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Review and Comparison of Vision- and LiDAR-based Methods for Autonomous Vehicle Localization

Bachelor’s thesis

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ABSTRACT:

A robust and accurate vehicle localization is a crucial element in the field of autonomous vehicles. It is needed for trajectory and path planning, tracking, and trajectory prediction. Normally this is achieved by relying on the global navigation satellite systems, but it is not always reliable. Here vehicles sensing modalities step in and take over the task of localization. This can be achieved by detecting features in the surroundings of the vehicle and localizing the vehicle either relatively or globally. Provided, an accurate map exists consisting of expected features, it is possible to match features extracted with sensing modalities to the map and thus the vehicle is able to make sense of the surrounding environment. Another possibility is to localize the vehicle relatively, for example, lane-level localization. Usually, a camera is used as the sensing modality. It is a relatively affordable, simple, and popular sensor. But in recent decades the Light Detection and Ranging (LiDAR) is offering heavy competition to cameras because it has produced more accurate results and can be used to extract more useful information from the environment. The aim of this work is to offer a review and comparison of vehicle localization using cameras and LiDARs as sensing modalities. In most cases, map-based localization is brought out, but in some cases also relative localization is discussed. The focus of the review is on the sensors, how they are used and what are their advantages or disadvantages. The categorization in the comparison chapter is based on features with which the localization is achieved – these include lane markings, road marks, curb detection, traffic signs and landmarks. In the end, the author concludes the work with suggestions for choosing the right sensor for localization of autonomous vehicle in desired operating conditions, based on reviewed papers.

KEYWORDS:

Autonomous driving, autonomy, localization, LiDAR, camera, map-based localization, relative localization

CERCS:

P170 Computer science, numerical analysis, systems, control

Ülevaade ja võrdlus isesõitvate sõidukite lokaliseerimisest kasutades LiDAReid ja kaameraid

LÜHIKOKKUVÕTE:

Käesoleval ajal on maailmas suure tähelepanu all isejuhtivad autod. Selleks, et saavutada autonoomia kõrgeim tase, on vaja teada sõiduki täpset asukohta. See on aluseks otsuste vastuvõtmisel ning edasise teekonna ja trajektoori planeerimisel. Isejuhtivate sõidukite integreerimiseks tavaliiklusesse on kohati katkendlik globaalse navigatsioonisüsteemi signaal ja meetrised mõõtevead ebapiisavad. Siin tulevad mängu erinevad nägemist matkivad sensorid, mis aitavad isesõitvat liikurit lokaliseerida kaardipõhiselt või relatiivselt. Kui on olemas täpne kaart, mis sisaldab tuvastatavaid objekte, siis on sõidukil võimalik nende objektide järgi määratleda oma asukoht kaardil või näiteks sõidureas. Tavaliselt kasutatakse ümbruse seiramiseks kaamerat. See on kulutõhus, lihtne ja populaarne andur. Kuid viimastel aastakümnetel pakub laserskanneerimisseade LiDAR kaamerale tugevat konkurentsi, kuna on täpsem ja annab keskkonna kohta rohkem teavet. Käesoleva töö eesmärk on koostada ülevaade ja võrrelda sõidukite lokaliseerimist, kasutades tuvastusviisidena kaameraid ja LiDAReid. Enamik juhtudel on välja toodud kaardipõhised lokaliseerimismeetodid, kuid mõnel juhul on käsitletud ka relatiivset lokaliseerimist. Töös keskendutakse sensoritele, millega ja kuidas tuvastatakse ümbritseva maailma elemente, nende plussidele ja miinustele. Kategoriseerimine toimub tegurite alustel, millega lokalisatsioon saavutatakse: reamärgistused, teemärgistused, liiklusmärgid, äärekivid ja maamärgid. Kokkuvõttes antakse autoripoolne hinnang sensori valimiseks autonoomse sõiduki lokaliseerimisel erinevates olukordades ja keskkondades.

VÕTMESÕNAD:

Isejuhtivad sõidukid, autonoomia, lokalisatsioon, lidar, kaamera, kaardipõhine lokalisatsioon, relatiivne lokalisatsioon

CERCS:

P170 Arvutiteadus, arvutusmeetodid, süsteemid, juhtimine (automaatjuhtimisteooria)

TABLE OF CONTENTS

1 INTRODUCTION

The current work falls in the context of autonomous driving. The field has gotten increased attention in recent decades. There are approximately one billion cars on the roads today and this number will increase in time [1]. Each year an estimated 1.3 million people die in car crashes and approximately 90% of the traffic accidents are attributed to human error [1], [2]. Inattentiveness, fatigue, health problems and other humane issues are things that robots do not possess. A quicker response is also a good quality in difficult and dangerous situations, which belongs to the robot vehicle instead of a human driver. In the bigger picture, it would even be possible to make the robot vehicles communicate with each other at a greater level than humans do in traffic. A moral question "If every vehicle in the world would be autonomous, would we have close to zero traffic collisions?" is yet unanswered. An untested hypothesis states, that bringing in autonomous vehicles should create a 90% drop in all traffic accidents [1].

1.1 THE IMPORTANCE OF LOCALIZATION IN AUTONOMOUS DRIVING

The dream of self-driving cars started already a hundred years ago [3], but recent decades have shown a breakthrough towards the end goal. Six levels of autonomy have been set by the Society of Automotive Engineers - Level 0 being fully manual and level 5 being fully autonomous [4]. The main key to achieving the highest level of autonomy is precise vehicle localization [4]. In rural areas, a decent global positioning system can produce quite accurate results, but in typical busy traffic scenes, it is error-prone. The cause may be multipath when the signal travels from global navigation satellite system (GNSS) satellite by bouncing off of reflective buildings [5] or sometimes the signal may not reach the receiver at all due to non-line-of-sight [6].

1.2 THE PROBLEM ADDRESSED IN THE THESIS

The aim of this work is to bring out how LiDARs and cameras are used in the localization of autonomous vehicle. The reason for this is that, to the knowledge of the author, this kind of overview does not exist, in the public archives at least. The main goal is to find papers, that use these two sensors separately to detect features like curbs, lane markings, road marks, traffic signs, landmarks and localize the vehicle according to these. The emphasis is on the research works in which the vehicle is localized globally i.e. map-based localization, but the literature is relatively in the domain especially considering each feature type. That is why it is also focused on relative localization.

Multiple feature types can be used together for the purpose of localization. Similarly, sensor-fusion (from multiple sensing modalities) can be performed, but for a better overview of the comparison of the two sensor types (i.e. cameras and LiDAR), one sensor per paper is preferred for this work.

Google scholar and IEEE databases were primarily used with search strings "LiDAR OR camera", "localization" and "self-driving vehicle OR autonomy". Most papers are from 2010 and onward, which was the aim of the study i.e. reviewing relatively recent works. A couple of papers are also referred from the '90s because these works have been built on later. Many papers were also found through the references of other relevant papers. (At the beginning of the thesis project, an initial set of relevant papers was provided by the supervisors.)

1.3 STRUCTURE

The remainder of the manuscript is structured as follows:

- In chapter 2, a general background is provided.
- In chapter 3, different research works and papers are brought out from the literature on autonomous vehicle localization, with the aim of comparing the two sensing modalities of cameras and LiDARs.
- In chapter 4, the above-mentioned comparison is concluded, with suggestions from the author of this work for choosing the right sensing modality for vehicle localization in desired operating conditions.
- The thesis concludes in chapter 5.

2 BACKGROUND

In this chapter, a general background is provided, including an overview of localization in general and an overview of algorithms, cameras and LiDARs used in the localization of autonomous vehicle.

2.1 OVERVIEW OF LOCALIZATION

To localize oneself is to estimate ones pose in reference to a coordinate frame [7]. Not only is the location of the robot vehicle necessary, but also the pose, meaning position and orientation [8]. The vehicle should be able to pinpoint its location on the map by using different sensing modalities and matching objects or markings to the map in a GNSS-denied environment. It is necessary for the vehicle to place itself in the surrounding environment to make decisions and plan further actions and paths [7].

The problem of localization can be approached either globally, relatively [7] or by simultaneous localization and mapping (SLAM) [9]. The latter method is achieved with LiDAR sensor and not with camera [10]. Relative localization uses odometry – cumulative measurements [7]. This work focuses on global as well as relative localization. Global localization is usually achieved through GNSS, but due to the system being error-prone, a map-based localization is being reviewed. The localization approach may work independently from GNSS as well as aid the system. Relative localization here means lane-level localization. Also, some SLAM methods and approaches are referenced, when SLAM is used to update maps.

2.1.1 Accuracy of localization

The location can be divided into three: macroscale – ca 10 meters, mesoscale – under 1 meter and microscale – accuracy is not really brought out, but it is insinuated, that it is in the level of parking a vehicle [11]. The necessary accuracy of localization for autonomous vehicle is an important determinant not yet unambiguously determined, but clearly, it needs to stay in microscale. It is crucial for the safety of integrating self-driving vehicles into real traffic. Fatal accidents have already happened on the US highway concerning the Autopilot of Tesla [12]. Also, Uber's autonomous vehicle caused an accident, which ended with a pedestrian fatality in the year 2018 [12].

According to Mercedes- Benz group [13] Germany was one of the first countries to legally regulate full and highly automated driving, but it still requires an operator present to take over in case of emergency. The liability never falls on the autonomy but on the operator, owner or manufacturer. The legal framework has or will be implemented in the near future by the United States and members of the European Union [13]. In 2019 Petovello [14] stated, that for safety, the localization accuracy needs to stay around 20 centimeters at the confidence level of 95%. In 2021 Rehrl and Gröchenig [15] brought out 10-centimeter accuracy at a 95% confidence level as a prerequisite for autonomy in real traffic as opposed to the report published in 2013 [16], which needed 0.7-meter accuracy at the same confidence level. It is hard to find a harmonized accuracy for localization, because probably internationally it does not yet exist [17], but as can be concluded from this, the need for accuracy increases every year, because the reality of self-driving taking over the roads is nearing [18].

2.1.2 Localizing with the help of sensors

For a human driver, it is a daily task to process input such as landmarks, lane sides, road markings, traffic signs, traffic lights, colors and so on. Also taking into account the behavior of other traffic participants comes naturally to human drivers. With experience comes the knowledge of how different car-owners drive and, for example, how a learner’s car may not follow the rules as expected. Humans can effortlessly predict children’s behavior beside the road. Human eyes are also more likely to achieve visuals in different weather and lighting conditions such as a blinding sun, darkness and heavy snow or rain conditions. For an autonomous vehicle to obtain a similar perception taking into account all the above-named factors, is very complicated [19].

The range of sensors that can be used for perception in autonomous vehicles is wide. In a world without financial constraints, a robot vehicle would make use of all the helpful sensors like different kinds of LiDARs, cameras, GNSS, IMU and radars [20]. To make autonomous vehicles more affordable and easily manufacturable, however, a conscious choice has to be made between the sensing modalities. In this work, two of the most popular sensors used in autonomous driving – LiDAR and camera, have been chosen to carry out a review and comparison.

2.1.3 Map-based localization

In the 90s, for position estimating, the approaches used almost only sensors [21]. This means, that it was not a map-based localization, but localizing a vehicle according to, for example, lanes. But nowadays, since so many accurate maps are available, the approaches make use of it to achieve an overall more robust localization of vehicles. This also allows the vehicle to follow a path, that is previously set [21].

Map-based localization can be divided into active or passive, depending on the sensor used [22]. LiDAR is the active sensor and camera is the passive one [22]. Another way to classify map-based localization is based on the maps used: feature maps, grid maps, topological maps and point-cloud maps [23]. This work does not concentrate on the maps themselves, but more on the sensors and features used for map-matching. Although it is all connected because different sensors and features require an accordingly appropriate map.

2.2 ALGORITHMS USED IN LOCALIZATION

In the following subsections, three main algorithms used in localization are introduced in a more basic way.

2.2.1 Kalman filter

According to W. Franklin [24], Kalman filter is an algorithm that is very efficient in estimating the parameters of a robot vehicle in its movement. The algorithm's ability to filter out noises in the input with high accuracy is the reason for its popularity in navigation estimation in real-time. Different devices produce data for the usage of the filter. Robot's internal system offers the movement variables which represent the transition of states. Environment is measured using sensors installed on the machine. The uncertainty of input data from the sensors is aggregated with the uncertainty of state transitioning [25]. W. Franklin [24] also states, that the diffusion of these with the Kalman filter produces more accurate results overall. The algorithm involves a prediction step within which a motion model is used to update the trajectory. Next up comes the correction step, where the prediction is updated according to new input data [19]. In Figure 1, the basic Kalman filter steps are brought out involving the prediction and the update step (which is also referred to as the correction step in literature).

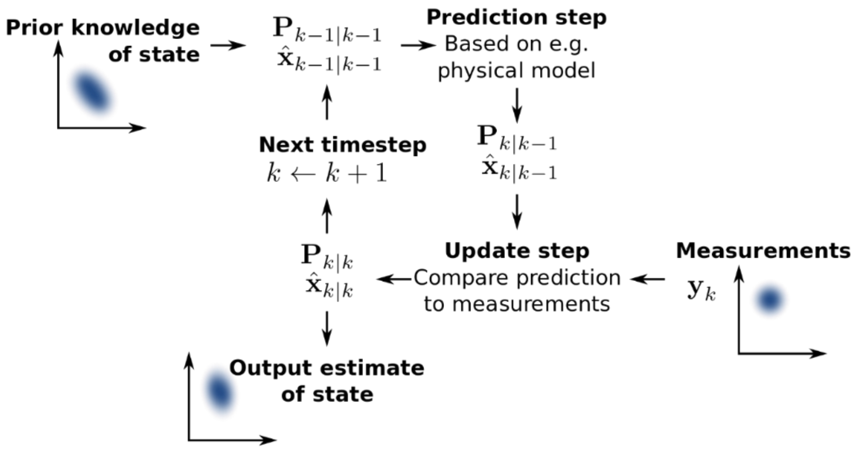

Figure 1. Basic Kalman filter steps explained [26].

2.2.2 Particle filter

The particle filter is also known as the Monte Carlo method [27]. It is stated by Nak and Kim [28] that the goal is to produce a posterior distribution of data from partial and noisy observations. It uses a set of particles to represent the posterior distribution. The prediction is updated based on statistics. The advantage of the particle filter in comparison to the Kalman filter is the robustness and more polished trajectory. The disadvantage is a longer computational time.

2.2.3 Simultaneous localization and mapping

SLAM stands for simultaneous localization and mapping [29]. The method is used for mapping the environment and determining the location of autonomous vehicle in the said environment at the same time [29]. This is also a big part of the autonomous driving field. For example, when global navigation sensors in combination with LiDAR or camera may suffer from a drift of error, then SLAM can compensate for this by building a global map and recognizing revisited places [9].

2.3 OVERVIEW OF CAMERAS

Cameras have been around for longer than LiDARs and essentially the work towards localization of a vehicle started with this sensor. In the following subsections, three kinds of cameras are introduced.

2.3.1 Monocular camera

A monocular camera, as the name states, has a single lens. These camera systems are used already in upper-middle-class cars, providing driver assistance being engaged with lane departure warning, forward collision warning, etc [19]. It would make sense to make use of the already existing sensors in localization also. A monocular camera has to be calibrated beforehand to perceive the location of the vehicle and pixels accordingly [30].

2.3.2 Stereo camera

The stereo camera system (*cf.* Figure 2) is based on the principle of human binocular vision [31].

Figure 2. An example of 3D stereo camera system [32].

It has two different lenses and the combination of the two outputs gives a three-dimensional result for output [31]. Although the images are actually two-dimensional, the correlation of objects present in the two images gives us depth information [31]. In the literature reviewed in this work, stereo vision is used more often than monocular cameras.

2.3.3 Around view monitor

The around view monitor (AVM) is a system, where typically four cameras are placed around the vehicle [33] – in the front, on both sides and in the back (*cf.* Figure 3).

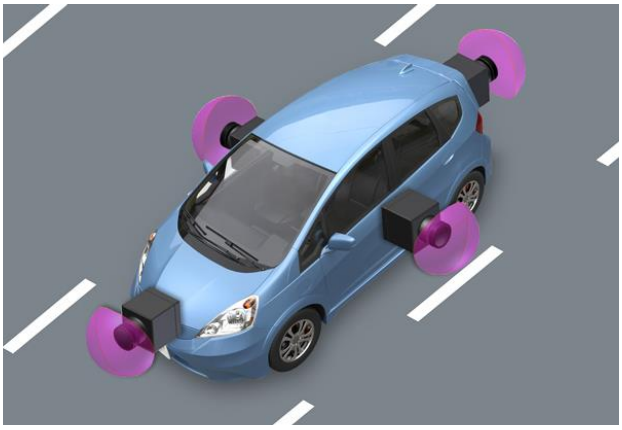

Figure 3. An around view monitor on a car, with 4 cameras, creates a bird's-eye view as can be seen above the car [34].

This also helps to capture a bird's-eye-view - view as seen from above the vehicle, like a bird [33].

2.4 Overview of LiDARs

LiDAR stands for "light detection and ranging" or sometimes also "laser imaging, detection and ranging" [35], [36]. The principle of how LiDAR works is that it actively emits laser beams in high density and measures the time of the reflection from the objects back to the sensor [37]. Since it is a laser system, which travels nearly at the speed of light (through the air it is a bit slower than in a vacuum), then this constant is used in the formula to calculate the distance [37] (*cf.* Figure 4).

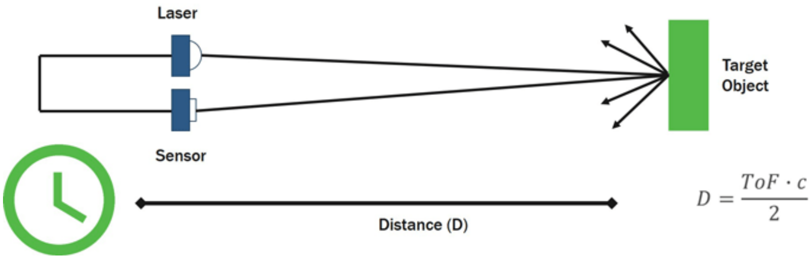

Figure 4. LiDAR principle of operation explained [38]. In the formula: ToF stands for time of flight and c stands for the speed of light.

2.4.1 2D LiDAR

2D LiDARs are recommended for the use of surface detection and ranging [39]. It emits a single laser beam as opposed to 3D LiDAR, which emits multiple laser beams. The difference is, that a single beam does not provide as much data [40].

2.4.2 3D LiDAR

3D LiDARs have the ability to capture nearly the entire surrounding environment [41]. These tend to be more expensive, than 2D LiDARS. In Figure 5 three LiDARs are pictured from an industry titan Velodyne. In 2018 they announced a new more cost-effective model – the LiDAR Puck, priced at 7999 dollars [42]. This is brought out to give a sense of the cost of LiDARs. The more accurate results are expected, the more the LiDAR costs.

Figure 5. From left to right: 3D LiDARs “HDL-64E”, “HDL-32E” and “LiDAR Puck” by the manufacturer Velodyne [42].

3 COMPARISON

In this chapter, a comparison is presented of LiDARs and cameras for localization of autonomous vehicle. In Figure 6 a categorization is presented for the comparison. The main idea is to offer an overview for each feature type (lane markings, road marks, curbs, traffic signs and landmarks) and how the two sensors were used to detect these features and achieve localization. If multiple features are used in one research work, then the work is categorized based on the main feature it focuses on. If feature types are reflected equally in one work, then the work is mentioned in both sub-sections. Most of the time testing results are brought out if mentioned in the according papers.

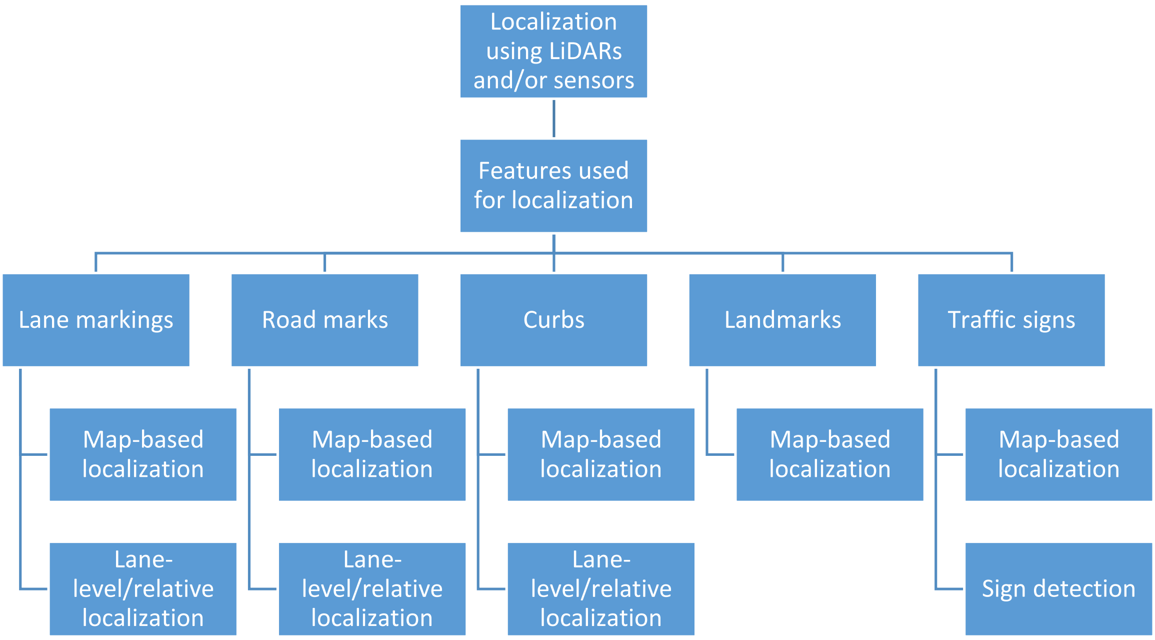

Figure 6. The categorization of research papers.

3.1 LANE MARKINGS

As is stated in the work of Schreiber et al. [21], nowadays, with newer driver assistance systems, lane marking detection is used in lane keeping assistance (LKA) and lane departure warning (LDW). This is a built-in function for most of the upper-middle and upper-class cars. Since the sensor mainly used for LKA and LWD is a camera, then it is considered a good prerequisite to use this modality instead of LiDAR, when trying to achieve a lane marking based localization for autonomous driving. Taking into account, that in commercial use, the cameras are able to detect lane markings even in adverse weather conditions (as long as they can also be seen by the human eye), then this is another contributory pro to choosing cameras.

According to Ghallabi [19], lane markings can be detected and extracted by their color or reflectivity, which is opposite to the asphalt's qualities. Ghallabi [19] also states, that the position of the sensor on the vehicle, which may alter the reflection detected by the LiDAR, does not matter because asphalt is not a reflective overlay and in most cases, lane markings are very reflective, which in turn makes the detection and extraction of the feature effortless. What needs to be taken into account is the height or the angle of a sensor, because when the road is not as smooth as expected, then the angle of the vehicle may cause the loss of data from sensors [11].

3.1.1 Map-based localization

Shunsuke et al. [43] used monocular cameras to aid the localization with GNSS and IMU. A previously obtained 2D map was used containing all the necessary lane markings. The lane detection algorithm is based on Aly's work [44]. Shunsuke's approach concentrated on the areas with tall buildings around – urban canyons. Testing was carried out in Hitotsubashi, Tokyo, which offers the appropriate environment for this. One onboard camera was attached to the front of the vehicle, which was used for lane detection. The algorithm detected the distance from the camera to both sides of the lanes. This input along with the GNSS and INS were integrated with the particle filter algorithm. The lane detection provided aid to localization, improving the effectiveness to 90% and the accuracy < 1 meter.

Schreiber et al. [21] have proposed an approach for visual localization with a stereo camera, where the road is initially mapped in a separate drive. The reason for beforehand mapping is that generally the exact road geometry is not involved in maps. Let it be acknowledged that the precision of localization also greatly depends on the accuracy of the map. The goal was to detect curbs and lane markings, more precisely solid, dashed, and stoplines. Testing was carried out over a 50-kilometer test track altering rural and suburban roads and also on a round track without curbs. This novel approach, which was using stereovision, Kalman filter, IMU data, lane marking, and curb detection with a previously created highly accurate map achieved a few centimeter precision on rural roads.

Nedevschi et al. [45] used a visual system to match landmarks to an extended digital map. This work was carried out with respect to an upcoming intersection, which is considered the most complicated task in driving scenarios. Among GPS and other landmarks, lane markings were used to localize the vehicle in the urban environment and mainly detect the correct lane. They proposed a lane boundary classification system with a variety of border classes: interrupted line, continuous line, merge line, no line, double continuous line, and double merge line. In testing the left lane was used for classification, because on the right side all the different classes may not occur. Out of 9830 frames were correctly classified 7969 which makes ~81% precision. Table 1 represents the results for each class. Though the true positive rate is not particularly high, the false positive rate is low enough to consider it a good and robust solution. A big part of the inaccuracy can be explained by the degraded markings. Next, the particle filter was applied.

Table 1. Lane delimiter classification results (TP – true positive, FP – false positive) [45].

Border class	Instances	TP rate	FP rate
No marking	3958	0.780	0.080
Continuous	1049	0.896	0.079
Interrupted	2413	0.804	0.052
Merge	144	0.792	0.014
Double continuous	2207	0.840	0.006
Double merge	59	0.831	0.002

Table 2 represents the results, where the previously classified lane was matched to an extended digital map. Correct and unique lane identification represents the correct estimation of the correct lane. Incorrect lane identification implies the sometimes absent or flawed data from stereovision. Correct but multiple lane identifications usually occur when there are more than three lanes and the lane markings are equal for some of them. The GPS, stereovision and extended digital map approach produced an error rate of 0.32 meters for the lateral and 0.2 meters for the longitudinal position.

Table 2. Lane identification results [45].

Lane Identification	Static BN [%]	Adding the particle filter [%]
Correct and unique lane identification	79.1	91.1
Correct but multiple lane identification	15.3	5.4
Incorrect lane identification	5.6	3.5

Tao et al. [11] described a lane marking aided vehicle localization with GPS. It used driver assistance video camera images and GPS to match the digital navigation map. It was brought out, that in 95% of the cases the error was under 1.25 meters, which is not sufficient enough for autonomous driving compared to other approaches in this comparison.

Ghallabi et al. [18] have approached the problem of localizing the vehicle based on lane markings with the use of multilayer LiDAR and an HD map. The map itself has an accuracy of 2 cm. During testing the speed of 80 km/ph was achieved where the localization worked as expected. The LiDAR used was Velodyne VLP32C and the spinning rate was increased to 20 Hz instead of the usual 10 Hz. Th first step is to segment the road and project road points onto a 2D grid. Hough Transform is performed next, which is an algorithm used for detecting lines in images with noise and partial occlusion. Although the LiDAR data is quite accurate, still the data needs to be filtered. First of all, the lines need to be parallel to the driving direction and secondly, when lines appear too close together, then they are interpreted as one line. These steps conclude the lane marking detection. Map-matching algorithm is implemented using particle filter and lane markings as features and the Kalman algorithm is used for tracking lane markings. The simplified Kalman algorithm is adequate since this experiment was conducted on the highway, where the course of the vehicle is mostly straight.

In Ghallabi's othe research work [19], previous to the lane marking detection, the road segmentation method is used to avoid inaccurate detections. Firstly, a two-dimensional horizontal reflectivity map is created from the data of reflective lane markings. Then an appropriate threshold is applied for the reflectivity data and a binary image is generated for the Hough Transform. It is stated that LiDAR data may suffer from low resolution and missing reflectivity returns which generates sparse data. This can be fixed with a dilation operator. Also bumps on the road disturb the pitch and roll. Dashed lines may not be detected, because of the high threshold for confidence – it is better to miss some than to falsely detect the lines. After the Hough transformation - only the lines which are parallel to the vehicle driving direction and to each other are kept. Also, lines detected too close to each other are merged to avoid doubling one same lane marking. Then a standard Kalman filter is applied to improve the detection. New measurements try to match the current active tracks and in case a new set of tracks is detected, then it is applied, when the width is more than half of one of the currently detected tracks. Track fusion is applied in the contrary case. Carrying out the testing on French highways with different velocities even the speed of 130 kilometers per hour was achieved. The study was very successful with the cross-track error under 20 centimeters in all velocities, but this was accredited to the fusion of lane markings and median barrier detection. Lane markings alone may cause the multi-lane hypothesis problem.

The before mentioned techniques are still stranded by weather conditions or environmental perquisites. Lee's work [46] uses both LiDAR and cameras as sensors. The around view monitor camera system, which offers a 360-degree view of the vehicle, usually used for parking, etc., may suffer from short-sightedness and, as always, bad illumination conditions. LiDAR on the other hand cannot detect lane markings accurately with wet pavement or degraded reflectivity. This way the LiDAR and camera create a symbiosis. The current work is greatly based on Kim's work [47] on the LiDAR sensor, but the goal was to combine two datasets into one. This proved to be a good idea, because promising results were presented on motorways and also in urban areas, keeping the speed slow.

3.1.2 Relative localization

Before the map-based localization, Pomerleau [48] introduced a successful system in 1995 called RALPH, which stands for rapidly adapting lateral position handler. It was able to locate the car with monocular cameras in accordance with the lane markings and was able to steer autonomously 96% of the time, intervened only because of other traffic participants. Aly et al. [44] also introduced a groundbreaking detection of lane markings in urban streets. These works have been built on towards map-based localization by others, for example, Shunsuke et al. [43], mentioned in the beginning of the previous sub-section.

3.2 ROAD MARKS

Besides lane markings also very accurate and robust features on the road comprise of road markings such as arrows, crosses, speed limits, etc. Road marks detection for localization is a bit more advanced but the technique is very similar to lane markings detection. It is usually used together with lane marking detection for localization. The marking points are extracted similarly due to the same material used in their making.

3.2.1 Map-based localozation

Hata and Wolf [49] also contemplated, that lane markings alone do not offer enough data for precise localization. They used a Velodyne HDL-32E sensor to extract as much information as possible concerning the reflective markings on the road. Curb detection was used to restrict the findings to the road, not outside of the area. Similarly to Kim [47], they also used Monte Carlo localization algorithm by matching the data to the 0.1-meter accuracy grid map. To prove, that road markings aid the vehicle localization robustness, tests were carried out only using curbs to localize the vehicle and then curbs together with road markings. The results were positive on the use of road markings. Longitudinal error dropped from average of 1.3174 to 1.1982 meters and lateral error from 0.5823 to 0.3119 meters.

3.2.2 Relative localization

The road markings are worn off over time so they have to be surveyed beforehand. Wu and Ranganathan [50] have implemented a practical system to recognize the road markings with camera sensor and continued their work in vehicle localization [51] building on top of the previous implementation. This work suffers from shadow regions and is announced to be insufficient for vehicle localization. In Figure 7, a recognition under different circumstances is presented. Red labels show the interpreted results.

Figure 7. Road marks recognition. Red labels show interpreted results [51].

Kim et al. [52] used a 32-channel LiDAR sensor and a previously created grid map. It is stated, that the sensor is calibrated according to its intensity information. This method uses all the lines provided on the road, including lane markings. In Figure 8, on the left side the uncalibrated data and on the right the calibrated data is displayed. Then the Monte Carlo localization algorithm is applied. This method achieved very good results on a 2.8 km test track with a deviation mean under 0.2 meters.

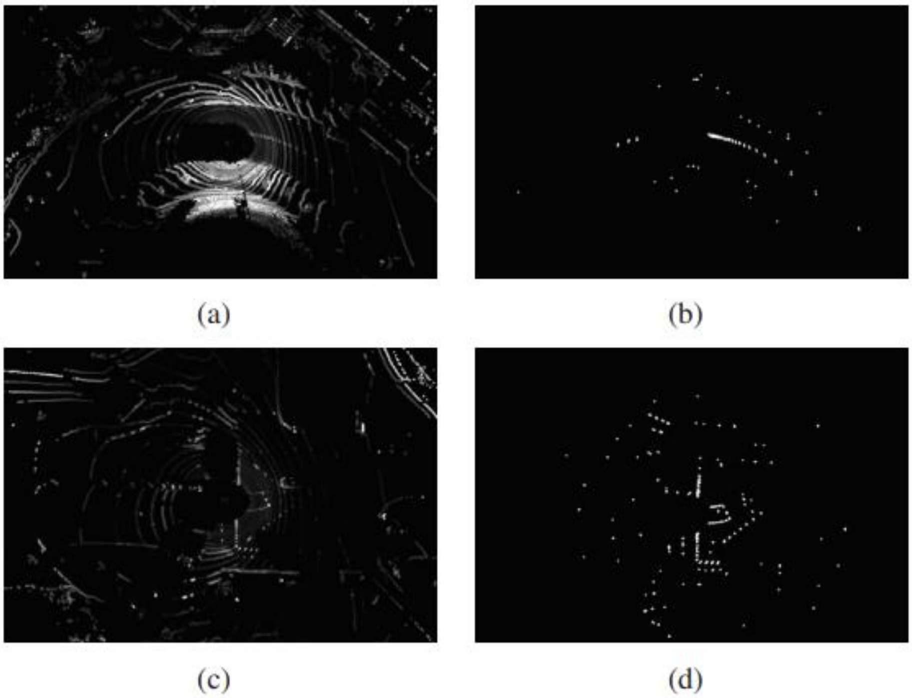

Figure 8. “(a) Uncalibrated raw intensity data of a LiDAR sensor on a curved road. (b) Extracted road feature from the LiDAR sensor on a curved road. (c) Uncalibrated raw intensity data of a multi-layer LiDAR sensor on an intersection. (d) Extracted road-feature from the LiDAR sensor on the intersection” [52, p. 2].

Two years later Hata and Wolf did a very similar approach [53]. The aim was once again to extract any kind of road marks as opposed to only lane markings. According to Hata and Wolf, previous authors have to change the threshold of intensity for detection too often. This paper also uses curbs as feature, which are referenced in the according section. Testing was carried out in two separate test tracks and lateral and longitudinal errors stayed under 0.3 meters.

3.3 TRAFFIC SIGNS

Traffic signs or otherwise known as road signs are reflective signs above or on the side of the roads, giving information about speed limits, directions, prohibitions, etc. The traffic signs detection for localization is mostly used as an aid for robustness. Typically, it is paired with lane markings or a curb detection approach.

3.3.1 Map-based localization

Welzel et al. [54] have stated that it is essential to create a database for the traffic signs to achieve feature recognition later. A very time-consuming approach is to manually record the environment beforehand. It can be done using a mobile GNSS device, which offers precise results of the position, height and type of the traffic signs. The accuracy achieved in preliminary work was around 1 meter and the database was built up. Another problem is the nonuniqueness of traffic signs. The detected traffic sign must be associated with the location and this presents to be a major challenge [6].

Welzel et al. [6] attached a color camera to the front of the vehicle to detect the traffic signs. Firstly, the color image is processed and the detected sign is captured in a so-called pixelbox and measured in pixel coordinates. Then the angle and distance from the camera to the sign are measured according to the previously known height of the sign from the database. It is tracked to improve the measurements. This will aid the multiple traffic sign matches problem. It is important to reduce the searching radius for the signs to the heading of the ego-vehicle. The tests were carried out using only "give way" and "priority road" signs detection. On the path sections without signs, GNSS was used. Beside very high buildings the localization jumped 15 meters, but when signs were detected, then the error was on average 1.3 meters. The algorithm successfully recognized the expected signs and localization worked accordingly. This work shows, that it is a promising area, that should be expanded upon.

Qu et al. [55] approached the problem similarly, by using traffic signs to help GNSS signal localization. A monocular camera was used to carry out the work. Paparoditis et al. [56] created a database consisting of geo-referenced traffic signs in a dense urban area beforehand which was also used in Qu's work and also the 3D reconstruction of traffic signs implemented by Soehilian [57] was used. Local bundle adjustment was the key factor generated through this work, which decreased the errors. The testing was carried out with simulated and real images in a dense urban environment on a short 1.1 km track. The purpose and advantage of using simulated images is to evaluate the localization algorithm's strength, it has no distortion of images and poses are exact. The purpose was to successfully match a traffic sign for every 100 meters, which creates a satisfactory localization level. The process takes too much time to call it a real-time application. Future work is planned for this to use other features and make the processing faster.

Ghallabi et al. [22] have proposed the detection of traffic signs, which extends the lane markings based localization [18] referenced in an earlier subsection. Since the traffic signs are not present on the road surface, then the road points are excluded from the data of detection. For the LiDAR-based approach, the next step is to identify the points in point cloud data with the highest reflectivity and cluster them together. Interfering agents that also are reflective enough to exceed the threshold may be the vehicles' license plates and other kinds of reflectors attached somewhere near the road, but in view of the map, these are not contained and therefore can also be excluded. The threshold is altered to the specific LiDAR selected for the experiment. The particle filter is used for the map-matching algorithm. Figure 9 pictures the capturing of a traffic sign.

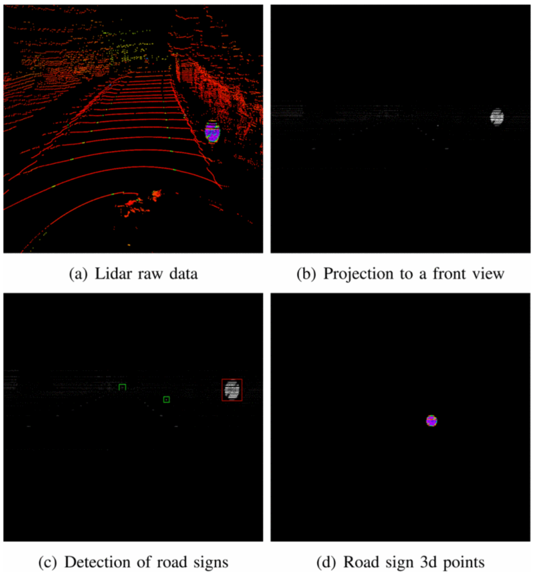

Figure 9. Detection of road signs from LIDAR points [22].

Testing was carried out on a highway with 30 km/ph and 90 km/ph vehicle speeds. The results can be seen in Table 3.

Table 3. Results' means of testing with sole use of GNSS and also added traffic sign detection at different speeds [22].

	Along track error (m)	Cross track error (m)
Integration of road signs at 30 km/h	Mean:1.49	Mean:0.09
GNSS only at 30 km/h	Mean: 2.81	Mean:0.15
Integration of road signs at 90 km/h	Mean: 0.78	Mean: -0.01
GNSS only at 90 km/h	Mean: 1.92	Mean: 0.03

LiDAR-based suffers from the scatteredness of points in the point cloud. For the LiDAR laser to make a whole turn in 0.1 seconds and when the vehicle travels 80 kilometers per hour, then this has to be corrected with a timestamp. For future work, the integration of the camera into the localization algorithm will be used. It is stated, that it proves to be more accurate.

3.3.2 Sign detection and recognition

Zhu et al. [58], who proposed a refinement algorithm, which further improves the confidence and accuracy levels of traffic sign detection and therefore the accuracy of localization, blamed the errors in detections on low lighting, multiple traffic signs located on top of each-other and falsely detectable round areas in images.

In literature, more references can be found for image-based traffic sign recognition, a big part of them from the ‘90s and early ‘00s, although LiDAR-based techniques have proven to be more accurate due to the coverage, measuring preciseness, independence from the illumination flaws [22].

Buyval et al. [59] used camera and LiDAR sensors fusion to detect and localize traffic signs. The idea was to detect the signs with the video feed and the LiDAR sensor was used to localize the sign and its pose in accordance with the vehicle. In Figure 10 the confidences of sign detections are brought out.

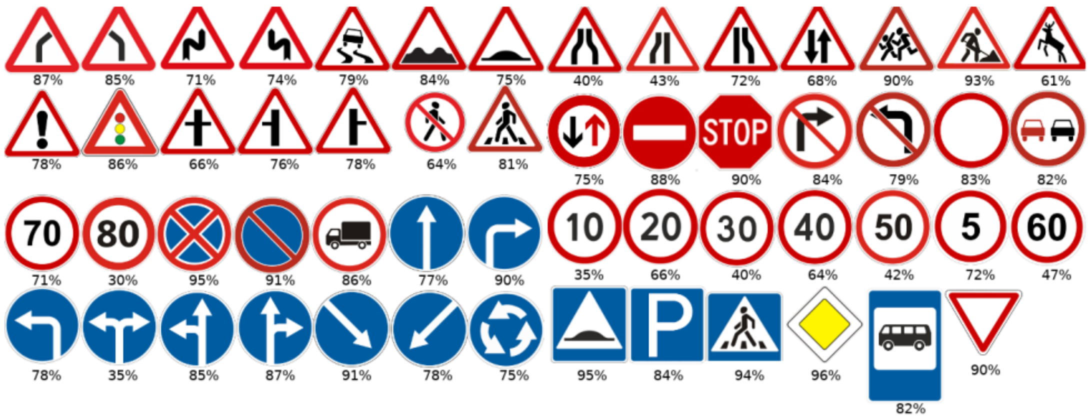

Figure 10. Accuracy of the detection of traffic signs using a convolutional neural network [59].

It is not yet integrated into vehicle localization methods, but it shows good results and the collaboration of detecting and classifying traffic signs with camera and LiDAR sensors.

3.4 CURBS

Curbs appear beside the roads in most urban environments. When the view from sensor is not blocked by parking cars and the streets are not too wide, then this can also be useful for localization. This feature type is not represented much in research papers.

3.4.1 Map-based localization

Wang et al. [7] used an HDL-32E LiDAR by Velodyne to detect curbs and match them to a high precision map. The sensor was mounted on the roof of the car. Curbs' height may vary, for example, when they are lowered for cycling convenience, but usually, they are 10-15 centimeters higher than the driving road. Curb detection was provided by Zhang et al. [60]. The map-matching algorithm was proposed in the year of 1992 by Besl and McKay [61], which is an iterative closest point algorithm. This algorithm is repeated and the result of detection and map are matched. For localization, the Kalman filters are used. The proposed algorithm achieved great results in the lateral error – 0.191 meters, but since straight curbs are not that distinctive lengthwise, then longitudinal error was 1.623 meters. The solution also is challenged, when obstacles hide the curb and it cannot be detected.

Wei et al. [62] also used an HDL-32E LiDAR to detect curbs, among reflection intensity, to make sense of the road marks and also height feature for the surrounding environment. Here, curbs help to make sense and reference the geometrics of the road. Kalman filter was applied in the localization step. Testing was carried out in Jiading campus in China, where the three features were used for the aid of localization accuracy. Advantage here is that when some feature detection may fail, then other features won't let the entire localization fail. Results proved to be a success with lateral error mean being 0.088 meters and longitudinal error mean 0.163 meters. The error was under 0.3 meters 90.1 % of the time. In the end, they still concluded, that a sensor-fusion with camera could help aid the sparse data and detection of visual information.

3.4.2 Relative localization

Hata et al. [53] implemented curb detection with a LiDAR. The choice of this sensor was justified with the attendant information of depth and accuracy. 2D LiDAR has the disadvantage before 3D LiDAR, because it cannot obtain dense point clouds all in the same time. This paper also extended the obstacle detection proposed by Montemerlo et al. [63]. The lateral error result was 0.52 meters. A few years later Hata et al. used LiDAR sensor to detect road marks (referenced in road marks section also) and curbs as features. The goal of the curb detection and application in more recent paper was to lessen occlusion, which was reached at the end. The lateral error dropped from 0.52 to under 0.3 meters.

3.5 LANDMARKS

Schlichting et al. [64] decided to approach the LiDAR data full-scaled, not using only lane markings, traffic signs or curbs, but all of the information the LiDAR sensor has to offer. Beforehand Mobile Mapping System was used to create an accurate map. The plan is to someday replace this step with the LiDAR itself creating the map. When collecting data all kinds of non-permanent objects are also captured like cars or pedestrians. This is why the step is repeated several times and in the end, only the objects captured at all times are contained in the map. Trees were also classified as dynamic and filtered out. In figure 11 it can be seen, that trees are recognized and marked as green, other non-permanent objects are marked with red and finally, the static objects are blue.

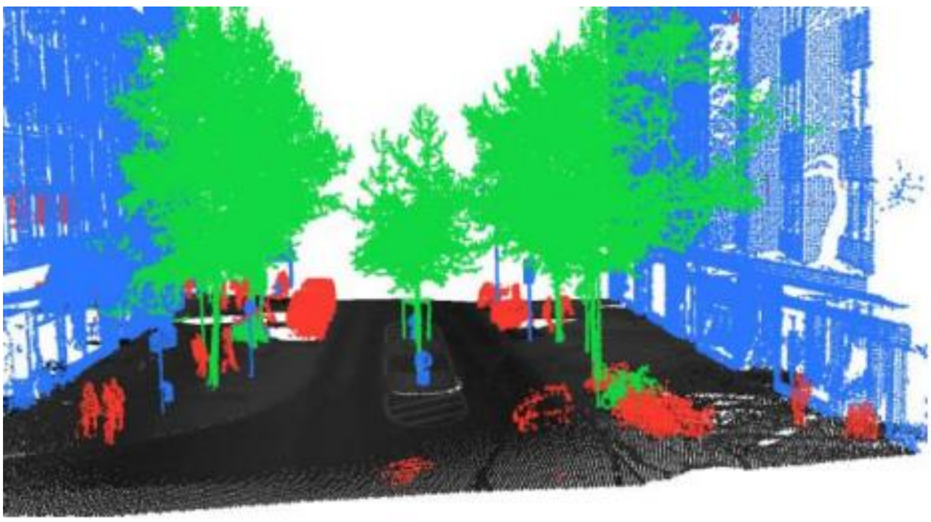

Figure 11. Point cloud with classified trees in green, detected dynamic objects in red and static objects in blue and the ground is colored by the point intensity values [65].

Tests were carried out in Hannover, Germany over a 13-kilometer track. In figure 12 it can be seen, that the narrower the street, meaning, the closer the objects beside the road are to the vehicle and LiDAR, the more accurate the localization is. At the bottom of the picture is a wider/bigger street, where the localization results are starting to lose accuracy. On the right side, the vehicle passes through a square, where the localization results cross the 0.5-meter boundary and are marked with lighting bolts. Since there are some trees, which might sometimes be against the buildings and in that case it is really hard to classify them. So this might be the reason for the poorer localization results.

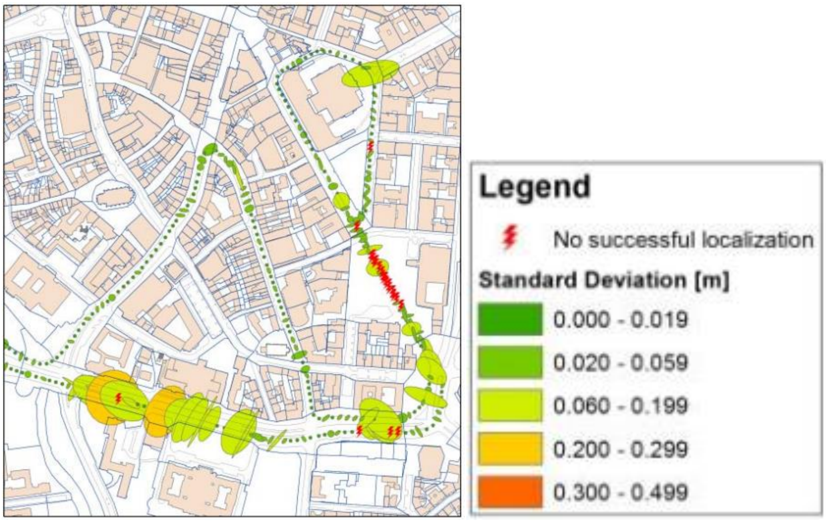

Figure 12 and 13. Localization results on a large street (bottom) and in the city center of Hannover, Germany with the corresponding legend [65].

Maddern et al. [66] used a low-cost 2D LiDAR to also grasp all the environment, but on top of changing objects they panned out the data collection for map creation to a year. This means capturing different weather conditions like bright sun, rain or snow. It is based on the work of Churchill et al. [67], where a stereo camera system was used to create new experiences of the same place and trying to localize the ego-vehicle relying on previous experiences, but at the same time also creating new ones (*cf.* Figure 14). Using the work of Baldwin and Newman [68] helped to avoid the use of more expensive 3D LiDAR.

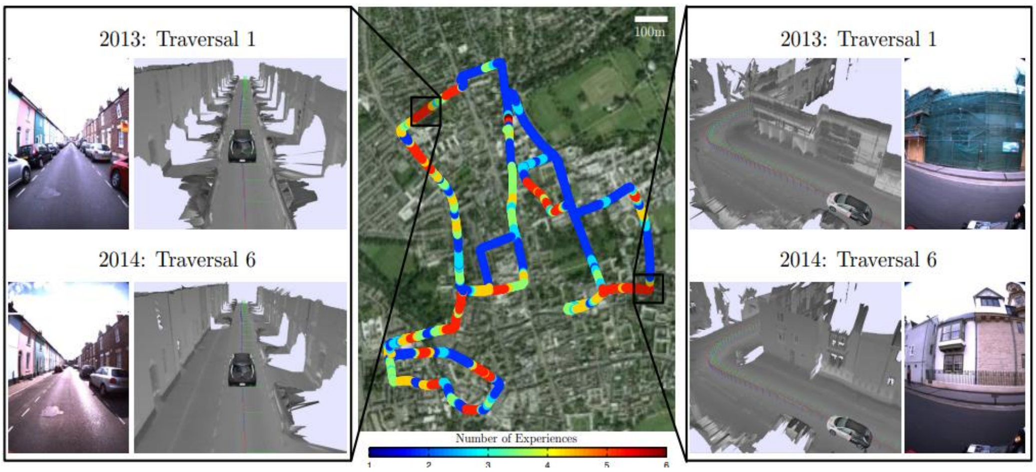

Figure 14. The trajectory of the testing carried out, four different depictions of traversals (change of parked vehicles and construction brought out), number of experiences shown along the track over six traversals [66].

GPS signal was also used for weak localization, meaning, that it is not a primary sensor, but aids to lessen the search field of the map and thus fastening the computational speed. The second time driving the previously driven route introduced 38.1% of new experiences. The more the route was driven, the fewer new experiences were introduced. The localization error after the sixth drive was 0.38 meters for x-axis and 0.07 meters for y-axis. The more the algorithm learns from experience, the better. This is useful for long-term localization.

Levinson et al. [27] proposed an idea to use inertial navigation and LiDAR to localize the vehicle on a map of the road's surface. It may contain lane markings and road markings, but the reason it was not discussed in the earlier sections is that it also takes features like pavement choice, tire marks, etc. and also the greenery beside the road. The localization is performed via the particle filter. During testing, the localization was performed with the use of a GPS inertial system and also without it. With GPS the localization error in an urban environment mostly stayed around 10 cm, but sometimes when taking a curve, it increased to 30 cm. Without the use of GPS, the localization was achieved through wheel odometry, steering angle and the LiDAR data. Using only odometry the results were unsatisfactory, but the aid of particle filter localization using a LiDAR sensor proved to be a success over 500-meter track with a maximum error of 28 cm. LiDAR sensor was also successful solo when tracking the speed and pose of the vehicle. Although, when operating the vehicle on roads without many features, then it is likely to fail.

Im et al. [17] accentuated on the usefulness of an extended line map because it holds information about road markings and vertical structures, which complement each other well providing high accuracy and confidence for localization. Since the size of the map is small and no verification step is required for the detected lines, then it works well for real-time localization. It uses lane markings and LiDAR to localize, but it is based on the extended line map. The results were very good with the lateral and longitudial errors being 0.136 meters and 0.223 meters respectively.

Yoneda et al. [69] used the generated 3D point cloud from Velodyne HDL-32E LiDAR for localization by matching it to a 3D reference cloud in real-time. One big disadvantage of this approach is that storing the reference cloud in a map requires much storage space. But it was aided with the help of [64]. This paper does not result in a real-time implementation. The features in the data were observed in different circumstances – urban area, residential area, riverside area, campus area and expressway area. The results show that each area or circumstance needs a beforehand choice of scan area, because the features to be scanned differ from one another.

In Figure 15 (on the next page) the papers about the localization of autonomous vehicle are categorized based on feature type, localization type and sensor type.

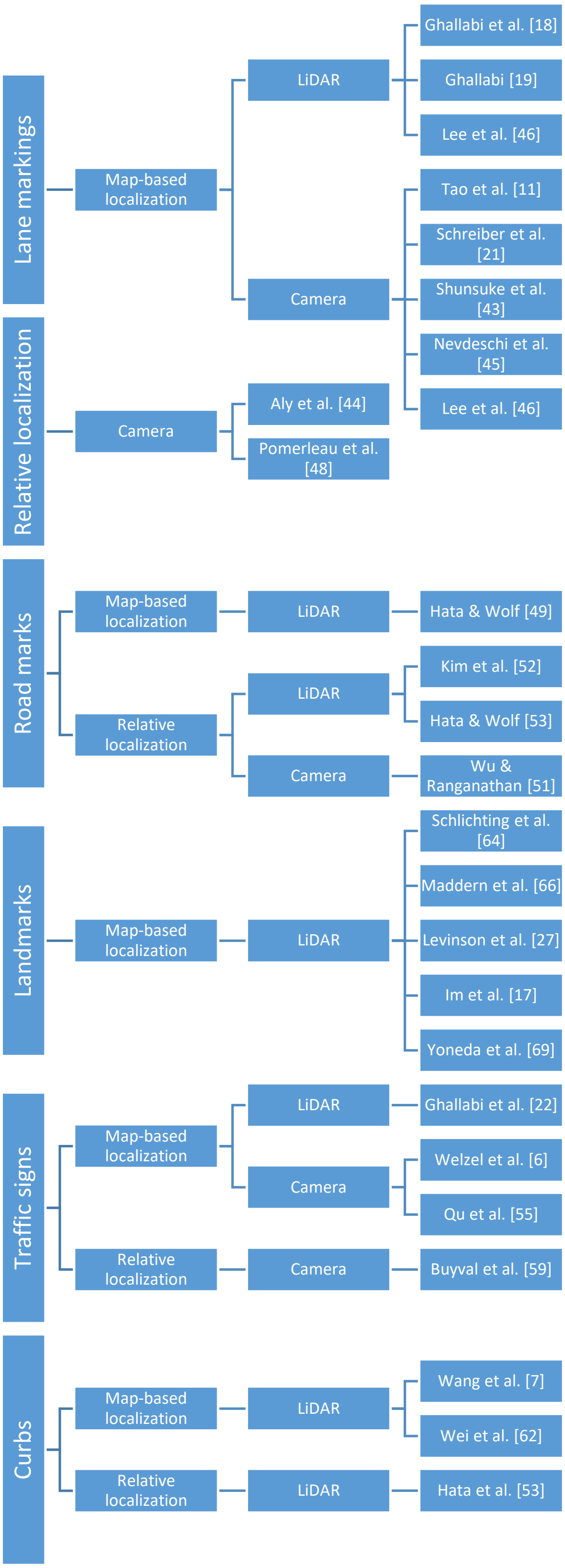

Figure 15. The referenced research papers about localization of autonomous vehicle categorized for overview.

4 SUGGESTIONS BASED ON REVIEWED PAPERS

In this chapter, suggestions are offered for the choice of sensing modality for vehicle localization. The suggestions are based on weather and lighting conditions, feature richness of roads on which the vehicle operates, cost-effectiveness and some additional qualities of LiDARs and cameras are brought out.

4.1 WEATHER AND LIGHTING CONDITIONS IN WHICH THE VEHICLE NEEDS TO OPERATE

Taken from the view of weather and lighting conditions, then usually LiDAR is the better choice, in some cases, the only choice between the two sensors.

Even humans have difficulties operating in heavy rain, but with a lighter rain, a choice can be made between the sensors. First of all, the prerequisite is that the sensors themselves are protected from getting wet (or wiped clean during rain) [70]. LiDAR sensor lasers suffer from the noise and consequently, false reflections produce inaccurate detections. For camera, image algorithms [70], [71] have been created to aid the vision sensor during the rainfall.

The result of a heavy rain is a wet pavement and according to Ghallabi [19], the LiDAR does not perform well on it. Provided it is more than just slightly moist, the laser sensor has difficulty obtaining the lane markings and road marks from it. If covered in water it is yet again falsely detected [52]. So when considering a self-driving vehicle in London or Seattle (the famous rainy cities), then presence of a camera is strongly advised.

In sunny conditions, the point goes to LiDAR, which is insensitive to the glaring external light [19] [72]. In fact, according to the referenced papers, LiDAR is an appropriate choice for dealing with shadows, while detecting landmarks and also in darkness without a good external light source. Cameras work well in daylight, but not in direct sunlight and without strong shadows. So in conclusion, cameras require an external light, but not too bright and LiDAR is independent from lighting conditions.

Previous suggestions are concluded in Table 4.

Table 4. Suggested choice between the sensors based on weather and lighting conditions.

Condition	Lidar	Camera
Rain		X
Wet pavement		X
Sunny	X	
Alternating cloudiness/shadows	X	
Dark	X	
Cloudy/no direct sunlight		X

4.2 Feature richness of roads on which the vehicle operates

Since lane markings are meant for human visuals, then cameras seem to be the right choice, but regarding the results of different studies and papers, LiDAR data has proven to be more accurate. It is capable of creating an accurate 3D model of the surrounding environment and is less sensitive to light [73]. According to the results of the studies, LiDAR is clearly more accurate and adaptive to multiple diversions. But as can be seen from the overview written in the previous chapter – more articles were referenced about using cameras for detection. Though there are many studies about LiDAR detecting lane markings, this is nearly always only one of several features detected. The author concludes, that approaches using cameras are precise enough for detecting lane markings and using them to localize the vehicle. LiDAR is such a complex, expensive and capable sensor, that the simpler task of detecting straight lines is not challenging enough.

Road marks, although in the same category as lane marks, are a bit more complex. The advantage of accuracy of a LiDAR sensor would really pay off when detecting different shapes, not just lines anymore.

For the detection of landmarks, LiDAR is the best choice. Although landmarks can be many different kinds of things, based on the papers referenced, the majority opts for LiDAR use. The reason is probably again the accuracy of the sensor.

Curbs are better detected with LiDARs, because cameras may not perceive depth as well as LiDARs [74]. Although stereo vision should be able to create a 3D visualization, then Hata et al. [53] state, that LiDARs prove to be more accurate.

Traffic signs are definitely meant for human visuals. Most traffic sign detection and recognition algorithms are referenced in vision-based papers. Also, cameras are able to detect color, which can be quite contributory to the detection step.

Previous suggestions are concluded in Table 5.

Table 5. Suggested choice between the sensors based on feature richness of the roads.

Environment	Lidar	Camera
Presence of lane markings		X
Presence of road marks	X	
Landmarks	X	
Curbs	X	
Traffic signs		X

4.3 COST-EFFECTIVENESS

There is no ambiguity here, that LiDARS exceed the cost of cameras by far.

Some examples of the cost of cameras:

- HD 360 AVM system with 720p universal camera – 241.249 € [75].
- 3D HD 360° Car Surround View Monitoring System, Bird View System, 4 Camera DVR HD 1080P Recorder / Parking Monitoring – 170.284 € [76].
- 360 3D Around View Monitor AVM System Surveillance Panoramic Security Camera Video D.VR Recorder for Motor Home Caravan Van Trail – 485.941 € [77].

Some more examples of the cost of LiDARs:

- Velodyne LiDAR Puck – 7567.644 € [42]. This was in the year 2014, LiDAR prices have since then dropped due to the bigger availability.
- Hokuyo UST-20LX – 2280 € [78].

- RS-LiDAR-16 – 2312,5 € [79].

As can be seen, LiDAR prices are 10 times more expensive and that is the reason, why cameras should or would be opted for if the conditions allow it.

4.4 CONSIDERATION BEYOND LOCALIZATION TASK

Few things to keep in mind beyond the localization task:

- Cameras do have an infinite range, but for feature detection LiDAR is more capable from afar. The field of view is typically about 100 meters [80]. This is contributory to tracking and early detection.

- LiDAR can provide a 3D representation of the environment with centimetric accuracy, so it can be useful to update maps [19].

- Processing the whole LIDAR points can be time-consuming and may not always be suitable for real-time applications [81].

- The placement of the sensor may play a role. In urban environments, the lower the sensor is, the more distracting vehicles and pedestrians it captures, but on a highway, lower sensor placement may help to more accurately extract features [69].

5 CONCLUSION

The aim of this work was to offer a review, that helps to understand the use of cameras and LiDARs for the localization task in autonomous driving. According to the best knowledge of the author, this kind of review does not exist, at least not in the public archives.

In chapter 3, research papers were brought out according to the features, with which the localization task was achieved. Features were landmarks, lane markings, road marks, traffic signs and curbs. References were brought out for map-based localization as well as relative localization. In chapter 4, the author of this work contributed by making suggestions for the choice of sensing modality for vehicle localization in autonomous driving. The suggestions were based on weather and lighting conditions, feature richness of roads on which the vehicle operates, cost-effectiveness and some additional qualities of LiDARs and cameras were also brought out.

According to suggestions, which are based on reviewed papers, LiDARs work better for localization of autonomous driving in difficult lighting conditions, but cameras work better with and after rain. Due to the price of LiDARs, cameras are suggested to use in average daylight, without the glaring sun and alternating clouds causing shadows. From the view of features in the environment, cameras should be used for lane markings based vehicle localization as well as traffic sign detection. LiDAR proves to be more useful when using road marks, curbs and landmarks for the localization of autonomous vehicle.

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