Assessment of Lane Detection Performance based on Different Lane Marking Properties under Optimal and Adverse Weather and Lighting Conditions

Eline van der Kooij

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Visibility of Lane Markings for Machine Vision

Assessment of Lane Detection Performance based on Different Lane Marking Properties under Optimal and Adverse Weather and Lighting Conditions

by

Eline van der Kooij

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Student number:	Eline van der Kooij	4500946
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Thesis committee:	Prof. dr. Bart van Arem,	TU Delft (Chair)
	Dr. ir. Haneen Farah,	TU Delft
	Dr. ir. Riender Happee,	TU Delft
	ir. Yongqi Dong,	TU Delft
	ir. Anastasia Tsapi,	Royal HaskoningDHV
	ir. Peter Morsink,	Royal HaskoningDHV

Preface

Dear reader,

In front of you lies my greatest accomplishment so far: my master thesis. This thesis can be seen as the grand finale, the crown jewel of my study career of 8 years. Conducting and writing the master thesis was challenging in many ways. But if it was not challenging, I would not have learned as much from it as I did. The largest challenge was to work on this thesis during the Covid-19 crisis. This situation has forced me, and many others, to work under extraordinary circumstances. There were only a handful visits to the office of Royal HaskoningDHV and up until the writing of this report I have never seen my TU supervisors in person. Almost all the work was done from home, resulting in a lot of self-awareness regarding motivation and discipline. Luckily there were many people that helped me to stay motivated.

I would like to express my endless gratitude to Dr. ir. Haneen Farah who, besides providing valuable guidance regarding the thesis and progress, helped me a lot to stay motivated at times when it got difficult. Together with Yongqi Dong we had fruitful meetings with interesting discussions and this thesis would not have been written without them.

Secondly I would like to thank Anastasia Tsapi and Peter Morsink for the great opportunity to conduct this research at Royal HaskoningDHV. This has led to more insights into the field of vehicle automation and valuable connections that were useful during this period.

Additionally I would like to thank Prof. dr. Bart van Arem en Dr. ir. Riender Happee for being part of the thesis committee. Their excellent knowledge of this field and conducting research in general has led to an increase of level of this thesis that would not have been reached otherwise.

Finally, I would like to thank everyone else that made this research possible for me. There are too many people to list them all, but all of their contributions, whether it was professional or motivational, mean a lot to me.

I wish you a very pleasant time reading this report.

Eline van der Kooij
Delft, June 2021

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Acronyms

ADAS Advanced Driver Assistance Systems.

AVs Automated Vehicles.

DDT Dynamic Driving Task.

HMI Human Machine Interface.

ISA Infrastructure Support for Automated driving.

LC Lane Centering.

LDW Lane Departure Warning.

LKA Lane Keep Assist.

ODD Operational Design Domain.

OEDR Object and Event Detection and Response.

Executive summary

Introduction
Mobility has been increasing in the last few years, and with that has the number of traffic accidents. In order to mitigate the increasing safety risks, the European Commission has ordered that all new vehicle models should be equipped with Advanced Driver Assistance Systems(ADAS) from 2022 onward. Lane Keep Assist (LKA) is part of the ADAS that helps the driver in the lateral control of the vehicle, potentially reducing the risk of run-off or head-on accidents. LKA, similar to human drivers, use lane markings to determine their position on the road. There is still a lot unknown about when LKA is able to function. Many factors were already listed to contribute to the functioning of LKA, such as environmental conditions, road and lane marking quality, and other road characteristics. However, detailed knowledge on the infrastructural requirements is still missing, while has the potential to increase availability of LKA and therefore road safety. This study aims to increase the knowledge on which lane marking properties can contribute to a higher detection of the lane markings by LKA. Additionally, different sensor types can be used for lane detection, but a comparison of sensor performance has not been done before. The main research question of this study was formulated as follows:

"How and to what extent do lane marking properties influence the detection performance of different Lane Keep Assist systems? "

The literature divides the lane marking visibility properties into daytime visibility (measured in diffuse luminance coefficient or contrast ratio), nighttime visibility (measured in retroreflectivity), and application type. Two lane marking application types (or marking types) can be distinguished: type 1 which is smooth, and type 2 which is profiled. The advantage of type 2 is that the profile can enhance rain drainage, which improves the visibility in wet conditions.

Additionally, different sensor types that are used for lane detection have been distinguished. Among the camera systems are mono camera, stereo camera, and mono camera with infrared. LiDAR was also found to be capable in detection of lane markings.

Research Methods
A field test was used to evaluate the performance of different sensor types used for lane detection and to collect data on road characteristics. Three different sensor types were included: mono camera, mono camera with infrared, and stereo camera. In total, 460 kilometers of Dutch provincial roads were covered during the field test by each vehicle. Approximately one-third of the roads had type 2 lane markings, two-third had type 1 lane markings.

GoPro cameras were used to collect data on the detection status, speed, and contrast ratio of the lane markings. The videos were processed using image recognition algorithms in Python and a lane detection algorithm. Retroreflectivity, lane width, marking type, and the presence of street lights were collected manually. The total number of observations was reduced to a resolution of 1 measurement per 20 meter. The final result of the data processing was two data sets, one for daytime and one for nighttime observations. The following table provides an overview of the variables included in the data sets:

Table 1: Variables in the data sets with type and range

Variables		Variable type	Value range
Speed		Continuous	65-104 km/h
Lane width		Continuous	275-350 cm
Retroreflectivity	**Left**	Continuous	100-466 mcd/m2/lux
	Right	Continuous	100-438 mcd/m2/lux
Contrast ratio	**Left**	Continuous	0,17-555
	Right	Continuous	0,04-564
Marking type		Categorical	1 (type 1) 2 (type 2)
Sensor type		Categorical	1 (mono camera with infrared) 2 (mono camera)
Conditions		Categorical	1 (daytime dry) 2 (daytime wet) 3 (daytime sunset) 4 (nighttime dry) 5 (nighttime wet)
Street lights		Categorical	0 (not present) 1 (present)

Results

The results of this study include a detection performance evaluation of the mono camera and the mono camera with infrared. The performance is presented by the percentage of observation for each detection category: both lines detected, left line detected, right line detected, and no line detected. Additionally, the performance is divided into the different conditions that were experienced during the field test. Tables 2 and 3 present the obtained detection performance results from the field test:

Table 2: Performance mono camera including infrared

Conditions	Both	Left	Right	None	Count
Sunset	91,44%	1,32%	3,73%	3,51%	456
Daytime - dry	76,01%	1,29%	6,80%	15,90%	2472
Daytime - wet	81,18%	1,64%	1,30%	15,88%	1461
Nighttime - dry	83,26%	0,74%	3,46%	12,54%	3900
Nighttime - wet	85,4%	3,87%	6,56%	4,17%	1342

Table 3: Performance regular mono camera

Conditions	Both	Left	Right	None	Count
Sunset	94,65%	-	-	5,35%	374
Daytime - dry	-	-	-	-	0
Daytime - wet	96,63%	1,48%	0,83%	1,06%	1690
Nighttime - dry	97,02%	0,89%	0,08%	2,01%	1341
Nighttime - wet	87,3%	0,11%	0,33%	12,27%	1817

The highest performance of the mono camera with infrared was obtained during sunset (91,4%), the lowest during daytime dry conditions (76 %). The regular mono camera reached the highest performance of 97% during dry nighttime conditions and the lowest performance, of 87,3% during nighttime wet conditions. Only during wet nighttime conditions, the two sensor types had a similar performance. For the other conditions, the mono camera had a significantly higher percentage of both lines detected than the mono camera with infrared.

The second part of the results consist of regression analysis models. Binary logistic regression was used to determine the significance and coefficients of the variables in a classification model for detection status. Because the data on contrast ratio and retroreflectivity were divided per line, the regression models were separated for each line as well. This resulted in regression models for daytime left line, daytime right line, nighttime left line, and nighttime right line. For each model, speed was found to be a significant variable. An increase of 1 km/h in driving speed led to an 1,060-1,078 times increased detection likelihood. In most models, the lane marking type was also significant. Marking type 2 led to a 6-8 times increase in detection likelihood for the mono camera with infrared, in comparison with marking type 1. This increase in likelihood was found to be smaller for the regular mono camera. Street lights were found to have a negative effect on the detection status during dry conditions. The effects during wet conditions are inconclusive, as no heavy rain was experienced during the field test. The two other lane marking visibility properties that were assessed in this study, contrast ratio and retroreflectivity, were not found to be significant.

Conclusion and Recommendations
The aim of this study was to increase the knowledge on how lane marking properties can affect the detection performance of different LKA sensors. Only one lane marking visibility property was found significant in this study: marking type. For both the mono camera with infrared and the regular mono camera, the detection likelihood increased when marking type 2 (profiled) was used in comparison to marking type 1 (smooth). Other lane marking visibility properties were not found to be significant in this study. Additionally, driving speed and street lights were found to affect the detection performance. Increasing the driving speed was found to have a positive effect on the detection performance, while the presence of street lights in dry conditions had a negative effect. Based on the results, road authorities might consider to increase the use of type 2 lane markings on the roads.

This study has led to the following recommendations for future research:

- This study ultimately compared two sensor types for lane marking detection: mono camera, and mono camera with infrared. For completion, stereo camera or LiDAR might be considered for future studies.
- To study more variability in road quality and lay-out, other road sections or roads in different countries might be interesting to consider
- It is recommended to include heavy rain in future studies. This study was not able to because of the limited test possibilities, resulting in inconclusive results regarding the effect of street lights in rain or the interaction between marking type and rain.
- This study found a correlation between the contrast ratio and weather conditions. Although this correlation was not logical due to the variable coding, more studies could be done to research this
- Finally, deep learning methods were discussed in this study, but were not included in the study. A comparison between the ’traditional’ image processing methods and deep learning could be interesting to consider once vehicles that use deep learning become commercially available. To gain more insights in this, it might be useful to collaborate with vehicle manufacturers.

1 Introduction

While mobility has been increasing in the last years, so has the number of traffic accidents. In 2019, 22.800 fatalities and approximately 120.000 serious injuries have been reported on European roads (European Commission, 2020). Similar in the United States, where there are over 35.000 annual fatalities in traffic accidents (National Highway Traffic Safety Administration and others, 2016). Over 90% of the total number of accidents are due to human error (Winkle, 2016). These accidents could potentially be eliminated when there is no human involved in the driving task anymore. This is expected from Automated Vehicles (AVs) (Shladover, 2018).

One essential system for vehicle automation is Lane Keep Assist (LKA) (K. Lee, Li, & Kum, 2018). LKA concerns the lateral control of the vehicle and is currently deployed in vehicles with increasing automation features. Vehicles without active automation are equipped with a Lane Departure Warning (LDW) system, which gives the driver an audible, haptic or visual warning when the vehicles approaches the lane markings. Lane Keep Assist goes one step further and is able to correct the steering wheel. Therefore it does not take over the driving task from the driver. Vehicles with limited automation features can perform the lateral control for a sustained period. This is usually done by Lane Centering (LC) systems (Galvani, 2019). For the remainder of this report, all these systems will be referred to as LKA.

The safety effects of LKA have been researched in several studies. Road departures are reported to be the cause of one third of the total number of fatal accidents, and LKA can prevent up to 36% of the crashes (based on US infrastructure), given the presence of lane markings (Scanlon, Kusano, & Gabler, 2016). A reduction of up to 30% in single vehicle accidents and head-on crashes has been found in a study by Sternlund, Strandroth, Rizzi, Lie, and Tingvall (2017). However, the sample size in this research was small and therefore the authors recommended to continue researching the effects of LKA under real-world circumstances. A more recent study in China concludes that LKA have a "considerable potential benefit" in China, predicted for 2025 and 2030 (Tan, Zhao, Hao, & Liu, 2020). Run-off crashes may be reduced by 60-80% due to good signage and lining, beside LKA and speed control (based on the assumption that half of the travel will be in AVs in 30-40 years from now) (Lawson, 2018).

These safety improvements are an important reason that LKA, amongst other Advanced Driver Assistance Systems (ADAS), will become mandatory in new vehicle models from May 2022 and in existing models two years later in the European Union (European Commission, 2019). However, the performance of LKA is dependent on several factors and conditions, which can be described by the Operational Design Domain (ODD) of a vehicle or system. The ODD is defined by the Society of Automotive Engineers (SAE) as: *'Operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics'* (SAE International, 2018). The ODD is seen as one of the limiting factors of vehicle automation (Leonard, Mindell, & Stayton, 2020), while knowledge about it is still incomplete. Researching the infrastructural requirements for LKA is important to increase the availability, and therefore the road safety (Li, Song, Li, Pike, & Carlson, 2018). This research proposes an infrastructural assessment of the ODD of different LKA based on various properties of lane markings. The benefit of such an assessment methodology is threefold: increased knowledge of the ODD in general for different LKA, an evaluation of the different lane marking properties and their effect on the performance of LKA, and potential guidelines for policy makers on how infrastructure(specifically lane markings) for vehicle automation can be improved.

This report is structured as follows: The second chapter contains the literature review. This includes different classification schemes for vehicle automation and infrastructure, an overview of literature on the ODD in general, an extensive description of LKA and lane markings, the State-of-the-Art on LKA performance and related studies, and finally the discovered research gaps. Chapter 3 contains the research questions based on the research gaps and the methods used to answer them. Chapter 4 discusses the first results of the research, including the performance evaluation of different LKA in different weather and illumination conditions, and a description of the variables that were collected. Chapter 5 contains the research results, which will be extensively discussed in chapter 6. Finally, chapter 7 contains the conclusion and recommendations.

2
Literature Review

This chapter contains a comprehensive literature review with the objective to assess the current state of research with respect to LKA. Since the review procedure is different for the different topics, it will be specified in the beginning of the sections. In the first section, two classification schemes important for vehicle automation will be discussed. In section 2.2, recent relevant papers on the ODD in general will be discussed, indicating the importance of research in this field. Thirdly, background information about lane keeping systems will be provided. As LKA uses lane markings as a reference, the properties of lane markings will be discussed after. Section 2.5 concerns the State of the art on LKA performance, including current performance and measures to indicate performance. This chapter ends with a conclusion and a list of identified research gaps.

2.1. Classifications in automated driving

There are two classification schemes that are relevant for this research: vehicle automation and road infrastructure.

Vehicle automation can be divided into different levels. SAE International provides a comprehensive overview of six levels of automation. A distinction is made between longitudinal/lateral control, Object and Event Detection and Response (OEDR), and fallback. Both longitudinal/lateral control and OEDR are part of the Dynamic Driving Task (DDT). Level 0 vehicles can have active safety systems which enhance the driver's performance, but the driver still performs the entire DDT. In level 1, the vehicle provides either longitudinal or lateral control, while the driver needs to perform the remaining DDT. In level 2, the vehicle performs both the longitudinal and lateral control. The driver needs to be available for the OEDR. This is not necessary anymore with higher levels of automation. In level 3, the vehicle is responsible for the entire DDT and the driver is only required to take back control during fallback. This is again eliminated in level 4 vehicles. While levels 1-4 can only be deployed within their specified ODD, level 5 will be operational everywhere (SAE International, 2018).

Based on the SAE levels for vehicle automation, a classification scheme for road infrastructure has also been introduced. This classification scheme entails 5 levels of Infrastructure Support for Automated driving (ISA) (Carreras, Daura, Erhart, & Ruehrup, 2018). An overview of the scheme can be found in Fig. 2.1.

	Level	Name	Description	Digital information provided to AVs: Digital map with static road signs	VMS, warnings, incidents, weather	Microscopic traffic situation	Guidance: speed, gap, lane advice
Conventional infrastructure	E	Conventional infrastructure / no AV support	Conventional infrastructure without digital information. AVs need to recognise road geometry and road signs.				
Conventional infrastructure	D	Static digital information / Map support	Digital map data is available with static road signs. Map data could be complemented by physical reference points (landmarks signs). Traffic lights, short term road works and VMS need to be recognized by AVs.	X			
Digital infrastructure	C	Dynamic digital information	All dynamic and static infrastructure information is available in digital form and can be provided to AVs.	X	X		
Digital infrastructure	B	Cooperative perception	Infrastructure is capable of perceiving microscopic traffic situations and providing this data to AVs in real-time.	X	X	X	
Digital infrastructure	A	Cooperative driving	Based on the real-time information on vehicle movements, the infrastructure is able to guide AVs (groups of vehicles or single vehicles) in order to optimize the overall traffic flow.	X	X	X	X

Figure 2.1: ISA levels (Carreras et al., 2018)

Level E is the lowest ISA level, which provide no digital information to vehicle with respect to the road infrastructure. Level D provides a digital map with static elements of the road, such as land marks or signs. Level C starts with more frequently providing information to vehicles, which includes dynamic speed information. Levels B and A require real-time connectivity between vehicles and infrastructure. Level B is able to provide information about traffic on a microscopic scale, while level A has the additional ability to provide advice on lane usage, speed, etc. in order to optimize traffic flow.

While several tests are being carried out for higher ISA levels, most road sections are qualified as level E and do not provide information to vehicles in a digital manner. This requires vehicles to perceive the road infrastructure and traffic using on-board sensors. An important subject for the operation of automated driving without digital infrastructure is the Operational Design Domain (ODD). Next section will therefore contain a description of the state of the art on this subject.

2.2. State of the art on ODD research

The SAE definition of the Operational Design Domain (ODD) entails different conditions, including environment and roadway characteristics. It is important to review recent literature to determine what is already known about the ODD with respect to the environment and infrastructure. The literature for this section was found by a combination of literature collected in a shared DropBox by industry experts, and literature found on Google Scholar. Terms such as 'Operational Design Domain', 'Road Infrastructure Autonomous Vehicles', or combinations of these terms have been used to search for literature. Additionally, techniques such as forward and backward snowballing have been used to find literature.

Gyllenhammar et al. (2020) break the ODD down into Use Cases (UCs), for which operating conditions are to be defined. The operating conditions are categorized into internal and external conditions: internal conditions entail the vehicle and the user, external entails the environment. Among the external conditions is scenery. The scenery contains elements such as road characteristics, trees, buildings, but also weather. Quantifying and modelling these operating conditions can lead to a better definition of UCs which are designed within the ODD. The authors recommend detailed models of each of the operating conditions as future work. To get a clear vision of recent work on operating conditions mentioned in the research of Gyllenhammar et al., literature has been reviewed with respect to infrastructure. Since the ODD is relevant for all levels of automation (except level 5), the review also includes research on fully automated vehicles.

A survey among international experts showed that 76% of the participants viewed physical infrastructure as very important. These experts were from R&D, academia, automotive industry and other sectors such as consultancy (Nitsche, Mocanu, & Reinthaler, 2014). Farah, Erkens, Alkim, and van Arem (2018) found that there is less scientific literature on physical infrastructure compared to digital infrastructure for automated vehicles. Based on reviews of potential test sites, both digital and physical infrastructural characteristics that are necessary for testing and facilitating fully automated vehicles were listed. Among the physical characteristics are pavement and lane marking, standard lane width and positioning of traffic signs. Research gaps regarding this subject have been identified as well, regarding road capacity, lane width, lane marking and human factors.

Lu (2018) researched the necessary infrastructure for level 4 vehicles by expert interviews. Most of these experts had a positive attitude towards level 4 vehicles in the future. Two scenarios are likely according to the expert: Basic infrastructure and Advanced infrastructure. The first scenario is based on a willingness of stakeholders to cooperate, but with a limited budget for infrastructure upgrades. Only the minimal required infrastructure will be available, examples are emphasized traffic signs and lane markings and V2I technology. In the Advanced scenario, there is a sufficient budget in combination with a willingness to cooperate, creating opportunities for dedicated infrastructure. This includes intelligent traffic controllers, camera and radar detection and magnetic lane markings. Lu recommends further research into future infrastructure requirements using a different method than scenario planning, including vehicle manufacturers into the discussion. Another research based on expert opinions was conducted by Morsink, Klem, Wilmink, and de Kieviet (2016). Experts of Royal HaskoningDHV, TNO and Rijkswaterstaat discussed the impact of self-driving vehicles on road design. Two main directions were researched: a complete implementation of level 5 vehicles, and a mix of different levels. For the level 5 deployment there are significant changes expected. The driving speed can be increased, lane widths can be reduced, and street lights can be adjusted to enhance the vehicle systems. For when there is a mix of vehicles with different levels, not much change in the physical infrastructure is expected. It is emphasized that lane markings and road edges are important for both machine vision and human vision, under every circumstance. In addition, on roads with multiple lanes one lane can be dedicated to level 5 vehicles (or a different separation between higher levels and lower levels).

Royal HaskoningDHV (2021) recently published a report on the physical and digital infrastructure for optimal functioning of ADAS. This report contains infrastructure requirements for both lateral and longitudinal control. For both control systems, fallback situations have been described. The fallback situations were created by varying factors such as road type, road design and temporary conditions (weather, day/night, traffic). Additionally expert interviews were conducted with companies and institutions related to ADAS. Experts from the automotive sector stated that vehicle manufacturers are always aiming to improve their systems, but physical infrastructure such as lane markings will remain important and should be of high quality. A high quality is defined as a sufficient contrast and reflection in all environmental conditions and it is recommended to test both measures. Additionally, conflicting information (such as both temporary and permanent lane markings, or partly removed lane markings) should be avoided as much as possible and standards for lane markings should be uniform. Finally locations with street lights should be assessed and potentially adapted to enhance machine vision. Why this is important will be discussed later in this chapter.

To conclude: several studies indicate that physical infrastructure is important regardless of the automation level. The next section will discuss lane keeping systems more in-depth to understand how road infrastructure is sensed by vehicles and different sensor types.

2.3. Lane Keeping Systems

The literature divides LKA (as part of automated vehicles) into three parts: Hardware, Software, and Environment. The hardware contains sensors, communication devices, and actuators (Pendleton et al., 2017). The software part consists of Perception, Planning and Control (Liu, Jiang, Tan, & Zhao, 2020), each with their sub parts. Perception concerns extracting information from the environment. The perceived environment can be used to detect static and dynamic obstacles, such as lane markings and pedestrians respectively. In addition, perception can be used for localization (i.e. using objects to identify the vehicles location). With the perceived information, the vehicle's mission, behaviour and motion can be planned. The mission is considered the highest planner, which is regarding the general task of the vehicle and the routes to be taken to accomplish the task. The behavioral planner plans the decisions regarding interaction with other road users while following traffic rules. The motion planner makes decisions on a local level, by generating paths and actions to achieve the decisions of the other planners. The most typical objective is to reach a region while avoiding collisions with obstacles

(Pendleton et al., 2017). Figure 2.2 contains an overview of how the different software and hardware parts interact with each other.

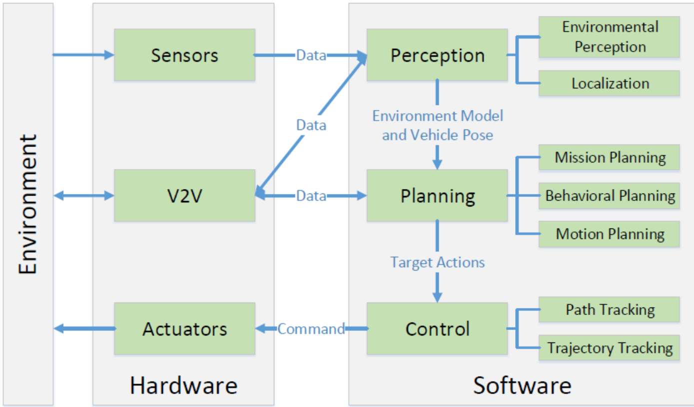

Figure 2.2: System overview of automated vehicles (Pendleton et al., 2017)

Since perception of the environment is a significant part of this research, next section will go into the sensors that are used for perception. Figure 2.2 shows that V2V (Vehicle-to-Vehicle) communication also provides information about the environment, but current vehicles are not equipped with these communication devices yet. This will therefore not be discussed.

2.3.1. Sensors

Each type of sensor in vehicle automation has its strengths and weaknesses. FEV Consulting (2019) provides a chart with a comparison of the main sensors used in the automotive industry: camera, radar, and LiDAR:

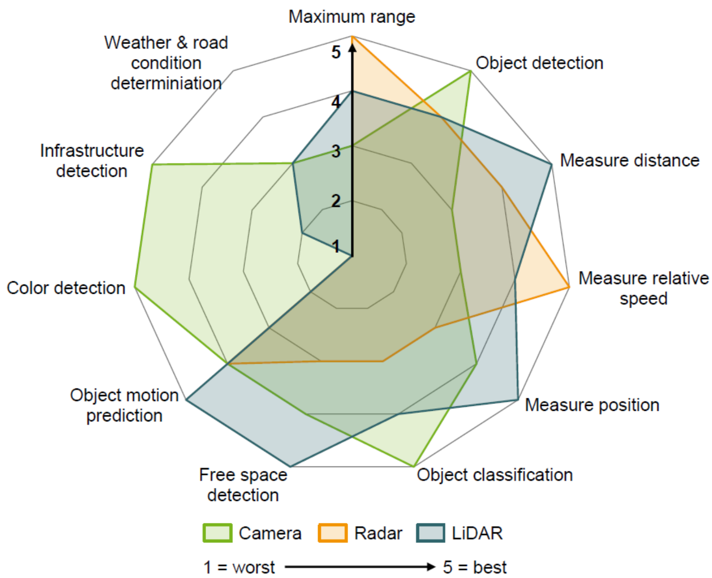

Figure 2.3: Sensor comparison based on different functionalities (FEV Consulting, 2019)

The chart demonstrates that cameras are the most suitable sensors to detect infrastructure. Several important capabilities of camera sensors in general are object detection and classification, infrastructure detection and color detection (FEV Consulting, 2019; Pendleton et al., 2017). The most commonly used sensor for lane markings in commercial vehicles is a frontal mono-camera. It makes sense that this sensor is suitable for lane detection, as lane markings are only perceivable in the visual domain (Hillel, Lerner, Levi, & Raz, 2014). Some of the strengths of this type of sensor are that it is versatile and cheap. These are reasons why one of the largest ADAS suppliers Mobileye stated that they will only focus on this sensor (Mobileye, 2020). A disadvantage of cameras is the decrease of detection performance due to visibility conditions. Cameras are heavily influenced by weather and illumination. Several solutions to this problem are higher quality cameras or infrared cameras (Liu et al., 2020). A twist of the mono-camera is the trifocal camera. This is essentially similar to a mono-camera, with three different ranges for each of the three cameras (Mobileye, 2019). This allows an optimized differentiation in function for each camera lens. The lens with a larger range can be used for obstacle detection, while the lens with a shorter range can be used for lane detection. Mono or trifocal cameras are usually less capable of 3D detection of the environment. This issue can be solved by using LiDAR or stereo camera.

LiDAR (Light Detection and Ranging) uses the same principle as Radar, only with light pulses. The emitted pulses are reflected by the environment, which provides a measurement of position. The scanning frequency can be up to 50 Hz and there can be up to 64 vertical scanning planes. LiDARs, or laser scanners, are now starting to appear in consumer vehicles to create redundancy. Audi is praised to be the most innovative car brand because of the presence of several cameras, radars and a laser scanner on some models. LiDAR used to experience lower performance with bad weather as well as cameras, however research and multi-echo measurements have solved this issue (Lindner, Richter, Wanielik, Takagi, & Isogai, 2009). While the future of LiDAR is still unsure due to its costs and complexity, there is plenty of research done on the sensor. Cheaper 2D LiDARS are also found to be capable of detecting lane markings (Zhiwei et al., 2015). LiDAR is able to differentiate lane markings from the road surface based on the difference in returned pulse intensity (Lindner et al., 2009; Hata & Wolf, 2014). Due to the ability to scan the total environment, it is additionally possible to detect roadside curbs which can be useful in performing the lane keeping task (Hillel et al., 2014).

Stereo vision entails two parallel camera lenses with a known distance between the lenses (baseline). Combining the images of the two cameras leads to a 3D image of the environment. Both LiDAR and stereo cameras provide data as a 3D point cloud (Broggi, Grisleri, & Zani, 2013). Several studies have used stereo cameras (in combination with LiDAR or radar) to test lane detection algorithms. Lattke et al. (2015) built two prototypes for a closed course test, one equipped with a mono camera and one with stereo cameras. The research paper only showed the results of the prototype with the mono camera, which does not provide the opportunity to compare results. Broggi et al. (2013) compared LiDAR with stereo vision for environment perception. Stereo was suggested to be cheaper and more robust than LiDAR. A significant amount of rain, snow or fog is needed to decrease the detection performance of the stereo cameras. Additionally, images can provide more information that can be used for classification and pattern recognition. Challenges with using stereo vision are the reliability on texture to detect depth and a higher probability of errors with an increased baseline.

The sensor that is the most robust during adverse conditions is radar (Feng, Li, Stolz, Kunert, & Wiesbeck, 2018). Radar is generally used for speed measurements and detection of obstacles (such as pedestrians), see Fig. 2.3. These functionalities contribute to automation systems such as Forward Collision Warning and Adaptive Cruise Control. For lane detection it is not suitable, as current lane markings lack the appropriate reflectors. When using lane markings applied with designed reflectors, lane detection might be executed by radar as well (Feng et al., 2018).

2.3.2. Lane detection process

In order to understand how the environment is sensed by the sensors discussed above, the lane detection process is discussed in this section. The literature can be divided into two methods. Several papers use the 'traditional' method of computer vision for lane detection. In the last years, deep learning has become a hot topic in research and several studies have used deep learning for lane detection as well. Both methods are discussed below.

Computer vision

Traditionally, the lane detection process using computer vision consists of three steps: Pre-processing, Feature extraction, and Tracking (Mammeri, Lu, & Boukerche, 2015). Hillel et al. (2014) found similar steps in their comprehensive survey, however the tracking step is split into two steps: Model fitting and Time integration. The decomposition of the lane detection process can be found in Fig. 2.4.

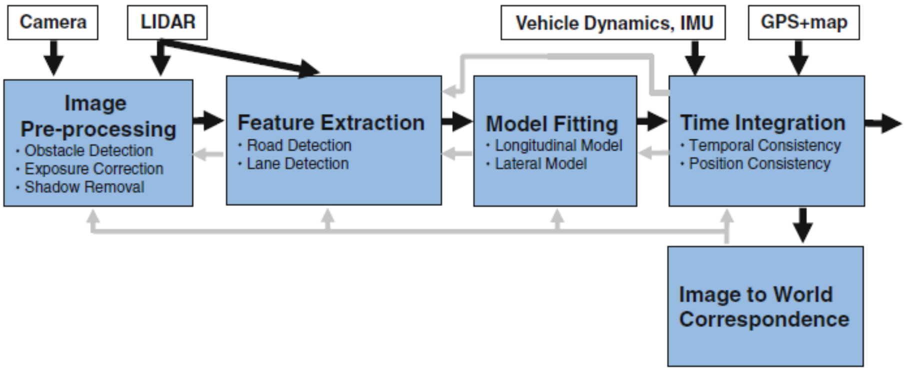

Figure 2.4: General steps in the lane detection process (Hillel et al., 2014)

Pre-processing consists conventionally of image smoothing and segmentation. An important part in this stage is to correct for illumination and shadows. In addition, Region Of Interest (ROI) extraction and Inverse Perspective Mapping (IPM) have been added in several studies in the pre-processing stage. Image smoothing is performed to reduce the noise in the image frame. The ROI is extracted afterwards to reduce the area in the image for computational efficiency. It can be a fixed area, but tracking algorithms can also be used to increase the probability of choosing the correct ROI. The ROI can be used for IPM, where the image of the road is transformed to a bird's eye view. In the process overview of Hillel et al. (2014), IPM is included in the Feature Extraction step. This process is useful for sensor fusion and lane tracking in a later stage. In the final step of pre-processing, segmentation based on colour or edges is used to prepare for the next stage.

Feature extraction can be edge-based, colour-based of based on a hybrid of edge and colour information. Edge-based feature extraction concerns the detection of shapes and lines in images, while colour-based extraction uses gray level and intensity. A combination (hybrid version) can enhance the detection results. Refinement methods can be applied to further refine the results.

Model fitting is used to create a representation of the path as input for decisions. Several points from the detected lane marking are used to fit a model to predict the direction of the path. Hillel et al. (2014) provide an extensive review of all the different model types that have been used in this step. The last stage is used to decrease false detections and to predict the future lane marking position. This has frequently been done by using Kalman filters or Particle filters. These steps combined can be considered the Tracking step as mentioned by Mammeri et al. (2015).

In Fig. 2.4, Image to World Correspondence is connected to each step. This entails connecting the 2D image with the 3D driving environment by means of the camera position, orientation, and calibration.

Deep learning
A more recent development in enhancing lane marking detection is deep learning. A common definition of deep learning entails the gaining of knowledge about the hierarchy of features (Zhang, Yang, Lin, Ji, & Gupta, 2018). In the case of image processing, these features can include edges, colors, shapes, etc. The difference with the traditional computer vision process is that with deep learning, the computer is not instructed to look for specified features, but tries to learn which features are relevant. When training a deep learning model, the input and output are paired (i.e. supervised learning) in a training data set. The goal of the model is to learn the structure between the input and the output. When that is successful, the model can potentially be used for prediction or classification of new driving scenes.

Several vehicle manufacturers such as Tesla and Waymo (Google) are developing autonomous vehicles that operate using deep learning technologies (Tian, Pei, Jana, & Ray, 2018). It is therefore noteworthy to mention the deployment in the field of lane detection research.Tang, Li, and Liu (2020) provide a comprehensive overview of the efforts made to increase the lane detection performance by deep learning models. One frequently used neural network model that has proven to be powerful for computer vision problems is the Convolutional Neural Network (CNN). A CNN consists of several convolutional and pooling layers in order to decrease the dimensionality of the image that is being processed. Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs) are also explored in this research domain with RNNs are usually used to model time-series features in frames of continuous images, and GANs could be adopted for image data augmentation. Several studies have resulted in a higher detection performance under different circumstances using these deep neural network models (CNNs, RNNs, GANs, etc.). A detection accuracy of 97% was reached in the study of Zou et al. (2019). More information about the current advancements in this field can be found in the overview of Tang et al. (2020).

Regardless of the improvements in accuracy, there are a few disadvantages when using deep learning methods. One is the parameter size of deep learning, resulting in a large amount of computational power needed to learn the features and train the model. Another disadvantage is that for supervised learning the data in the training set has to be labelled with the ground truth, which can be a time-consuming task. Additionally, situations that have not appeared in the training set are much harder to adjust to (Tang et al., 2020).

2.4. Lane Marking Properties

Lane markings are frequently listed as an important part of the physical infrastructure for ADAS and AVs. The previous section discussed how lane markings are detected by vehicles. This section provides more insights into the properties of lane markings. Again, Google Scholar was used to find relevant literature, using search terms such as 'Road Marking Material', 'Horizontal Road Markings', and 'Machine Vision'. Other information was provided by industry experts from Triflex and 3M. First, relevant studies and insights regarding lane marking properties in general will be discussed. Finally, lane marking properties with respect to machine vision will be discussed.

2.4.1. General properties

Most literature and regulations on lane markings are based on enhancing human vision. While lane marking properties for machine vision is the subject of this research, it is of utmost importance that lane markings are visible for both human and machine vision, under different weather and lighting conditions, independent of the age of the driver (in case of human vision) (European Commission, 2018). Visibility is one of the most important characteristics of lane markings. A division can be made between daytime and nighttime visibility, and dry and wet visibility. During the day, the lane markings are lit by sunlight coming from multiple directions. This generally provides enough information for a human driver to navigate (Burns, Hedblom, & Miller, 2008). Several studies have used detection distance by human drivers to determine visibility of lane markings (Babić, Fiolić, Babić, & Gates, 2020). With larger speeds, it is important that the detection distance is sufficient for a human driver to look ahead. Another measure that is being used for daytime visibility is the luminance coefficient under diffuse illumination Q_d (CEN, 2018). It is a measure of reflectivity in daylight conditions or with artificial lighting. According to the European standards for road markings, a Q_d between 100 and 200 mcd/m2/lux is required depending on the color of the markings and the type of road surface. CEN also prescribes standards for the color of the lane markings, given by x and y coordinates for the chromaticity diagram (CEN, 2018).

For nighttime visibility, retroreflectivity is used as a measure for visibility. With retroreflective materials, light that is directed towards the material is reflected back to the source, as opposed to reflection in a mirror (see Fig 2.5).

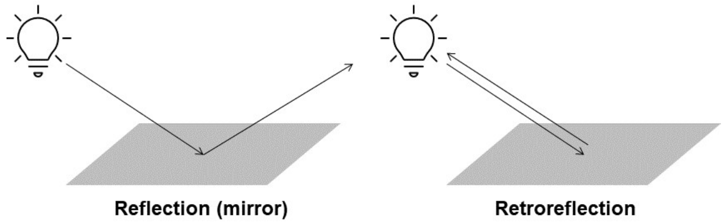

Figure 2.5: Difference between reflection and retroreflection (adapted from 3M (2020))

Retroreflection in lane markings can be established by adding optical glass/ceramic spherical beads. Light entering such a bead from headlights is refracted in a way that it directs back to the eyes of the driver (or a sensor). How the light is refracted depends on the Bead Refractive Index. Air has an index of 1, indicating that light is not refracted. Water has a an index of 1.3. For dry conditions, beads with a refractive index of 1.9 are the most effective. However, due to the refraction that happens in water, these beads are not that effective anymore in wet conditions. A refractive index of 2.4 is more suitable in that case (Triflex, 2020). Usually a mix is used to provide sufficient luminance for both situations. Gibbons, Williams, and Cottrell (2012) have tested the visibility of different lane marking types in different weather conditions. For both wet and dry conditions, a retroreflectivity value of 150 mcd/lx/m2 was found to be adequate. Similarly, The European Union Road Federation states that good road markings have a performance level of 150 mcd/lux/m2 and are 150 mm wide (European Union Road Federation, 2018).

The application technique also influences the visibility of lane markings under different conditions. Lane marking can be applied using different methods. Several techniques, such as paint or tape, lead to smooth lane markings. This is referred to as type 1 lane markings (CEN, 2018). There are also application techniques that lead to lane markings with a profile such as dots. This is called type 2 lane markings and has an advantage that it provides drainage for rain. The result is that this type has a higher visibility in wet conditions. Additionally it can provide drivers a warning when they are about to cross the line as driving on it would cause a vibration (Burghardt, Mosböck, Pashkevich, & Fiolić, 2020). Examples of these application types can be seen in figures 2.6 and 2.7.

Figure 2.6: Application type 1 (paint or tape)

Figure 2.7: Application type 2 (dots or drops, profiled)

A final property for lane markings is the skid resistance. Because this is not relevant for the visibility, this will not be further discussed.

2.4.2. Lane Markings for Machine Vision

While machine vision relies on the same cues as human vision, there are several cases where humans are more capable to determine the presence/location of the lane markings: Obstruction of lane markings, quality and condition of the road and the lane markings, etc. (Burghardt et al., 2020). Li et al. (2018) developed a lane marking quality assessment methodology for machine vision based on three metrics: correctness, shape, and visibility. The correctness metric is based on the divergence between the actual measured lane markings and the expected lane markings based on a prior map in geographic information system (GIS). The shape metric concerns whether the shape and width of the lane are conform standards. The visibility metric compares intensity of the lane marking with the intensity of the road surface. Because this research is focused on the color and contrast of lane markings, the visibility metric of Li et al. is further specified. In the research of Li et al., both LiDAR and a frontal-view camera is used for sensing. The visibility metric is based on the maximum contrast of either the LiDAR measurements or the camera measurements. This is mathematically specified as follows:

$$\mu_v = max\{\frac{\mu_{m,L}}{\mu_{b,L}}, \frac{\mu_{m,I}}{\mu_{b,I}}\} \tag{2.1}$$

The contrast is calculated by dividing the mean intensity of the lane marking (denoted with a small m) by the mean intensity of the background (denoted with a small b). LiDAR measurements are denoted with a capital L and camera measurements with a capital I. The different metric calculations were tested on different sequences from a pre-recorded dataset. While the paper contains several graphs of the metrics, there is not much discussion of the results.

Pike, Barrette, and Carlson (2018) conducted a research with the objective to identify lane marking properties that enhance the performance of lane marking detection by machine vision. Their experiment took place at a former Air Force base in the U.S., using two Ford vehicles equipped with Mobileye cameras to collect data. A wide range of lane marking set-ups were used in the experiment. The set-ups differed in colour(white and yellow lane markings), material (paint and tape), structure(profiled, flat), pattern(solid, broken), lane marking length (250-490 ft.), and distance from/to next lane marking(130-190 ft.). In addition, tests were done under different conditions (night/day, dry/wet) and different speeds. Access to the Mobileye camera data resulted in a performance evaluation based on confidence ratings between 0-3. During dry daytime conditions, a luminance contrast ratio of 2.8 or higher produced detection confidence ratings higher than 2 (on a scale from 0-3). The wet daytime conditions could not be evaluated due to the presence of glare. For nighttime performance evaluation, the coefficient of retroreflected luminance was used. Contrast values of 2.4 and higher yielded confidence ratings of minimal 2. Additionally, retroreflectivity values of at least 34 mcd/m2/lux resulted in detection confidence ratings of 2 and higher. In wet nighttime conditions, a minimal contrast value of 2.1 was found to yield confidence ratings of 2 or higher. Markings with a wet recover retroreflectivity level of minimal 9 mcd/m2/lux resulted in detection confidence ratings of 2 or higher. This level of wet recover retroreflectivity had a contrast ratio of 4.7. Another important finding in this research is that the day and night characteristics depended on the viewing geometry of the machine vision system (i.e. field of view). It is also important to keep in mind that the confidence ratings were reported as integers, which makes small changes in the infrastructure harder to compare. While the application type was listed in this study, it was not further evaluated. Driving speed was included and reported to decrease performance during daytime conditions, while partly increased the detection confidence at night.

Pike, Whitney, Hedblom, and Clear (2019) conducted a more detailed research into the retroreflective optics of different types of lane markings for both machine and human vision. Different types of lane markings were installed in a rain tunnel (simulated rain environment). It was found that lane markings with a higher wet retroreflectivity returned more light, which is beneficial for human and machine vision. This contributes to a higher robustness. The Weber contrast ratio was used as a measure to calculate the contrast between the pavement and the markings, but all the lane markings were found to have a sufficient contrast with the pavement below. The authors mention that the results are preliminary and more research can be done on the effect of glare.

The studies discussed above focussed on lane marking properties for machine vision, but did not include results regarding the performance of LKA. The next section contains an review of studies regarding the following subjects: Factors affecting the performance, empirical studies related to infrastructure and resulting LKA performance, and measures to evaluate the performance.

2.5. State of the art on Lane Keeping performance

It is important to take into account the factors that can influence the LKA performance. Therefore, literature describing current LKA performance, factors affecting performance, or related subjects has been reviewed. The literature contains field test studies by previous students or other researchers. Terms such as 'Performance Lane Keep Assist' and 'Semi-Autonomous Vehicle Performance' have been used in Google Scholar, while using the forward and backward snowballing searching techniques.

The experts in the research of Nitsche (2014) were asked to rate in which extent several factors influence the performance of LKA. This lead to Fig. 2.8:

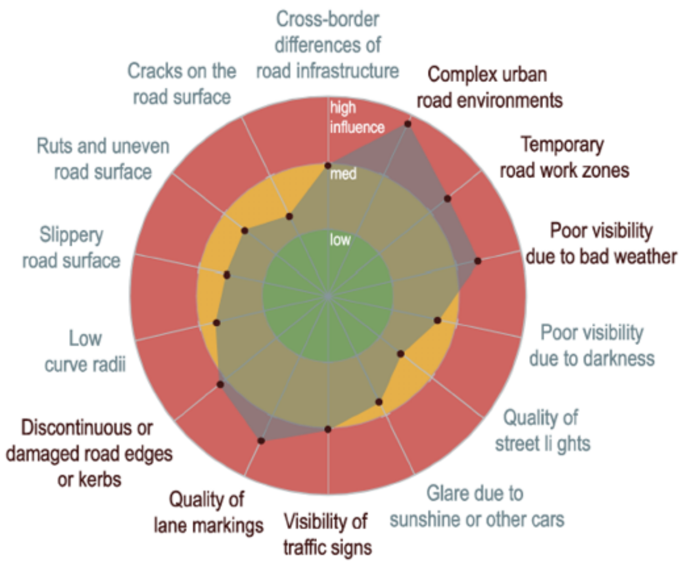

Figure 2.8: Factors influencing the lane detection performance (Nitsche et al., 2014)

Six factors were classified as 'High influence': Complex urban road environments, Temporary road work zones, Poor visibility due to bad weather, Visibility of traffic signs, Quality of lane markings, and Discontinuous or damaged road edges or kerbs.

Xing et al. (2018) define four different types of factors that have an influence on the lane detection performance: Lane and road factors, hardware factors, traffic factors and weather factors. Lane and road factors comprise factors as crosswalks, lane style and color, road curvature, lane markings and road structures. Hardware factors are related to the sensors inside vehicles, mostly related to cameras. Among traffic factors are surrounding vehicles, shadow and other illumination issues. Finally, weather factors include sun glare, rain, snow and fog.

Some empirical research on lane keeping performance from an infrastructural point of view has recently been done, including attempts to quantify and model certain conditions. Reddy (2019) conducted a field operational test to research the required infrastructure changes to increase the Lane Keeping performance in level 1 vehicles. By driving in different conditions (i.e. weather and luminance), the performance of Lane Keeping Systems in terms of detection and lane position was collected using cameras directed towards the Human Machine Interface (HMI) and the road. Computer image processing and multiple linear regression were used to obtain the performance and relevant infrastructural properties. Three factors were found to be significant: Lane width, Curves, and Speed. Additionally, the detection status in multiple visibility conditions and speed categories was evaluated. The vehicles used in this research were a Volkswagen Golf GTE and a Toyota Auris. The highest performance, 94,7%, was achieved in dark, dry conditions without streetlights. The lowest performance, 61,6% was during wet, dark conditions with streetlights. The full overview of obtained results in different conditions are presented in Fig. 2.9.

Visibility category	Percentage Both Lines Detection	Percentage No Lines Detection
Clear	90.3%	5.6%
Cloudy	92.4%	5.4%
Rainy	92.9%	4.6%
Dark	94.7%	3.3%
Dark_Rainy	82.0%	6.3%
Streetlights	90.0%	6.6%
Streetlights_Rainy	61.6%	15.4%

Figure 2.9: Detection performance during different visibility conditions (Reddy, 2019)

This research led to several recommendations for infrastructure, such as a high contrast between lane markings and the pavement, and no repair patches that might resemble lane markings. Recommendations for further research are a deeper understanding of the systems, collecting lane marking quality and configuration data, and using different vehicle manufacturers to account for market variability.

Van der Linde (2020) researched the relation between speed and curvature of roads on the performance of LKA. One of the findings of his field operational test was that none of the vehicles used for the experiment were capable of driving with maximum allowed speed through curves. With lower speeds, vehicles equipped with LKA tend to drive more stable. Three different vehicles were used in this experiment: a 2018 Hyundai Kona Electric, a 2019 Volvo S60 and a 2015 Volkswagen Golf GTE. A few recommendations of this research was to collect data according to the SAE guidelines (discussed later in this chapter) and to use different types of vehicles. Similar results were found in the study of García, Camacho-Torregrosa, and Baez (2020). Disengagements of LKA inside the test vehicle (BMW 520d) were strongly correlated with driving speed and curvature. A new speed concept was introduced based on the speed that could be handled by LKA in curves: the Automated Speed. It was found that the Automated Speed was lower than both the design speed and the operating speed for curves sharper than 550 m and 450 m respectively. The authors also introduced two new parameters: the automated driving consistency and the Level Of Service for Autonomous Driving (LOSAD). These refer respectively to the difference between automated and operating speeds, and the readiness of a corridor for certain vehicle automation systems based on the corridor geometry and the automation system capabilities. Both this paper and the study of Van der Linde do not contain an in-depth analysis of the cause of the LKA disengagements in curves.

The lane width is expected to influence the performance of semi-autonomous vehicles as well. García and Camacho-Torregrosa (2020) did a field operational test using a BWM520d with LKA, where different lanes with different widths were tested. Each lane was tested at least 10 times under optimal weather conditions. The results suggest that LKA does not perform in lanes that are less than 2.5 meter wide. The minimum lane width for LKA to be effective was found to be 2.75 meter. Similar results were reported by Reddy (2019), whose regression model indicated that lane widths below 2.5 meter result in a significantly lower detection performance.

In the study of Cafiso and Pappalardo (2020), a field experiment has been conducted during daytime conditions to look at different requirements of road infrastructure for Lane Support Systems (LSS). Rural roads have been used for this experiment because of low traffic volume and variable infrastructure conditions. Several independent variables have been measured and linked to the detection performance by using logit regression, such as marking luminance coefficient, curvature radius, speed and retroreflectance. A Mobileye 6.0 was used for collection of lane detection status, by accessing the sensor data of the Mobileye. 735 sections have been analyzed and an error percentage of only 2,59% has been found, meaning that LKS functioned in over 97% under optimal conditions. Because multicollinearity was found between diffuse luminance and retroreflectance and the former was found to be dominant, only the diffuse luminance coefficient has been used. This is consistent with the research of Pike et al. discussed earlier, indicating that the diffuse luminance coefficient could be used for daytime visibility. A threshold for the diffuse luminance was found to be 125 mcd/m2/lux. The best logistic regression model contains only two independent variables: Marking quality (Qd) and the curvature radius. Cafiso and Pappalardo underline the importance of controlled field tests for the current state of the art on ODD research. Because their field test took place in dry daytime conditions, it is recommended to also consider different lighting, weather and driving conditions.

2.5.1. Performance evaluation

In order to assess lane keeping systems, it is important to look into the possible performance evaluation measures. In the literature, there are several directions for performance measures. The SAE provides standardized definitions of different driving measures, which include measures for lateral control and statistics (Green, 2013). These measures are not necessarily for vehicle automation, but for driving in general. The lateral control measures are related to lane position, road/lane departures and time to lane crossing. In addition, steering wheel information can be used. The lateral lane position can be extended by the mean lane position and standard deviation of lane position (SDLP). Satzoda and Trivedi (2014) have adopted the Lane Position Deviation (LPD) and the cumulative deviation in time as measures for vehicle automation performance evaluation.

Several measures are based on the detection accuracy. A well known detection measure is the receiver operating characteristic (ROC) curve, which compares the true positive rate with the false positive rate. This measure was used by Gopalan, Hong, Shneier, and Chellappa (2012) to compare the detection performance of different algorithms for lane detection. Another detection accuracy measure was proposed by Satzoda and Trivedi (2014). They state that detection accuracy is important for each step in the detection process. The proposed accuracy measure can be calculated by the sum of the true positives and true negatives, divided by the sum of the true positives, true negatives, false positives and false negatives. Previous research of the same authors used the detection rate as a performance indicator (Satzoda & Trivedi, 2013). Son, Yoo, Kim, and Sohn (2015) calculated the detection rate by dividing the number of correctly detected frames by the total number of frames. Reddy (2019) makes a distinction between both lines detected and no lines detected and provides a guideline for high, medium and low performance. The detection rate for both lines detected should be larger than 90% to be considered a high performance. Similarly, the percentage for no lines detected should be below 5%.

2.6. Conclusion

The literature review in this chapter demonstrated that research regarding LKA is an emerging topic at the moment. Several important topics regarding LKA and lane markings have been discussed. While ADAS/ semi-autonomous vehicles are emerging, there is still much unknown about the conditions and environmental characteristics contributing to their performance. In order to understand the whole system, the sensors and detection process inside vehicles have been discussed. Similarly, different environmental characteristics related to LKA have been identified. Among these characteristics are weather, illumination, and road and lane marking quality. Fig. 2.10 contains a system overview of how the the environment interacts with the LKA.

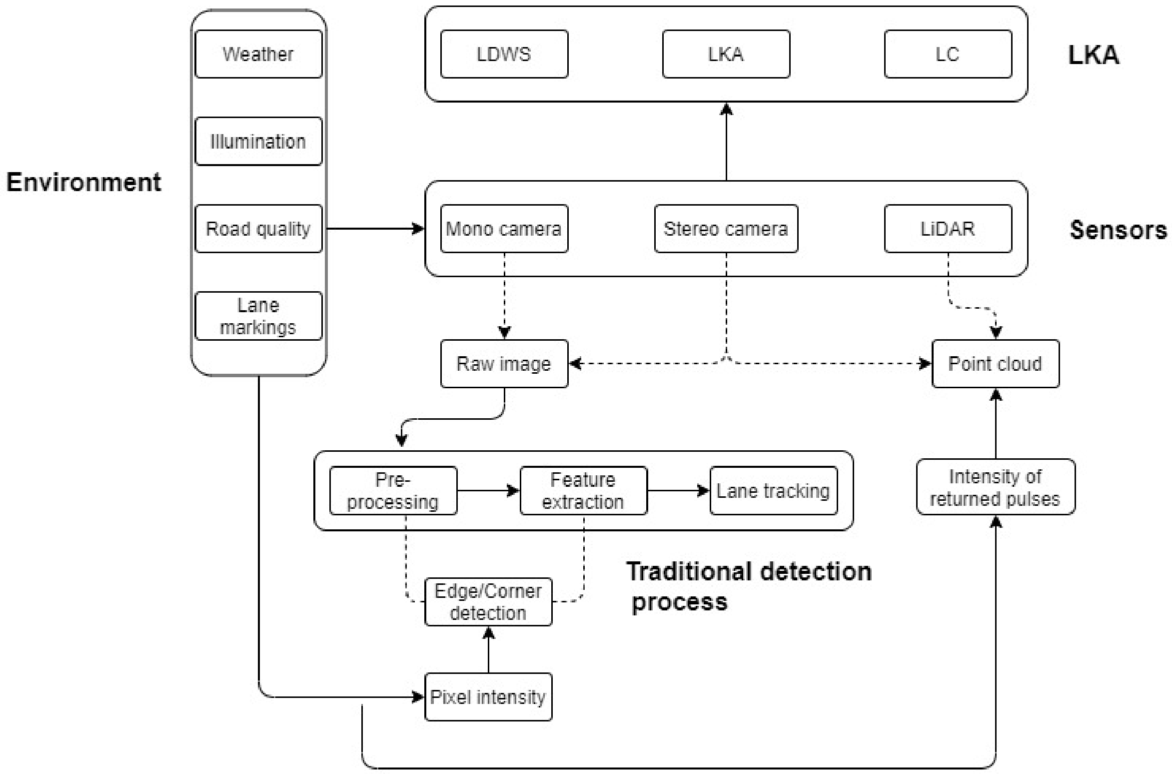

Figure 2.10: System overview containing relevant interactions

The environment is sensed by the two main sensor types: camera and LiDAR. The dashed line below each sensor type indicates the processing of the sensed information. For the mono camera and the stereo camera, a raw image is the input for the traditional detection process. The deep learning process is out of scope for this study. While the environment is sensed by the sensors, it is expected that there is an effect of the environment on the pixel intensity and pulse intensity. The output of the detection process is used for input for the decision-making in the LKA, depicted above the sensors.

While lane markings are designed for human vision, they are currently being used for machine vision as well and are expected to remain useful for machine vision in the future. The literature review revealed two important factors relating to lane marking visibility: contrast ratio and retroreflectivity. Additionally, the application type can affect the visibility of lane markings. While road policies suggest a minimum retroreflectivity of 150 mcd/lx/m2, studies have shown that lower values are also adequate for machine vision under wet and dark conditions. During dry daytime, a contrast ratio of 2.8 was found to be sufficient.

Several field tests have been conducted in order to test the influence of certain road conditions and properties on the performance of lane keeping systems. Lane width and curvature have been found to have a significant influence on the detection performance. Lane widths of 2,75 m were found to be sufficient for lane detection. Additionally, speed has been identified as a significant factor. Current performance is reported to range from 61,6% (detection of both lines) under dark, wet conditions with streetlights, to 97,4% in optimal conditions.

2.6.1. Research gaps

Different sensors for lane detection have been discussed. A few studies have tried to compare the different sensors, but a comprehensive comparison of the main sensors for lane detection (mono-camera, stereo vision and LiDAR), specifically looking at the infrastructural requirements, does not exist. Previous studies also recommend to investigate the LKS performance under adverse conditions regarding weather and illumination.

Beside machine vision, an upcoming sensor in commercial vehicles is LiDAR. The main purpose of this sensor is to make accurate 3D images of the environment, which can be used for localization and object detection (Liu et al., 2020). However, it can also be used for lane marking detection based on reflectivity difference between the pavement and lane markings (H. Lee et al., 2017; Lindner et al., 2009). There is not much known about these infrastructure requirements either yet, for both optimal and adverse conditions.

Several studies that have been conducted with the objective to find lane marking requirements for machine vision have executed experiments in a controlled environment, such as a air field base. Only one study has included retroreflectivity in a field operational test, which was under optimal weather conditions during the day. Performing a field operational test under adverse conditions which include the assessment of retroreflectivity is also identified as a research gap.

The next chapter will discuss how these gaps/recommendations lead to this research.

3

Research Questions and Methods

This chapter contains the research questions and the methods to answer these questions. This chapter is structured as follows: first the research questions and the objectives for this research will be listed. After that, the method for data collection will be described. Finally, the methods for data processing and analysis will be discussed.

3.1. Research questions and objectives

Based on the research gaps defined in the previous chapter, a main research question was formulated. The following research question will be answered in this report:

"How and to what extent do lane marking properties influence the detection performance of different Lane Keep Assist systems? "

Several sub questions are used to answer the main research question:

1. How are different systems selected for the research?
2. Which lane marking properties will be evaluated?
3. How are the different visibility properties of lane markings affected by weather and illumination?
4. What is the performance of different Lane Keep Assist systems under optimal and adverse weather and illumination conditions?

Most of the sub questions can partly be answered by the literature. However, the other parts are expected to be answered with this research. For each sub question, the objective and hypotheses will be listed.

Sub question 1 aims to determine which Lane Keeping Systems are interesting and appropriate to take into consideration for this research. This question is already partly discussed in the literature, where a distinction is made between different sensor types (mono camera, LiDAR, and stereo camera). Based on the literature review, it can be expected that the mono camera has a lower overall performance than LiDAR and stereo since it has more difficulty performing in poor weather and illumination conditions. Differences between the influence of lane marking properties on the detection performance of the different sensor types are not expected.

Sub questions 2 determines the selection of lane marking properties that will be evaluated in this research. Several properties have been discussed in the literature review, such as contrast, retroreflectivity and application method. Based on the theoretical lane detection process explained in the previous chapter, it is expected that the contrast ratio is relevant for daytime detection. The retroreflectivity in lane markings is assumed to have a positive effect on the nighttime visibility, because the light emitted by the head lights will be reflected back towards the sensor. A larger value for retroreflectivity is expected to result in a higher contrast with the road and therefore a higher detection performance. The application method is expected to affect the detection performance only during rainy conditions, since type 2 lane markings were specifically designed to increase visibility in wet conditions. These three visibility properties will explicitly be collected and assessed in this study.

Sub question 3 is added to understand how external conditions, such as rain, can affect the perception of lane markings. This is already mostly discussed in the literature chapter, but will be used in this research to potentially identify other interactions. It is expected that a wet road surface due to rain can lead to glare, which can have a negative effect on the visibility of the lane markings.

Sub question 4 looks into the detection performance of the different systems in this research. In order to find lane marking properties that affect the detection performance, a baseline should be established to see how the performance of the system is affected in different weather and illumination conditions. Only for the mono camera there exist little knowledge about the performance in optimal conditions. It is expected, based on previous studies, that LiDAR and stereo vision have a higher performance and a higher robustness in adverse weather conditions. During nighttime conditions, it can be expected that the detection in dry weather conditions is better than during daytime, however that might depend on the quality of the lane marking with respect to the retroreflectivity. Detection during wet nighttime conditions was previously found to have the lowest performance. For nighttime conditions, a distinction can be made between the presence or absence of street lights. It is expected that the presence of street lights negatively influences the detection performance, as it may result in a lower contrast between the road and the lane marking (especially in rain it can lead to more glare).

The objective of this research can be divided into two parts:

1. To determine the influence of different lane marking properties on the detection performance in different conditions
2. To determine whether the influence of different lane marking properties on the detection performance varies between different sensor types

3.2. Data collection method

Based on the recommendations and research gaps, a field test was conducted to collect data. During the field test, several vehicles equipped with LKA drove on Dutch provincial roads. This section describes which vehicles were used, the test routes, the data collection set-up, and the conditions of the field test.

3.2.1. Test vehicles

The literature divides the main sensors for lane detection into camera sensors and LiDAR. Based on this division, a categorisation of vehicle manufacturers was made to determine which vehicle uses which sensor type. Three vehicles have been selected for the field test, each of them equipped with a different sensor. Unfortunately, it was not possible to obtain a vehicle equipped with LiDAR, therefore the third vehicle was equipped with a mono camera in combination with infrared. The vehicles with their corresponding specifications are summarized in Table 3.1.

Table 3.1: Overview of test vehicles with specifications

Specification	Hyundai Kona	Subaru Outback	Audi RS Q8
Year	2018	2020	2020
Sensor used for lane detection	Mono camera	Stereo camera	Mono camera + infrared
Activation speed	60 km/h	60 km/h	65 km/h

All vehicles were equipped with Lane Departure Warning and Lane Keep Assist, the Hyundai Kona was also able to follow the lanes without human intervention. Audi provides additional information about the camera settings. They state that the camera can observe the road at least 50 meters ahead and has a field of view of 40 degrees. The Audi active lane assist is also able to differentiate yellow lane markings (Audi, 2011). The Subaru has a baseline of 35 centimeters. The sensor in each of the vehicles was installed in the windshield behind the rear view mirror.

In this field test the three vehicles were driving simultaneously to control for weather and illumination variability for each vehicle. Several studies used the same driver for all tests to control for driver behaviour variability (García et al., 2020; García & Camacho-Torregrosa, 2020). That was not possible for this field test, several different drivers were needed. Each driver was instructed to drive according to the local traffic rules and keep as much distance from the preceding vehicle as possible. Additionally, each driver had to sign a consent form in case of video footage containing personal information and a COVID-19 form, stating that they did not have any symptoms or were not tested positive for COVID-19.

3.2.2. Test routes

Two different routes were driven during the field test. The first route, of 75 kilometer, started in Deventer and ended on the Dutch-German border (see Fig. 3.1). This route was planned using information from the province of Overijssel about the age and the type of the lane markings. The lane markings on this route have a different year of application, ranging from 2008 to 2018. Another important factor for this choice of route was the curvature of the road. Sharp curves were rarely found on the provincial roads and only a few roundabouts were encountered. Only a small section of this route was applied with type 2 lane marking (appr. 5 kilometers). It was recommended to include both types in the experiment by industry experts and therefore another route was included.

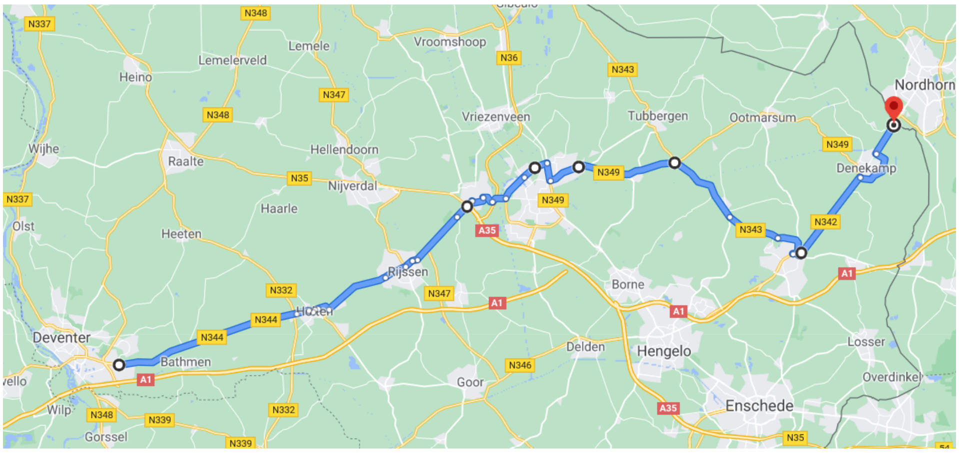

Figure 3.1: Route 1 (Deventer - German border, 75 km, mostly type 1 markings)

The second route started and ended in the same place (Deventer) and was approximately 50 kilometers long (see Fig. 3.2). This route was located in a different province than the first route (Gelderland instead of Overijssel), which is why there was no information available regarding the age and type of the lane markings. Inspection using Google Maps revealed that most of this route is applied with type 2 lane markings.

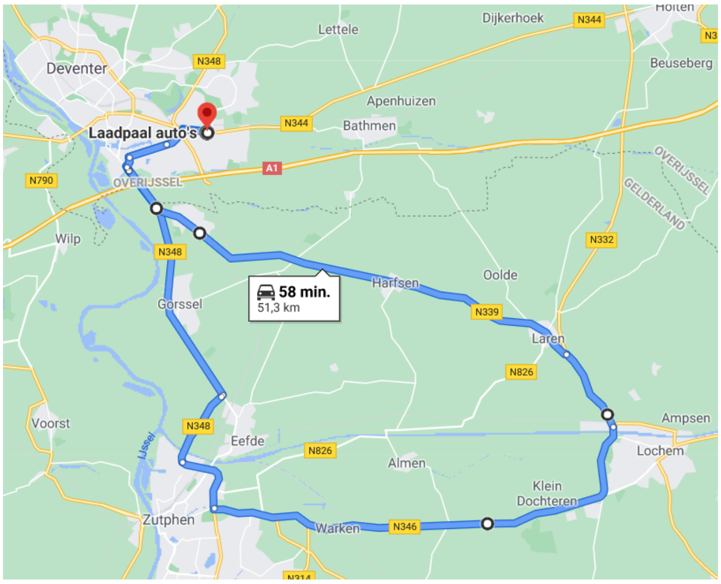

Figure 3.2: Route 2 (Deventer - Deventer, 51 km, mostly type 2 markings)

3.2.3. Data collection set-up

During the drives, information regarding detection and road conditions was collected by cameras. GoPro cameras were installed in the vehicles to capture the road in front of the vehicle and the detection status on the dashboard/ head-up display. One camera inside each vehicle was equipped with GPS in order to retrieve location and speed at a certain timestamp. When the cameras started recording, the actual (atomic) time was displayed on a mobile phone and held in front of the lens.

Figure 3.3: Position dashboard camera (Audi)

Figure 3.4: Position front camera (Subaru)

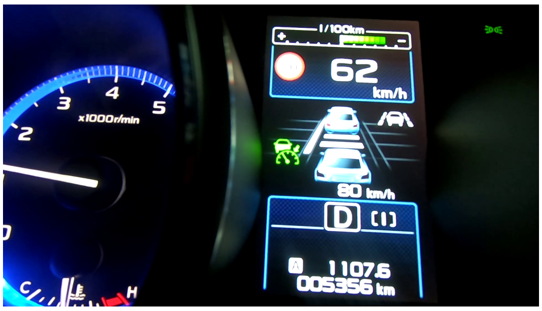

Figure 3.5: View dashboard camera (Subaru)

Figure 3.6: View front camera

3.2.4. Field test conditions

The field test took place on the 24th, 25th and 26th of November 2020. During the first two days the weather conditions were good, it was overall sunny and during the nights the sky was clear as well. There was one challenging situation for the vehicles' cameras: sunset. During the sunset, the sun was shining directly into the cameras at some moments. On November 26, there was a little precipitation during the day and night, which also caused a lower visibility during the night at some points. Because no heavy rain was present during the field tests, glare has not been experienced.

Different environments were encountered during the drive. Most of the time the driving environment was a mixture of forest and countryside. Although urban environments were part of the routes, these were mostly outside of the vehicles' operational design domain due to the activation speed.

3.3. Data processing method

Fig. 3.7 contains an overview of the collected variables, how the variables were collected and how they were processed. A more detailed description of the processing steps can be found below.

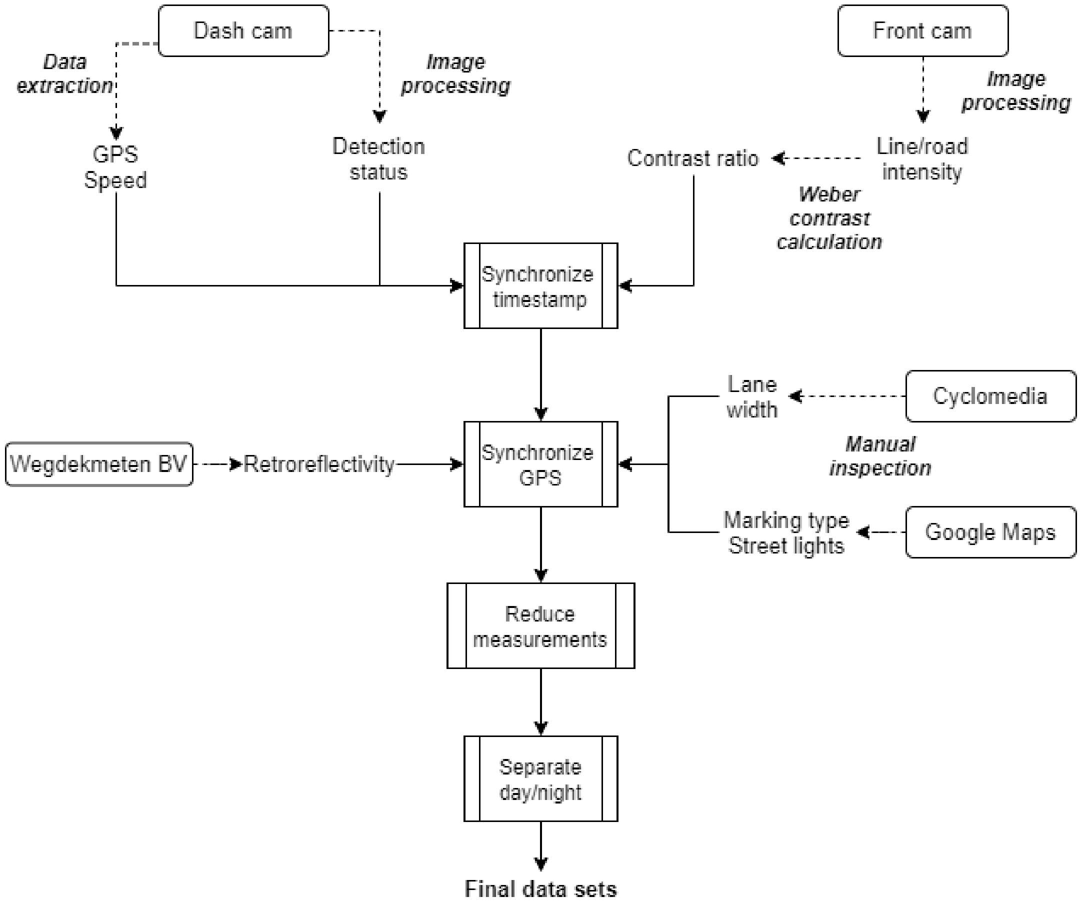

Figure 3.7: Route 2 (Deventer - Deventer, 51 km, mostly type 2 markings)

The collected videos were saved in multiple, separate files. The first step was to combine the files for each video and synchronise the dashboard and front camera videos. This was done using audio synchronization in Adobe Premiere Pro. When no audio was available, the atomic time that was recorded was used to synchronize the videos manually. Using an online GoPro tool the GPS coordinates and speed could be retrieved. This was only possible to retrieve for each separate file and not for the synchronized and merged videos. Unfortunately, the frequency of the GPS measurements was different than the set frame rate of the videos (18 Hz opposed to 30Hz respectively). In order to connect these separate data sources, each frame of the synchronized videos was timestamped. The recorded atomic clock was used to indicate the start of the video. A Python script was used to loop through the frames, indicate the frame rate and add the passed time using the frame rate. This list was used to connect the GPS measurements to the information in the videos by comparing the timestamps in both sources.

The videos of the dashboard cameras, collecting the detection status, were analyzed with both template matching and a line detection technique. Template matching entails using a template of how a line detection would look like, and comparing that to the video frame that is being processed. A line detection technique searches for straight lines in the frame and uses the pixel values to determine when the line was lit up (in case of detection) or not. Python was used to process the videos and the scripts were provided by data scientists of RHDHV. The detection status of the Audi was indicated with different colors. Both green and red indicated that a lane was detected (red meaning that the vehicle has crossed the lane marking), no lane detected was indicated in grey. This color indication resulted in an accurate retrieval of the detection status. The detection status for the Hyundai Kona and the Subaru Outback were indicated in a similar way, however the interfaces looked entirely different. For the Kona, the camera was directed towards the Heads-Up Display, where each line was bright white when detected and grey when not detected. Additionally, when Cruise Control was activated, white lines between the lane indicators were displayed to indicate the distance to the preceding vehicle. This caused a disturbance for perceiving the lane detection status and was turned off for most of the drives. The detection status for the Subaru was also indicated by a bright white line, see Figure 3.5). The analysis of the dashboard videos resulted in a classification of the detection status per frame using four categories: Both, Left, Right, or None. Since the contrast ratio and the retroreflectivity was available per separate line, the detection status was split into a binary categorisation for both the left and the right line. This resulted in a 1 when the line was detected, and 0 when the line was not detected.

The videos of the road facing cameras were processed using a lane detection algorithm adapted from Udacity. The full script can be found here: https://github.com/elinevdk/self-driving-car. Fig. 3.8 shows an example of the output of the algorithm. For both lines separately, the intensity was found by taking the average of each pixel array within the indicated area (red for left line, blue for right line). A pixel array consists of three values in the red, green and blue colorspace. These values can range from 0 to 255. Since dashed lines are included in the projected lines, taking the average intensity of the line would result in a lower value than the actual intensity of the lane marking. To correct for this, the maximum intensity has been reported. For the road intensity, the average intensity of a fixed square within the green area was returned.

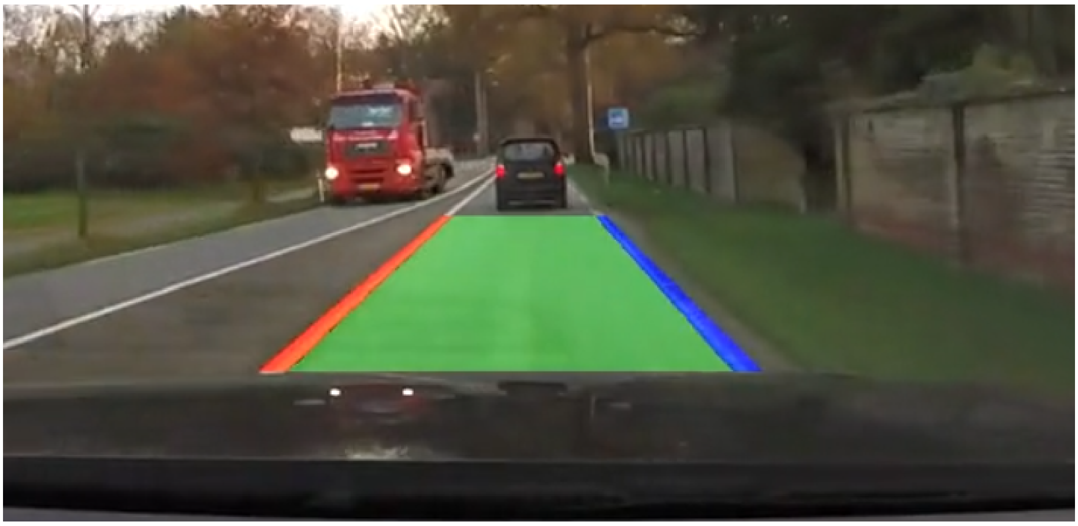

Figure 3.8: Output of the lane detection algorithm

With the intensity values of the lines and the road, a contrast ratio can be calculated. The Weber contrast (Equation 3.1) is often used for smaller objects on a uniform background, which is often the case with lane markings on roads. Additionally it was used by previous studies of Pike to calculate the contrast ratio.

$$C_w = \frac{I_m - I_r}{I_r} \tag{3.1}$$

The retroreflection values of the lane markings on the route have been provided by Wegdekmeten B.V., a company specialized in measuring roads. The possibility to have measured this as part of this research was limited by the costs of dynamic equipment rent or the impracticality of using static equipment. The provided measurements were taken 20 meter apart and dated from 2018, meaning that they do not represent the actual retroreflectivity that has been encountered during the tests. The lane markings are degraded over time, meaning that the actual retroreflectivity during the field test has been lower than the data provided.

The lane width, marking type, and street lights were added to the data set based on the GPS coordinates. A manual measurement was done in Cyclomedia to obtain the lane widths along the route.

This has been validated by the road design guidelines from CROW. Google Maps provided the GPS coordinates where street lights were present and the sections with marking type 1 or 2.

Because the frequency of the GPS measurements, video frames, and retroreflectivity data were all different, the number of observations in the data set have been reduced to match the rate of the retroreflectivity measures, e.g. one measurement every 20 meter. This has been done by a Python script that calculates the distance between two GPS coordinates.

3.4. Data analysis method

In order to assess the contribution of each variable on the detection status, regression analysis will be used. In this case, the detection status is the dependent variable and speed, lane width, retroreflectivity, etc. are the independent explanatory variables. The main goal of a regression analysis is to build a mathematical model that is able to predict the dependent variable by adding weights to the different explanatory variables. Additionally, the model can also be used to assess the significance and impact of the explanatory variables on the dependent variable.

Linear regression analysis can only be used when the dependent variable is continuous. In this research, the dependent variable is not only categorical, it is dichotomous. The explanatory variables are on both continuous and categorical scales. An appropriate method is therefore Binary logistic regression (Osborne, 2008). The logistic regression equation can be found in Equation 3.2.

$$Y = \frac{exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_i X_i)}{1 + exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_i X_i)} \tag{3.2}$$

The non-linear relationship is described with an exponential equation. The exponential in the numerator can also be regarded as the odds that the dependent variable takes on a certain value with certain weights and values for the independent variables. When the odds are divided by 1+ odds, a probability (Y) for this event can be calculated.

Determining which of the explanatory variables are significant and estimating the values of the betas was done using IBM SPSS 26. The results can be found in Chapter 5. First, in Chapter 4, the overall performance results and data description is presented.

4

Descriptive Statistics and Performance Evaluation

This chapter contains the performance evaluation and the description of the data that has been collected during and after the field test. The description includes the distribution for each variable and the evaluation of the performance of the vehicles for the defined categories of the variable.

During the field tests, a total of 460 kilometer has been driven. Most of the drives were during dry nighttime conditions. An overview of the amount of kilometers driven during each condition is presented in Table 4.1. Sunset is included in the dry daytime conditions. Additionally, the lane marking type is included.

Table 4.1: Overview of kilometers driven in different conditions with lane marking types

		Day	Night
Dry	**Type 1**	69,6 km	139,2 km
	Type 2	55,4 km	60,8 km
Wet	**Type 1**	23,7 km	69,6 km
	Type 2	35,1 km	5,4 km

4.1. Performance evaluation

This section contains the performance of the three different sensors(mono camera with infrared, mono camera, stereo camera) under different conditions. The performance is evaluated using the percentages of the measurements that fall within a detection category. The total amount of measurements for each condition is stated in the most right column of the tables. Since the vehicles showed the detection per line, the detection status is categorized as follows: Both lines detected, Left line detected, Right line detected and None (no lines detected). The performance is color-coded from green for the highest percentage to red for the lowest percentage.

Table 4.2 contains the performance of the mono camera with infrared. A z-test was performed to see whether the proportions of the detection status per condition were significantly different (see Appendix A.1). For both dry and wet conditions, the sensor has a higher percentage of both lines detected during nighttime than during daytime. However, there is no significant difference between the nighttime wet and dry, and between nighttime dry and daytime wet ($p > 0.05$). The best performance was obtained during sunset conditions. However, it should be noted that there are less observations for sunset conditions than for other conditions.

Table 4.2: Performance mono camera including infrared

Conditions	Both	Left	Right	None	Count
Sunset	91,44%	1,32%	3,73%	3,51%	456
Daytime - dry	76,01%	1,29%	6,80%	15,90%	2472
Daytime - wet	81,18%	1,64%	1,30%	15,88%	1461
Nighttime - dry	83,26%	0,74%	3,46%	12,54%	3900
Nighttime - wet	85,4%	3,87%	6,56%	4,17%	1342

The performance of the regular mono camera is shown in Table 4.3. Due to the poor quality of the video of the detection status during daytime conditions, there is no reliable data on the detection performance. Additionally, a different method for detection status collection was used during the sunset drive, resulting in only Both or None categorisations.

Table 4.3: Performance regular mono camera

Conditions	Both	Left	Right	None	Count
Sunset	94,65%	-	-	5,35%	374
Daytime - dry	-	-	-	-	0
Daytime - wet	96,63%	1,48%	0,83%	1,06%	1690
Nighttime - dry	97,02%	0,89%	0,08%	2,01%	1341
Nighttime - wet	87,3%	0,11%	0,33%	12,27%	1817

The percentage of both lines detected during nighttime wet conditions is significantly lower than for the other conditions ($p < 0.05$, see Appendix A.2). The percentage of no lines detected for the same condition is similarly significantly higher than for the other conditions.

Table 4.4 contains the performance for the stereo vision detection. This sensor has performed significantly worse than the previous two sensors.

Table 4.4: Performance stereo camera

Conditions	Both	Left	Right	None	Count
Sunset	5,14%	6,80%	2,65%	85,41%	1206
Daytime - dry	-	-	-	-	0
Daytime - wet	15,94%	7,11%	1,12%	75,83%	5094
Nighttime - dry	8,77%	5,12%	1,70%	84,41%	2714
Nighttime - wet	6,4%	3,37%	1,95%	88,26%	1900

It is highly unlikely, with these performance results, that valid conclusions can be drawn from further analyses. The most logical explanation for these results is that the provincial roads within the test routes are not within the specified ODD of the vehicle. The results for the stereo camera are therefore excluded from further analyses. An elaboration on this can be found at the end of this chapter.

A comparison can be made between the remaining two sensor types for different conditions. During daytime wet conditions, the regular mono camera has a significantly higher percentage for both lines detected ($p < 0.05$, see Appendix A.3). The mono camera with infrared has a significantly higher percentage for no lines detected. For left or right lines detected, there is no significant difference between the sensor types during daytime wet conditions. During nighttime dry conditions, similar results are found (see Appendix A.4). For nighttime wet conditions, there is no significant difference between the sensor types for both lines detected ($p > 0.05$, see Appendix A.5). For the other detection categories, there is a significant difference. For sunset conditions, there is no significant difference between the sensor types for all detection categories ($p > 0.05$, see Appendix A.6).

4.2. Descriptive statistics variables

In order to obtain more information about the variables that might contribute to the detection performance, some statistical descriptions per variable are included in this section.

4.2.1. Speed

As described in the methodology chapter, speeds below the activation speeds of the vehicles' LKA were removed from the data set. Since the activation speed of the regular mono camera (60 km/h) is lower than the activation speed of the mono camera with infrared (65 km/h), there are two speed distributions (see Fig. 4.1 and 4.2).

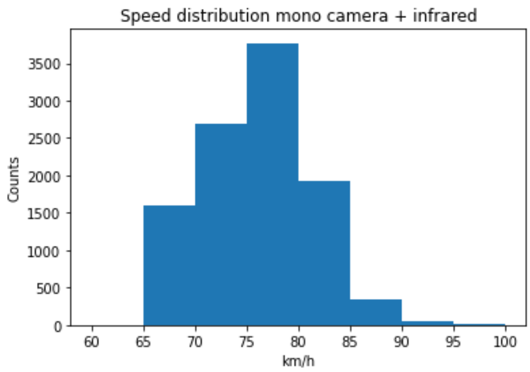

Figure 4.1: Speed distribution mono camera + infrared

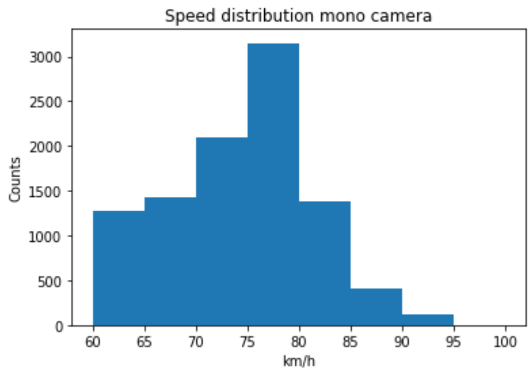

Figure 4.2: Speed distribution mono camera

As can be seen in the above figures, the speed distributions for both sensor types appear similar. Both sensor types have the most observations between 75 and 80 km/h. However, an Independent Samples T-Test shows that the two samples are significantly different ($p < 0.05$, see Appendix A.7). The mean speed of vehicle equipped wit the mono camera with infrared is higher than the mean speed of the vehicle with the regular mono camera. This is not surprising, given the fact that the activation speed for the mono camera with infrared is higher. To find out how the detection performance varied for different speeds, the detection status for different speed categories is plotted below for both sensor types:

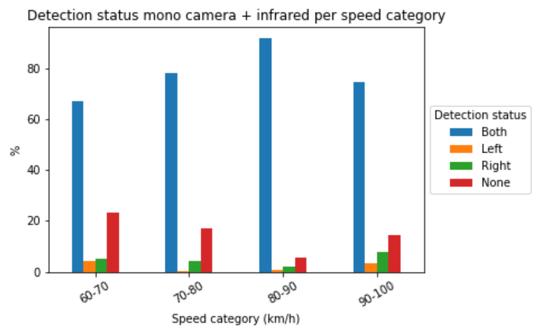

Figure 4.3: Detection mono camera + infrared per speed category

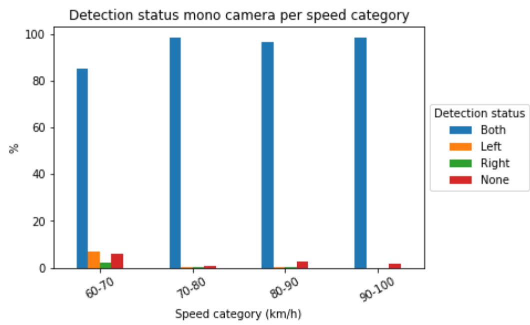

Figure 4.4: Detection mono camera per speed category

For both sensor types it can be observed that the best performance is achieved for speeds between 80-90 km/h. It is remarkable that the performance of the mono camera with infrared decreases with speeds above 90 km/h. There is a relatively low number of observations within this speed category in the data set, so it might be coincidental. Another possibility is that there is a non-linear relationship between speed and detection status, which was also found in the study of Reddy (2019).

4.2.2. Lane width

Figure 4.5 shows the distribution of lane width in the total data set:

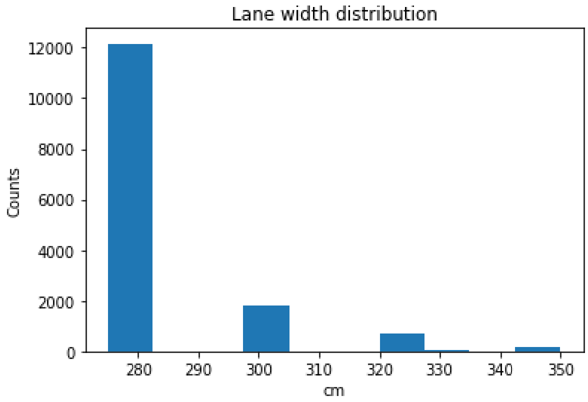

Figure 4.5: Lane width distribution

The most observed lane width in the data set by far is 275 cm. Roughly four categories of lane width can be distinguished: 275, 300, 320 and 350 cm. For these four categories the detection status of each sensor type is plotted below:

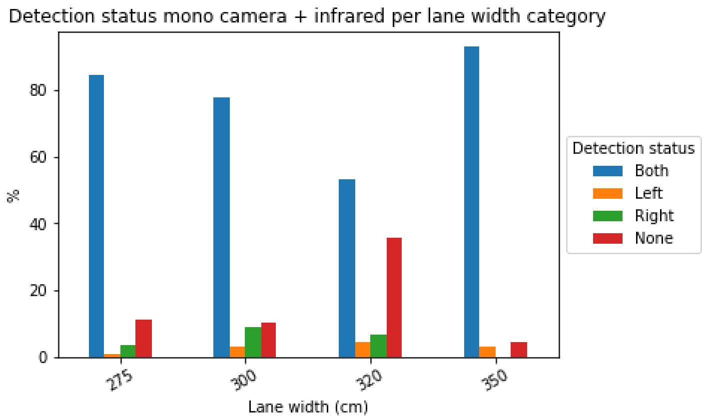

Figure 4.6: Detection mono camera + infrared per lane width category

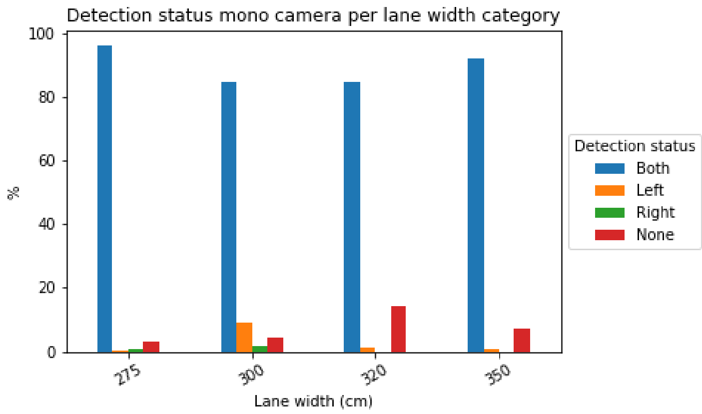

Figure 4.7: Detection mono camera per lane width category

It seems that the detection performance decreases with increasing lane width, except for a lane width of 350 cm. This could be caused by the presence of intersections and roundabouts in the observations. At these locations, the roads are wider than on ongoing roads, and because most of the roundabouts/intersections had two or more lanes, there were possible lane switches. A lane width of 350 cm was more commonly observed at ongoing roads. However, this decrease in performance can also be a result of a lower number of observations for lane widths other than 275 cm.

4.2.3. Retroreflectivity

The retroreflectivity was provided for the left and right line separately. The distributions for both lines are shown in Fig. 4.8 and 4.9:

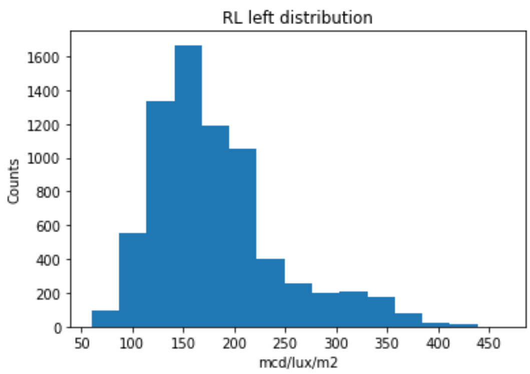

Figure 4.8: RL left distribution

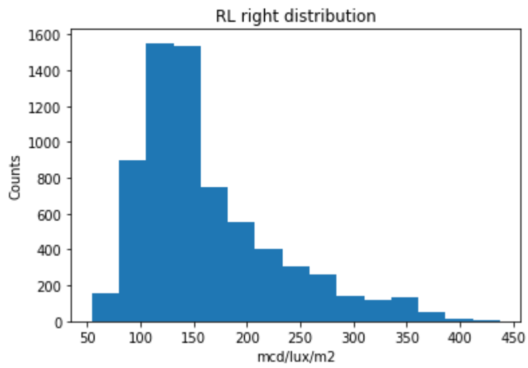

Figure 4.9: RL right distribution

Most observations are between 100 and 200 mcd/lux/m2 for both sides. The values for the left line are significantly higher than the values for the right line retroreflectivity ($p < 0.05$, see Appendix A.8). Both lines have a correlation of 0.314, which is only moderate. Assuming that both lines were applied on the road at the same time, it would be reasonable to expect similar distributions and a higher correlation, which is not the case. The graphs below indicate the detection performance per retroreflectivity category, for both lines and both sensor types:

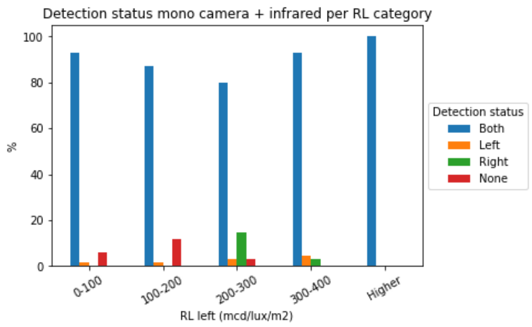

Figure 4.10: RL left plot mono camera + infrared

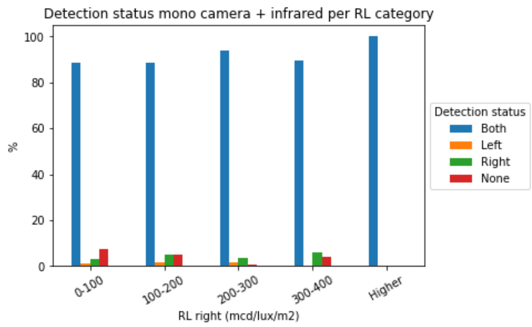

Figure 4.11: RL right plot mono camera + infrared

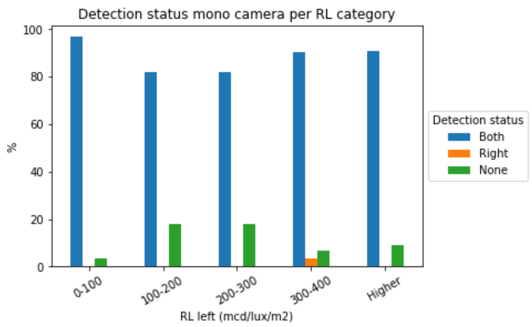

Figure 4.12: RL left plot mono camera

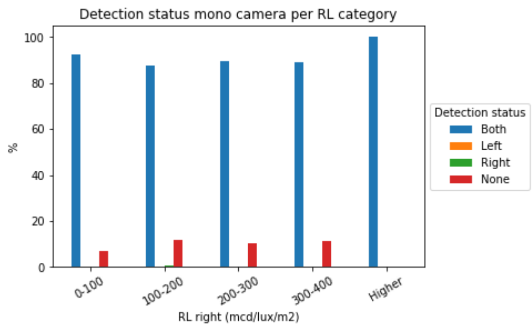

Figure 4.13: RL right plot mono camera

It appears that there is an increasing detection performance with an increasing value of retroreflectivity. Only retroreflectivity values below 100 produce different results. Since the retroreflectivity measurements are dated from 2018, it is likely to assume that some roads that were part of the test route have been updated since then. This was also observed during the field test. Observations with a retroreflectivity value of below 100 will therefore be excluded from further analyses.

4.2.4. Contrast ratio

Similar to the retroreflectivity, the contrast ratio is collected for the left and right line separately. Figures 4.14 and 4.15 contain the distributions for the collected contrast ratios.

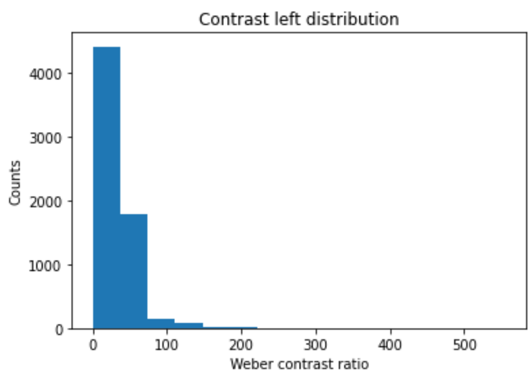

Figure 4.14: Contrast left distribution

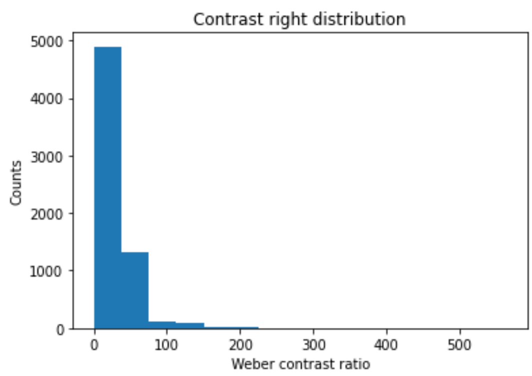

Figure 4.15: Contrast right distribution

Both distributions are heavily skewed to the left. There are only a few observations with a contrast ratio higher than 200. Similar to the retroreflectivity, the contrast of the left line is significantly higher than the contrast of the right line ($p < 0.05$, see Appendix A.9). The values for contrast ratios for both lines are strongly correlated (0.961), which could be explained by the use of the same value for road intensity for calculating the Weber contrast ratio. The graphs below indicate the detection performance per contrast category, for both lines and both sensor types:

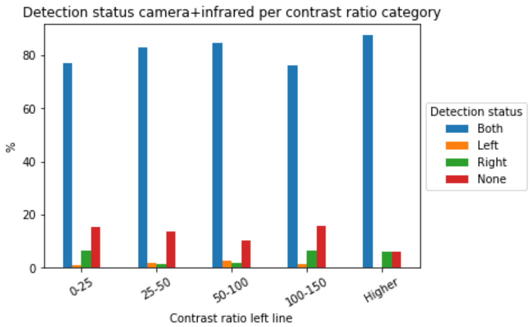

Figure 4.16: Contrast left plot mono camera + infrared

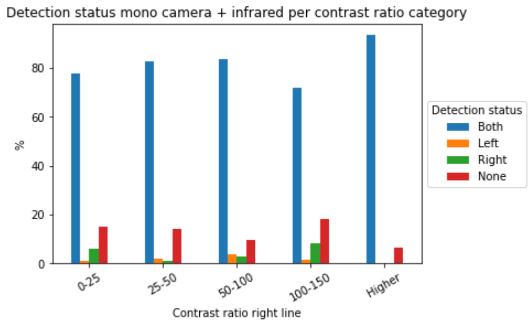

Figure 4.17: Contrast right plot mono camera + infrared

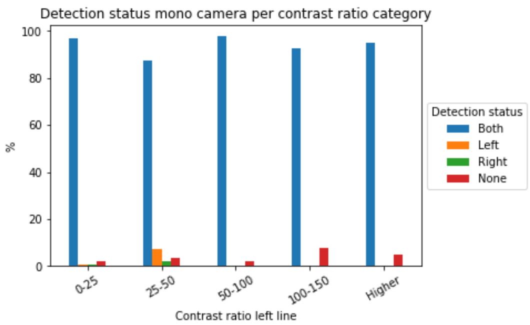

Figure 4.18: Contrast left plot mono camera

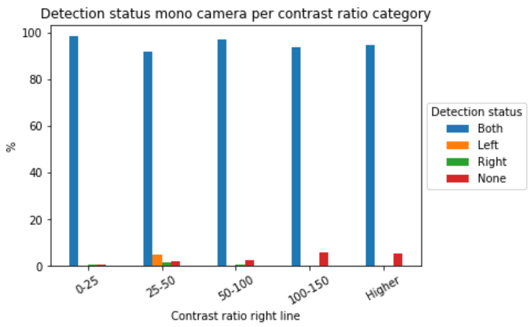

Figure 4.19: Contrast right plot mono camera

It appears that there is no obvious trend between the detection performance and the contrast ratio. However, a more in-depth analysis of the relation between the detection status and the contrast ratio will be necessary to determine this.

4.2.5. Marking type

Two types of lane markings have been encountered during the field test: type 1 (flat, paint or tape) and type 2 (profiled, dots or drops). Table 4.5 contains the number of observations for each type:

Table 4.5: Number of observations with marking types 1 and 2

	Type 1	**Type 2**	**Total**
Count	11890	2963	14853

It is clear that there are less observations with type 2 in the data set. Figures 4.20 and 4.21 contain the detection performance for each type of lane marking for both sensor types:

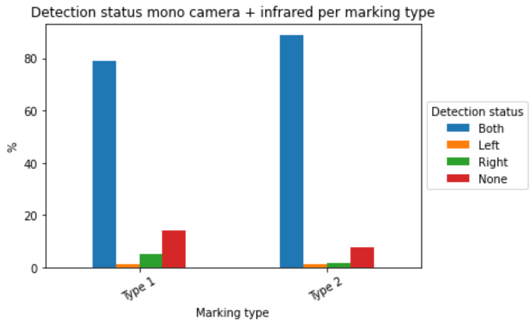

Figure 4.20: Marking type plot mono camera + infrared

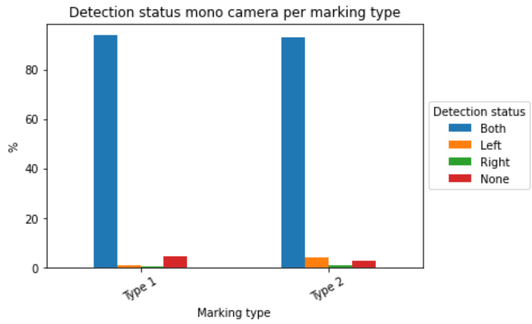

Figure 4.21: Marking type plot mono camera

While the regular mono camera has a high performance with both marking types, it appears that the mono camera with infrared has a better performance with lane marking type 2.

4.2.6. Street lights

Finally the presence of street lights during the nighttime observations is presented. Table 4.6 contains the number of observations with and without street lights present:

Table 4.6: Number of observations with and without street lights

	Streetlights	**No street lights**	**Total**
Count	956	6347	7303

There are less observations where street lights were present as opposed to absent. Figures 4.22 and 4.23 show the detection performance for both categories:

Figure 4.22: Street lights plot mono camera + infrared

Figure 4.23: Street lights plot mono camera

It appears that the presence of street lights result in a higher detection performance than without street lights. Based in the literature, it was expected that the presence of street lights would have had a negative effect on the detection performance.

4.3. Challenges data collection and preparation

A few challenges have been encountered during the execution of the field test and the preparation of the data. These challenges and their implications are listed below:

- The test routes were mostly outside of the scope for the Subaru Outback. The vehicle manual is referring to U.S. terms of roads and state that the LKA of the Subaru can be used on freeways, interstate highways, expressways, and toll roads. The lanes should have a width between 3 and 4,5 meters, while the mostly encountered lane width was 2,75 meters wide. Another limitation stated in the manual is a double lane marking, which might have had a negative influence on the detection performance as well as most of the provincial roads had a double marking in the middle of the road (see Fig. 3.6)
- The first video of the detection status of Audi was by accident recorded in timelapse mode. This means that less frames have been captured. With Adobe Premiere Pro the video could be transformed to the actual duration, but it resulted in a loss in frame rate. This is the reason why for the sunset conditions a lower number of observations is available. Because the GPS coordinates have been used to select the same observations for the other vehicles, the sunset observations for the other two vehicles are similarly lower.
- According to the Province of Overijssel and other sources, the straight road towards the border with Germany as part of Route 1 was supposed to be in a less good condition than that was encountered during the field test. This resulted in a higher overall quality of road sections with only little variation.
- Due to the limited availability of data scientists at RHDHV, the lane marking detection Python script for retrieving the contrast ratios was written with help of Computer Science master students. While a lot of effort was put into the adaptation of an existing script from Udacity for self-driving vehicles to make it compatible with the collected videos, the presence of double lane markings in the center of the road caused some instability. In addition, the algorithms could not track the lane properly when there was a gap. This could lead to different values for line intensity than was encountered during the field test.

5

Logistic Regression Analysis Results

This chapter contains the results of the logistic regression analysis. The previous chapter discussed several potential relationships between the measured variables and the detection status. This chapter aims to provide a more in-depth analysis to whether these relationships exist in the data. In order to determine which variables should be included in the logistic regression model, Chi-square tests have been performed. These outcomes are discussed in the first section. The second section contains the model outcomes of the regression analysis. The last section demonstrates the detection performance by means of geographical plots of the observations.

5.1. Variables for regression analysis

This section contains the Chi-square tests for independence between the detection status and the variables discussed in the previous chapter. The Chi-square test uses the null hypothesis that the detection status and the variable are independent. The following variables are considered in this study, including variable type and value range:

Table 5.1: Considered variables with type and range

Variables		Variable type	Value range
Speed		Continuous	65-104 km/h
Lane width		Continuous	275-350 cm
Retroreflectivity	**Left**	Continuous	100-466 mcd/m2/lux
	Right	Continuous	100-438 mcd/m2/lux
Contrast ratio	**Left**	Continuous	0,17-555
	Right	Continuous	0,04-564
Marking type		Categorical	1 (type 1) 2 (type 2)
Sensor type		Categorical	1 (mono camera with infrared) 2 (mono camera)
Conditions		Categorical	1 (daytime dry) 2 (daytime wet) 3 (daytime sunset) 4 (nighttime dry) 5 (nighttime wet)
Street lights		Categorical	0 (not present) 1 (present)

Table 5.2 contains the results of the Chi-Square test for all the variables and the detection status:

Table 5.2: Pearson Chi-square test for independence between variables and detection status

Variables	χ^2	df	p-value (2-sided)	N of Valid Cases
Speed	614, 097	123	<0.0001	14853
Lane width	416,933	12	<0.0001	14853
Retroreflectivity-left	1287,574	891	<0.0001	6951
Retroreflectivity-right	1209,031	864	<0.0001	6096
Contrast ratio-left	947,393	468	<0.0001	6453
Contrast ratio-right	935,407	462	<0.0001	6453
Marking type	248,250	3	<0.0001	14853
Sensor type	408,036	3	<0.0001	14853
Conditions	351,860	12	<0.0001	14853
Street lights	184,706	3	<0.0001	7303

The results of the Chi-square tests are significant for all variables ($p < 0.05$), meaning that the detection status and each one of the variables are not independent. There is a relation between the two, therefore all the variables should be considered for the regression model.

5.1.1. Variable coding

For ease of data processing, some of the original values of the categorical variables in the data sets have been recoded. SPSS adds another variable coding to process them in the logistic regression. How the categorical variables of the daytime and nighttime dataset are coded can be found in Tables 5.3 and 5.4:

Table 5.3: SPSS variable coding for daytime dataset (* = reference)

Variable	Original value	Initial coding	SPSS coding (1)	SPSS coding (2)
Marking type	Type 1 (smooth)	1	0*	
	Type 2 (profiled)	2	1	
Sensor type	Mono camera + infrared	1	0*	
	Mono camera	2	1	
Conditions	Dry	1	0*	0*
	Wet	2	1	0*
	Sunset	3	0*	1

Table 5.4: SPSS variable coding for nighttime dataset (* = reference)

Variable	Value	Initial coding	SPSS coding
Marking type	Type 1 (smooth)	1	0*
	Type 2 (profiled)	2	1
Sensor type	Mono camera + infrared	1	0*
	Mono camera	2	1
Conditions	Dry	4	0*
	Wet	5	1
Street lights	Not present	0	0*
	Present	1	1

The variable values that are coded 0 by SPSS are the reference values, denoted with a *. This means that marking type 1, sensor type 1 (mono camera with infrared), the absence of street lights, and dry conditions are set as the reference for both the daytime and nighttime data sets. Since there are three conditions in the daytime data set, there are two different variable codings. The variables Speed, Lane width, Retrereflectivity, and Contrast ratio are continuous variables and are therefore not recoded.

5.1.2. Interaction effects

Besides using the above-mentioned variables, also referred to as main effects, there is also a possibility for interaction effects between the variables. According to experts, different types of lane marking applications have a better visibility in different conditions. This indicates a potential interaction. To test whether this interaction exists within the observations, a two-way(univariate) ANOVA test have been performed in SPSS. Tables 5.5 and 5.6 show the results of the tests:

Table 5.5: Test of interaction between marking type and conditions, left line detection

Tests of Between-Subjects Effects

Dependent Variable: Leftlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	56,033[a]	9	6,226	57,490	,000	,034
Intercept	2724,058	1	2724,058	25154,117	,000	,632
Markingtype	10,022	1	10,022	92,540	,000	,006
Conditions	2,209	4	,552	5,098	,000	,001
Markingtype * Conditions	5,536	4	1,384	12,780	,000	,003
Error	1588,359	14667	,108			
Total	12790,000	14677				
Corrected Total	1644,391	14676				

a. R Squared = ,034 (Adjusted R Squared = ,033)

Table 5.6: Test of interaction between marking type and conditions, right line detection

Tests of Between-Subjects Effects

Dependent Variable: Rightlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	27,241[a]	9	3,027	31,310	,000	,019
Intercept	2806,518	1	2806,518	29031,525	,000	,667
Markingtype	7,514	1	7,514	77,723	,000	,005
Conditions	1,059	4	,265	2,738	,027	,001
Markingtype * Conditions	2,846	4	,711	7,359	,000	,002
Error	1403,572	14519	,097			
Total	12920,000	14529				
Corrected Total	1430,813	14528				

a. R Squared = ,019 (Adjusted R Squared = ,018)

The interaction is denoted by Markingtype*Conditions. Since the interaction is significant ($p < 0.05$), it should be considered for the regression model along with the main effects.

Another potential interaction can be found between the conditions and the sensor types. The performance evaluation already indicated a difference in detection performance between the two sensor types under different conditions. Tables 5.7 and 5.8 contain the tests for interaction effects between conditions and sensor types:

Table 5.7: Test of interaction between sensor type and conditions, left line detection

Tests of Between-Subjects Effects

Dependent Variable: Leftlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	70,530[a]	8	8,816	82,165	,000	,043
Intercept	7319,184	1	7319,184	68212,982	,000	,823
Sensortype	9,811	1	9,811	91,437	,000	,006
Conditions	17,633	4	4,408	41,085	,000	,011
Sensortype * Conditions	15,853	3	5,284	49,249	,000	,010
Error	1573,862	14668	,107			
Total	12790,000	14677				
Corrected Total	1644,391	14676				

a. R Squared = ,043 (Adjusted R Squared = ,042)

Table 5.8: Test of interaction between sensor type and conditions, right line detection

Tests of Between-Subjects Effects

Dependent Variable: Rightlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	43,091[a]	8	5,386	56,358	,000	,030
Intercept	7535,669	1	7535,669	78847,133	,000	,844
Sensortype	5,184	1	5,184	54,244	,000	,004
Conditions	8,129	4	2,032	21,263	,000	,006
Sensortype * Conditions	16,549	3	5,516	57,718	,000	,012
Error	1387,722	14520	,096			
Total	12920,000	14529				
Corrected Total	1430,813	14528				

a. R Squared = ,030 (Adjusted R Squared = ,030)

The tests show that the interaction between conditions and sensor types (Sensortype*Conditions) is significant as well ($p < 0.05$) and should be considered for the regression model.

For completion, other interaction effects have been explored. The interaction effect between marking type and sensor type was also found to be significant. For the nighttime data set, interaction effects between conditions and street lights, and sensor types and street lights were found to be significant. The full results can be found in Appendix A.3. These interactions will all be considered forthe regression model, which will be discussed in the next section.

5.2. Regression analysis

This section contains the process of the regression analysis. There are several steps taken in order to build the regression models. First, the variables need to be checked for correlations among them in order to avoid multicollinearity and to ensure independence. After that, the regression analysis can be performed and the results can be interpreted.

5.2.1. Correlation matrix

This section contains the correlation matrices for the daytime and nighttime data sets. Because not all variables are on a continuous scale and a normal distribution cannot be assumed, Spearman's rho is the most appropriate method to check for correlations. Tables 5.9 and 5.10 present the correlations between the variables for the daytime and nighttime data sets:

Table 5.9: Spearman's rho correlation matrix of the daytime data set

Correlations

		Speedkmh	Contrastleft	Contrastright	Lanewidth	Markingtype	Sensortype	Conditions
Speedkmh	Correlation Coefficient	1,000	,032*	,016	-,019	-,067**	-,024	,054**
	Sig. (2-tailed)	.	,011	,189	,131	,000	,056	,000
	N	6453	6453	6453	6453	6453	6453	6453
Contrastleft	Correlation Coefficient	,032*	1,000	,937**	,139**	,357**	,443**	,839**
	Sig. (2-tailed)	,011	.	,000	,000	,000	,000	,000
	N	6453	6453	6453	6453	6453	6453	6453
Contrastright	Correlation Coefficient	,016	,937**	1,000	,156**	,338**	,443**	,804**
	Sig. (2-tailed)	,189	,000	.	,000	,000	,000	,000
	N	6453	6453	6453	6453	6453	6453	6453
Lanewidth	Correlation Coefficient	-,019	,139**	,156**	1,000	-,120**	,102**	,062**
	Sig. (2-tailed)	,131	,000	,000	.	,000	,000	,000
	N	6453	6453	6453	6453	6453	6453	6453
Markingtype	Correlation Coefficient	-,067**	,357**	,338**	-,120**	1,000	,227**	,511**
	Sig. (2-tailed)	,000	,000	,000	,000	.	,000	,000
	N	6453	6453	6453	6453	6453	6453	6453
Sensortype	Correlation Coefficient	-,024	,443**	,443**	,102**	,227**	1,000	,479**
	Sig. (2-tailed)	,056	,000	,000	,000	,000	.	,000
	N	6453	6453	6453	6453	6453	6453	6453
Conditions	Correlation Coefficient	,054**	,839**	,804**	,062**	,511**	,479**	1,000
	Sig. (2-tailed)	,000	,000	,000	,000	,000	,000	.
	N	6453	6453	6453	6453	6453	6453	6453

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5.10: Spearman's rho correlation matrix of the nighttime data set

Correlations

		Speedkmh	RLleft	RLright	Lanewidth	Markingtype	Streetlights	Sensortype	Conditions
Speedkmh	Correlation Coefficient	1,000	,195**	,149**	-,256**	,037**	-,422**	-,147**	,023*
	Sig. (2-tailed)	.	,000	,000	,000	,001	,000	,000	,038
	N	8400	7417	7191	8400	8400	8400	8400	8400
RLleft	Correlation Coefficient	,195**	1,000	,306**	-,007	-,205**	-,147**	,012	-,036**
	Sig. (2-tailed)	,000	.	,000	,533	,000	,000	,296	,002
	N	7417	7417	7191	7417	7417	7417	7417	7417
RLright	Correlation Coefficient	,149**	,306**	1,000	,121**	-,180**	-,094**	-,028*	,194**
	Sig. (2-tailed)	,000	,000	.	,000	,000	,000	,017	,000
	N	7191	7191	7191	7191	7191	7191	7191	7191
Lanewidth	Correlation Coefficient	-,256**	-,007	,121**	1,000	,073**	,547**	-,023*	,228**
	Sig. (2-tailed)	,000	,533	,000	.	,000	,000	,038	,000
	N	8400	7417	7191	8400	8400	8400	8400	8400
Markingtype	Correlation Coefficient	,037**	-,205**	-,180**	,073**	1,000	,005	,069**	,247**
	Sig. (2-tailed)	,001	,000	,000	,000	.	,649	,000	,000
	N	8400	7417	7191	8400	8400	8400	8400	8400
Streetlights	Correlation Coefficient	-,422**	-,147**	-,094**	,547**	,005	1,000	,079**	-,012
	Sig. (2-tailed)	,000	,000	,000	,000	,649	.	,000	,283
	N	8400	7417	7191	8400	8400	8400	8400	8400
Sensortype	Correlation Coefficient	-,147**	,012	-,028*	-,023*	,069**	,079**	1,000	,319**
	Sig. (2-tailed)	,000	,296	,017	,038	,000	,000	.	,000
	N	8400	7417	7191	8400	8400	8400	8400	8400
Conditions	Correlation Coefficient	,023*	-,036**	,194**	,228**	,247**	-,012	,319**	1,000
	Sig. (2-tailed)	,038	,002	,000	,000	,000	,283	,000	.
	N	8400	7417	7191	8400	8400	8400	8400	8400

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The significant, strong correlations are marked yellow. Only in the daytime data set strong correlations were found. The strong correlation between contrast left and contrast right has been explained in the previous chapter. Two other strong correlations were found regarding the contrast ratios, between the contrast ratios of both lines and conditions. Both correlations are positive, meaning that the contrast ratio increases for the conditions categories in the order dry, wet, and sunset. Lower contrast ratio values indicate a lower contrast between the road and the lane marking. According to this correlation, during optimal weather conditions the contrast ratios are low. This does not make sense for these conditions, as it can be expected that the lines are well distinguishable from the road surface. These two correlations will therefore be ignored.

5.2.2. Binary logistic regression models

The binary logistic regression models have been built with SPSS. After the variable coding, SPSS generates a null model, which only contains a constant and assumes that all the independent variables are not relevant for the classification. After that, a full model containing all the variables is created. The variables that are significant in the full model ($p < 0.05$) are used to create a final model. Based on the distinction between daytime and nighttime visibility variables (contrast ratio for day, retroreflectivity for night), separate models for daytime and nighttime detection were developed. The final regression models for daytime left and right, and nighttime left and right detection are presented below.

Final model daytime left line detection

Table 5.11 contains the variables that are significant in the detection model for the left line in daytime conditions ($p < 0.05$). B denotes the weight of each variable in the equation. Since the logistic equation is exponential, taking the exponential of B leads to a change in likelihood when the variable would increase one unit.

Table 5.11: Regression results daytime left line

	B	p-value	Exp(B)
Speed increase	,059	<.0001	1,060
Marking type 2	2,085	<.0001	8,044
Regular mono camera	1,495	<.0001	4,460
Dry conditions		.026	
Wet conditions	-,249	.007	,780
Sunset conditions	-,101	.640	,904
Marking type 2 by regular mono camera	-1,481	<.0001	1,830
Conditions * Sensor type interaction effect		<.0001	
Wet conditions by regular mono camera	1,394	<.0001	3,010
Constant	-3,272	<.0001	,038

The direction of B indicates an increase or decrease in likelihood based on the increase of the variable with one unit. The magnitude of the likelihood change can be found in the column Exp(B). The increase or decrease in likelihood is always compared to the reference value in case of a categorical variable. To demonstrate that with the results of this model: it is approximately 8 times more likely that the left line will be detected with marking type 2 than with marking type 1. It is important to note that this only yields for the reference values of other variables, for example the likelihood increases 8 times with marking type 2 for sensor type 1 (mono camera with infrared). Similarly, it is 4,5 times more likely that the left line is detected by sensor type 2 (regular mono camera) than by sensor type 1 (mono camera with infrared). The likelihood of detection decreases a little during rain and sunset conditions. For the continuous variable speed, each km/h increase leads to a 1,06 increase in likelihood of detection of the left line.

There are also some interaction effects significant in this model ($p < 0.05$). The interaction effects need to be combined with the main effects in order to interpret them. First, the B of the interaction effect needs to be added to the B of the main effect. The exponential of the product results in the change in likelihood adjusted for the interaction effect. In the case of the interaction between marking type and sensor type, the weight parameter of the interaction (-1,481) needs to be added to the weight parameter of marking type (2,085). Exp(2,085 - 1,481) = 1,83, which means that the likelihood of left line detection is 1,83 times larger with marking type 2 for sensor type 2 (regular mono camera). Similarly, the likelihood of line detection increases approximately 3 times in rainy conditions for the regular mono camera.

The constant was found to be significant in this model ($p < 0.05$). The value of the constant is negative, meaning that there is a decrease in likelihood that cannot be explained by any of the variables in the model. This indicates that there are other relevant variables that are not considered in this research. Based on the coefficient estimates and a threshold value of 0.5, the model has a classification performance of 86,1%, see classification table 5.12. Appendix A.1 contains the classification probabilities for this model.

Table 5.12: Daytime left line model classification table (threshold = 0.5)

		Predicted		
		Not detected	**Detected**	**Percentage correct**
Observed	**Not detected**	0	897	0
	Detected	0	5556	100
	Overall percentage			86,1

Final model daytime right line detection
Table 5.13 contains the regression model variables for the right line detection.

Table 5.13: Regression results daytime right line

	B	**p-value**	**Exp(B)**
Speed increase	,075	<.0001	1,078
Marking type 2	1,981	<.0001	7,247
Regular mono camera	1,930	<.0001	6,886
Dry conditions		<.0001	
Wet conditions	-,479	.121	,620
Sunset conditions	,452	<.0001	1,571
Marking type 2 by regular mono camera	-2,499	<.0001	0,625
Conditions * Sensor type interaction effect		.001	
Wet conditions by regular mono camera	1,255	.001	2,000
Contrast ratio	-,005	.006	,995
Constant	-4,083	<.0001	,017

An increase of 1 km/h leads to a slight increase in likelihood of right line detection (1,078). Detection is approximately 7 times more likely with marking type 2 than with marking type 1 for the mono camera with infrared. A regular mono camera leads to an increased likelihood of detection by 7 times for the reference conditions. Wet conditions lead to a 1,6 times decrease in detection likelihood for the mono camera with infrared. Sunset conditions have no significant contribution in this model. An increase in contrast ratio results in a slightly decreased likelihood of detection.

This model contains again two interaction effects. Similar to the model for left line detection, there is an interaction between marking type and sensor type. However, for this model it is 1,6 times less likely that the right lane is detected with marking type 2 with a regular mono camera. The other interaction effect, between conditions and sensor type, results in a 2 times higher likelihood of detection by the regular mono camera in rainy conditions.

Again, this model has a negative constant that is significant ($p < 0.05$). It is of the same magnitude as in the left line model. This model has a classification performance of 88,1% (see classification table 5.14). The classification probabilities can be found in appendix A.2.

Table 5.14: Daytime right line model classification table (threshold = 0.5)

		Predicted		
		Not detected	Detected	Percentage correct
Observed	Not detected	1	765	,1
	Detected	1	5686	100
	Overall percentage			88,1

Final model nighttime left line detection
Table 5.15 contains the variables and the weight estimates for the nighttime detection of the left line:

Table 5.15: Regression results nighttime left line

	B	p-value	Exp(B)
Speed increase	,064	<.0001	1,066
Marking type 2	1,914	<.0001	6,779
Regular mono camera	2,751	<.0001	15,666
Street lights present	-1,035	<.0001	,276
Lane width increase	-,023	<.0001	,977
Wet conditions	,249	.102	1,282
Wet conditions by regular mono camera	-2,944	<.0001	,071
Marking type 2 by regular mono camera	-2,499	<.0001	1,05
Wet conditions by Street lights present	1,411	<.0001	5,3
Regular mono camera by Street lights present	-,711	.023	7,7
Constant	3,615	.052	37,139

Again, 1 km/h increase in speed results in a slightly higher likelihood of detection of the left line at night. The presence of street lights result in a decreased likelihood of detection of 3 times by the mono camera with infrared. In the reference conditions, the regular mono camera is 16 times more likely to detect the right lane than the mono camera with infrared. A centimeter increase in lane width results in a decreased detection likelihood of 0,983. Detection is almost 7 times more likely with marking type 2 than with marking type 1 for the mono camera with infrared, while with interaction effects the likelihood of detection only increases slightly (1,05) with marking type 2 for the regular mono camera.

There are interaction effects between conditions, sensor type and streetlights. The variable conditions is not significant in this model, but two interactions with conditions are. Detection is 14 times less likely by the regular mono camera in rainy conditions and 5,3 times more likely in rainy conditions with street lights for the mono camera with infrared. During dry conditions, detection is 7,7 times more likely for the regular mono camera with the presence of street lights. The constant in this model is not significant ($p > 0.05$). This model has a 89,3% classification performance (see classification table 5.16). Appendix A.3 contains the classification probabilities of the model.

Table 5.16: Nighttime left line model classification table (threshold = 0.5)

		Predicted		
		Not detected	Detected	Percentage correct
Observed	Not detected	4	743	,5
	Detected	3	6201	100
	Overall percentage			89,3

Final model nighttime right line detection
Table 5.17 contains the variables and weights for the right line detection in nighttime conditions:

Table 5.17: Regression results nighttime right line

	B	p-value	Exp(B)
Speed increase	,069	<.0001	1,072
Regular mono camera	1,797	<.0001	6,030
Street lights present	-1,059	<.0001	,347
Wet conditions	,461	.001	1,585
Wet conditions by regular mono camera)	-2,416	<.0001	,14
Wet conditions by Street lights present	,504	.022	2,6
Constant	-3,007	<.0001	,049

As with all the other models, speed has a slightly positive effect on the likelihood of detection. The presence of street lights has a similar result as with the left line detection, it is 3 times less likely to detect the right line with street lights using the mono camera with infrared. In the reference conditions, the regular mono camera is 6 times more likely to detect the right line than the mono camera with infrared. The mono camera with infrared is 1,5 times more likely to detect the right line in rainy conditions as opposed to dry conditions. However, the interaction effect results in a 7 times decreased likelihood of detection by the regular mono camera in rainy conditions. The presence of street lights result in a 2,6 times increased detection likelihood by the mono camera with infrared in rainy conditions. A negative constant was found to be significant in this model ($p < 0.05$). The classification performance of this model is 90,6% (see classification table 5.18). See appendix A.4 for the classification probabilities.

Table 5.18: Nighttime right line model classification table (threshold = 0.5)

		Predicted		
		Not detected	**Detected**	**Percentage correct**
Observed	**Not detected**	0	570	0
	Detected	0	5526	100
	Overall percentage			90,6

5.2.3. Overview of findings

A lot of results were discussed in the previous section. Below is a brief overview of the findings:

- Speed is significant for detection of both lines in daytime and nighttime conditions. The increase in likelihood of detection is in the same order of magnitude for each line and each condition (1,060 - 1,078). There is no differentiation of the effect of speed for each sensor type.
- Except for the nighttime right detection model, all models include marking type as a significant variable. Marking type 2 has a higher likelihood of being detected by both sensor types, however the mono camera with infrared appears to be more sensitive. The interaction effect between marking type and conditions was not found to be significant in any of the models. It was expected to be a relevant interaction, however the lack of significance might be explained by the fact that no heavy rain or wet road surface (glare) was experienced during the field test.
- The sensor type is a significant variable in all of the models, and the regular mono camera was found to have a higher detection likelihood in dry (reference) conditions, which is according to the expectations. The detection likelihood of the regular mono camera in rainy conditions varied, but were according the performance results discussed in Chapter 4.
- For the daytime models, rainy conditions have a negative effect on the detection likelihood by the mono camera with infrared. During nighttime conditions the detection likelihood increases during rainy conditions. This is again in line with the performance results in Chapter 4.

- Street lights were found to have a negative effect on the detection likelihood during dry conditions and a positive effect on the likelihood during rainy conditions. It was expected that street lights would have a negative influence on the detection performance during rainy conditions as well. However, this can be explained by the lack of heavy rain or glare during the field test.
- Lane width as a significant variable appears only in the model for nighttime left line detection. The increase of the lane width was found to have a negative effect on the detection likelihood. A possible explanation for this is that on-ramps for intersections and roundabouts, which had a higher lane width than straight sections, still appeared in the data set and that lane switches have resulted in a lower detection performance.
- The classification performance of the models ranges between 86,1% and 90,6%. Because almost all models include a negative constant, there are other variables of influence that have not been considered in this research. The classification probability graphs indicate that a change in threshold value does not improve the model detection accuracy. The model accuracy appears to depend on the ratio detected/not detected observations.
- Two of the main visibility properties of lane markings, contrast ratio and retroreflectivity, have not been found significant in the regression models. It was expected that these variables would have been significant, the data collection and processing methods might have been the reason for this. A more extensive reflection on this can be found in the Discussion.

5.3. Geographical observations

While assembling the data sets, the choice was made to include the GPS coordinates of the observations in the data set. This has led to the advantage that the exact locations of no lines detected('None') observations can be plotted onto a map. Several clusters of these observations are visualized below. A distinction is made in nighttime observations denoted in red and daytime observations denoted in blue. Yellow dots refer to observations with street lights.

The first observation was at curves. While attention was paid to avoiding curves when setting the route for the field test, it could not be entirely avoided that curves would be encountered. Fig. 5.1 demonstrates that 'None' observations were found at curves during nighttime and daytime drives. Because this particular road section was encountered four times in total, the LKS did not work 50% of the encounters during the field test.

Figure 5.1: 'None' observations at curves

Another observation is the LKS had trouble with oncoming intersections. The observations visualized in Fig. 5.2 show that the LKS could not always detect lane markings when driving near the striped area or when driving towards the intersection with two lanes, possibly due to a change in lane marking shape.

Figure 5.2: 'None' observations at intersections

Another section with a white striped area where the LKS did not always detect the lines is shown in Fig. 5.3. This section also contains a lane merge, lane split and street lights. All of these features could have contributed to the 'None' observations.

Figure 5.3: 'None' observations at merging points with street lights

Fig. 5.4 again demonstrates a road section with multiple road features that could have contributes to a low detection performance. This section has various observations that could be caused by the median with street lights (situated at the street light observations), a slight curve, or the trees surrounding the section.

Figure 5.4: 'None' observations at median with street lights in a forest environment

Another interesting finding is the LKS performance in a tunnel. Fig. 5.5 demonstrates that the Hyundai kona (regular mono camera) did not detect the lane markings during nighttime when passing through a tunnel. This was the only 'None' observation around tunnels in all the observations.

Figure 5.5: 'None' observations at a tunnel (only Hyundai)

Finally, the Audi (mono camera with infrared) has experienced some inexplicable moments where no lines were detected. An example is visualised in Fig. 5.6. During both daytime and nighttime conditions the LKS did not detect the lines at this section. It is a straight section, no street lights, high quality lane markings and there are no obstructions on the road side. Since Audi provides little to no specific information about where their systems can be used, it can be challenging to find the cause. A possible explanation could be a system failure.

Figure 5.6: 'None' observations on a straight section (only Audi)

6 Discussion

This chapter contains the discussion and reflection of the research. In the first section, the results will be evaluated based on expectations and previous studies. Section 6.2 contains the evaluation of the methodology. After that, the limitations of this research will be listed. Finally, the future relevance of this study will be discussed.

6.1. Evaluation of the results

The results in this study are twofold: the performance of different sensor types were assessed, and the lane marking properties and several other road characteristics have been assessed in relation to the detection performance.

This study aimed to provide a comprehensive comparison of the sensor types that are currently being used for lane detection. Two sensor types were ultimately compared: a mono camera with infrared and a regular mono camera. The highest detection performance of the mono camera with infrared during the field test, 91,4%, was found during sunset conditions, the lowest detection performance (76%) during daytime dry conditions. The highest detection performance of the regular mono camera was found to be 97% in nighttime dry conditions and 87,3% in nighttime wet conditions. The detection performance for the vehicle equipped with the mono camera with infrared sensor increased in night conditions for both wet and dry conditions. The regular mono camera had a higher performance during dry nighttime conditions than during dry sunset conditions. This is similar to the results of Reddy (2019). One possible explanation for the increasing performance of the mono camera with infrared during (wet) nighttime conditions is a higher robustness due to the infrared sensor, which is stated in the overview of Liu et al. (2020). It is however remarkable that the regular mono camera reached a higher performance than the mono camera with infrared in most conditions. The highest performance of the regular mono camera was obtained during dry night conditions, and together with the daytime wet performance it is significantly better than the mono camera with infrared. The statement that the infrared sensor improves robustness does not hold in this case when compared to the vehicle without it. The decreased performance of the regular mono camera during nighttime wet conditions is according to expectations, as regular camera sensors are less able to cope with rain and poor illumination (Liu et al., 2020).

The second goal of this study was to evaluate lane marking visibility properties with respect to the detection performance. Three lane marking visibility properties identified in the literature have been evaluated: Contrast ratio, Retroreflectivity, and Application type. The contrast ratio between the lane markings and the road, used for daytime visibility, was partly found to be significant for the right line detection. However, the correlation between the contrast ratio and conditions was not as expected and indicated that the obtained values for the contrast ratio might not be correct It would have been expected based on the field test observations that lower contrast ratios were measured during rainy conditions. Instead, the lowest values for the contrast ratios were found during sunny, dry conditions. A possible explanation for this can be found in the methodology that was used to obtain the contrast ratio. This will be evaluated in the next section. Retroreflectivity was considered in the studies of Pike et al. (2018), Pike et al. (2019) and Cafiso and Pappalardo (2020) for machine vision, and was argued to be important for human vision as well. Retroreflectivity values of 150 mcd/lux/m2 of higher were found to be sufficient for both human and machine vision (European Union Road Federation, 2018; Gibbons et al., 2012). In this study, the retroreflectivity was not found to be significant for lane marking detection. Values below 100 mcd/lux/m2 were prior excluded in this study because it was assumed that these lane markings were maintained between the moment of the measurements (in 2018) and the field test, based on the comparison between the detection performance in that category and the detection performance with higher values and observations during the field test. Pike et al. (2018) found that values between 9-34 mcd/lux/m2 were already sufficient to reach high confidence ratings in detection. This would be a reasonable explanation why retroreflectivity was not significant in this study. A lane marking visibility characteristic that has not been evaluated for machine vision before is the application type. The literature divided this into type 1 (smooth) and type 2 (profiled) and both types were encountered during the field test. The marking type was found to contribute significantly to the detection performance, with detection being more likely with marking type 2 than with marking type 1. Only in the regression model for the right line it was found that marking type 1 leads to a higher detection likelihood, but only for the regular mono camera. Unlike the expectation that type 2 would improve detection during wet conditions, an improvement was found mostly during dry conditions. The interaction effect for weather conditions and marking type was not found to be significant and the effect of the lane marking type under different conditions is therefore inconclusive.

Several road characteristics were additionally evaluated. Driving speed was found to be a significant factor contributing to the detection performance. An increase in speed lead to an increase in detection likelihood in all the regression models. According to the preliminary analysis presented in Chapter 4, speed seemed to have a non-linear relationship with the detection status for the mono camera with infrared. Due to the lower overall detection performance and the small number of observations of speeds above 90 km/h, a non-linear relationship might be unlikely.

The effects of street lights in this study were found to be contradicting. During dry conditions, street lights decreased the detection likelihood while during rainy conditions, the street lights increased the detection likelihood. That last finding is opposite of the results of Reddy (2019), who found a low performance (61,6%) during rainy conditions with street lights. Heavy rain or glare was not experienced in this study, which might explain the different findings. The decrease of detection likelihood for dry conditions with street lights as opposed to no street lights are similar to what was reported by Reddy (2019). Lane width as a significant variable appeared only in the nighttime model for the left line detection. Based on this single finding, in combination with the assumption that lane switches appeared at sections with higher lane widths, lane width will be regarded as not significant in this study.

While road curvature was not evaluated in this research, the geographical observations show that several No lines detected observations can be traced back to curves. Given that there are significant constants in the regression models, it is likely that road curvature plays a significant role in the detection performance. This would be in line with the findings of García et al. (2020), Van der Linde (2020), and Cafiso and Pappalardo (2020).

It should be noted that the accuracy of the models is mostly related to the ratio of observed detected/not detected measurements. This suggests that the model does not fit the data properly, which might be caused by the lack of other relevant variables. The fact that all predicted values by the model are above 0,5 and do not have a clear differentiation between detected and not detected observations (see classification tables A.1 - A.4) suggests that the model is not good enough to capture the individual variability of each observation.

6.2. Evaluation of the methodology

The evaluation of the methodology is twofold. First, the data collection methodology (i.e. field test) will be evaluated. After that, the data processing will be discussed.

Earlier studies have demonstrated that field tests are a powerful method to collect various data to evaluate the detection performance, and this study is no different. The ability to include three different vehicle types posed some logistical challenges, but resulted in a great potential to compare sensor types. A few minor issues were encountered during the field test, such as the wrong camera settings (timelapse mode) for the first drive in sunset conditions. This has led to a decrease in observations, a more thorough inspection of the camera settings before the drive could have prevented this.

Due to the limited availability of the test vehicles, there were only three days that could be used to execute the field test. In contrast, the field test of Reddy (2019) consisted of 7 days. Other field tests appeared to have been executed in only one day (Cafiso & Pappalardo, 2020; García et al., 2020; García & Camacho-Torregrosa, 2020). These field tests were executed under optimal weather and illumination conditions, while the field test of this study was also executed under less optimal conditions. There were sufficient observations in nighttime conditions, but the observations with rainy conditions were limited. Only a little precipitation was encountered.

Two GoPro cameras per vehicle were used to collect data on the detection status of the vehicle and the road in front of the vehicle. The videos of the detection status were processed using image recognition techniques, similar to the research of Reddy (2019). Cafiso and Pappalardo (2020) and Pike et al. (2018) used Mobileye cameras to obtain detection status. The latter has a higher reliability, but resulted in confidence ratings between 0-3, which are more difficult to interpret. Using videos of the vehicles' dashboard has led to a better understanding of the differences between the vehicle types.

The GoPro camera directed to the road in front of the vehicle was used to determine the contrast ratio. The main idea was that this camera would 'see' the same road image as the cameras of the vehicles. In theory this could be a suitable solution for when the vehicle data cannot be accessed. However, it should be noted that different camera settings (such as ISO value) could lead to different results for intensity and contrast. This method has, to the researchers' knowledge, not been used in other studies before.

Beside the data collection methodology, the daytime visibility was also evaluated differently than in previous studies, where the luminance coefficient under diffuse illumination was used (Pike et al., 2018) (Cafiso & Pappalardo, 2020). Because specialized equipment is necessary to measure this, it was not used in this study. Instead, the intensity of the lane markings and road was approached by computer vision techniques. This was partly in line with the visibility metric proposed by Li et al. (2018), which also included LiDAR measurements. Instead of dividing the intensity of the markings by the intensity of the road, the Weber contrast ratio was used. While the data processing methodology until this point was found to be useful, the algorithm to detect the lane markings in the videos and retrieve the pixel intensity might not be regarded as suitable for this study. As mentioned before, the contrast ratios for the different conditions were not logical. It is likely that the algorithm had issues with detection of the lane markings, especially with gaps and double markings in the center of the road.

Using a binary logistic regression model to evaluate the contribution of different variables to the detection status was found to be an extensive, useful method. The division between nighttime and daytime, and left and right lane resulted in four different models, but because several variables had values for each lane separate, this division was found to be appropriate. It also could lead to the opportunity to compare left and right headlight settings, however this was not in the scope of this research. The addition of interaction effects to the models lead to a more in-depth analysis.

6.3. Limitations of the research

While this research was conducted thoroughly and carefully, there were some issues that were not or could not be included in this study due to time and budget constraints. These limitations and their implications are listed below:

- The retroreflectivity data of the lane markings on test route 1 was supplied by an external company. The main reasons for this were that the equipment for dynamic measurements it is quite expensive, and static measurements were not possible in this case. The provided data was measured in 2018, which is approximately two years before the field test took place. One of the earlier discussed implications is that older lane markings, with low retroreflectivity values, have been replaced during the period between the measurements and the field test. This has been corrected in the data by removing all values below 100 mcd/lux/m2. Another implication is that the retroreflectivity value of the lane markings have been decreased in the period between the measurements and the field test. This could potentially have led to a distorted result.

- The collected data for the Subaru vehicle, equipped with stereo cameras, was eventually not suitable to include in the analysis due to the low reliability of the detection status data. This would have led to a more extensive comparison between sensor types.
- The encountered weather conditions during the field test were better than expected. Due to the limited availability of the vehicles, the field test had to be conducted within three days. Only during the third day there was a little precipitation. The amount of rainfall was not reported. It would have been more complete if different levels of rainfall and glare were included in the field test.
- The detection status of the vehicle was retrieved by GoPro cameras and processed by computer vision algorithms in this research. While the algorithms were tweaked and randomly checked for each of the different vehicles, the reported detection status is not 100% true at all times.
- The correlation between the contrast ratios for both lines and conditions was ignored in this research because the results did not make sense. However, there could still be a possible relation between the contrast ratio and the weather during the day. This has been left out of this research.
- Curvature was eliminated as much as possible in the planning phase of the experiment, but is not entirely removed from the data set. Similar to intersections and roundabouts. It can be argued that curvature had a significant contribution to the detection status because of the constants in the regression models and the observations from the field test.
- The results do not account for different driving styles during the field test. Even though the drivers were instructed to drive in the middle of the lane and keep their distance from preceding vehicles, some variance in the driving behaviour can be expected.

6.4. Future relevance of this research

This research was focused on lane markings for the functioning of Lane Keep Assist. Lane markings will be inarguably present in the future, as human drivers rely on them to keep their position on the road. For AVs, this guidance does not necessarily has to be in the visual domain. Several studies have mentioned the possibility of guiding AVs through magnetic lane markings (Lu, 2018) or roadside reflectors (Feng et al., 2018). These guidance systems are considered to be more robust than visual guidance, as both camera and LiDAR systems are not sufficiently able to sense the road and lane markings with, for example, a layer of snow. Changing from visual guidance to other methods will require serious investments in changes on both the infrastructural side, as well as on the vehicle manufacturer side. It it therefore not expected to change in the near future.

The literature review of this study contained an infrastructure classification scheme for automated driving (ISA). Currently, there are only a few roads that are equipped to provide vehicles digital information regarding the infrastructure and road conditions. This information can from the location of land marks and signs up until the advice for lane changes and speed in order to optimize the traffic flow. While this information is undoubtedly important for vehicles of higher automation levels, it does not include any information regarding the actual position in the lane or the position of lane markings. Higher ISA levels will most likely not have an effect on the use of lane markings.

7 Conclusion and Recommendations

The number of traffic accidents has been increasing in the past few years due to the increase of mobility. In the European Union, 120.000 serious injuries and 22.800 fatalities have been reported. In order to reduce these numbers, the European Commission has ordered that all new vehicles models have to be equipped with Advanced Driver Assistance Systems (ADAS) in 2022. Lane Keep Assist (LKA), as part of ADAS, assists the driver with the lateral control of the vehicle. Similar to human drivers, LKA uses lane markings to determine the vehicle's position in the lane. However, the effect of the quality of lane markings on the performance of LKA is still largely unknown. The objectives of this research were to determine the influence of different lane marking properties on the detection performance both in different conditions and between different sensor types. This study aimed to contribute to the knowledge about the Operational Design Domain of Lane Keep Assist, and might potentially help to increase the availability of LKA.

Different sensors can be used to detect the lane markings: a mono camera, a stereo camera, and LiDAR. Infrared in combination with a mono camera was also listed in the literature. Previous studies that have tried to evaluate LKA performance used vehicles equipped with a mono camera. Performance evaluations of other sensor types, and a comprehensive comparison between sensor types, have not been studied before. The second objective of this study was to provide insights into the performance of different sensor types for LKA.

In order to fulfill the objectives listed above, several questions were answered. These questions and their respective answers will be presented first, before the main research question will be answered.

1. How are different systems selected for this research?

The literature divided the sensors that are useful for lane marking detection into camera systems and LiDAR. Unfortunately, no vehicles equipped with LiDAR could be found to evaluate. Three different camera systems were chosen instead: mono camera, stereo camera, and mono camera with infrared. A desk research was conducted to discover which vehicle manufacturers use which type of sensor for LKA. Ultimately three vehicles were found and used during the field test: a 2018 Hyundai Kona (equipped with a mono camera), a 2020 Subaru Outback (equipped with stereo camera), and a 2020 Audi RS Q8 (equipped with a mono camera with infrared).

2. Which lane marking properties will be evaluated?

LKA uses the same visual cues as human vision, and there lane marking properties that are relevant are therefore in the visual domain. The visibility of lane markings can be divided into daytime and nighttime visibility. During daytime conditions, the visibility is evaluated by using the luminance coefficient under diffuse illumination. Because this measure requires dedicated measuring equipment, the intensity of the lane markings and the road were used to calculate the Weber contrast ratio.

During nighttime visibility, the retroreflected luminance, or retroreflectivity, was used as a measure for visibility. This is a measure for the reflected light that originates from the vehicles' headlights and returns to the driver.

A final lane marking property that was evaluated was the application type. Two types of application techniques can be distinguished: type 1 resulting in a smooth lane marking, type 2 resulting in a profiled lane marking. The advantage of type 2 lane markings is that the profile can enhance drainage during rainy conditions, which leads to a higher visibility.

3. How are the different properties of lane markings affected by weather and illumination?

The retroreflectivity of the lane markings is established by optical, spherical beads in the paint. These beads have a certain Bead Refractive Index, that indicates how the incoming light is refracted. Water also refracts light and therefore rain on the lane markings can lead to a lower visibility because the light is refracted in a different direction. Usually a mix of different optical beads is used to ensure visibility in all conditions. Rain can also lead to glare, which can be mitigated by the application type. How the daytime visibility (contrast or diffuse luminance coefficient) can be affected by weather and illumination is not found in this study.

4. What is the performance of different Lane Keep Assist systems under optimal and adverse weather and illumination conditions?

A field test was conducted in order to assess the performance of the different LKA systems and to evaluate lane marking properties (and additionally other environmental characteristics). Five different weather and illumination conditions have been encountered: sunset, daytime dry, daytime wet, nighttime dry, and nighttime wet. The performance of the different LKA under these conditions are presented in Figures 7.1 and 7.2.

Conditions	**Both**	**Left**	**Right**	**None**	**Count**
Sunset	94,65%	-	-	5,35%	374
Daytime - dry	-	-	-	-	0
Daytime - wet	96,63%	1,48%	0,83%	1,06%	1690
Nighttime - dry	97,02%	0,89%	0,08%	2,01%	1341
Nighttime - wet	87,3%	0,11%	0,33%	12,27%	1817

Figure 7.1: Performance regular mono camera

Conditions	**Both**	**Left**	**Right**	**None**	**Count**
Sunset	91,44%	1,32%	3,73%	3,51%	456
Daytime - dry	76,01%	1,29%	6,80%	15,90%	2472
Daytime - wet	81,18%	1,64%	1,30%	15,88%	1461
Nighttime - dry	83,26%	0,74%	3,46%	12,54%	3900
Nighttime - wet	85,4%	3,87%	6,56%	4,17%	1342

Figure 7.2: Performance mono camera including infrared

The performance of the stereo camera was considered too poor to deem useful for this research. Significant differences in percentages of both lines detected were found in most conditions.

Based on the answers of the sub questions, the research question can be answered. The research question was posed as follows:

"How and to what extent do lane marking properties influence the detection performance of different Lane Keep Assist systems? "

Only one lane marking property was found to have a significant effect on the detection performance in this study, which is the marking type. For detection with the mono camera with infrared, the detection likelihood increased up to 8 times with marking type 2 (profiled) in contrast to marking type 1 (smooth). An increase in detection likelihood with marking type 2 was also observed for the regular mono camera, although the effect was not that large. The advantage of the profiled lane markings during rain was not found in this study, as no heavy rain was experienced during the field test. The contrast ratio and retroreflectivity were not found to be significant in this study, however it is expected that these properties are still important for the lane detection.

Other environmental characteristics that are considered significant for the detection performance is the driving speed and the presence of street lights. An increase in speed increases the detection likelihood slightly. During dry nighttime conditions, the presence of street lights have a negative effect on the detection performance. The effect of street lights during rain was found to be inconclusive due to the lack of heavy rain.

This research has contributed to the knowledge base by identifying a lane marking property that has not been researched before in relation with automated vehicles. Additionally, this research can contribute by serving as a reference for future field tests.

7.1. Recommendations

This research has led to more questions regarding the lane marking requirements, which is why future research is recommended. A list of scientific recommendations is presented below. After that, practical recommendations will be listed.

7.1.1. Scientific recommendations

- This research aimed to provide a comparison between mono camera, stereo camera, and LiDAR for lane detection. Ultimately it was possible to compare only two sensor types: mono camera, and mono camera with infrared. The data of the stereo camera turned out to be unreliable for this study and it was not possible to obtain a vehicle equipped with LiDAR. To complete the knowledge on the performance of other sensor types, future studies might consider to include stereo camera or LiDAR.

- The Dutch provincial roads in this study all had a similar lay-out and level of quality. It could be interesting to repeat this study in different environments with a different (lower) road and lane marking quality. A larger variety in quality of lane markings and roads might lead to more in-depth knowledge and requirements for infrastructure.

- This research was only the second study that has been done on the effect of street lights on the detection performance. Further research could be done on the effect of different types or the placement of street lights. Additionally, the effect under different levels of rain can be evaluated.

- The literature review of this study briefly touched upon the developments in the field of deep learning for lane marking detection. While studies on pre-recorded data sets show promising results, it would be interesting to compare the performance of deep learning to the traditional computer vision techniques in a real driving environment.

- While efforts have been made to cooperate with road authorities to share information, the data in this research was mostly gathered manually or using different sources. Because this is a time-consuming task, it is recommended to collaborate closer with road authorities or other governmental organisations (such as provinces or national authorities) to ease the process. In order to be able to collaborate, it is also recommended for road authorities to keep their database with road information up-to-date.

- In this study, a strong correlation was found between the contrast ratio and weather conditions during daytime. The correlation did not make sense in this case, but it might be interesting to research this more in-depth. This would increase the knowledge on the influence of weather conditions on the lane marking properties, and can therefore contribute to a more in-depth knowledge of infrastructure requirements.

- The sight distance of one of the test vehicles was reported in this study, however it has not been used for analysis. In addition, there is no existing literature assessing the lane keeping performance with limited visibility. This would be an addition to the literature to gain more insights into the vehicles' limitations.

7.1.2. Practical recommendations

- This study has resulted in a first evaluation of the lane marking type on the detection performance. Marking type 2 was found to increase the detection performance in comparison to marking type 1. Although these results are preliminary, road authorities might consider using type 2 lane markings on the road.
- In order to maintain the high standard of infrastructure quality and to enable similar field tests in the future, it is recommended that road authorities maintain their data base with regards to the status of the infrastructure.
- During the field test it was observed that several intersections and roundabouts had quite long on-ramps with two lanes. The vehicle speed when arriving at the on-ramp was still above the activation speed, resulting in LKA being engaged at these on-ramps. In order to have a more clear boundary of the ODD for the driver, road authorities might consider to have drivers/vehicles lower their speed more in advance.

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Assessment of Lane Detection Performance based on Different Lane Marking Properties under Optimal and Adverse Weather and Lighting Conditions

Eline van der Kooij

Abstract— **Advanced Driver Assistance Systems (ADAS) are becoming more available and will become mandatory for all new vehicle models from 2022 onward. In order to achieve the highest safety benefits, it is important that these systems are available. Lane Keep Assist (LKA) is part of ADAS and assists the driver in the lateral control of the vehicle. Lane markings are used by both human drivers and machine vision to stay on the road, but factors contributing to lane marking detection in different driving conditions are mostly unknown. A field test was conducted on Dutch provincial roads to evaluate lane marking visibility properties in relation to the LKA detection performance of different sensor types. The LKA detection performance of the mono camera was found to be higher in most weather and illumination conditions than the detection performance of the mono camera with infrared. The mono camera with infrared had a higher detection performance during rain in nighttime conditions than during dry daytime conditions. The highest detection performance for the mono camera and the mono camera with infrared were 97% in dry nighttime conditions and 91,4% in sunset conditions, respectively. Binary logistic regression was used to determine the effect of lane marking properties on the lane detection performance. A profiled lane marking type was found to increase the detection likelihood by 6-8 times as opposed to a smooth lane marking type. Other visibility properties, such as retroreflectivity and contrast with the road surface, were not found to be a significant contributor to the detection performance.**

Index Terms— **Vehicle Automation, Lane Markings, Machine Vision, Detection Performance**

I. INTRODUCTION

In order to promote road safety, the European Commission has announced that Advanced Driver Assistance Systems (ADAS) will become mandatory in all new vehicle models in 2022 [1]. Among ADAS are Lane Keep Assist systems (LKA). LKA concerns the lateral control of the vehicle and can potentially reduce the number of road departure crashes [2]–[5]. The optimal functioning of LKA is dependent on several variables, which are described by the Operational Design Domain (ODD) of a vehicle. The ODD is defined by SAE as: 'Operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics' [6]. Especially lane markings are important for the functioning of LKA, while knowledge on the effects of lane markings on the performance of LKA is lacking. Increasing the availability of LKA is important to increase road safety [7], which is why infrastructural requirements have to be researched. This research aims to increase the knowledge on LKA performance in relation with lane marking properties. In addition, this research provides an overview of the performance of different LKA sensor types under different weather and lighting conditions.

A. Sensors used for LKA

Lane markings are perceived in the visual domain for humans, causing LKA to rely mostly on machine vision. Therefore the most commonly used sensor for LKA is the mono camera [8]. A few advantages of the mono camera are the versatility and the lost costs. However, it is easily influenced by weather and illumination [9]. Higher quality cameras or infrared cameras are listed as potential solutions for this. In order to differentiate in function, trifocal cameras also appear in several vehicles. Each camera lens is optimized for different sight distances, a long range camera can be used for object detection while short range cameras can be used for lane detection. Since the mono camera is able to capture the environment only in 2D, other sensor are used for 3D detection. Examples of these sensor types are LiDAR and stereo cameras. LiDAR (Light Detection and Ranging) emits light pulses, which are reflected by objects in the environment (similar to radar). LiDAR has experienced similar issues with bad weather as cameras, which have been reported to be solved by research and multi-echo measurements [10]. While LiDAR measurements are mostly used for localization of the vehicle and object detection, the difference in returned pulse intensity can be used to differentiate lane markings from the road surface [10], [11]. The costs of LiDAR increase with the number of scanning planes which also increases the detail of information, however low cost 2D LiDARS were also found to be capable of detecting lane markings [12]. A similar sensor that can be low-cost is stereo vision. This sensor type consists of two parallel camera lenses with a known baseline (distance between the lenses). A combination of the images of the two cameras results in a 3D image of the environment. A comparative study between vision-based sensors and LiDAR has been done by [13]. It was reported that stereo vision is less costly and more robust than LiDAR. Additionally, the stereo camera images can be used for object detection and classification. Reported challenges for the stereo vision sensor are the reliability on texture to perceive depth and a higher error probability with an increased baseline.

B. Lane Marking Properties

Because lane markings provide a visual guidance for drivers, it is important to determine which lane marking properties contribute to the visibility. Daytime and nighttime visibility can be distinguished, as can dry and wet visibility. During the day, the lane markings are lit by sunlight reflected from multiple directions, which generally provides enough information for a human driver to navigate [14]. The measure that is used for official European regulations is the luminance coefficient under diffuse illumination Q_d [15]. European standards state that a Q_d between 100 and 200 mcd/m2/lux is required, depending on the lane marking color and the type of road surface. Nighttime visibility can be measured using retroreflectivity. Retroreflectivity entails the reflection of light in the same direction as it originated from. This can be accomplished by adding optical glass/ceramic spherical beads to the lane marking materials. The Bead Refractive Index indicates how the light is refracted. In dry conditions, beads with an index of 1.9 are the most effective. However, due to the refraction of light in water, these beads are not effective anymore during rainy conditions. An index of 2.4 is more suitable in that case. Usually a mixture of beads with different indices is used to provide sufficient luminance in all conditions. A retroreflectivity level R_L of 150 mcd/m2/lux was found to be sufficient for human vision [16]. In order to increase the wet visibility of lane markings, an application type leading to profiled lane markings can be used. This is also referred to as type 2 lane markings and because of the profile, this type provides drainage for rain. Additionally, it gives a haptic warning to a human driver when they are driving on the lane marking [17]. Examples of type 1 (original) and type 2 (profiled) lane markings can be found in Fig. 1 and 2.

Fig. 1. Type 1 lane marking (paint or tape)

A few studies have been conducted to research the requirements of lane marking properties for machine vision or LiDAR measurements, which are used by ADAS. An extensive experiment to research lane marking properties that can enhance machine vision was conducted by [18]. Mobileye devices were installed in test vehicles to assess the effectiveness of a wide range of different lane markings types and configurations. The tests were conducted during different conditions (day/night, dry/wet) on a closed test course. For dry daytime visibility, a luminance contrast ratio of 2.8 or higher resulted in a detection confidence rating higher than 2 (scaled from 0-3). The wet daytime visibility could not be evaluated due to the presence of glare. For dry and wet nighttime visibility, R_L values of 34 and 9 mcd/m2/lux or higher respectively resulted in detection confidence ratings of 2. While the application type was listed in this study, it was not further evaluated. A later study reported that higher values of wet retroreflectivity returned more light, which is beneficial for both human and machine vision [19].

Fig. 2. Type 2 lane marking (dots or drops, profiled)

C. LKA Performance

Several recent studies have been researching the performance of LKA with respect to the ODD. Factors affecting the performance can be categorised into: 'lane and road factors, hardware factors, traffic factors and weather factors' [20]. Nitsche et al. [21] list several factors that were labelled 'High influence' by experts: 'Complex urban road environments, Temporary roadwork zones, Poor visibility due to bad weather, Visibility of traffic signs, Quality of lane markings, and Discontinuous or damaged road edges or kerbs'. Among lane and road factors are road curvature, lane width, and lane marking quality. Speed and curvature were found to be related to LKA performance [22], [23]. The test vehicles in their studies were unable to keep LKA engaged when negotiating curves at the design speed or operating speed. García et al. and Reddy et al. [24], [25] found that LKA disengagements are also related to lane width. The studies reported that LKA does not engage on roads with a lane width smaller than 2.5 meter or have a significant lower detection performance. The minimum lane width for the functioning of LKA was reported to be 2.75 meter. Driving speed has been evaluated in three studies, resulting in different conclusions in different driving conditions. In the study of [25], the LKA performance was highest at intermediate speeds (70-90 km/h). In the field test of [26], speed was not found to be significant. Detection confidence in the study of [18] generally decreased with increasing speed during daytime conditions, while in some cases the confidence slightly improved with increasing speed during nighttime conditions. To the author's knowledge, only two studies that evaluate LKA performance and aim to relate that performance to road infrastructure factors exists.

Reddy et al. [25] conducted an extensive field test in order to evaluate LKA performance of two vehicles under various driving conditions. The performance was evaluated using the percentage of observations with both lines detected. The highest percentage of both lines detected (94,7%) was found during dry nighttime conditions without street lights. The lowest percentage (61,6%) was found during wet nighttime conditions with street lights. Lane width, Road curvature, and speed were found to be significant contributors to the detection performance. A high contrast between the lane markings and the road surface was recommended, but minimal requirements for the contrast are lacking. The study recommends to gain a deeper understanding of LKA systems and to use lane marking quality data for more detailed results. The study of [26] had a similar experiment set-up, but was less extensive. One vehicle, equipped with a Mobileye camera, was used during dry daytime conditions. The result of this experiment was an error percentage of 2,59%, and the diffuse luminance coefficient and the curvature radius were the only variables found to be significant.

D. Research gap and questions

Recent studies have demonstrated that there are still knowledge gaps regarding the LKA performance under different driving conditions in relation to road infrastructure factors. Additionally, there has not been a comprehensive comparison between the detection performance of different sensor types. Therefore the aim of this study is to assess the performance of different sensor types for LKA, under different weather and illumination conditions, in relation to lane marking properties. Therefore, the main research question is: "How and to what extent do lane marking properties influence the detection performance of different Lane Keep Assist systems? ".

II. RESEARCH METHOD

Previous studies demonstrate the importance of field tests to study the performance of LKA. Therefore a field test was conducted in this study in order to answer the research question. Vehicles with different sensor types for LKA have been tested in different conditions with respect to weather and illumination. Collecting the detection status of the vehicles while driving within the ODD lead to an assessment of the detection performance. Finally, logistic regression was used to determine which infrastructural factors contributed to the detection performance of the different sensor types.

A. Experiment Set-up

On November 24-26 2020, three vehicles with different sensor types were driven simultaneously along two different test routes. The following test vehicles were selected: a 2020 Audi RS Q8 equipped with a mono camera with infrared, a 2018 Hyundai Kona Electric with a regular mono camera, and a 2020 Subaru Outback with a stereo camera. This vehicle selection contains every sensor that is available in commercial vehicles. Each of the vehicles was equipped with two GoPro cameras; one to collect data on the detection status through the Human Machine Interface (HMI) on the dashboard, and one to capture the road characteristics from behind the windshield. The placement of the GoPro cameras is demonstrated in Fig. 3 and 4.

Fig. 3. Camera set-up to capture detection status

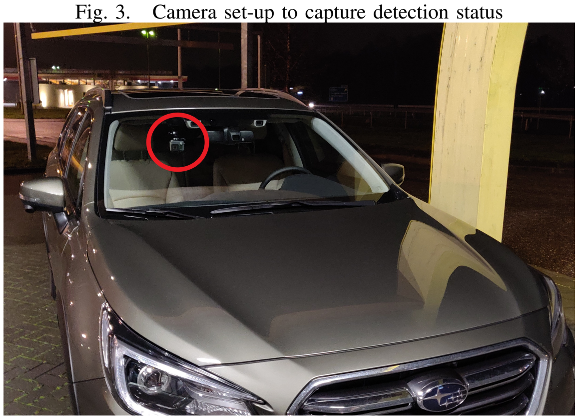

Fig. 4. Camera set-up to capture road characteristics

The dashboard GoPro collected, in addition to the detection status, the GPS coordinates and speed of the vehicle. The videos produced by the road-facing GoPro were used to calculate the contrast ratio between the lane marking and the road surface.

B. Test routes and conditions

Two test routes have been selected for the experiment. The first route (75 km, see Fig. 5) was selected based on the age of the lane markings as provided by the Province of Overijssel. This route only contains a small section with type 2 lane markings (5,4 km), which is why a second route (51 km, see Fig. 6) was included. Additionally, the routes were chosen for their straight sections, to potentially reduce the effect of curvature on the performance. During the first two days of the field test, the weather was clear and mostly sunny. During the third and last day, there was a little precipitation, which lead to minor fog and lower visibility during the night. Table I provides an overview of the amount of kilometers driven in dry/wet conditions, daytime/nighttime conditions, and per type of lane marking.

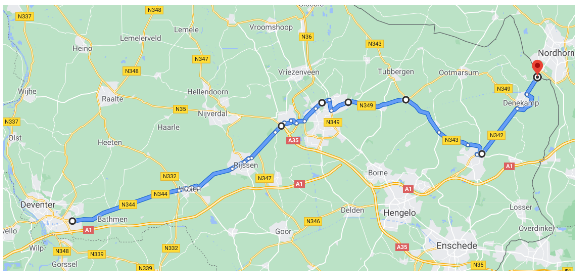

Fig. 5. Test route 1

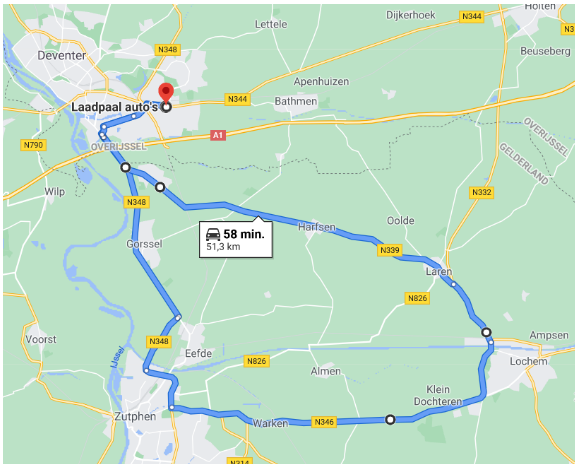

Fig. 6. Test route 2

In total, approximately 460 kilometers were driven, of which two-third was equipped with Type 1 lane markings.

The retroreflectivity of the lane markings on the test routes were provided by an external company. For both the left and the right line, measurements dating from 2018 were available. The distributions of the left and right line measurements are presented in Fig. 7 and 8.

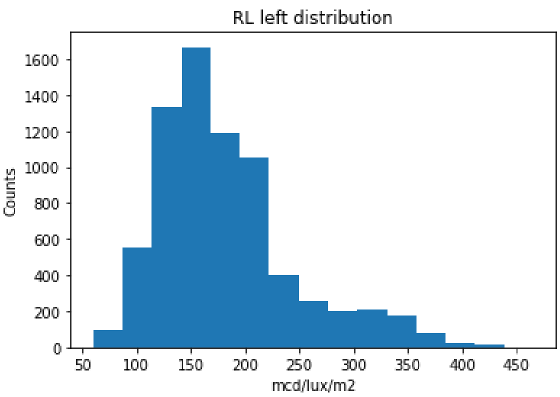

Fig. 7. RL distribution for the left line

Other factors relating to the road infrastructure in general have been collected as well. The driving speed was collected by the GPS measurements of the GoPro camera. The median of the speed observations was 75-80 km/h. This corresponds

TABLE I

OVERVIEW OF KILOMETERS DRIVEN IN DIFFERENT CONDITIONS WITH LANE MARKING TYPES

		Day	Night
Dry	**Type 1**	69,6 km	139,2 km
	Type 2	55,4 km	60,8 km
Wet	**Type 1**	23,7 km	69,6 km
	Type 2	35,1 km	5,4 km

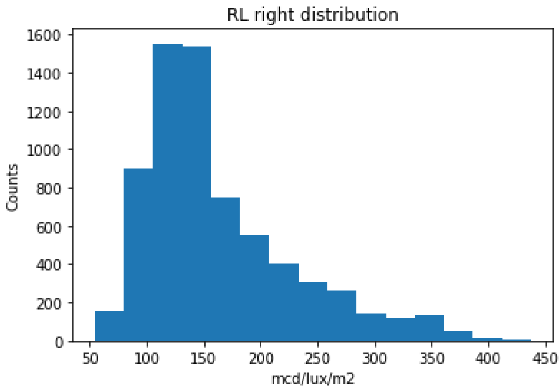

Fig. 8. RL distribution for the right line

with the maximum speed of 80 km/h on the selected roads. The standard lane width for Dutch provincial roads is 2.75 meter, although lane widths of 3, 3.2 and 3.5 were found at sections near roundabouts or intersections. At approximately 13% of the route sections, street lights were present.

C. Data Processing

Several steps have been taken to process the data and to merge the data from different sources. An overview of the steps that were taken can be found in Fig. 9.

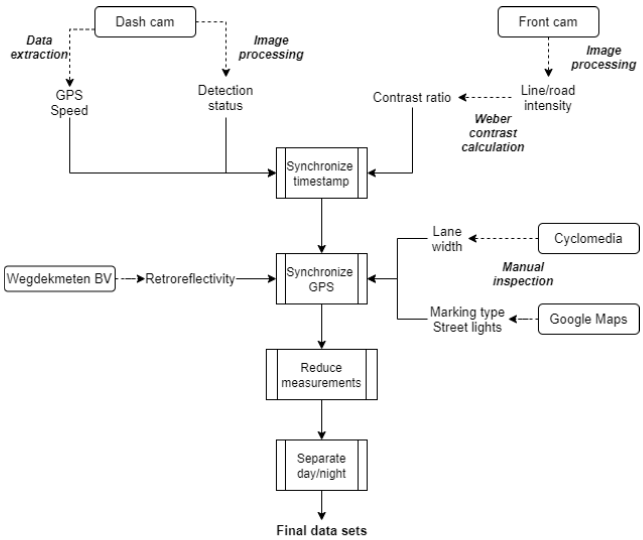

Fig. 9. Overview of the data processing method

The detection status of the vehicles were retrieved using computer image processing techniques in Python for each frame of the collected videos. The detection status observations of the vehicle with the stereo camera were found to be unreliable and were therefore excluded from further analysis. The same GoPro collected the GPS and speed measurements, which could be extracted using an online tool.

The front-facing camera was used to collect the contrast ratio. Before the intensity of the lines and the road surface could be extracted, a lane detection algorithm adapted from Udacity was used to find the lane markings in each frame. The final contrast ratio was calculated by using Weber's formula (Eq. 1). This contrast ratio was used in a previous study and was found to be useful for images with smaller objects on a large uniform surface [19].

$$C_w = \frac{I_m - I_r}{I_r} \tag{1}$$

I_m depicts the intensity of the lane marking, I_r the intensity of the road. Similar to the retroreflectivity, the contrast ratio was calculated for each line separately. Fig. 10 and 11 demonstrate the distribution of the contrast ratio.

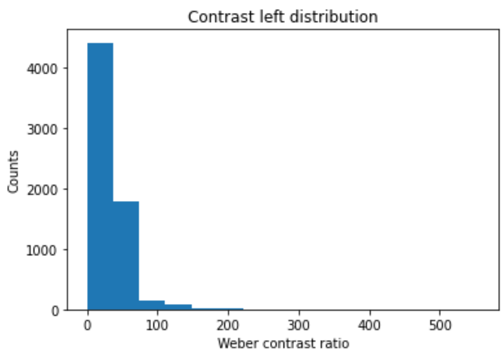

Fig. 10. Contrast ratio distribution for the left line

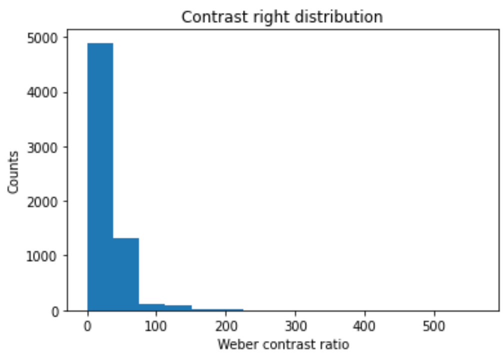

Fig. 11. Contrast ratio distribution for the right line

The distributions are heavily skewed to the left, with most observations being between 0 and 30. A few outliers with values above 500 were removed from the data set.

The retroreflectivity measurements were provided by an external company (Wegdekmeten BV). The measurements dated from 2018, theoretically meaning that the retroreflectivity of the lane markings at the time of the field test were expected to be lower than the measurements due to degradation. However, on some section where poor quality lane markings were expected, the lane marking appeared recently applied. To correct for that, the observations with values lower than 100 mcd/m2/lux were removed from the data set. The retroreflectivity measurements, together with the data on lane width, marking type and street lights, were merged with the video data based on the GPS coordinates. The final resolution of the observations was reduced to one measurement per 20 meter, as this was the lowest resolution in the data. Because the measures for visibility are different between daytime and nighttime, the total data set was separated into day and night.

III. RESULTS

The results of this study are presented in this chapter. First, the performance evaluation for the mono camera and the mono camera with infrared is discussed. This is followed by the results of the regression analysis. The choice was made to separate the left and the right line of the lane markings, which allowed to perform a binary logistic regression analysis. A logistic regression allows both continuous and categorical variables to be included, making it a suitable method for this study. It was also used in the study of [26] to determine the contribution of road factors to the detection performance.

A. Performance Evaluation

The observations during the field test could be categorised into four categories: Both lines detected, right line detected, left line detected, and no lines detected. The percentage of observations that fall in each category, per weather and illumination condition, is presented in Fig. 12 and 13, for each sensor types separately. In the most right column, the number of observations for each condition is stated.

Conditions	Both	Left	Right	None	Count
Sunset	91,44%	1,32%	3,73%	3,51%	456
Daytime - dry	76,01%	1,29%	6,80%	15,90%	2472
Daytime - wet	81,18%	1,64%	1,30%	15,88%	1461
Nighttime - dry	83,26%	0,74%	3,46%	12,54%	3900
Nighttime - wet	85,4%	3,87%	6,56%	4,17%	1342

Fig. 12. Detection performance mono camera with infrared

Conditions	Both	Left	Right	None	Count
Sunset	94,65%	-	-	5,35%	374
Daytime - dry	-	-	-	-	0
Daytime - wet	96,63%	1,48%	0,83%	1,06%	1690
Nighttime - dry	97,02%	0,89%	0,08%	2,01%	1341
Nighttime - wet	87,3%	0,11%	0,33%	12,27%	1817

Fig. 13. Detection performance regular mono camera

The color coding scheme indicates the highest and lowest percentages in the tables. For both sensor types, the highest percentages are found in the Both lines detected category, however there are significant differences between the sensor types and between conditions for the same sensor type. A z-test with IBM SPSS was used to compare the percentages. The mono camera with infrared performed significantly better during dry and wet nighttime conditions, as opposed to the same conditions during daytime ($p<0.05$). There is no significant difference between the nighttime conditions, and between nighttime dry and daytime wet conditions. The highest performance was obtained during sunset conditions, although less observations were collected.

For the regular mono camera in daytime dry conditions, the detection status extracted from the videos was not reliable. Additionally, an alternative data collection method was used during the sunset conditions drive, resulting in only Both and None categories. Situations where only one line was detected by the vehicle were categorized as None. The highest performance for the regular mono camera was found during nighttime dry conditions. Only during nighttime wet conditions the performance was significantly lower than for the other conditions ($p<0.05$).

Between the sensor types during the same driving conditions, significant differences in performance have been found. During wet daytime and dry nighttime conditions, the regular mono camera has a significant higher percentage for Both lines detected. The differences between the other detection categories for these two conditions are also significant. There is no significant difference in the percentage Both lines detected during nighttime wet conditions, while there is a difference between the sensor types for the other categories. Finally, for the sunset conditions, no difference between the sensor types were found for the Both and None detection categories.

B. Logistic Regression Model

The first step to building a logistic regression model is determining which of the variables should be included. In order to assess this, the Chi-square for independence have been tested between each variable and the detection status. An overview of the results can be found in Table II.

TABLE II

PEARSON CHI-SQUARE TEST FOR INDEPENDENCE BETWEEN VARIABLES AND DETECTION STATUS

Variables	χ^2	df	p-value	N of Valid Cases
Speed	614, 097	123	<0.0001	14853
Lane width	416,933	12	<0.0001	14853
Retroreflectivity-left	1287,574	891	<0.0001	6951
Retroreflectivity-right	1209,031	864	<0.0001	6096
Contrast ratio-left	947,393	468	<0.0001	6453
Contrast ratio-right	935,407	462	<0.0001	6453
Marking type	248,250	3	<0.0001	14853
Sensor type	408,036	3	<0.0001	14853
Conditions	351,860	12	<0.0001	14853
Street lights	184,706	3	<0.0001	7303

The p-value for all variables is reported to be lower than 0.001, meaning that each variable is not independent from the detection status and should therefore be included in the analysis. The next step is to test for correlations among the variables in order to avoid any multicollinearity that may distort the regression results. Because not all variables are continuous and it cannot be assumed that the variables follow a normal distribution, Spearman's rho is the most appropriate method to test for correlations. In the daytime data set, three significant strong correlations were found: contrast left with contrast right (value), contrast left with conditions (value), and contrast right with conditions. The correlation between the contrast ratios of the left and the right line can be explained by the formula of Weber that was used for the calculation. Both contrast ratio calculations used the same value for road surface intensity. The correlations between the contrast ratios and conditions are positive, meaning that higher contrast ratios are found during wet conditions and lower contrast ratios during dry (optimal) conditions due to the coding of the variables. It can be expected that the lane markings are well distinguishable from the road surface during optimal conditions, therefore these correlations will be ignored. The final step in the preparation for the logistic regression models is to test for interaction effects between the categorical variables. One expected interaction effect is between conditions and marking type, as marking type 2 is designed specifically to enhance the retroreflectivity during wet conditions. A two-way (univariate) ANOVA test was used to determine the potential interactions. The following interactions have been found: Marking type * Conditions, Sensor type * Conditions, Marking type * Sensor type, Conditions * Street lights, and Sensor type * Street lights.

In total, four different binary logistic regression models have been built, for daytime/nighttime detection of each line separately. The dependent variable could take on 1 (detected) or 0 (not detected). Tables III - VI contain the results of the logistic regression analysis. Only the variables and interaction effects that were found to be significant are considered in the models. The coefficient of each variable in the model is denoted by B. The exponential of B indicates the likelihood of detection with an increase of the variable of one unit (for continuous variables). For categorical variables, the change in likelihood is based on a change within the category. It is important to note that the likelihood change is always relative to the initial value. The interaction effects have been calculated by adding the B-values of the original variable and the interaction, and then taking the exponential. The original B-value is stated in the tables, while the combined exponential is stated to demonstrate the change in likelihood with the interaction.

Tables III and IV contain the estimated model coefficients for the daytime regression analysis.

The models contain the same significant variables, only the model for the right line additionally includes the contrast ratio. Both models indicate that an increase in speed with 1 km/h result in a slightly higher detection likelihood

TABLE III

REGRESSION RESULTS DAYTIME LEFT LINE

	B	p-value	Exp(B)
Speed increase	,059	<.0001	1,060
Marking type 2	2,085	<.0001	8,044
Regular mono camera	1,495	<.0001	4,460
Dry conditions		.026	
Wet conditions	-,249	.007	,780
Sunset conditions	-,101	.640	,904
Marking type 2 by regular mono camera	-1,481	<.0001	1,830
Conditions * Sensor type interaction effect		<.0001	
Wet conditions by regular mono camera	1,394	<.0001	3,010
Constant	-3,272	<.0001	,038

TABLE IV

REGRESSION RESULTS DAYTIME RIGHT LINE

	B	p-value	Exp(B)
Speed increase	,075	<.0001	1,078
Marking type 2	1,981	<.0001	7,247
Regular mono camera	1,930	<.0001	6,886
Dry conditions		<.0001	
Wet conditions	-,479	.121	,620
Sunset conditions	,452	<.0001	1,571
Marking type 2 by regular mono camera	-2,499	<.0001	0,625
Conditions * Sensor type interaction effect		.001	
Wet conditions by regular mono camera	1,255	.001	2,000
Contrast ratio	-,005	.006	,995
Constant	-4,083	<.0001	,017

(1,06 - 1,078). The marking type has a larger effect on the detection performance. Marking type 2 has led to a 7-8 times higher detection likelihood as opposed to marking type 1 for the mono camera with infrared. Including the interaction effect between marking type en sensor type, it was found that marking type 2 leads to an increase in detection likelihood of 1,83 for the left line, but an decrease of 1,6 for the right line when using the regular mono camera. Under dry conditions, the regular mono camera has a 4,4-6,8 times higher detection likelihood than the mono camera with infrared. During wet conditions, the detection likelihood decreases in comparison with dry conditions for the mono camera with infrared. During sunset conditions, the detection likelihood decreases for the left line and increases for the right line. During wet conditions, the regular mono camera has an increased detection likelihood (2-3 times) compared to the mono camera with infrared. The coefficient for contrast ratio in the right line model indicates that a higher contrast ratio results in a lower likelihood of detection (0,995). Both models contain a negative significant constant, implying that there are other variables relevant for the detection performance that have not been considered in this study. The models for the left line and the right line have a classification accuracy of 86,1% and 88,1% respectively.

Tables V and VI contain the model estimates for the nighttime detection.

TABLE V

REGRESSION RESULTS NIGHTTIME LEFT LINE

	B	p-value	Exp(B)
Speed increase	,064	<.0001	1,066
Marking type 2	1,914	<.0001	6,779
Regular mono camera	2,751	<.0001	15,666
Street lights present	-1,035	<.0001	,276
Lane width increase	-,023	<.0001	,977
Wet conditions	,249	.102	1,282
Wet conditions by regular mono camera	-2,944	<.0001	,071
Marking type 2 by regular mono camera	-2,499	<.0001	1,05
Wet conditions by Street lights present	1,411	<.0001	5,3
Regular mono camera by Street lights present	-,711	.023	7,7
Constant	3,615	.052	37,139

TABLE VI

REGRESSION RESULTS NIGHTTIME RIGHT LINE

	B	p-value	Exp(B)
Speed increase	,069	<.0001	1,072
Regular mono camera	1,797	<.0001	6,030
Street lights present	-1,059	<.0001	,347
Wet conditions	,461	.001	1,585
Wet conditions by regular mono camera)	-2,416	<.0001	,14
Wet conditions by Street lights present	,504	.022	2,6
Constant	-3,007	<.0001	,049

The nighttime model for the right line contains less significant variables than the model for the left line. Both models contain Speed as significant variable, which has a similar effect on the detection likelihood for the left and the right line (1,066-1,072). Again the regular mono camera has a higher detection likelihood, ranging between 6-15 times more likely than the mono camera with infrared. The presence of street lights have a negative effect on the detection likelihood during dry conditions (3 times less likely), but a positive effect during wet conditions (2,6-5,3 more likely). The variable Conditions was not found to be significant in the left line model, however wet conditions did increase the detection likelihood of the right line by the mono camera with infrared. Detection of the lane marking by the regular mono camera during wet conditions was 7-14 times less likely than by the mono camera with infrared. Only the model for the right line contains a significant constant. In the model for the left line, it was found that marking type 2 increases the detection likelihood by 6,7 times in comparison with marking type 1 for the mono camera with infrared. For the regular mono camera, this only increases by 1,05. Furthermore, a centimeter increase in lane width decreases the detection likelihood by 1,023. The model for the left line detection has a classification accuracy of 89,3 % and the model for the right line detection an accuracy of 90,6%.

IV. DISCUSSION

The findings of this study can be categorised into two parts: performance evaluation of sensor types, and the evaluation of the effect of lane marking properties on the detection performance.

A. Reflection on performance evaluation

One of the goals of this study was to evaluate the performance of the different sensor types that are being used for LKA. This study ultimately succeeded in comparing two sensor types: a regular mono camera and a mono camera with infrared. Due to unreliable detection status data, the third sensor type (stereo camera) could not be further analysed. The performance range of the regular mono camera was found to be between 97% in nighttime dry conditions and 87,3% in nighttime wet conditions. This is similar to findings from the previous studies of Cafiso et al. [26] and Reddy et al. [25], although [26] only evaluated the performance under dry daytime conditions. Different sensor types have not been evaluated in field tests before, which enables the possibility to compare the performance results of the mono camera with infrared with other findings. Although Liu et al. [9] state that infrared could be a possible solution to deal with weather and illumination issues, this study found that the detection performance of the mono camera with infrared in most conditions was significantly lower than the regular mono camera. The highest detection performance of the mono camera with infrared (91,4%) was reached during sunset conditions and the lowest detection performance (76%) during daytime dry conditions. No conclusion could be drawn as to why the performance was lower than the mono camera.

B. Reflection on lane marking properties evaluation

This study presented an extensive evaluation of lane marking properties that contribute to the detection performance. Binary logistic regression analysis was used to obtain significant variables in the detection model. Based on the variable coefficients in the model, the effect of the variables was derived. Speed was found significant in all the models with comparable effects (1,060-1,078 increase in detection likelihood per km/h increase in speed). The marking type was reported to be significant in most of the models, with marking type 2 increasing the detection likelihood under most conditions. To the author's knowledge, this is the first time this variable has been evaluated in the literature. The effects found for conditions and sensor type are relatable to the detection performance evaluation. The presence of street lights were found to have a negative effect during dry nighttime conditions, and a positive effect during wet nighttime conditions. This is opposite than the results of the study of [25], however only little rain was experienced during the field test. More rain leading to a wet road surface could have resulted in a negative effect of street lights, however this cannot be concluded from this study. Contrast ratio and lane width only appeared in one model and are therefore not considered relevant. The fact that contrast ratio was not significant might have been caused by the method that was used for data collection. The lane width was most likely not found significant because the minimum lane width during the field tests was reported to be 2.75 meter, which was found to be sufficient in the studies of [24], [25]. Finally, the retroreflectivity did not appear in any of the regression models. A potential cause for this may be the outdated measurements provided by the external company. Road curvature was not considered in this study, but based on previous studies and the constant in the models it could be argued that it would have had an effect on the LKA performance.

C. Research Limitations

While this study was conducted with great care, imperfections could not be avoided. One of the main limitations in this study was the use of image processing techniques to obtain the detection status and the contrast ratio. Image processing, as opposed to using vehicle data, is prone to errors in classifying whether the vehicle has detected the lane markings. This is why the data of the stereo vision vehicle and the mono camera during dry daytime were ultimately unreliable. Having access to the vehicle data would have lead to a more extensive comparison. Image processing was also used to retrieve the contrast ratio. This method has not been used in previous studies, as the diffuse luminance coefficient is a more often used measure of lane marking quality for daytime visibility. However, measurements have to be done with specialized equipment which was not possible in this study. Instead, the vehicle camera view was reproduced by the GoPro camera facing the road. The algorithms used for lane detection in the videos were adjusted for this study, however it turned out that it was not possible to fit the model perfectly to the driving scenes. As a result, the contrast ratio measurements might not always be reliable, although the ratios were in the same order of magnitude as the study of [18]. Another main limitation of this study was the outdated retroreflectivity measurements. Because of this, some observations had to be excluded from the analysis, as the expected quality did not match with the encountered quality during the field test. While curvature was taken into account when planning the test routes, it could not be entirely avoided. This is also the case for intersections and roundabouts. It might be possible that these factors have distorted a small part of the observations. Finally, there was only little information collected regarding the weather and illumination during the field test. The amount of precipitation, for example, has not been recorded. Additionally, no different levels of precipitation have been encountered due to the lack of time for the execution of the field test.

V. CONCLUSIONS AND RECOMMENDATIONS

A. Conclusion

Advanced Driver Assistance Systems (ADAS) are bound to appear more on the roads, since the European Commission has announced that several ADAS, amongst others Lane Keep Assist(LKA) systems, will become mandatory in new vehicle models from 2022 onward. These systems are designed to promote road safety, and for them to function optimally, they should be available at all times. The functioning of LKA relies on different factors, such as road and lane marking quality, environmental characteristics, and other road characteristics. Since knowledge about the road and lane marking quality for LKA is lacking, the aim of this study was to provide insights into the effect of lane marking properties on the detection performance of several sensors that are used for LKA. Simultaneously, the detection performance of two sensor types have been compared in this study. A field test was used to collect data on the detection status.

The two sensor types that were compared were a mono camera with infrared and a regular mono camera. During most conditions, the regular mono camera had a higher percentage of both lines detected than the mono camera with infrared. Only during wet nighttime conditions, this percentage was similar for both sensor types. The highest percentage of both lines detected for the mono camera with infrared (91,4%) was found during sunset conditions, the lowest percentage of both lines detected (76%) was found during dry daytime conditions. The percentage both lines detected for the regular mono camera ranged between 97% during dry nighttime conditions, and 87,3% during wet nighttime conditions.

Binary logistic regression analysis was used to determine the effect of different lane marking properties and other road characteristics on the detection performance. Speed was found to have a positive effect on the detection performance. Additionally, profiled lane markings (marking type 2) appeared to increase the detection likelihood as opposed to flat lane markings. Street lights were found beneficial for the detection performance during rain, while during dry conditions the effect is opposite. Other lane marking visibility properties, such as contrast ratio and retroreflectivity, were not found to be significant in this study.

B. *Recommendations*

The findings of this study has led to more angles for future research. First of all, the aim of this study was to compare the detection performance of different sensor types for LKA. Ultimately, only the mono camera and the mono camera with infrared were compared. Future studies might consider assessing the detection performance of stereo vision or LiDAR for LKA, as this remains unknown to this point. Secondly, this study found a correlation between the contrast ratio and the weather conditions during the day. Although it was ignored in this study because the correlation did not seem logical, there might be some relation between the two. This can be worth researching to gain more knowledge on the effect of weather on the visibility of lane markings. Including conditions in field tests with moderate or heavy rainfall might also be considered to increase the knowledge on the effect of street lights and marking type during these conditions. Additionally, developments within the field of deep learning may lead to a future where deep learning can be used for lane detection in vehicles. It might be interesting to research how these systems use road infrastructure and compare this to 'traditional' methods that are currently used. Finally, the field test in this study was executed on Dutch provincial roads. Since there was not much variation in this road, it might be interesting to consider repeating this study on other types of road, or in other countries.

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A

Statistical analyses

A.1. Z-Tests

Detection * c1 Crosstabulation

% within c1

		c1					
		1,00	2,00	3,00	4,00	5,00	Total
Detection	Both	76,0%$_{a}$	81,2%$_{b}$	91,4%$_{c}$	83,3%$_{b,\ d}$	85,4%$_{d}$	81,8%
	Left	1,3%$_{a,\ b}$	1,6%$_{b}$	1,3%$_{a,\ b,\ c}$	0,7%$_{a}$	3,9%$_{c}$	1,5%
	None	15,9%$_{a}$	15,9%$_{a}$	3,5%$_{b}$	12,5%$_{c}$	4,2%$_{b}$	12,3%
	Right	6,8%$_{a}$	1,3%$_{b}$	3,7%$_{a,\ c}$	3,5%$_{c}$	6,6%$_{a}$	4,4%
Total		100,0%	100,0%	100,0%	100,0%	100,0%	100,0%

Each subscript letter denotes a subset of c1 categories whose column proportions do not differ significantly from each other at the ,05 level.

Table A.1: Column proportions (z-test) for mono camera + infrared

Notation of the conditions (c1): 1 = daytime dry, 2 = daytime wet, 3 = sunset, 4 = nighttime dry, 5 = nighttime wet

Detection * c1 Crosstabulation

% within c1

		c1				
		2,00	3,00	4,00	5,00	Total
Detection	Both	96,6%$_{a}$	94,7%$_{a}$	97,0%$_{a}$	87,3%$_{b}$	93,3%
	Left	1,5%$_{a}$		0,9%$_{a}$	0,1%$_{b}$	0,7%
	None	1,1%$_{a}$	5,3%$_{b}$	2,0%$_{a}$	12,3%$_{c}$	5,5%
	Right	0,8%$_{a}$		0,1%$_{b}$	0,3%$_{a,\ b}$	0,4%
Total		100,0%	100,0%	100,0%	100,0%	100,0%

Each subscript letter denotes a subset of c1 categories whose column proportions do not differ significantly from each other at the ,05 level.

Table A.2: Column proportions (z-test) regular mono camera

Notation of the conditions (c1): 1 = daytime dry, 2 = daytime wet, 3 = sunset, 4 = nighttime dry, 5 = nighttime wet

Detection * Sensortype Crosstabulation

% within Sensortype

		Sensortype 1	Sensortype 2	Total
Detection	Both	81,2%a	96,6%b	89,5%
	Left	1,6%a	1,5%a	1,6%
	None	15,9%a	1,1%b	7,9%
	Right	1,3%a	0,8%a	1,0%
Total		100,0%	100,0%	100,0%

Each subscript letter denotes a subset of Sensortype categories whose column proportions do not differ significantly from each other at the ,05 level.

Table A.3: Column proportions (z-test) daytime wet conditions

Detection * Sensortype Crosstabulation

% within Sensortype

		Sensortype 1	Sensortype 2	Total
Detection	Both	83,3%a	97,0%b	86,8%
	Left	0,7%a	0,9%a	0,8%
	None	12,5%a	2,0%b	9,8%
	Right	3,5%a	0,1%b	2,6%
Total		100,0%	100,0%	100,0%

Each subscript letter denotes a subset of Sensortype categories whose column proportions do not differ significantly from each other at the ,05 level.

Table A.4: Column proportions (z-test) nighttime dry conditions

Detection * Sensortype Crosstabulation

% within Sensortype

		Sensortype 1	Sensortype 2	Total
Detection	Both	85,4%a	87,3%a	86,5%
	Left	3,9%a	0,1%b	1,7%
	None	4,2%a	12,3%b	8,8%
	Right	6,6%a	0,3%b	3,0%
Total		100,0%	100,0%	100,0%

Each subscript letter denotes a subset of Sensortype categories whose column proportions do not differ significantly from each other at the ,05 level.

Table A.5: Column proportions (z-test) nighttime wet conditions

Detection * Sensortype Crosstabulation

% within Sensortype

		Sensortype		
		1	2	Total
Detection	Both	91,4%a	94,7%a	92,9%
	Left	1,3%a		0,7%
	None	3,5%a	5,3%a	4,3%
	Right	3,7%a		2,0%
Total		100,0%	100,0%	100,0%

Each subscript letter denotes a subset of Sensortype categories whose column proportions do not differ significantly from each other at the ,05 level.

Table A.6: Column proportions (z-test) sunset conditions

A.2. T-Tests

Group Statistics

	Sensortype	N	Mean	Std. Deviation	Std. Error Mean
Speedkmh	1	9631	76,00318056	5,310403211	,0541117783
	2	5222	74,51292049	6,750625798	,0934169322

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Speedkmh	Equal variances assumed	421,335	,000	14,805	14851	,000	1,490260073	,1006573139	1,292959282	1,687560863
	Equal variances not assumed			13,804	8776,696	,000	1,490260073	,1079574350	1,278638204	1,701881941

Table A.7: Independent samples T-test for speed

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	RLleft	177,024	7191	67,5405	,7965
	RLright	155,130	7191	72,5579	,8556

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	RLleft & RLright	7191	,314	,000

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	RLleft - RLright	21,8943	82,1250	,9685	19,9959	23,7928	22,607	7190	,000

Table A.8: Paired T-test for left and right retroreflectivity

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Contrastleft	27,99684597	6453	29,32064579	,3649998609
	Contrastright	25,03422050	6453	28,38263608	,3533229893

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Contrastleft & Contrastright	6453	,961	,000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	Contrastleft - Contrastright	2,962625472	8,157409925	,1015480187	2,763557669	3,161693276	29,175	6452	,000

Table A.9: Paired T-test for left and right contrast ratio

A.3. ANOVA Tests of Between-Subjects Effects

Tests of Between-Subjects Effects

Dependent Variable: Leftlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	68,660[a]	3	22,887	213,118	,000	,042
Intercept	7612,971	1	7612,971	70890,977	,000	,829
Sensortype	9,222	1	9,222	85,871	,000	,006
Markingtype	15,878	1	15,878	147,855	,000	,010
Sensortype * Markingtype	9,451	1	9,451	88,005	,000	,006
Error	1575,731	14673	,107			
Total	12790,000	14677				
Corrected Total	1644,391	14676				

a. R Squared = ,042 (Adjusted R Squared = ,042)

Table A.10: Interaction effects sensor type - marking type (left)

Tests of Between-Subjects Effects

Dependent Variable: Rightlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	38,332[a]	3	12,777	133,280	,000	,027
Intercept	7711,519	1	7711,519	80439,016	,000	,847
Sensortype	3,604	1	3,604	37,589	,000	,003
Markingtype	8,701	1	8,701	90,761	,000	,006
Sensortype * Markingtype	7,165	1	7,165	74,741	,000	,005
Error	1392,481	14525	,096			
Total	12920,000	14529				
Corrected Total	1430,813	14528				

a. R Squared = ,027 (Adjusted R Squared = ,027)

Table A.11: Interaction effects sensor type - marking type (right)

Tests of Between-Subjects Effects

Dependent Variable: Leftlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	32,864[a]	3	10,955	107,460	,000	,038
Intercept	3697,321	1	3697,321	36268,985	,000	,815
Streetlights	20,154	1	20,154	197,698	,000	,023
Conditions	2,186	1	2,186	21,441	,000	,003
Streetlights * Conditions	4,853	1	4,853	47,604	,000	,006
Error	837,961	8220	,102			
Total	7234,000	8224				
Corrected Total	870,824	8223				

a. R Squared = ,038 (Adjusted R Squared = ,037)

Table A.12: Interaction effects street lights - conditions (left)

Tests of Between-Subjects Effects

Dependent Variable: Rightlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	26,788[a]	3	8,929	98,978	,000	,035
Intercept	3805,081	1	3805,081	42177,840	,000	,839
Streetlights	22,345	1	22,345	247,684	,000	,030
Conditions	,113	1	,113	1,254	,263	,000
Streetlights * Conditions	,551	1	,551	6,110	,013	,001
Error	728,217	8072	,090			
Total	7233,000	8076				
Corrected Total	755,005	8075				

a. R Squared = ,035 (Adjusted R Squared = ,035)

Table A.13: Interaction effects street lights - conditions (right)

Tests of Between-Subjects Effects

Dependent Variable: Leftlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	46,780[a]	3	15,593	155,548	,000	,054
Intercept	3899,506	1	3899,506	38898,327	,000	,826
Streetlights	25,686	1	25,686	256,226	,000	,030
Sensortype	18,454	1	18,454	184,082	,000	,022
Streetlights * Sensortype	8,076	1	8,076	80,559	,000	,010
Error	824,044	8220	,100			
Total	7234,000	8224				
Corrected Total	870,824	8223				

a. R Squared = ,054 (Adjusted R Squared = ,053)

Table A.14: Interaction effects street lights - sensor types (left)

Tests of Between-Subjects Effects

Dependent Variable: Rightlinedetected

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	36,308[a]	3	12,103	135,931	,000	,048
Intercept	4035,296	1	4035,296	45322,185	,000	,849
Streetlights	23,409	1	23,409	262,913	,000	,032
Sensortype	9,144	1	9,144	102,699	,000	,013
Streetlights * Sensortype	5,911	1	5,911	66,392	,000	,008
Error	718,697	8072	,089			
Total	7233,000	8076				
Corrected Total	755,005	8075				

a. R Squared = ,048 (Adjusted R Squared = ,048)

Table A.15: Interaction effects street lights - sensor types (right)

A.4. Probability distributions of regression models

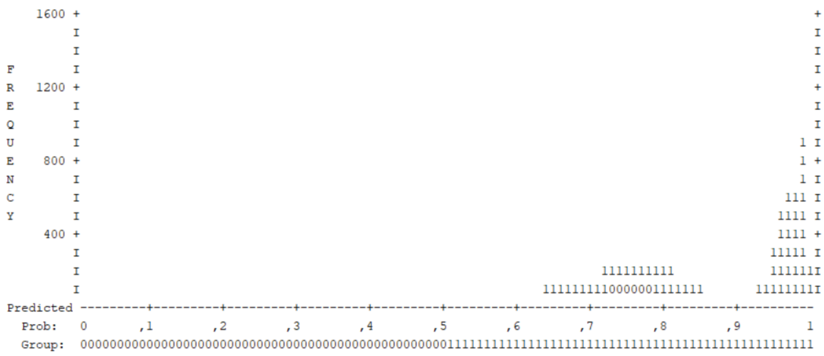

Figure A.1: Classification probabilities for daytime left model

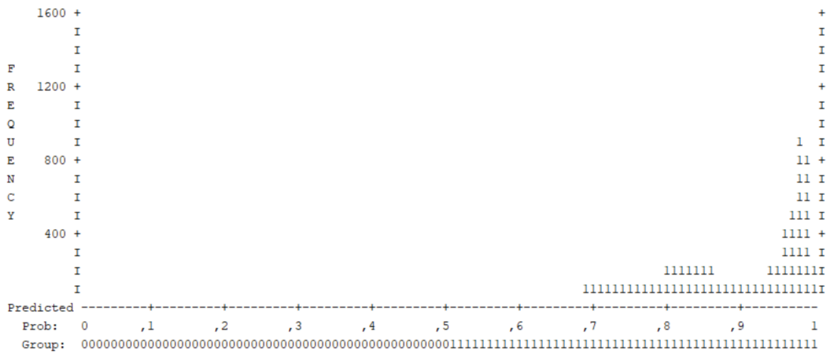

Figure A.2: Classification probabilities for daytime right model

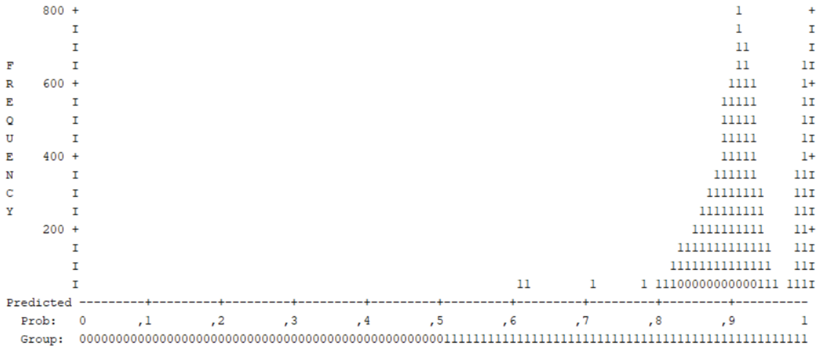

Figure A.3: Classification probabilities for nighttime left model

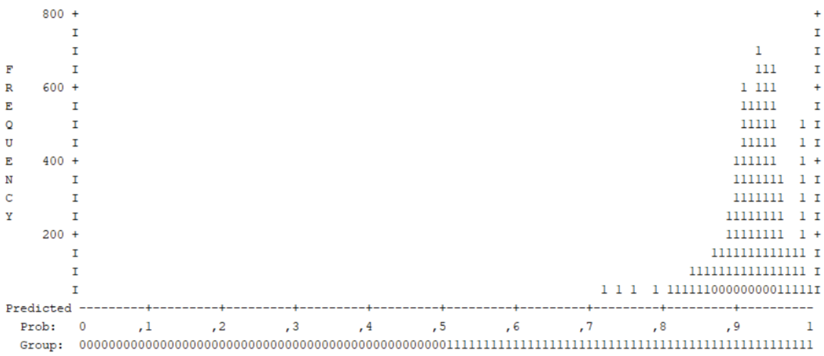

Figure A.4: Classification probabilities for nighttime right model