNSS positioning of the vehicle during the drives of the second experiment. Figure 5.10 shows positions where the road geometry provided by the map does not follow the center of the road properly which caused some of the smaller errors in some parts of the experiment.

The used LIDAR sensor could also be used to measure the width of the road to a certain extent. The LIDAR agreed with the road width described on the map with an error of 0.5 m 67.8% of the time and with an error of 1.5 m 94.8% of the time. Intersections and bus stops were the causes of largest differences in the measured road width and the road width provided by the map. The measurement of the road width could be used as an additional trust parameter of either LIDAR accuracy or the map accuracy. Figure 5.11 shows the difference between LIDAR measured road width and the road width provided by the Digiroad map. Figure 5.12 shows LIDAR images, red spots on the point cloud show measured road curb spots. Images A and B on the figure 5.11 show measurements where road curbs are easily detected and the measured road width matches the road width of the map. Images C and D on the figure 5.12 show measurements where road curb detection is difficult and the measured road width is poor in quality.

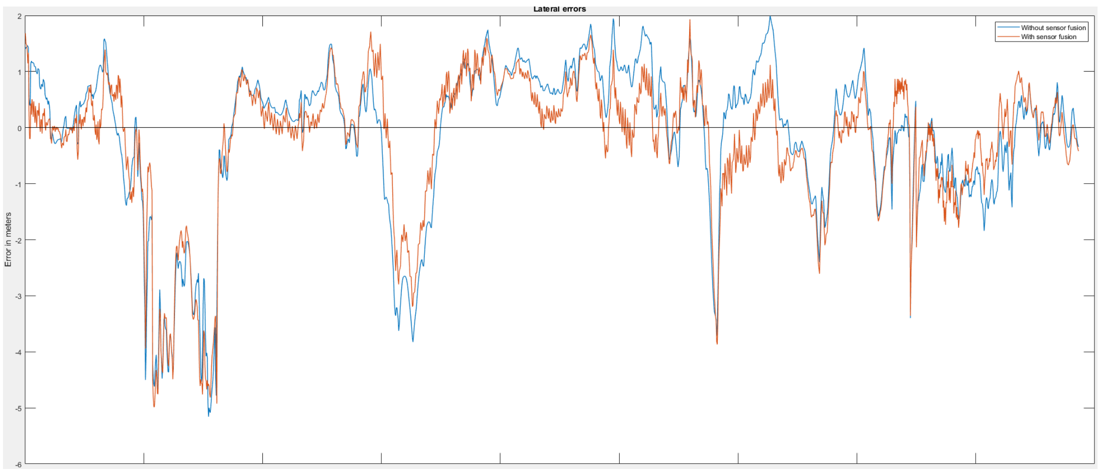

Figure 5.7: The lateral error of GNSS of the second experiment with and without IMU sensor fusion including the erroneous measurements. The black line represents evaluated ground truth.

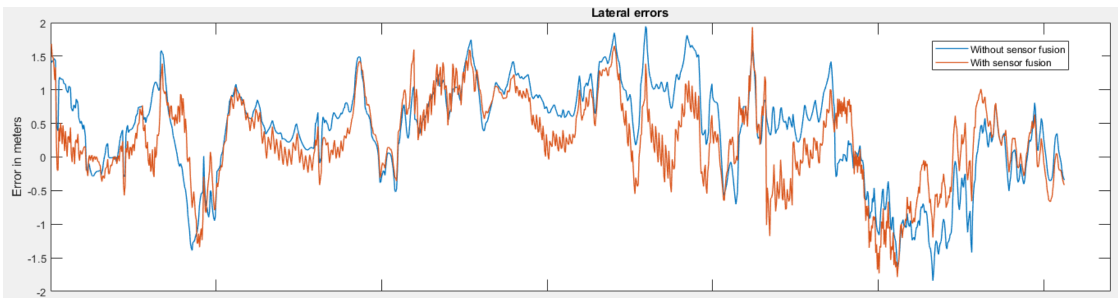

Figure 5.8: The lateral error of GNSS of the second experiment with and without IMU sensor fusion without the erroneous measurements.

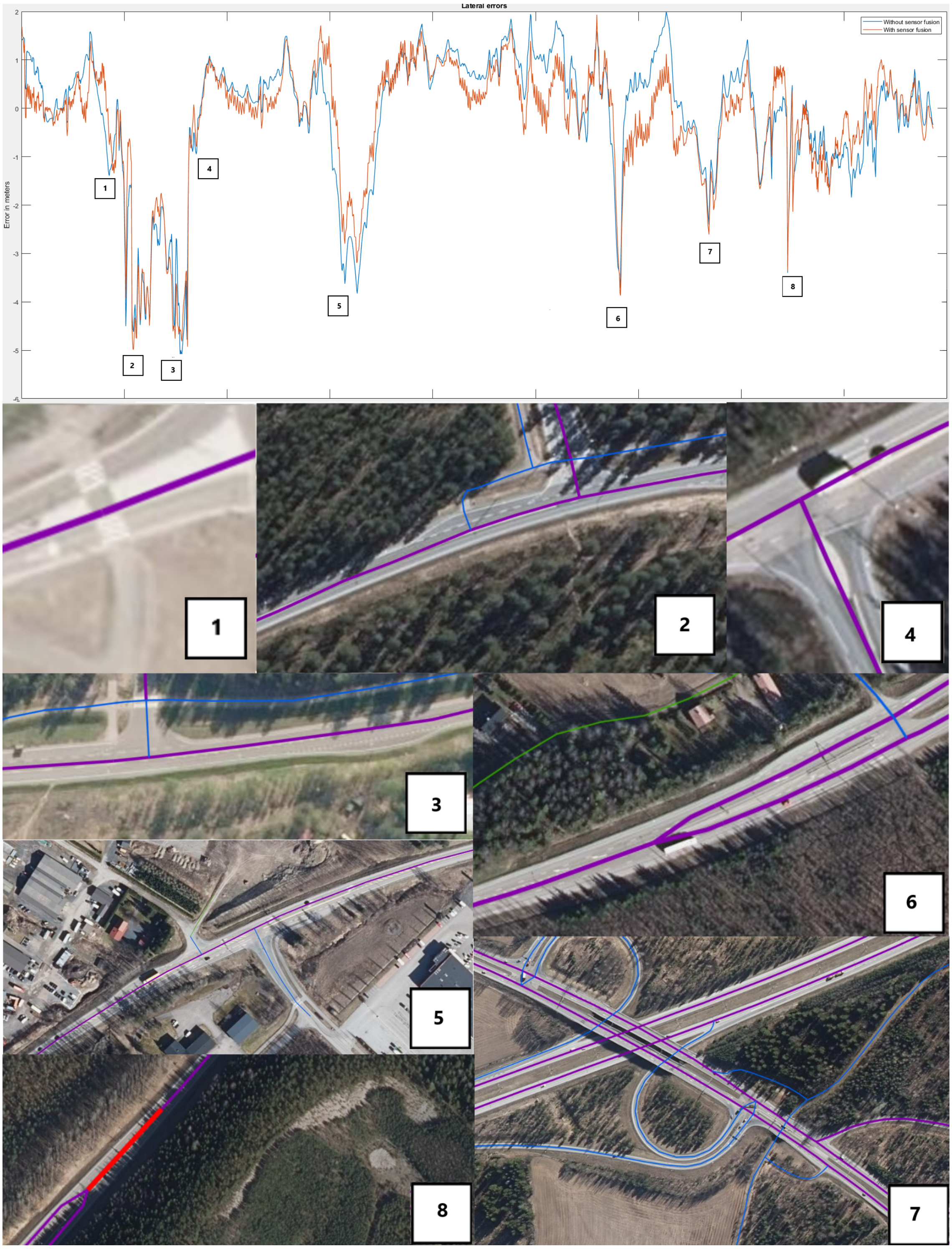

Figure 5.9: The sources of largest erroneous measurements in the second experiment.

Figure 5.10: Road positions on the map that do not follow the center of the road.

Figure 5.11: LIDAR measurement of road width compared to road width provided by the map.

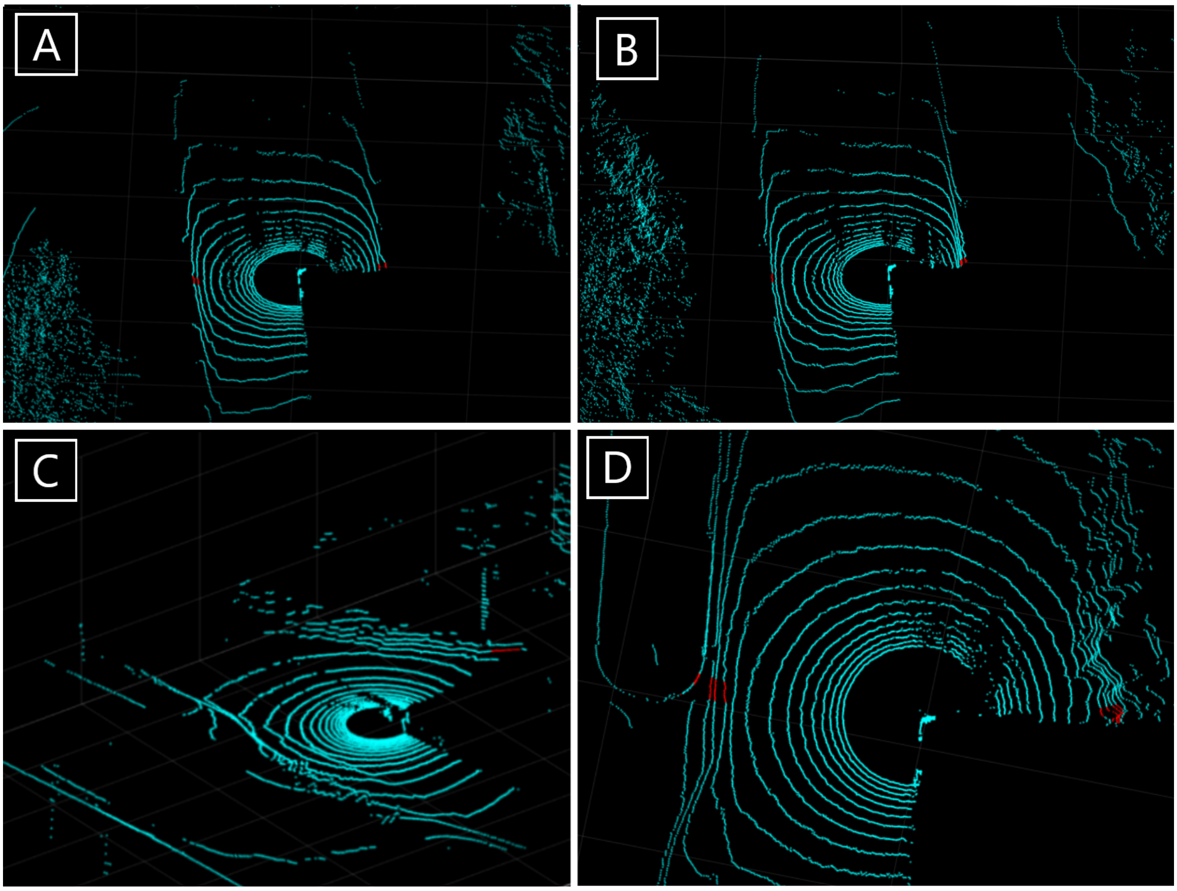

Figure 5.12: LIDAR point cloud measurements with red spots as measured road curbs.

5.2.1 Implications of results in regards to autonomous driving

For autonomous driving, the alert limit in the environment of the second empirical experiment should be 0.57m laterally with 1.5 degree orientation accuracy as per chapter three. Raw GNSS measurements were within this alert limit with 53% availability if the largest causes of errors on the map and LIDAR curb detection were ignored. Sensor fusion with IMU increased the level of 0.57 meter positioning availability to 68%. For lane level localization, the GNSS sensor could provide 1.5 meter accuracy with 96.4% availability and when combined with IMU sensor, this availability increased to 99.1%. Figure 5.13 visualises the lateral error of GNSS with and without sensor fusion in relation to the accuracy required for safe autonomous driving.

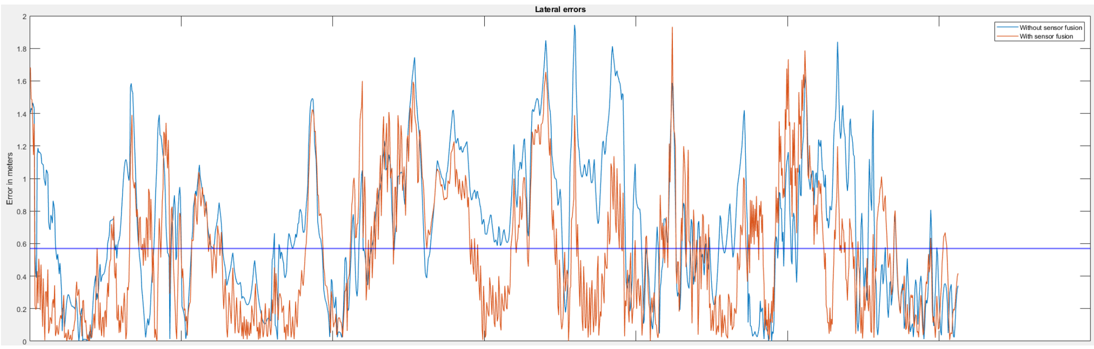

Figure 5.13: The absolute lateral error of GNSS of the second experiment with and without IMU sensor fusion without the erroneous measurements. The blue line is 0.57 meters lateral error.

6 Comparisons of results to results of other research

6.1 Localization accuracy results of other research

There exists much empirical research about the accuracy of various different GNSS receivers and their reliability in autonomous driving. The results in different studies vary greatly and are dependent on many factors such as the used equipment, the used algorithms/technologies and the location of testing.

In 2019, Humphreys et al. [46] achieved a 17 cm level 3D accuracy with 95% probability in urban environments for 2 hours using GNSS with real time kinematics (RTK) in an urban setting. The GNSS used GPS and Galileo satellite constellations. This level of accuracy is attributed to well performing real time kinematic GNSS positioning that was specifically tailored for deep urban environments. In their experiments, a GNSS solution was available over 87% of the time.

In 2018, Reid et al. [63] reported about GNSS performance on a drive of 30,000 km on North American highways. The research used one production-grade GNSS and one survey-grade GNSS. The survey-grade GNSS achieved 1.05 m horizontal accuracy with 95% probability. The production-grade system achieved 5.30 m horizontal accuracy with 95% probability. Vertical accuracy was 9.42 meters with 95% probability for the production-grade GNSS and 1.34 meters with 95% probability for the survey-grade GNSS. The survey-grade GNSS was capable of lane determination level accuracy (< 1.5 m) 98.1% of the time and had RTK fix for positioning nearly 50% of the time. The production grade GNSS used L1 frequencies and the survey grade GNSS used both L1 and L2 frequencies for position fix.

Joubert et al. [42] reports that Swift Navigation data collection campaign in 2019 collected data from a 1,300 km drive with Code-based differential GNSS capable navigation system. The GNSS achieved 0.35 m accuracy with 95% probability over the 12 hours that the drive lasted. The GNSS used L1 + L2 frequencies and GPS + Galileo satellite constellations. The experiments were mostly done in highway areas.

In 2020, Nie et al. [64] achieved a 0.32 m horizontal and 0.17 m vertical accuracy with a low-cost dual-frequency GNSS device in an automotive experiment by using dual frequency PPP. Their method combined dual-frequency measurements with single-frequency ionosphere corrected code measurements to improve positioning accuracy and the time it takes to achieve accurate position fix. Their device used both L1 and L2 frequencies.

Prochniewicz et al. [65] achieved horizontal accuracy of 0.20 m with 95% availability with RTK over a day. The GNSS was not specified to be in motion. The experiment evaluated the accuracy and reliability of the positional data by using quality indicators such as the amount of visible satellites, satellite geometry, noise and the applied method of ambiguity estimation.

All of these experiments used a GNSS device in a automotive environment proving that it is possible to reach decimeter levels of GNSS positioning accuracy with autonomous vehicles. The best accuracies were achieved with RTK corrections. However, the 0.1 meters or less lateral/longitudinal accuracy with 95% probability specified in chapter three is not achieved in these experiments with a stand alone satellite navigation device.

Wan et al. [15] achieved 0.1 m RMSE accuracy with sensor fused GNSS RTK, LIDAR and IMU. The data was gathered with a 60 km drive in an urban environment with real traffic. Their method also used a pre-built single Gaussian distribution model LIDAR map of the area. The used map is a form of a 3 dimensional point cloud map. The sensor fusion used an error-state Kalman filter with strap-down inertial navigation system (SINS) prediction model to fuse the data of the sensors.

In 2016, Cornick et al. [66] achieved 4 cm RMSE localization accuracy using a localizing ground penetrating radar (LGPR) aided by GPS and IMU. The localization tests were done in an optimal environment for the sensors and a RTK GPS with IMU was used for the ground truth. For map creation, the car was first driven in a loop around the driving area with an LGPR that recorded the subsurface environment of the road. This map was then used with the LGPR to localize the vehicle.

In 2014, Wolcott et al. [67] achieved a root mean square deviation localization accuracy of 0.14 m laterally and 0.19 m longitudinally. This was achieved by using a single camera for localization in a high-quality LIDAR generated map. GPS was also used for corrective positional updates and initial position. The localization accuracy of the system was significantly worse in an area with infrequent lane markings.

Miguel et al. [28] used an adaptive Monte Carlo localization with LIDAR, GNSS and IMU along with an environmental map for a localization experiment. The standard deviation of the localization error was 0.18 m. Their method could handle maps that had parts where there was less key elements in the environment by switching between GNSS and LIDAR priorities depending on the amount of nearby key features in the map.

Li et al. [68] used 3d-point cloud matching with NDT (Normal Distributions Transform) for localization with LIDAR, IMU and GNSS. GNSS was used to measure the initial position of system. It was also used for destabilization detection. The experiment used an accurate map that was manually corrupted with noise and missing data to simulate inaccuracies of real 3d maps. The results for localization errors were a standard deviation of 0.1 m both laterally and longitudinally.

Wolcott et al. [5] achieved a 0.07 m RMSE horizontal localization accuracy for a 525 km drive by using LIDAR and IMU. The system used in the experiment was more resistant to errors caused by poor weather and other dynamic changes in the environment. The map used for localization was a Gaussian mixture map that was created with a high-quality LIDAR, IMU and GPS.

Ort et al. [31] studied the accuracy of the trajectories that an autonomous vehicle would take when using a less accurate topological map such as OpenStreetMap. The vehicle used Lidar, GPS and IMU sensors and 99.3% of the vehicle's predicted driving trajectories were within road boundaries (3 m). The driving trajectories were predicted up to 35 meters ahead. Additionally, the largest deviations in accuracy were typically far ahead in the road. The results had a 0.75 m RMSE deviation from the road center.

Altoaimy and Mahgoub [69] researched v2v localization with vehicular ad hoc networks (VANETs) and GPS systems by using fuzzy logic and WCL (weighted centroid localization). when localizing the vehicles, their distances to each other, their heading and SNR was taken into account during the information exchange between vehicles. The research tested 20 to 200 vehicles and localization accuracy was better the more vehicles were in the network. A localization accuracy of 0.85 meters was achieved with 20 vehicles and an accuracy of 0.25 meters was achieved with 200 vehicles.

Conde et al. [70] studied vehicle-to-infrastructure (v2i) communication based localization with GNSS and WAVE communication devices in 2015. By using relative positioning techniques with double differencing, they achieved a localization accuracy of 0.698 meters RMSE in their experiments. However, the orientation error was over 7 degrees in heading and over 40 degrees in roll on average. The orientations were estimated by placing two GNSS receivers longitudinally on the cover of the vehicle so that the distance between them was maximised. Then the differences in the position data of the receivers was used to estimate orientation of the vehicle.

In 2019 Atia et al. [7] achieved 0.2667 m RMSE horizontal positioning error with map-aided adaptive extended Kalman filter fusion of GNSS and IMU with maximum horizontal positioning error of 0.8456 m. The sensor fusion technique used in the paper used map matching and error and bias mitigating adaptive filtering to achieve accurate positioning.

Some of these experiments show that by using sensor fusion with high quality devices with high quality maps, a 0.1 or less meter lateral/longitudinal accuracy with 95% probability specified in chapter three is possible. There are many different approaches to the autonomous vehicle localization problem but no method so far has proved to be the objectively optimal solution in terms of accuracy, availability and reliability. The results of the experiments of other research are summarized in table 6.1.

6.2 Comparisons to our measurements

Reid et al. [63] achieved a lateral accuracy of 0.73 m with survey-grade RTK GNSS and a lateral accuracy of 3.88 m with standard automotive GNSS. The automotive GNSS achieved a "which lane" accuracy ($<$ 1.5 m) with 56.7% availability. The RTK GNSS achieved "which lane" accuracy ($<$ 1.5 m) with 98.1% availability. When compared to our non-processed measurements of the first experiments, our standalone GNSS performed better than the classical automotive GNSS, however it was well outperformed by the RTK GNSS. The same is true for the second experiment. However, with sensor fusion the second experiment outperformed the RTK GNSS in terms of lane determination (99% availability).

When looking at the improvements extended Kalman fitler (EKF) sensor fusion

Table 6.1: Summary of results of other research

Experiment	Used sensors	horizontal accuracy
[46] - 2019	RTK GNSS	0.17 m 95% availability
[63] - 2018	GNSS/RTK GNSS	1.05 m 95% availability
[63] - 2018	GNSS	5.3 m 95% availability
[42] - 2020	CDGNSS	0.35 m 95% availability
[64] - 2020	PPP GNSS	0.32 m
[65] - 2016	RTK GNSS	0.20 m 95% availability
[15] - 2018	RTK GNSS	0.1 m RMSE
[28] - 2020	RTK GNSS/Lidar/IMU	0.18 m standard deviation
[66] - 2016	LGPR/GPS/IMU	0.04 m RMSE
[67] - 2014	Lidar/Camera/GPS	0.24 m RMSE
[69] - 2014	v2v/GPS	0.25 m average
[71] - 2015	IMU/Camera/GPS	0.73m mean
[70] - 2015	v2i/GNSS	0.698 RMSE
[68] - 2020	GNSS/LIDAR/IMU	0.1 m standard deviation
[5] - 2017	LIDAR/IMU	0.07 m RMSE
[7] - 2019	GNSS/IMU	0.2667 m RMSE

with an IMU unit provided to our measurements of the first experiment, we could see a significant improvement in localization accuracy. Comparing our relative increase in accuracy with the filter to the relative increase in accuracy done with map-aided adaptive EKF by Atia et al. [7] we can see that their method resulted in greater relative increase in accuracy with sensor fusion. The positioning accuracy results from the first or the second experiment did not outperform those of Atia et al.

7 Conclusions

7.1 Contributions of this thesis

This thesis has evaluated various techniques and algorithms used to improve GNSS based positioning of autonomous vehicles. The properties of GNSS sensors and other sensors used in autonomous vehicles were surveyed. The localization accuracy requirements for safe autonomous driving were also surveyed. GNSS sensor can provide valuable global positioning measurements for autonomous vehicles as an independent sensor and is well complemented by the independent measurements of an IMU sensor. This research has provided insight on various methods used to improve GNSS positioning in autonomous driving and tested those methods with empirical experiments. The experiments showed that sensor fusion with IMU increased the vehicle localization accuracy and when used in combination with a trust based algorithm, the average localization accuracy was even further increased when compared to standalone GNSS sensor based localization.

The results of the experiments were compared to the localization requirements of safe autonomous driving. Due to small data sample size, no objective positioning improvement could be proved. Based on the experiments, the current performance of low-grade GNSS and IMU cannot guarantee a constant lane-level accuracy for autonomous vehicles. However, GNSS combined with a high-grade IMU can drastically improve lane determination accuracy availability for autonomous driving systems.

The limiting factors of the experiments in this thesis were the small data sample size, unoptimised EKF parameters, limited map accuracy and unreliable road curb determination with LIDAR.

The techniques and results of autonomous vehicle localization (particularly by utilizing GNSS and sensor fusion) of other research were also surveyed. Autonomus vehicle localization results of the other research were compared to the localization results of the experiments of this thesis. High-quality sensors and maps used in other research provide high accuracy measurements and they can even reach the accuracy levels required for safe autonomous driving. However, both the experiments of this thesis and the experiments of other research showed that various techniques and algorithms can be used to reduce errors in sensor based positioning. These techniques may not only improve the positioning accuracy of autonomous vehicles but may also make relatively inaccurate measurements valuable for accurate autonomous vehicle localization.

7.1.1 Future work

I recommend further research on the benefits of reliability evaluation of sensor measurements and its uses in autonomous vehicle positioning and decision making. Using trust functions as weights in an extended Kalman filter might improve the positioning accuracy of autonomous vehicles that use extended Kalman filter sensor fusion and due to possible localization and decision making improvements, more experimentation with trust models in autonomous vehicles is recommended. Additionally, further research on localization inaccuracies caused by road objects that are hard to represent on a map is recommended.

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