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Machine-readability of road markings in the Nordic countries



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Summary:

The project AVRM (autonomous vehicles and road markings) aimed to examine how vehicles' advanced driver assistance systems (ADAS) are constructed, how they function and how they detect road markings on the Nordic road network. Focus was on the systems lane departure warning (LDW) and lane keeping assist (LKA).

The project was divided into four different parts, namely a literature study, an empirical pilot study, an analysis of a large dataset and an empirical main study.

The literature study was carried out with the aim to compile knowledge about the technology, construction, and function of LDW and LKA, differences in quality and function and how the physical environment influences detection of road markings. It consisted of a literature search where empirical studies on machine-readability of road markings were included, as well as interviews with a series of informants to acquire more knowledge of the construction and technology of ADAS. The literature study revealed that many parameters affect machine-readability. From the interview survey, it was found that exact performance properties of road markings do not directly correspond to machine-readability and that a combination of data collection technologies is often used. Both the literature study and the interview study concluded that if the human eye can detect the road marking, then the road marking is machine-readable. However, only a few studies had been conducted in wet conditions relating machine-readability to road marking functionality.

The pilot study aimed to test equipment and to find a method to connect machine-readability data with contrast ratio under various weather and light conditions, and to reveal possible problems before conduction of a main study. The pilot study focused on the contrast ratio between the road marking and the road surface in both dry and wet weather conditions. The pilot study confirmed that there are many parameters affecting machine-readability that are not related to road marking functionality. Hence, contrast ratio alone could not infer machine-readability. Results from both the literature study and the pilot study pointed out that wear and lack of road markings were the parameters related to road markings per se that contributed to poor machine-readability.

A large dataset (total road marking length of around 5800 km) on machine-readability of dry road markings in daylight in Norway and Sweden was analysed within the project. The analysis showed that in daylight, there was no strong relationship between machine-readability and conventional road marking performance parameters. In addition, machine-readability was higher on multilane roads (99%) compared to on two-lane roads (93%), which may be explained for example by fewer curves on larger roads. Although data showed that machine-readability of broken lines was somewhat worse than that of solid lines of line width 0.1 m, this could be an effect of factors related to the (minor) roads where broken lines with 0.1 m width are commonly used.

The empirical main study data collection was carried out on varying types of roads with different types of road markings in Sweden and Denmark. Data was collected both in dry and wet conditions, both in daylight and at night-time. The main study data collection showed an overall high machine-readability (average 98%) on edge lines on motorways and 2+1 roads, irrespective of weather and light conditions. In the wet night-time condition, there was some difference between the flat Swedish lane lines and the profiled Danish lane lines on motorways but machine-readability was still high, 93% in Sweden and 98% in Denmark. The lowest machine-readability, 36%, was achieved in the wet night-time condition on small roads without centre line, where the road marking was always the same (a flat broken line with a width of 0.1 m). However, it is reasonable to believe that the road type had a large impact on machine-readability. Flat road markings did not differ much from profiled markings in the wet night-time condition on a straight and flat road without glare. It should also be remembered that machine-readability for LKA or LDW systems can never be expected to be 100%, because there are not, and should not be, road markings everywhere along the road network, due to the existence of intersections, crossings, etc.

In sum, there are many factors unrelated to road markings that influence machine-readability. There are no clear relationships between machine-readability and conventional performance parameters. It should also be kept in mind that since retroreflectivity is a parameter measuring the performance in night-time, it could not be expected to affect daylight readability. As long as the road markings are visible for the human eye, they can be expected to be machine-readable as well. Hence, missing and very worn road markings should be remedied in agreement with current requirements.

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The report has been made web accessible.

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1 List of abbreviations

A list of abbreviations used in the report is given in Table 1.

Table 1. List of abbreviations.

AD Autonomous Driving ADAS Advanced Driver-Assistance System AVRM Autonomous Vehicles and Road Markings CAV Connected and Autonomous Vehicle CNN Convolutional Neural Networks CR Contrast Ratio ELKS Emergency Lane-Keeping System GNSS Global Navigation Satellite System LDW Lane Departure Warning LiDAR Light Detection and Ranging LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity TEN-T Trans-European Transport Network	Tuble 1: List of apple viations.	
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CAV Connected and Autonomous Vehicle CNN Convolutional Neural Networks CR Contrast Ratio ELKS Emergency Lane-Keeping System GNSS Global Navigation Satellite System LDW Lane Departure Warning LiDAR Light Detection and Ranging LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	ADAS	Advanced Driver-Assistance System
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CR ELKS Emergency Lane-Keeping System GNSS Global Navigation Satellite System LDW Lane Departure Warning LiDAR Light Detection and Ranging LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	CAV	Connected and Autonomous Vehicle
ELKS GNSS Global Navigation Satellite System LDW Lane Departure Warning LiDAR Light Detection and Ranging LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	CNN	Convolutional Neural Networks
GNSS LDW Lane Departure Warning LiDAR Light Detection and Ranging LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	CR	Contrast Ratio
LDW LiDAR Light Detection and Ranging LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	ELKS	Emergency Lane-Keeping System
LiDAR Light Detection and Ranging LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	GNSS	Global Navigation Satellite System
LKA Lane Keeping Assist LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	LDW	Lane Departure Warning
LKS Lane Keeping System Qd Luminance Coefficient RL Retroreflectivity	LiDAR	Light Detection and Ranging
Qd Luminance Coefficient RL Retroreflectivity	LKA	Lane Keeping Assist
R _L Retroreflectivity	LKS	Lane Keeping System
	Qd	Luminance Coefficient
TEN-T Trans-European Transport Network	RL	Retroreflectivity
	TEN-T	Trans-European Transport Network

2 Introduction

2.1 Background and aim

In January 2021, The Danish Road Directorate, on behalf of NordFoU, invited organisations to bid for a tender on a project called "Autonome køretøjers detektering af vejmarkeringer" (AVRM). The project aimed to examine how vehicles' advanced driver assistance systems (ADAS) are constructed, how they function and how they detect road markings on the Nordic road network. Moreover, the project should focus specifically on the systems lane departure warning (LDW) and lane keeping assist (LKA), where detection of road markings was considered to be crucial. In addition, studies should be carried out in order to deliver knowledge about how these systems detect road markings, focusing on the Nordic road network. The results of the project should contribute to that the road authorities can act professionally in a future road infrastructure, where vehicle equipment was expected to dictate functionality of the road markings. Furthermore, the project results should deliver background data for establishing specifications and procedures for road markings to be effectively readable and visible for both human drivers and ADAS. One of the original tasks was also to identify the minimum level of road marking functionality (in terms of conventional road marking performance parameters) for an LDW system to work. In addition, recommendations for how these minimum levels of road marking functionality could be achieved should be specified.

A consortium consisting of three partners from Sweden and Denmark, i.e., the Swedish National Road and Transport Research Institute, Ramboll, and the Danish Technological Institute, decided to bid for the tender. After an evaluation process this consortium won the bid and will henceforth be referred to as the project group. The NordFoU partners participating in the steering group of the project are the Danish Road Directorate, the Finnish Transport Infrastructure Agency, the Norwegian Public Roads Administration, and the Swedish Transport Administration.

The present report describes the result of the entire project, which was divided into different parts to achieve as much information as possible and to fulfil the aim of the project. The four parts were:

- A **literature study** on empirical studies on machine-readability of road markings, and of the construction and technology of ADAS,
- an empirical pilot study based on the results of the literature study, in different weather and light conditions,
- an analysis of a large and unique dataset on machine-readability of dry road markings in daylight,
- and an empirical main study based on the results of the literature study and the pilot study, on machine-readability on Nordic roads, with focus on wet conditions.

2.2 Road markings in the Nordic countries

The project should have emphasis on road markings on the Nordic road network, with the weather, light, and road conditions that prevail there. Some basic features of road markings used in the Nordic countries are given in this section.

Longitudinal road markings vary in how they are applied, and which pattern is used. A marking applied without gaps is often referred to as a solid or continuous line, while a road marking with large gaps between each marking can be referred to as a broken, dashed or intermittent line. In turn, each solid and broken line may have a pattern/profile to enhance the visibility in wet conditions. Examples of solid and broken lines are given in Figure 1, while examples of some profiles used in the Nordic countries are given in Figure 2, together with a flat road marking (no profile).

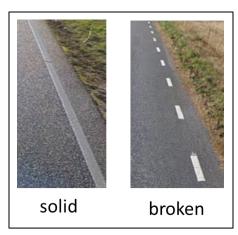


Figure 1. Example of a solid and a broken line (both with flat road marking pattern).

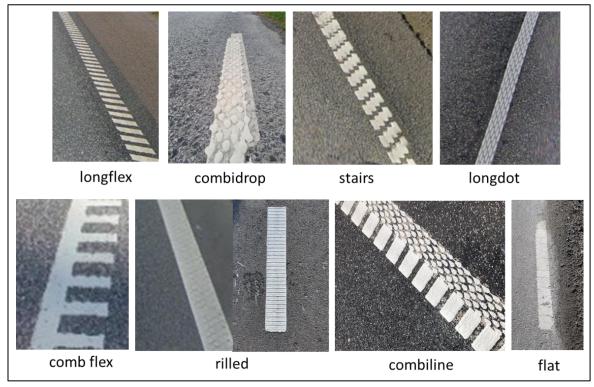


Figure 2. Examples of road markings with different profiles and a (worn) flat marking.

Table 2 gives an overview of terms used for road marking types in the Nordic countries.

Table 2. An overview of road marking terms used in the Nordic countries.

English	Danish	Swedish	Norwegian	Finnish
Longflex	Longflex		Longflex	Longflex
Combidrop		Kombidrop, drop- par på plan	Dråpekombi	Yhdistelmädroppflex / kombidroppflex
Stair flex		Trappflex		Trappa / trappflex
Dotted line	Multidot	Droppflex, drop- par	Dråpeflex	Pisara / droppflex
Longdot	Longdot			Longdot
Rilled		Rillad		
Comb flex		Kamflex	Kamflex	Kamflex
Chess pattern		Schackruta	Sjakkmønster	Shakkiruutu
Flat	Plan	Plan	Plan	Sileä (flat)
"Combiline"	Kombilinje			

3 Project process

The project has been carried out as an iterative process. Over the course of the project, results from the different steps have been discussed between the project group and the steering group, which has led to that the project has changed its goals from the beginning to the end.

First, a literature study on advanced driver-assistance systems was conducted with a focus on contrast between road marking and road surface, where previous studies were summarized, and an interview survey was completed.

From the results of the literature study, a pilot study was planned and performed. The results of the pilot study revealed some new information, that led to the decision that the main study would be performed in a different way with a different focus. Another decision was also to use data collected in a previous NordFoU project (ROMA) to get a vast amount of data from daylight conditions.

Due to the iterative process where the results along the way have guided the planned work ahead, the project has contributed to fill some of the knowledge gaps that are associated with vehicle detection of road markings.

3.1 Distribution of work

This project has involved many people contributing to the results in different ways.

The literature review of section 4.1.1, 4.2.1 and 4.3 was conducted by VTI whereas the Danish Technological Institute performed the literature review in section 4.2.2 and the interview survey in 4.5. The data collection in all three empirical studies of chapter 5 was carried out by Ramboll, while VTI analysed the data. VTI finalized the report.

The steering group has taken an active interest in the project by being involved in every part of the project process and having a constant dialogue with the project group.

Apart from the members of the project group and the steering group, there are more people that have contributed to this work. We would especially like to thank the participants in the interview survey, and the drivers of the measurement vehicles, who have spent many hours carrying out measurements day and night, in dry and wet weather conditions.

4 Literature study

Background and aim

Advanced driver-assistance systems (ADAS) are advanced technologies developed to help the driver of a vehicle in various situations. Within this group of technologies and functions, some are specifically related to detection of road markings, e.g., lane departure warning (LDW) systems and lane keeping assist (LKA) systems. An LDW system uses auditory, tactile, or visual means to warn the driver that the vehicle either will deviate or has already deviated from the lane. By this, the driver is made aware and can correct the path of the vehicle. An LKA system, on the other hand, pro-actively takes control of the vehicle with the purpose of keeping it safely within the lane.

Both LDW and LKA systems are constructed to detect road markings to decide on where the lane is situated in relation to the vehicle. The aim of the literature study is to compile knowledge about the technology, construction, and function of LDW and LKA, differences in quality and function and how the physical environment influences detection of road markings. The literature study focusses on road and weather conditions in the Nordic countries. It consists of a literature search where empirical studies on machine-readability of road markings are included, as well as interviews with a series of informants to acquire more knowledge of the construction and technology of ADAS.

4.1.1 Contrast and contrast ratio

In the literature, contrast is mentioned as crucial for detection of road markings. Contrast describes the relation between road marking and road surface, but it is defined and used in different ways for different systems and in different studies.

Lundkvist and Fors (2010) state that road marking visibility is given by the Weber luminance contrast, C, according to the following equation:

$$C = \left| \frac{L_{road\ marking} - L_{road\ surface}}{L_{road\ surface} + L_{S}} \right| (1),$$

where L refers to the luminance and Ls refers to luminance in the eye caused by glare from oncoming vehicles or from low sun.

They use the following equation for contrast with vehicle lighting without oncoming traffic:

$$contrast_{R_L} = \left| \frac{{}^{R_{L,road\ marking} - R_{L,road\ surface}}}{{}^{R_{L,road\ surface}}} \right| \ (2),$$

and the corresponding equation for daylight contrast:
$$contrast_{Qd} = \left| \frac{Qd_{road\ marking} - Qd_{road\ surface}}{Qd_{road\ surface}} \right| \ (3).$$

According to the references in general, the contrast ratio is defined by:

$$contrast\ ratio = \frac{measured\ value\ of\ road\ marking}{measured\ value\ of\ road\ surface}\ (4)\ .$$

Hence, for daytime visibility, the contrast ratio is:

contrast ratio is:
$$contrast \ ratio_{Qd} = \frac{Qd_{road \ marking}}{Qd_{road \ surface}} \ (5)$$

For night-time visibility, the contrast ratio is, consequently:

$$contrast\ ratio_{RL} = \frac{R_{L,road\ marking}}{R_{L,road\ surface}}$$
 (6)

The definitions in Eq. (5) and (6) are used by Pike, Barrette, and Carlson (2018), Marr, Benjamin, and Zhang (2020), and probably Reddy, Farah, Huang, Dekker, and Van Arem (2020). For Storsæter, Pitera, and McCormack (2021), Eq. (4) is used, where *measured value* is substituted for *return signal* of road marking and road surface, respectively.

In the Austrian laboratory studies (Burghardt et al., 2021), contrast ratio is defined as: $contrast\ ratio = \frac{L_{road\ marking} - L_{background}}{L_{background}}, \text{ which is the definition used for } contrast\ (\text{not } contrast\ ratio) \text{ in } \\ \text{Eq. 1 by Lundkvist and Fors (2010), without glare present. However, in (Burghardt et al., 2021) it}$

Eq. 1 by Lundkvist and Fors (2010), without glare present. However, in (Burghardt et al., 2021) it seems that the definition is also used for conditions with glare. Taking luminance in the eye into account would mean that the contrast would be lower, as a higher L_s component means decreased Weber luminance contrast.

As can be noted from above, there is a difference between the definitions of *contrast* and *contrast* ratio, that should be kept in mind when comparing results from different studies in the following. (In the pilot study, the contrast ratio according to equations (5) and (6) is used. In essence, the difference between contrast and contrast ratio is a constant term of 1 that should be subtracted from the contrast ratio to achieve the contrast. Hence, the results when comparing different road markings would not be significantly affected by whether contrast ratio or contrast is used, as long as the same definition is used within the same comparison.)

4.2 Previous knowledge

4.2.1 Studies 2010–2020

As part of a VTI report (*Infrastruktur för bilar med automatiserade funktioner – Ett kunskapsunderlag om behov av nödvändig anpassning*), a literature review on infrastructure for connected and autonomous vehicles (CAVs) with respect to road markings was made (Sjögren, Arvidsson, Fors, & Käck, 2022). Literature published until the end of 2020 was included in the draft used here, and several studies relevant for LDW and LKA were referred to. The review is reported in Swedish and to achieve synergy effects, important findings from the most relevant studies (Lundkvist & Fors, 2010; Marr et al., 2020; Pike et al., 2018) with respect to LDW and LKA systems from the review are given in the following.

An early field study on road markings and ADAS was carried out in Sweden by VTI in 2010 on real roads and under varying light and weather conditions (Lundkvist & Fors, 2010). The aim was to investigate what levels of luminance coefficient Qd and retroreflectivity R_L were needed for the Volvo LDW system to function. The LDW system was based on a camera reading the road markings at up to 30–40 m in front of the vehicle. Dry retroreflectivity of the road marking was captured using a mobile measurement system (RMT, Ramböll RST) based on a reflectometer and an optocator, and predictions of wet retroreflectivity and luminance coefficient were made by means of prediction models. The results basically showed that the LDW system would function if the current requirements of luminance coefficient Qd and retroreflectivity R_L , were fulfilled:

- In daylight, the LDW system needed the luminance coefficient of the road marking to be 5 mcd/m²/lx higher than that of the road surface. Since the luminance coefficient of an asphalt surface typically is 50–100 mcd/m²/lx, while the current requirement for the luminance coefficient of (white) road markings in Sweden is 130 mcd/m²/lx, the LDW system functioned well also for Qd levels far below the requirement.
- At night-time conditions, the system demanded that the retroreflectivity for dry road markings was 70 mcd/m²/lx. This is also below the current requirement of 150 mcd/m²/lx (white road markings in Sweden).
- The retroreflectivity of wet road markings at night should be at least 20 mcd/m²/lx to be detectable for the LDW system. The current requirement in Sweden is 35 mcd/m²/lx.

The field study also showed that, irrespective of road marking functionality, the LDW system had difficulties to detect road markings at low (opposing) sun, glare from oncoming vehicles at wet night-time conditions, curvy roads, and sunken shoulders on roads without centre lines. The study concluded that the LDW showed very good performance in most weather and lighting conditions, but to improve the performance even more, the use of road markings developed for wet conditions should increase.

Within the American research program called National Cooperative Highway Research Programme (NCHRP), a comprehensive study on how road marking characteristics affect machine vision was conducted on a test track, under varying weather and lighting conditions (Pike et al., 2018). A post-mounted Mobileye system was used, reading markings at 10–15 m in front of the vehicle. Road markings of different colours (white/yellow) and retroreflectivity were used, all 10 cm wide (4 inches). Functional characteristics used were retroreflectivity R_L for dry and wet markings, luminance coefficient Qd, luminance 1 Y and colour coordinates, as well as contrast ratios 2 for retroreflectivity, luminance and luminance coefficient. The results showed that:

- On dry road surface and in daylight, the system was able to detect all white road markings (26 in total) in the study, irrespective of luminance coefficient and contrast ratio for the luminance coefficient. (The luminance coefficient Qd used was 57–227 mcd/m²/lx and the contrast ratio for Qd was 1.1–4.6 for the markings studied.)
- For wet road markings in daylight, no relation between road marking function and ADAS detection could be established, due to sunlight reflected in the road surface.
- For dry conditions at night-time, the road markings were detected if the retroreflectivity was at least 34 mcd/m²/lx, and the contrast ratio for R_L was at least 2.5.
- For wet conditions at night-time, the wet road marking retroreflectivity needed to be at least $4 \text{ mcd/m}^2/\text{lx}$ and the contrast ratio for R_L at least 2.1 for the detection to work.
- It was indicated that higher retroreflectivity and contrast ratios could be needed for the road
 marking to be detectable with glare from oncoming vehicles at night-time compared to without
 glare.
- Solid road markings were detected to a somewhat higher extent than broken markings, especially in daylight.
- Vehicle speed decreased the performance of the system in daylight but not at night-time.
- There were indications of that road lighting could decrease performance (but the number of observations was few).

Pike et al. (2018) discuss that the camera system detects road markings more or less as the driver would, but closer to the vehicle, with a different observation angle and where the road surface is well lit by the vehicle headlights. Hence, it was concluded that the system cannot fully take advantage of road markings with high retroreflectivity.

Austroads, which is an organisation for Australasian road transport and traffic agencies, examined thoroughly how properties of longitudinal road markings affect automated steering functions (Marr et al., 2020). The study included a literature review, discussions with road authorities, manufacturers and supply organisations, field tests and analyses of cost efficiency. In the field test, seven different vehicles and camera-based LKA systems were used. One vehicle was equipped with the Mobileye postmounted system, and the other six brands were unknown. The results of the field study showed that:

- The contrast ratio in daylight (Qd) between road marking and road surface should be at least 3:1 for good ADAS detection of the road marking under various conditions.
- At night-time, the ADAS worked well for contrast ratios (R_L) between road marking and road surface of between 5:1 and 10:1. Lower contrast ratios were not investigated in the study, and hence no minimum value could be stated.
- A bright road surface can decrease the possibilities for camera-based ADAS to detect road markings, because of reduced contrast ratio.

¹ Luminance Y is a measure of daylight visibility, which is not included among the European functional measures defined by EN 1436.

² contrast ratio = measured value of road marking / measured value of adjacent road surface

- Longitudinal road markings should be at least 10 cm wide, which implies that for new markings a requirement of at least 15 cm could be considered, to allow for wear.
- Broken road markings are more likely than solid road markings to be difficult for machine-vision lane detection.

Also in this study, it was concluded that the prevailing standards for road markings (in Australia) are sufficient for machine vision to detect the road markings. Other observations were that (Marr et al., 2020):

- lane detection tended to be less effective in daylight than at night-time, due to larger visual complexity in daylight,
- different systems (brands) functioned differently, which can make it hard to evaluate the effect of possible changes in the infrastructure,
- the speed of the vehicle affected the performance of the investigated systems, so that some of them performed better and some worse with increased speed,
- wet roads could both increase and decrease detection depending on the ambient light, where a high level of ambient light makes the road surface produce specular reflections that will decrease the detection.

In summary, it was concluded by Sjögren et al. (2022) that road markings that fulfil the present performance requirements are expected to be machine readable and that the most relevant performance parameter probably is the contrast ratio, whereas road marking width had less importance. Factors decreasing machine-readability include glare from low sun and oncoming vehicles, small curve radii, dirt, ice, snow, fog, shadows, sudden changes in light conditions, and poor road surface condition. For CAVs road markings are useful but not critical since the systems require redundancy and hence, road markings are not the only source of information. It was also mentioned that there is a lack of studies involving the automotive industry, which means that there might be a knowledge gap concerning systems and data used.

4.2.2 Primary ADAS technologies

Three primary technologies are used to support ADAS in performing LKA and LDW: Camera technology, which is the most used technology at scale, and LiDAR technology and mapping technology, which are being explored in addition to cameras in more advanced ADAS.

4.2.2.1 Camera technology

This section is written based on the following sources: (Ding, Zhang, Xiao, Shu, & Lu, 2020; GeeksforGeeks, 2020; Gurucharan, 2020; Saxena, 2016; Simonyan & Zisserman, 2014; Wu, 2017).

A common approach for detecting road markings is to use cameras for data collection together with artificial intelligence, i.e., deep learning models, applied for image processing. Examples are object recognition, feature detection, and image classification. The most used deep learning model for image processing is convolutional neural networks (CNN), and more recently also fully convolutional neural networks (FCNN). These models can be trained to detect significant features in images without human supervision.

In general, CNN consists of a series of processes carried through convolutional, pooling and fully connected layers. The basic architecture of CNN is depicted in Figure 3.

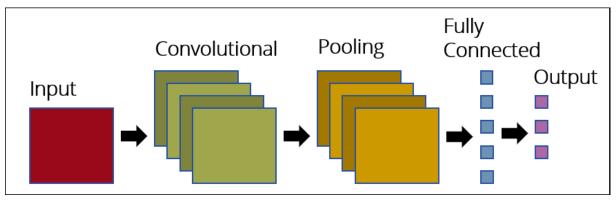


Figure 3. Typical CNN architecture. Adapted from Abyaneh, Foumani, and Pourahmadi (2018).

The <u>input</u> normally consists of a height and width corresponding to the image size. Additionally, colour depth as an input is typically given through the RGB (red-green-blue) colour model, which provides a depth of three. In the case of detection of road markings, a data input could be a slice of an image, as displayed in Figure 4.

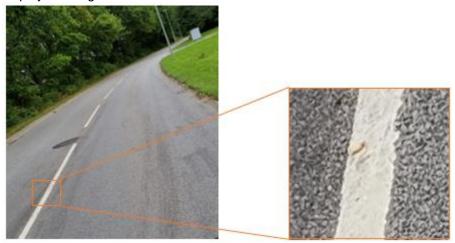


Figure 4. Photo used for CNN of road in Denmark.

In each <u>convolutional</u> layer, the image is evaluated based on a filter that defines a search for a specific feature. This process is described as a merging of two sets of information. Utilizing camera technology and image recognition, these two sets of information are the image and a filter, where the filter is swept through the image to identify the specific feature. The results are merged through multiplication and sum and gathered in the feature map.

In relation to detection of road markings, a filter can e.g. define a search for edges or shapes. This is shown as a simplified example in Figure 5, where the filter represents a search for a vertical line with bright colours (the transition in colour is understood as an edge). In the example, a low number represents little difference in colour, while a larger number shows that a high difference in colour was detected. The filter in the example of Figure 5 multiplies each entry with its corresponding entry in the image. The result of the sum of multiplication is transferred to the feature map.

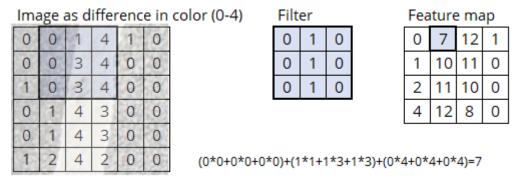


Figure 5. Simplified example of feature map from filter and image.

As the amount of data can be substantial, a <u>pooling</u> action is performed in conjunction with a convolutional layer to reduce the amount of data. In Figure 6, "max pooling" is performed on an area of 2x2. In the max pooling layer, the maximum value is saved, as shown in Figure 6. Through this action four entries are reduced to one. After pooling actions are performed, the results are restructured in a <u>fully connected</u> layer, which is used to determine if the feature searched for was detected or not.

The output of the model is a score that provides the possibility of each feature being detected. Referring to the example of detection of road markings, the fully connected layer of Figure 6 shows that the lane marking was detected, meaning the output was a positive recognition.

Fea	ature	e ma	ар	Max pooling	Fully connected	Output
0	7	12	1	10 12	12	1 Lane
1	10	11	0	12 10	12	
2	11	10	0		10	
4	12	8	0		10	

Figure 6. Simplified example of pooling and fully connected layers.

The flow of data evaluation can be changed according to complexity of the input. It can be changed by adding additional convolutional, pooling, fully connected or other layers. A commonly used model is Vgg16, which consist of 13 convolutional layers, 5 pooling layers and 5 fully connected layers.

The camera technology has low cost and does not require high computation power. However, training of the model used for detection does require a significant amount of computational power. Especially for this reason, cameras are often used at scale as the data collection technology in ADAS. Camera technology can recognize other relevant features in addition to road markings, e.g. road signs, road edges, pedestrians, vehicles etc.

4.2.2.2 LiDAR technology

This section is written based on the following sources: (Ghallabi, Nashashibi, El-Haj-Shhade, & Mittet, 2018; Jung & Bae, 2018; Mazzari, 2019; Pei, 2021).

LiDAR is a sensing technology that measures the distance to an object by use of eye-safe laser light beams. The light beam pulses are emitted from the LiDAR and based on the time it takes the light to travel from the source to the object and back, the distance is calculated. Besides measuring the distance to the object, the LiDAR can also detect how much light is reflected.

LiDAR vision systems can generally be divided into three categories: 1D, 2D and 3D. All three are displayed in Figure 7 in context of a vehicle, which is displayed from a top view.

- 1D LiDAR can be used to determine the distance to a specific point.
- 2D LiDAR collects data between two points. The angle between these two measured points
 creates a two-dimensional plane, which constitutes the registered area. The angle and the
 area can be minimised or enlarged depending on the information required for the observation.
 The maximum angle is 360 degrees, which is represented as one circle in the 3D example of
 Figure 7.
- 3D LiDAR functions similarly to 2D, but instead of collecting data only between two points, the data collection can be performed in a 360° angle creating one plane, while simultaneously registering data in a 360° angle of additional planes, forming a 3-dimensional range area. Therefore, 3D LiDAR typically has several laser light pulses emitted at different angles to significantly expand the range area, as displayed in Figure 7. Similarly to 2D, the 3D LiDAR can be limited to a specific relevant field of view, if for instance only specific areas around the vehicle are considered relevant for a specific ADAS function.

A simplified example of data collection using LiDAR is displayed in Figure 7.

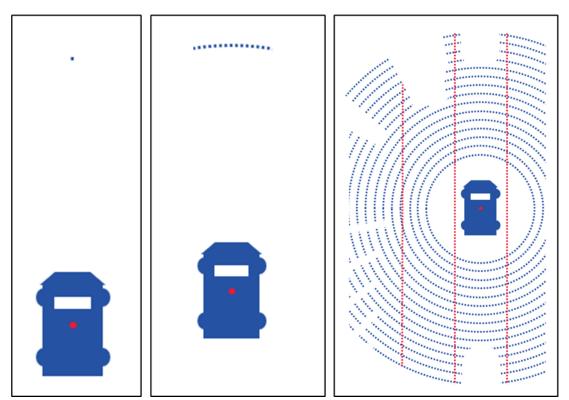


Figure 7. LiDAR as 1D, 2D and 3D.

An example of use of LiDAR technology related to ADAS is continuous detection of the distance to the vehicle in front of you. In this case, a limited angle and range area is required. The definition of range area has great importance since it determines the amount of data that is collected and processed. Related to detection of road markings, LiDAR technology can be used to detect how much light is reflected from a surface. The data collected via LiDAR can be evaluated using machine learning.

LiDAR has limitations in heavy rain, snow, fog, or other weather conditions that affect the light spectrum. Besides the limitation related to detection, LiDAR collects large amounts of data, which requires high processing power to analyse.

4.2.2.3 Mapping technology

Mapping or high-definition (HD) mapping is a technology that accumulates anonymous data from other technologies such as LiDAR, radar, cameras, other sensors, satellite imagery and GPS (Haydin, 2020; Mobileye, 2021). Data is continuously collected by sensors integrated in cars and stored in a database. As such, mapping technology is not a data collection tool, it relies on other data sources.

As an example of mapping applied in ADAS, the data input for the database could include 360°-registrations of the surroundings along a specific road section. Data could include registrations of road markings, traffic signalling, curves, road signs, etc. Accumulated, such data is used to generate a 3D-map of all objects relevant for support of LKA and LDW. The database can be utilized in real-time by connected vehicles. Also, these individual vehicles can continuously contribute to the database since they can contribute with real-time collected data and alignment of this data with data sets stored in the database. The result is a 3D-map that is updated with essential information needed for support of AD. This alignment of data provides the foundation for high precision positioning of the vehicle in the respective 3D-map.

Updating and processing of such mass of data requires high processing power and high bandwidth if the information is to be shared between vehicles via a cloud service. Especially for this reason, the technology is applied at high cost and is currently not yet deployed at scale.

4.2.2.4 Pros and cons of the highlighted ADAS technologies

Table 3 gives an overview of the pros and cons of the highlighted ADAS technologies.

Table 3. Pros and cons of the highlighted ADAS technologies.

	Camera	Lidar	Mapping
Technology	Data collection	Data collection	Data accumulation
Pros	The collected data can	High precision in deter-	Can be used for constant
	be used to detect objects	mining distance to ob-	verification of the position
	and textures via image	jects.	of the vehicle.
	recognition.		
		Performs measurements	A plausible technology
	Low cost both in acquisi-	at high frequency.	when visibility of road
	tion and data processing.		markings is limited.
Cons	Limitations in visibility is	Large mass of data is re-	Requires continuous up-
	the main challenge, e.g.,	source demanding in	dating and validation of
	due to certain weather	data processing.	data.
	conditions (rain, snow,		
	glare, etc.) or other con-	Is sensitive to weather	Requires a large amount
	ditions that obscure visi-	conditions that affect re-	of data and extensive
	bility (wear, leaves, etc.)	flection of light.	data processing for opti-
			mal gain.
	Has same limitations as	Expensive technology.	
	human vision.		Expensive technology.

4.3 Supplementary literature search

To supplement the literature study draft of April 2021, published in (Sjögren et al., 2022), a literature search was conducted in the Summon database for the period of 2020-12-01 to 2021-05-28. It was noted that many publications propose new algorithms or approaches, but they are not used on the market and evaluated. Hence studies on existing systems used in traffic are often lacking, with a few exceptions. (See more about contrast and contrast ratio in Section 4.1.1.)

4.3.1 Empirical and laboratory studies

A field study using one vehicle equipped with LDW (Toyota Auris) and one vehicle with a Lane Keeping System, LKS (Volkswagen e-Golf), driven on two 600 km routes at repeated sessions was conducted in the Netherlands to investigate the effect of driving environment on performance (Reddy et al., 2020). Different times of day and different weather (clear, cloudy, and rainy) conditions were tested. Because of minimum speed limits for activation of the respective systems, only speeds above 60 km/h were evaluated. Worst detection performance for both systems was found for night-time driving with road lighting during rain. For daytime conditions, the detection performance patterns were more similar for both systems (over 90% detection of both markings), even during rain. The highest detection performance was found for night-time driving in clear weather, which was explained by the higher contrast between the lane marking and the road surface at night. The results also showed that the LKS followed other lines than road markings, such as pavement repair patchwork and the high contrast between road surface and the shoulder of the road. In addition, the LKS was sensitive to lane width, where more narrow lanes (250 cm or less) led to LKS steering the vehicle more to the left of the lane, and to curves, where the vehicle was more to the left side of the lane in left curves. Reddy et al. (2020) propose that it would be interesting to collect lane marking quality and lane marking configuration data.

An LDW system was tested in an empirical study in Norway, under various lighting conditions and on different kinds of roads (Storsæter et al., 2021). The aim of the study was to determine to what extent a mobile retroreflectometer (Laserlux G7 from RoadVista) could predict the LDW detection of lane markings. The study was conducted on dry roads, for daytime (cloudy weather) and night-time. The results showed that the best prediction of road marking detection occurred for night-time conditions. Ambient light, which was either high (around 10.000 lx) or very low (0-11 lx), and retroreflectivity did not influence prediction success to any larger extent. For ambient light, this may be due to the limited range of values used and that the vehicle headlights provided sufficient lighting for detection. The contrast ratio between road marking and road surface was found more important than road marking retroreflectivity. Contrast ratio threshold values could be suggested for night-time driving only, where it was found to be 2.7 for freeway and 8 for county roads. In addition, vehicle speed had a large effect on predicting the detection, which was ascribed to more data collected per time unit in comparison to the machine vision. Edge smoothness of the road markings was also suggested to be of importance for machine vision algorithms, although it was not studied in the test.

An LDW system (MobilEye 630) was tested with artificial rainfall during daytime on a test track in Korea, where the view range, i.e. the distance from the current position of the vehicle to the most distant lane recognized by the LDW, was measured (Roh, Kim, & Im, 2020). The results showed that without rain the view range was 80 m regardless of vehicle speed, whereas rain up to 20 mm/h and vehicle speeds of 30–60 km/h led to median view ranges of 40 m and more. At 30 mm/h and 30 km/h the view range was 30–40 m but at vehicle speeds of 48 or 60 km/h the view range dropped to 0.

EuroRAP initiated a project called SLAIN that included investigating how the infrastructure should be adapted to automated vehicles (Konstantinopolou, Jamieson, & Cartolano, 2020). They assessed CAV readability of longitudinal road markings on roads of the core trans-European transport network (TEN-T) in Spain, Italy, Greece, and Croatia which means the most important connections linking the most important nodes (https://ec.europa.eu/transport/themes/infrastructure/ten-t_en). MoMa (Mobile Mapping, TomTom) data was used for analysing the road markings and consists of mobile LiDAR and a 360° imagery capture system. The results showed that for line detection using 360° imagery and machine vision techniques, road markings across most of the core TEN-T network were CAV readable. However, due to low lighting levels, the image-based system used could not detect lines in tunnels. With a mobile LiDAR, road markings, also in tunnels, could be detected, given that the difference in the "intensity of return" between road marking and road surface is sufficient. The difference was sufficient if the intensity of return value was at least 20 for the road marking and did not exceed 10 for the road surface, irrespective of line width. The authors concluded that the line width was less important

than the road marking condition, and that the proximity of the road marking to items such as concrete shoulders and concrete safety barriers decreased the ability for CAV systems to identify the road markings, as they have similar properties from a machine-vision perspective.

Laboratory trials on eight types of road markings, unexposed to traffic, were conducted in a climatic wind tunnel in Austria, where a total of four rain intensities, four wind speeds and four levels of fog were used in a stationary setting with cameras as well as LiDAR for road marking detection (Burghardt et al., 2021). The road markings consisted of two structured markings, two tapes and four paints. These were evaluated for machine vision response in terms of contrast ratio and LiDAR intensity. Daylight and night-time conditions and glare from an oncoming vehicle were simulated. The results showed that for the cameras used, contrast ratio (CR)³ above 2.0 was sufficient for recognizing road markings. In dry conditions, all road markings had a sufficient CR but simulated glare caused a reduction in contrast ratio by 30–34%. On average for all road markings, introduction of rain caused CR to drop by 80% and the LiDAR response intensity by 84%, but the minimum rain intensity used was quite high, 15 dm³/h (corresponding to 15 mm/h). Wind caused a marginal improvement of contrast ratio.

4.3.2 Other studies (reviews and crash data)

In a thorough review by Chen et al. (2020), LDW systems are evaluated with respect to construction and functionality. LDWs basically consist of vehicle and road state perception, a lane departure decision-making algorithm, and warning signal sending. A forward-looking system, which has a video capture device in front of the vehicle and is aiming at the lane ahead, can be used even on roads without good road markings since it has more road information to use. However, it can be challenged by other information in the front image of the road, such as pedestrians or other vehicles, which can make it hard to determine the transverse position of the own vehicle. One of the conclusions by the authors was that for vision-based systems there is a problem with varying weather conditions and the influence of light changes. Adapting LDW system algorithms to adapt to different weather conditions and influence of light changes and shadows is seen as a development trend. Another problem is that of other vehicles (especially white ones) interfering with the identification of road markings. The authors suggest, among other things, that further research should focus on use of multiple sensors to obtain more road information and classifying adverse weather and road situations using a special method or algorithm.

The results from an analysis of crash data in Finland implied that around one fourth of fatal head-on and single-vehicle crashes could potentially have been prevented with LKA (Utriainen, Pöllänen, & Liimatainen, 2020). It was also stated that related to the visibility of lane markings, road maintenance and snow clearance could improve the safety potential of LKA. Another proposed option was to use digital lane markings in the future.

An analysis of Swedish fatal passenger car crash data from 2010 found that LDW systems could potentially prevent around one third of the fatal head-on and single vehicle crashes (Sternlund, 2017). For the data used, the typical lane departure crash without prior loss of control occurred on undivided roads in rural areas with posted speed limits of at least 70 km/h, with visible centre and edge road markings.

That lane detection is critical for automated vehicles and that most lanes are defined by lane markings that can be detected by visual sensors was stated in a literature review focusing on winter conditions by Ødegård and Klein-Paste (2021). They acknowledged that the sensors must be able to detect worn and unclean lane markings, as well as to handle night-time conditions and adverse weather. While cameras perform poorly in bad weather and are sensitive to light, a combination of cameras, LiDAR, and prior path information may limit the impact of adverse weather conditions. The authors discuss

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³ The definition of contrast ratio used here was CR= (Luminance of road marking – Luminance of background)/(Luminance of background)

that snow, slush, ice, lack of daylight, poor illumination and polar nights affect sensors and cameras in a negative way. Fog and heavy rain make LiDAR have difficulties recognizing lane markings and Li-DAR also fails when snow disturbs the sensors. It was noted that for camera-based systems, the lane marking detection rate at night-time was similar to that of daytime. For the systems to work, the winter maintenance level required is extremely high. Where GNSS service is unavailable, automated vehicles need bare roads to detect lane markings etc., and the winter maintenance needs to be even higher for a fully autonomous transportation system. A solution suggested is to introduce a specific winter maintenance class for certain main routes, where automated vehicles are common. For this specific maintenance class, visible lane markings should be restored immediately after a weather event and the road surfaces should be swept along with mechanical snow removal.

4.4 Discussion of results from literature

Many parameters are reported to affect the performance of LDW and LKA, including road environment (curvy roads, shoulders close to road markings), road maintenance (sunken shoulders, missing road markings), weather and light conditions, and vehicle speed.

Concerning road markings, the contrast ratio between road marking and road surface is the most crucial parameter for LDW and LKA systems. The contrast ratio is influenced by many parameters and the combination thereof, such as weather (rain and snow), glare (low sun or headlights from oncoming vehicles), visibility (retroreflectivity at night-time and luminance coefficient at daytime) of road marking and of road surface, and ambient light (road lighting, tunnels). In Table 4, an attempt to summarise the findings of minimum requirements is made. For dry roads, contrast ratio values of 3 for daylight conditions and around 3 at night-time have been reported. Only a few studies measured road marking and road surface functionality in wet conditions, resulting in threshold road marking retroreflectivity of 4 vs. 20 mcd/m²/lx, and a contrast ratio of 2.1.

Other issues found in the literature was that broken road markings can be harder to detect than solid lines and that road lighting can decrease performance. Additionally, night-time detection of road markings can be better than in daylight.

Overall, the main conclusion is that if the road markings are visible for a human driver, then the systems are also able to detect them.

Table 4. Minimum requirements found from literature review.

Reference	Aim of study	LDW/LKA sys-	Qd_dry	Qd_wet	Contrast_dry	Contrast_wet	RL_dry	RL_wet	Contrast_dry	Contrast_wet
		tem used	[mcd/m ² /lx]	[mcd/m ² /lx]	(Qd)	(Qd)	[mcd/m ² /lx]	[mcd/m ² /lx]	(RL)	(RL)
(Lundkvist &	investigate interaction be-	Volvo LDW	≥65	≥65	≥0.08⁴	≥0.08⁵	≥70	≥20	≥3.7 ⁶	≥3.0 ⁷
Fors, 2010)	tween Volvo LDW and									
	road markings, at different		Qd(road	Qd(road						
	light and weather condi-		marking)≥	marking)≥						
	tions in the field		Qd(road sur-	Qd(road sur-						
			face)+5	face)+5						
(Pike et al.,	explore effect of road	Mobileye 5 se-		no relation	1.1 or less		≥34	≥4	≥2.5 (for	≥2.1 (for RL≥4
2018)	marking quality on detect-	ries		could be es-	(no lower				RL≥34	mcd/m ² /lx)
	ability by machine vision			tablished	contrast				mcd/m ² /lx)	
	systems				tested)					
(Marr et al.,	explore how road mark-	7 LKA sys-			≥3	≥3	100 or less		5 or less (no	
2020)	ings affect automated	tems with					(not statisti-		lower con-	
	steering functions, e.g., by	model year					cally signifi-		trast tested)	
	testing 7 LKA systems in	2018, includ-					cant for less			
	daylight/ nighttime/tunnel,	ing Mobileye					than 100)			
	for broken/solid lines, for	aftermarket								
	asphalt/concrete road sur-	equipment								
	face									
(Reddy et	estimate impact of driving	Volkswagen e-								
al., 2020)	environment on LDW och	Golf with LKS								
•	LKS, by driving in e.g., dif-	+ Toyota Auris								
	ferent weather and lighting	with LDW								
	conditions									

⁴ Estimated contrast using Eq. (3) and Qd(road surface) = 60 mcd/m²/lx.

⁵ Estimated contrast using Eq. (3) and Qd(road surface) = 60 mcd/m²/lx.

⁶ Estimated contrast using Eq. (2) and RL(road surface) = 15 mcd/m²/lx.

 $^{^{7}}$ Estimated contrast using Eq. (2) and RL(road surface) = 5 mcd/m²/lx.

Reference	Aim of study	LDW/LKA sys- tem used	Qd_dry [mcd/m²/lx]	Qd_wet [mcd/m²/lx]	Contrast_dry (Qd)	Contrast_wet (Qd)	RL_dry [mcd/m²/lx]	RL_wet [mcd/m²/lx]	Contrast_dry (RL)	Contrast_wet (RL)
(Storsæter et al., 2021) ⁸	investigate whether a mo- bile retroreflectometer can predict the performance of	car with built- in LDW (un- known)								
	LDW, using on-road dry day/night conditions									
(Roh et al., 2020)	measure effect of rainfall intensity on LDW on test track	Mobileye 630								
(Konstantino polou et al., 2020)	road assessment, quality of road markings etc. on real road	Mobile Map- ping, TomTom			2 ⁹					
(Burghardt et al., 2021)	test different road marking materials in laboratory study with rain, fog and glare	2 common Li- DARs+3 cam- eras							2 ¹⁰	

^{8 2.74 (}freeway), 8 (county road) is reported for dry night-time contrast ratio but since the equipment used did not report R, comparison is not possible.

⁹ Intensity of return values in tunnels

¹⁰ The definition of contrast ratio used here was CR= (Luminance of road marking – Luminance of background)/(Luminance of background).



4.5 Interview survey

4.5.1 Research approach

A series of semi-structured interviews have been conducted to acquire new knowledge of the construction and function of ADAS technologies.

Two rounds of interviews were conducted. The first round focused on general aspects with the aim of understanding the types of ADAS technologies that are used in the industry, including the limitations of each identified technology and the potential for future development. The second round had its focus on the technical aspects of the applied technologies, to understand into detail the construction and function of ADAS. Six interviews were conducted in total. Interviews were requested approaching five additional respondents, but the enquiry was unsuccessful.

As part of the first round, representatives from respectively a car manufacturer that applies ADAS technology, an operator of autonomous vehicles and a supplier of ADAS technology were interviewed. Respondents of round one:

- Volvo a car manufacturer using ADAS
- Holo operator of autonomous vehicles
- Arriver a supplier of ADAS

As part of the second round, representatives from respectively a supplier of ADAS, an experienced, private autonomous car user and a knowledge institution were interviewed.

Respondents of round two:

- Mobileye a supplier of ADAS
- Tesla car user
- FORCE Technology a technological consulting and service company

4.5.2 Collected interview data

Each of the following sections provides information collected from the interviews. The interviews give insight into perspectives for each company alone, therefore some views are only valid for the single company and not the entire industry.

4.5.2.1 Volvo

Volvo is a multinational vehicle manufacturer headquartered in Sweden. Volvo provides vehicles to the global market and has integrated ADAS in all newer cars. Volvo uses subcontractors for ADAS hardware and software. The company constantly works to develop new technology to support drivers in making the right decision when operating behind the wheel. Volvo aims to be progressive in pushing the transition to AD globally, e.g. through investments in development of autonomous trucks and taxis, and through collaborations with innovative start-ups within the field.

Use of technology

Detection of road markings is a primary parameter used by Volvo's ADAS. Volvo uses camera technology for detection of road markings, and has several cameras positioned around the car. The positioning of the cameras enables 360° registration of the surroundings, but only one camera, placed by the windshield, is used for detection of road markings.

Volvo does not have a hardcoded minimum requirement for measures of contrast, contrast ratio, luminance coefficient or retroreflectivity, instead image recognition is used for the detection of road



markings. LiDAR is also used in Volvo's ADAS. However, currently LiDAR technology is not used for detection of road markings, but the potential is being investigated.

Potential future development

Volvo is constantly contributing to develop the ADAS to overcome current challenges with the applied technologies. Currently, Volvo is e.g. working to improve the system regarding detection of road edges.

Challenges with detection of road markings are generally due to limited visibility during certain seasons. During fall and winter, certain weather conditions, such as snow or fallen leaves, obstruct the visibility of the road markings. Salting and wear on road markings, e.g. due to use of studded tyres, similarly have a negative influence on the ability of the ADAS to detect the road markings. These are significant issues since detection in those cases might not be possible or the confidence level is reduced. Therefore, Volvo emphasizes higher service levels as one initiative supporting road markings to become a more reliable data input for ADAS.

Volvo also points at the possibility of a shared global database as a potential future development, since an open database would decrease the load of data processing currently being handled by the operators individually.

4.5.2.2 Holo

Holo is a Copenhagen-based company that operates pilot projects with autonomous vehicles. The company mainly operates minibuses for passenger transportation deployed in the Nordic countries. Common for all projects is autonomous driving on a predefined route. Holo is not an ADAS technology developer, instead they use subcontractors for hardware and software for customized ADAS for the individual pilot projects.

Use of technology

Holo uses LiDAR technology to collect primary input for navigation of the vehicles. Data for navigation is also collected via GNSS, odometer, accelerometer, and gyroscope. These technologies are in conjunction used to ensure correct positioning of the vehicle in relation to the predefined route.

LiDAR sensors are placed at different heights and angles on the vehicles, to enable data collection in all relevant directions. The LiDAR technology is considered the best suited technology for range assessment in ADAS. Holo does currently not use LiDAR to detect road markings.

Camera technology is not yet utilized by Holo's vendors as part of their ADAS. There are plans to incorporate camera input in future versions of the autonomous software, cameras for collecting this data are already installed on the vehicles. Even though detection of road markings is not used as a primary parameter, it is part of the overall validation of the navigation. As an example, contrast values are not evaluated based on hardcoded criteria, but high value in contrast provides a higher confidence level for the evaluation. For lane markings to be detectable, they most likely have to be visible at a distance of more than around 5 m in front of the vehicle. Therefore, a limitation is found in urban areas and other areas where road curves with small radius are frequent. Cameras also register surrounding objects relevant for navigation.

A combination of the data collection technologies (LiDAR, cameras, GNSS, odometer etc.) applied by Holo should enable navigation according to the route in all conditions all year round.



Potential for future development

The technology used to register road markings is not sufficiently developed to be used as a primary input parameter in Holo's pilot projects. This is especially due to the potential risk of road markings being undetectable e.g., as a result of certain weather conditions, wear or sediments on the markings. Development within detection of road markings has reached a point of slow progress. A breakthrough is needed for the technology to be applicable at scale. Such development requires a lot of resources, therefore a breakthrough depends on larger car manufacturers or technology developers to apply pressure on the industry.

Simple camera sensors for detection of road markings are a good and cost-effective option for ADAS, but more complex ADAS use more precise technologies, such as LiDAR, because the camera and deep learning technologies are immature. Therefore, road markings have a high potential to be a widely used parameter, especially for minor companies looking for cost-effective and easily deployable solutions.

Holo points at road markings potentially becoming a more reliable input parameter if the quality and visibility of the road markings is constantly maintained, ensuring high contrast between road surface and road marking at all road sections.

4.5.2.3 Arriver

Arriver is a software company and brand, which was founded in 2021 to deliver scalable ADAS with advanced functions and features to support the development of AD systems.

The solutions provided by Arriver are currently fully functional on highways and on rural roads, whereas urban and city-driving is at a level where human control is required. Arriver believes that over the next decade, AD technologies will assist and not replace the driver.

Use of technology

Arriver uses camera technology for detection of road markings. A forward-mounted camera, installed at the wind shield, is used for collection of data input. The camera also detects other objects that influence the driving of the vehicles, such as pedestrians, road signs, road edges, etc. Cameras are used as they are cost-effective in comparison to other alternative technologies. Additionally, they can collect supplementary information to support other functions in the ADAS system, such as reducing speed because of recognized objects or vehicles on the road. If the system is to be used for AD, the requirements for the setup are higher than if the system is only focused on LDW and LKA. Any number of cameras and other types of sensors can be integrated into the system, but a single camera is most common for Arriver's solution.

Potential for future development

Arriver has found that a series of conditions challenges detection of road markings. They have e.g. found that glare and wet conditions are some of the conditions affecting the visibility of the road markings. Both parameters have influence on values of e.g. retroreflectivity and contrast ratio, therefore they can also be expected to influence the recognition of road markings. However, exact limits for these properties are not used as data input. Data collected via LiDAR is used for comparison with the camera detections. Some drawbacks with LIDAR are that it is expensive and that camera technology is still needed for other vision functions.



Arriver points at different colours and types of road markings as challenging for the system. This is especially important moving towards AD, as distinctions between regular lane markings, bike lanes or bus lanes are not always intuitive, and choice of colours varies between countries. Arriver has also found that Botts' dots, which are raised pavement markings, are harder for the ADAS to detect.

Arriver is continuously developing the image recognition technology and related deep learning models to improve detection in challenging conditions. In general, the acceptance criteria applied are the same as for the human eye, i.e., if the road markings are visible for the human driver, then the systems are also able to detect the road markings.

According to Arriver, there are cases where ADAS systems perform better in detection than human drivers. Mainly because the systems can focus on the entire camera field of view at once, they do not get distracted, and they can make decisions much faster. The systems also perform better in estimating the exact distance to objects in the surroundings.

4.5.2.4 Mobileye

Mobileye is a globally represented supplier of software that enables ADAS. The company, which is based in Jerusalem, offers both software and hardware, and it has more than 25 partners among car manufacturers. Intel Corporation acquired Mobileye in 2017, and jointly Intel and Mobileye aim to develop safe and scalable AV solutions to make autonomous driving a reality.

Mobileye uses cameras and deep learning for image recognition as the core of their ADAS. They consider this technology most versatile given the relatively low cost and the ability to identify both objects, e.g., vehicles or shapes, and textures, e.g., text on traffic signs and lane markings. The data input is evaluated via CNN, which identifies assets such as lane markings, road arrows, road edges, traffic lights and more. Besides the camera technology, LiDAR and mapping technologies are also utilized.

The newest version of Mobileye's software, EyeQ6, operates with a setup of 11 cameras. The solution consists of 4 short range cameras for parking and 7 long range, front-facing cameras for remaining ADAS functions. The collected data from the cameras is stored in a database, i.e., Mobileye's Road Experience Management system (REM). Data in the REM is continuously updated through ongoing data collection from individual vehicles, and it is applied by the individual vehicle for instant adjustments to the trajectory of the route and positioning of the vehicle. Mobileye is currently (2021) running tests using LiDAR in a subsystem supporting detection of road markings. Data collection from the LiDAR is also stored in REM.

Mobileye uses mapping technology as a third element of the ADAS, in addition to camera and LiDAR technology. Mapping is a technology that crowd-sources and accumulates data from the ADAS technologies. Hence, REM is the core of how Mobileye develops and applies the mapping technology. Using REM, data collected from individual vehicles is aligned, and the accumulated data continuously updates information of the registered road infrastructure, which is considered essential to ensure vehicle safety. As an example, in cases where the road marking is non-detectable, e.g., because of snow, worn markings or other circumstances, previous recordings from REM is used to predict the trajectory based on information from vehicles that travelled that same route.

There is a correlation found in high visibility of the road marking, i.e., clean markings with visible contrast ratio between the road marking and the road surface, and the ability of the ADAS technologies to



detect it. However, the evaluation done by Mobileye is based on image recognition, not hardcoded criteria using exact values of performance properties.

Generally, if the road marking is visible and detectable for the human eye, it is also detectable with Mobileye's ADAS technology. The current system in development, EyeQ6, which is not yet installed in cars commercially, is fully ready to uphold autonomous driving in all weather conditions. Mobileye does not consider speed a limitation.

4.5.2.5 Tesla car user

Jens is a passionate, private motorist who has owned and driven Tesla for more than five years. Jens has been a user of several Tesla cars that have operated with different versions of ADAS. Between each new version, Jens has experienced an increase in reliability of the autonomous driving functions and an increase in comfort of the driving experience.

The current ADAS version (FSD AP3.0) fully relies on cameras for detection of elements in the surrounding area. On the in-car screen, the driver can follow which elements in the surroundings that the car uses for navigation and lane keeping. It is Jens' impression that the road markings are used for LKA at most times in the autonomous driving state. In situations where it is not possible to detect the road marking, then the system changes to e.g. road edges or other reliable elements in the surroundings. If no input is considered reliable for the ADAS, then the warning sets in and the car requests for driver assistance.

Jens has e.g. experienced issues when performing a left turn in an intersection where, if several different lane markings are present, it can be a challenge for the ADAS to detect the correct lane. Another issue with detection of road markings occasionally occurs when the ADAS detects crack sealings, i.e., repair work on longitudinal cracks, as a lane marking surface. It seems to be the case that the cameras detect contrast ratio, i.e., difference in colour, between road markings and the road surface, but it does not register which of the two is lighter in colour tone. Since crack sealings are not straight or necessarily follow the trajectory of the road, the ADAS will quickly detect irregularity and request for driver assistance.

Jens has also been a user of a previous version (AP1.0) where radar was incorporated in the vehicles. That version would follow the car in front as part of the LKA function. That is no longer the case with the newest version, which seems to rely more on detection of road markings for keeping the trajectory of the road in autonomous driving state. Jens is of the impression that the cameras' reliability in terms of detecting road markings generally exceeds the human eye. This is especially the case during non-optimal conditions e.g., during heavy rain or night-time.

4.5.2.6 FORCE Technology

FORCE Technology is a technological consulting and service company. FORCE Technology is known for the development in retroreflectometers, which are sold and used by road authorities worldwide.

The retroreflectometers measure the retroreflectivity of a material or an object. Retroreflectometers are used to determine the condition of the road markings. Awareness of the condition supports road managers and owners in decision-making related to maintenance planning.



The European standard EN 1436:2018 is developed to ensure a required level of quality of road markings. The standard outlines the levels of performance that are approved for contract specifications, it also describes methods for measuring the performance characteristics.

In Denmark, the warranty period for road markings is 4 years. Since the operation and maintenance contracts for road marking are typically not renewed every 4 years, condition monitoring is essential to ensure high-quality road markings at all times. High-quality road markings are considered essential for road safety.

Wear on road markings is one aspect affecting the performance measure. FORCE Technology underlines that development in road marking materials to improve resistance to wear, is a current focus area of the industry. Investment in high-performance materials is another way to ensure good quality in road markings long term.

Studies on requirements of minimum performance properties for detection of road markings vary significantly. The experts at FORCE Technology emphasize that a contrast ratio of 3 cannot always be obtained and is not always the necessary level for humans to detect road markings. FORCE Technology is a partner of a project run by BASt (Bundesanstalt für Strassenwesen), which aims to examine into detail which parameters that affect the detection of road markings using camera technology, and if minimum requirements for performance properties can be determined.

4.5.3 Discussion of results from interview survey

Cameras for data collection and machine learning for image recognition are technologies typically used in ADAS at scale for detection of road markings. Other technologies, such as LiDAR, GNSS, gyroscope and mapping, are also utilized to support the ADAS in the detection process. If applied, LiDAR is used to support other ADAS functions, and by some ADAS developers the technology is used on test basis to investigate how it can support detection of road markings.

The interview survey has shown that recognition of road markings does not rely on exact measures of performance properties, i.e., contrast ratio, contrast, retroreflectivity or luminance coefficient. However, these parameters affect the data input that is used to determine the confidence level. A high contrast ratio influences the detection of road markings of the ADAS since difference in colour affect the image recognition.

The main challenge for the ADAS to detect road markings is when visibility is obscured. This is typically due to certain weather conditions (rain, snow, glare, etc.) or other conditions limiting the visibility (wear, leaves, ambient light etc.). It is a common understanding that if the human eye can detect the road marking, then the ADAS can as well. Machine learning for detection of road markings can in some cases perform better than humans, especially since the system enables focus on the entire range area without distractions, and it can make decisions faster than a human.

Improvement in service level, performed by road authorities to keep the condition of the road markings at a high standard, is essential. Condition monitoring of road markings is an important input for maintenance planning.

Technology for improvement in detection of road markings is constantly developed, e.g. to ensure a high confidence level when the different circumstances challenge the visibility. A common practice is to rely on more than one data collection technology. High-definition mapping is a newer technology



currently used in complex ADAS. Use of advanced technology comes at a high cost, which is limiting for the application at scale.

4.6 Overall discussion and conclusions from literature study

Both similarities and differences have been identified in the current literature study. Knowledge gained through the reported research and interview survey show the following similarities:

Road markings is a key input parameter in ADAS for support of LKA and LDW. Camera technology is used at scale in commercial solutions, while technologies such as LiDAR and HD mapping are used mainly on test basis. Often, a combination of data collection technologies is applied, and always in combination with machine learning for data processing.

Visibility is key for detection of road markings. It is generally accepted that if the road markings are detectable for humans, then they can also be detected by ADAS. It is the perception that in some cases, machine learning performs better than humans at detecting road markings. However, more research is needed, e.g., to develop new knowledge on improvement of detection in challenging weather conditions.

The literature search and the interview survey deviate on one key item; where the literature emphasizes contrast ratio as a crucial parameter, the interviews indicate that it is of less significance because detection via machine learning is not based on the exact value of this property. Contrast ratio is none-theless essential since difference in colour between the road surface and the road marking affect the image recognition process.

For the field study in the AVRM project, it is considered important to investigate adverse weather conditions. While some studies have been carried out during night-time, showing no problem in detection compared to daytime, only a few studies have been reported to examine functionality parameters for road marking and road surface in wet conditions. Although other adverse conditions such as snow or fog could be of interest to examine, it is not reasonable to do so, due to time and budget limitations. Therefore, the recommendation from the literature study is to focus on wet conditions in the field study.



5 Empirical studies

5.1 Pilot study

From the results of the literature study, the pilot study was determined to focus on the contrast ratio between road marking and road surface, including both daylight and night-time, dry and wet conditions. The pilot study aimed to test equipment for LDW/LKA, to find a method to connect LDW/LKA data with contrast ratio and to reveal possible problems before a main study was conducted.

5.1.1 Method

A total of 30 road objects in Skåne, Sweden, were measured by Ramboll using the mobile equipment *Ramboll Road Marking Tester* (RMT) in connection to regular measurements. For each road object, the edge line in both directions was measured, and sometimes also additional road markings, such as the centre line. Mobile RMT measurements of RL and Qd of the road markings were carried out on dry roads at daytime. Simultaneously, Mobileye equipment (Mobileye 630) for lane departure warning (LDW) was activated and data from the Mobileye system collected. In addition to the daytime dry condition, Mobileye data was also collected for each road object in at least one of the following conditions:

- daytime, wet (after a rainfall)
- daytime, rain (present rainfall)
- night-time, dry
- · night-time, wet
- night-time, rain.

Table 5. Total number of Mobileye measurements per condition. Note that each object was measured in the dry day-

light condition and in at least one additional condition.

Condition	daylight	night-time
dry	30	4
wet/rain	24	9

5.1.1.1 Handling data

All data was collected by Ramboll. RMT data and Mobileye data had different sampling rates and Mobileye data could not be directly viewed on-site. Instead, when all mobile measurements were carried out, measurement data was transferred from Ramboll to VTI through a file server. Data included pictures every 10 m from a camera integrated with the RMT equipment and used for all conditions.

There were uncertainties about the Mobileye parameters, and in particular which parameter should be used to determine whether Mobileye has detected a road marking or not. Ramboll contacted Mobileye and got some clarifications. The parameter "LANE_TYPE_RIGHT" which refers to the line type (not lane type) at the road marking to the right of the vehicle, was used as the available measure for detection in the pilot study, where 0 indicated lack of road marking. However, not all other values of the parameter, which range from 0 to 7, indicated presence of road marking, as for example the value 3 indicated road edge. This parameter was however the only one that could be used for detection of road markings irrespective of vehicle speed¹¹. Henceforth, the parameter "LANE_TYPE_RIGHT" will be abbreviated to LT.

¹¹ This was altered for the main study but in the pilot study this was the best option.



From the mobile measurements carried out, VTI created a Matlab code to visualise the data for edge lines, see example in Figure 8. In the figure, the scale on the y-axis refers to the blue line of dry retroreflectivity only. The black and red lines correspond to the LT signal but multiplied by 10 to make them easier to see in the graph (they range from 0 to 7 in their original form). A constant value of 80 has been added to the red line to separate it from the black line. The asterisks at the bottom of the black and red lines indicate LT=0, i.e., when the system could not detect the road marking in the day-light dry condition (black) and night-time wet condition (red), respectively. The red asterisks on the right-hand side of the figure shows the positions on a map in which LT=0 for the night-time wet condition.

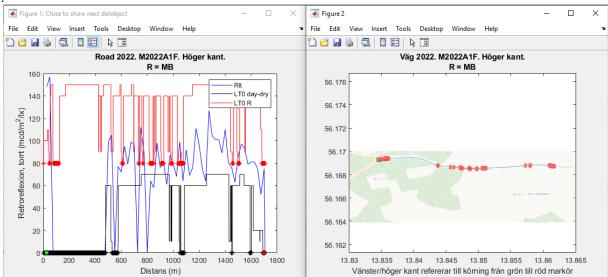


Figure 8. Example of visualisation of data, object M2022A1F, right edge.

From these visualisations of data, objects were selected by VTI for handheld measurements, where LT was 0 for some road stretch, i.e., where Mobileye did not detect any road marking in at least one condition. A corresponding road stretch of the same object where LT was higher than 0 for that condition was also selected for handheld measurements.

5.1.1.2 Handheld measurements

For handheld measurements, only non-major roads were selected, due to difficulties connected to performing these kinds of measurements on major roads. In addition, measurements were only carried out for right-hand side edge lines (and the road surface next to it).

Handheld measurements were carried out by Ramboll on a total of 11 objects. For each object, two positions of the road were measured – one where no road marking could be detected (LT=0) and one where road marking detection was not 0 (LT \neq 0).

For each position, three measurement points on three adjacent road markings were selected and additionally three on the corresponding road surface next to each road marking (see illustration in Figure 9). At each measurement point, Qd and RL were measured in the dry and wet condition, according to the standard procedure for handheld measurement of road markings, TDOK 2013:0462. By this procedure, $3(measurement\ points) \times 2(road\ marking/road\ surface) \times 2(dry/wet) \times 2(RL/Qd) = 24\ handheld\ measurements\ were\ made\ at\ each\ position.$



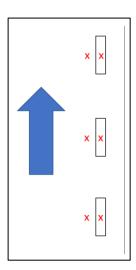


Figure 9. Illustration of measurement points (marked with a red "x") at a measurement position.

5.1.2 Results

5.1.2.1 Mobile measurements

Mobile measurements were performed in the daytime dry condition on all roads, and an overview of when the Mobileye system could not detect the different road marking objects in this condition is given in Table 6. (The percentage of 4% was arbitrarily selected but intended to visualise in the table what a quite strict limit for non-detection would imply.)

Table 6. LT0 per type of road marking object in the daytime dry condition.

Type of road marking object	Average per- centage LT0	Number of road marking objects with LT0>4%	Total number of road marking objects	Share of road marking objects with LT0>4%
Edge markings	11.97	32	59	54%
Lane markings	0.72	0	6	0%
Centre markings	7.01	6	14	43%
Left markings on roads with multiple lanes (at road centre)	1.36	0	6	0%

Most data were collected on edge markings, which sum up to around 70% of the total number of road marking objects measured. Figure 10 shows the distribution of LT0 for the edge markings to the right of the vehicle. Note that a bar of 100% would refer to a case where no right edge marking could be found over the whole road object. In addition, each bar represents one road marking object, i.e., a specific edge marking (right or left) on a specific road object.



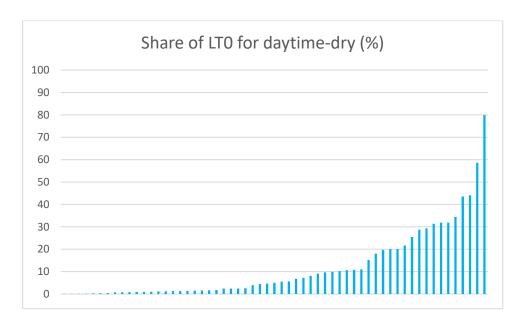


Figure 10. Edge markings measured with Mobileye 630 in the daytime dry condition. Share of LT0, sorted in ascending order. Each bar represents one road marking object.

The two edge markings where the share of LT0 was over 50% (the two bars farthest to the right in Figure 10) are edge lines in two directions of the same road. Looking at the data and comparing photos for edge markings, the non-detection at this road (see Figure 11) can be attributed to lack of road marking, road markings placed directly at the road edge and wear connected to that, and presence of intersections.



Figure 11. Examples of instances of the road where detection of edge markings was lowest. Missing road markings and road markings placed directly at the road edge.

Overall, the most common reason for LT0 in the daylight dry condition is presence of intersections, junctions, and roundabouts. Lack of road markings is another obvious and common reason for non-detection. In curves where the road markings are worn, leading to low RL or completely missing road markings, non-detection is also common. For around 8 of the 32 edge lines with LT0>4%, RL values were below the requirement of 150 mcd/m²/lx. Other plausible reasons for non-detection were use of edge markings directly at the road edge, overlapping markings where an old edge line has not been



removed before application, bright or red road surfaces, shadows, sun reflections, barriers close to the right edge road markings, dirt or leaves on the road marking.

Figure 12, Figure 13, and Figure 14 show the distribution of LT0 for the markings measured with RMT in the daytime dry condition for, respectively, centre markings, lane markings, and left markings on roads with multiple lanes. From the figures, non-detection of road markings seems to be a bigger problem for centre markings, which is probably due to wear. However, the number of lane markings and left markings on roads with multiple lanes measured here was low.

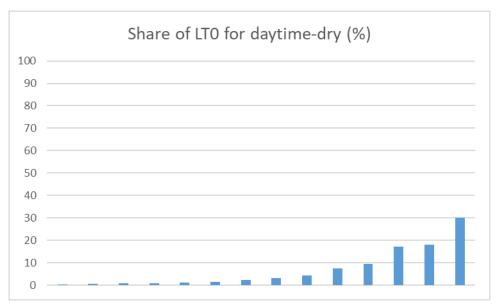


Figure 12. Centre markings measured with Mobileye 630 in the daytime dry condition. Share of LT0, sorted in ascending order. Each bar represents one road marking object.

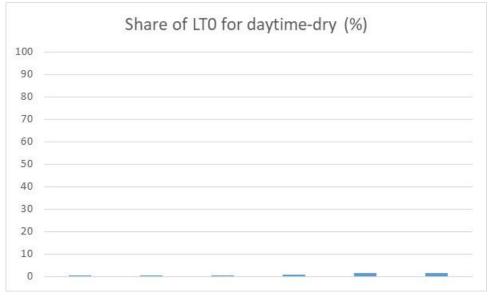


Figure 13. Lane markings measured with Mobileye 630 in the daytime dry condition. Share of LT0, sorted in ascending order. Each bar represents one road marking object.



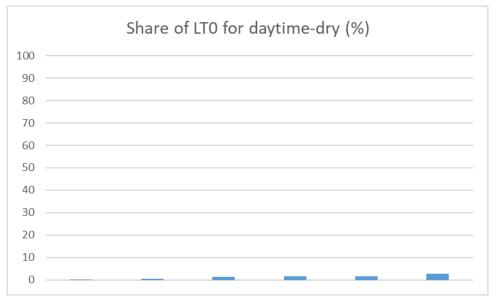


Figure 14. Left marking on road with multiple lanes (marking at road centre) measured with Mobileye 630 in the daytime dry condition. Share of LT0, sorted in ascending order. Each bar represents one road marking object.

5.1.2.2 Handheld measurements

Note that all handheld objects refer to edge lines on the right-hand side of the road. All contrast ratios, CR, have been calculated as:

$$CR(x) = \frac{x(road\ marking)}{x(road\ surface)}$$

where x is the variable that the contrast ratio is calculated for. This is in line with equations (5) and (6) in 4.1.1.

Table 7 shows an overview of all objects that have been measured by handheld instruments, and the digits refer to the corresponding contrast ratios according to the formula above.

The table should be understood as follows:

- object refers to the specific road marking object that was measured
- conditions with ME system refers to the conditions under which Mobileye was active, and should be interpreted as: DD=daytime dry; DW=daytime wet; DR=daytime rain; NW=nighttime wet; NR=night-time rain
- pos1 and pos2 refer to the positions along the road chosen for handheld measurement, where LT=0 (no road marking detection by Mobileye) for one of the positions and LT≠0 for the other
- CR(RLt) refer to the handheld measure of contrast ratio for night-time dry conditions
- CR(Qdt) refer to the handheld measure of contrast ratio for daylight dry conditions
- CR(RLv) refer to the handheld measure of contrast ratio for night-time wet conditions
- CR(Qdv) refer to the handheld measure of contrast ratio for daylight wet conditions
- **red** cell means LT=0, i.e., that the road marking at that specific position was not detected by Mobileye in that condition
- **green** cell means LT≠0 for that specific position and condition
- white cell means that no Mobileye measurement was carried out in that condition.



Table 7. Overview of contrast ratios from handheld measurements.

object	conditions with ME	pos1	pos2	CR(RLt)	CR(RLt)	CR(Qdt)	CR(Qdt)	CR(RLv)	CR(RLv)	CR(Qdv)	CR(Qdv)
	system	[m]	[m]	pos1	pos2	pos1	pos2	pos1	pos2	pos1	pos2
M2022A1F	DD/NW	240	1440	1.47	-	1.23	-	0.50	-	1.76	-
M2022A3B	DD/NW	1540	1570	1.37	4.22	1.05	1.16	-	-	0.67	0.93
M1328A1F	DD/DW	430	760	6.46	13.75	2.16	3.65	3.00	9.33	1.73	2.28
M1252A3B	DD/DW/NW	1540	1590	1.23	6.78	0.95	2.00	1.03	2.08	0.86	0.86
M1750A1F	DD/DW	2260	2520	13.63	5.96	2.75	2.30	4.83	2.57	2.21	1.59
M1252A1F	DD/NW	2610	3150	-	5.54	-	1.90	-	1.60	-	1.82
M1321A3B	DD/DR	3000	3900	6.90	5.01	2.45	1.68	3.19	1.25	2.58	0.81
M1212A3B	DD/DW/NW	3540	3600	20.54	17.02	2.91	3.03	6.98	8.50	3.08	2.56
M1329A1F	DD/DR	1200	1980	2.48	4.41	1.37	1.80	2.11	4.44	1.74	2.91
M1923A3B	DD/DW/NR	860	1100	5.12	8.63	2.22	2.77	11.33	-	2.65	4.00
M1922B3B	DD/DR/NR	1800	1870	1.89	6.46	0.92	2.22	-	5.17	1.42	2.30



5.1.2.3 Different positions

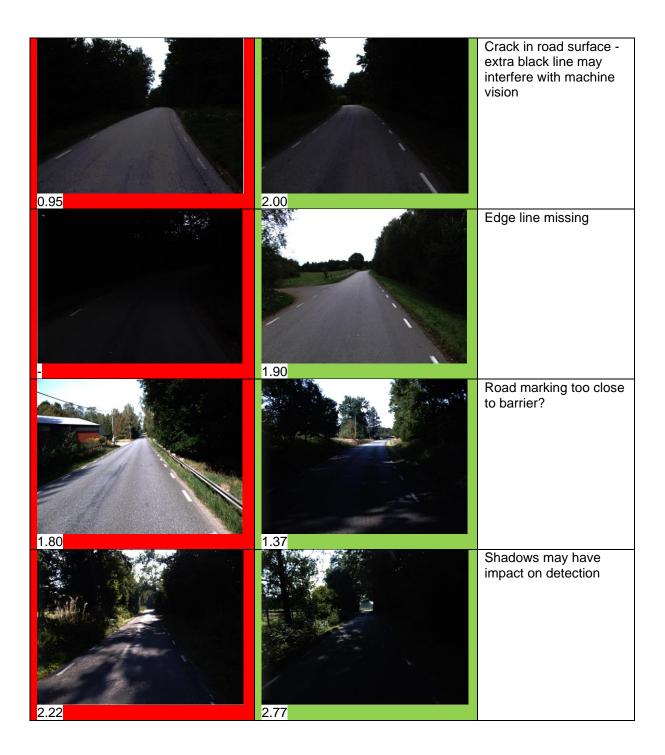
In the following, an instance at a position of the road where LT=0 is compared with another position on the same road where LT≠0. A photo of the road is shown together with the contrast ratio at the respective position. A possible explanation of the difference in detection of the right edge line between the two positions is also given in the table. Each road and road marking object is represented by one row per table and have their equivalent in Table 7.

5.1.2.3.1 Daylight dry (Qdt)

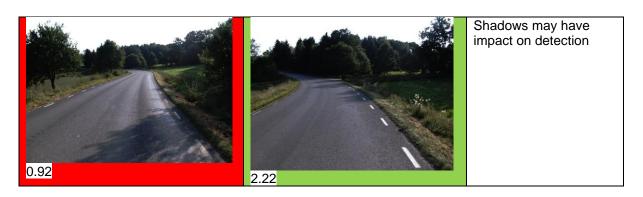
Table 8 shows daylight dry conditions.











5.1.2.3.2 Daylight wet (Qdv)

Table 9 shows daylight wet conditions, i.e., when the road is wet after a rainfall.





5.1.2.3.3 Daylight rain (Qdv)

Table 10 shows daylight rain conditions, i.e., during a rainfall.

Table 10. Photos and contrast ratios for daylight rain conditions.

LT=0

LT≠0

Comment, possible explanation

Glare due to reflections in road surface

0.81

2.58

Road marking too close to barrier?

1.74

Glare due to reflections in road surface

Glare due to reflections in road surface



5.1.2.3.4 Night-time dry (RLt)

Night-time dry Mobileye measurements were only carried out on major roads, and hence no handheld data could be achieved. In Table 11, occurrences of when LT=0 for these roads are shown together with possible explanations.



5.1.2.3.5 Night-time wet (RLv)

Table 12 shows night-time wet conditions, i.e., when the road is wet after a rainfall. Since the photos were all black, no photos are shown.

Table 12. Contrast ratios for night-time wet conditions.

LT=0	LT≠0	Comment, possible explanation
		Worn road markings when LT=0 (RLv(LT=0):
1.03	2.08	2, 3, 5 and RLv(LT≠0): 3, 10, 12)
		Edge line missing at LT=0
-	1.60	

41



5.1.2.3.6 Night-time rain (RLv)

Table 13 shows night-time rain conditions, i.e., during a rainfall. Since the photos were all black, no photos are shown.

Table 13. Contrast ratios for night-time rain conditions.

able 10: Contract ratios for hight time rain conditions.						
LT=0	LT≠0	Comment, possible explanation				
11.33	i .	No obvious explanation, compare with road 7 of Table 8 (CR(Qdt) 2.22 and 2.77)				
		For LT≠0: no contrast ratio could be calculated due to low road surface values (RLv 0-1)				
1	5.17	For LT=0: no contrast ratio could be calculated due to very low RLv values (1-2 for road marking; 0-1 for road surface)				

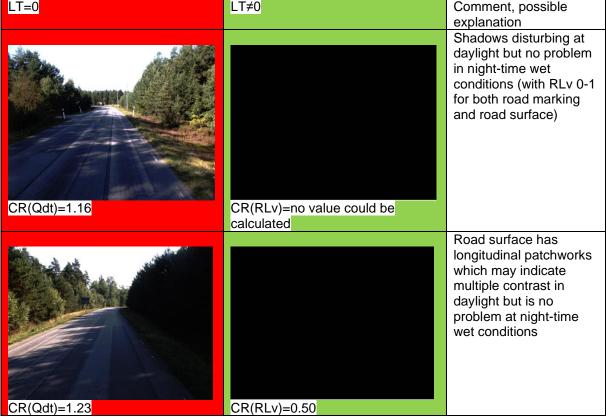
5.1.2.4 Comparisons

In the following, occurrences where daylight (Qd) detection was problematic but where the night-time (RL) wet condition was not, are compared.

5.1.2.4.1 Daylight dry vs night-time wet (Qdt vs RLv)

In Table 14 below, instances of the same position where no detection is indicated at the daylight dry condition but where detection (LT) is not zero for the night-time wet condition are shown, together with the corresponding contrast ratios.

Table 14. Photos and contrast ratios comparing daylight dry with night-time wet conditions.





5.1.2.4.2 Daylight wet vs night-time wet (Qdv vs RLv)

In Table 15 below, an instance of the same position in wet conditions is shown, where no detection is indicated in daylight but where detection (LT) is not zero at night-time. The corresponding contrast ratios are given in the table.

Table 15. Photos and contrast ratios comparing daylight wet with night-time wet conditions. LT=0 LT≠0 Comment, possible explanation Glare due to sun reflections in road surface at daylight CR(Qdv)=3.08

5.1.2.5 Summary of results

For the positions analysed by contrast ratio in the pilot study, factors connected to road markings, such as missing road markings, wear, and too low contrast, could explain some of the instances where Mobileye could not detect the road marking. However, most problems for the system to detect road markings could be attributed to factors unrelated to road marking performance, such as presence of shadows, competing longitudinal structures (e.g., cracks, barriers, ruts, multiple lines, patchworks), and reflections in the road surface.

CR(RLv)=6.98

From the mobile measurements in daylight dry conditions, it seems that the largest problems with nondetection are present at intersections, junctions, and roundabouts, i.e., at special road sections. In addition, curves where road markings are missing or worn is another problem. It is important to note that when road markings are not present for one reason or another, the system should not detect them, and hence the average percentage of LT0 in Table 6 is somewhat misleading in terms of 'hit rate'.

5.1.3 **Experiences from pilot study**

- With the setup used in the pilot study, Mobileye data could not be studied directly on-site.
- Mobileye data (version Mobileye 630) was not easy to interpret in terms of whether the system had detected road markings or not. This was however corrected for the main study.
- The confidence level of the Mobileye data could not be assessed. This was however corrected for the main study.
- RMT photos at night-time, at least in the wet condition, were too dark to distinguish any objects.
- The method for handheld measurements worked for assessing contrast ratios.
- For non-major roads, Mobileye night-time measurements in dry weather were not made, and hence no handheld measurements either.



Note: After the pilot study was reported, it was discovered that the data stream package was wrong for the LT parameter (and for the parameter lane confidence) and a new data software was installed and used. Since the analysis in the pilot study only used LT=0, an initial analysis of lane confidence and LT=0 in this study was performed and it was clear that these parameters agree to a large extent, which was interpreted as that the analysis of the pilot study was still ok.

5.2 Machine-readability of dry road markings in daylight

5.2.1 Introduction and aim

The aim of this part of the AVRM project was to investigate the machine readability of road markings in daylight on dry roads, in Norway and Sweden. Four research questions were formulated:

- What percentage of the road markings is machine-readable, per road type?
- What are the lengths of road marking segments that are not machine-readable?
- Is there a difference in machine-readability between solid and broken lines?
- Is there a relationship between machine-readability and conventional performance parameters?

The data used for this study had been collected in the NordFoU project called *State assessment of road markings in the Nordic countries* (ROMA), which was carried out in 2017–2021 (NordFoU, 2022a). In this project, annual assessments of road marking retroreflectivity and some other parameters were done on a sample of randomly selected roads, using vehicle-mounted measurement equipment. One of the vehicles was also equipped with a MobilEye system, which continuously registered the detectability of the road markings.

5.2.1.1 Road markings in Norway and Sweden

The road marking types, including dimensions and colour, typically used in Norway and Sweden are shown in Table 16 and Table 17. Regarding centre lines, variants including warning lines and double lines may be used instead of the ordinary line types shown in the tables. In Sweden, edge lines on two-lane roads are most often broken, but solid edge lines may also be used. Further information about line types and dimension can be found in (Vegdirektoratet & Statens vegvesen, 2015) and (Trafikverket, 2022).

In Norway, lines separating traffic moving in opposite directions are yellow while all other road markings are white. In Sweden, all road markings are white.

Table 16. Road marking types in Norway.

Road marking	Туре	Mark + gap (m)	Width (m)	Colour
Motorway, right edge line	solid	-	0.3	white
Motorway, left edge line	solid	-	0.3	yellow
Motorway, lane line	broken	3+9	0.15	white
Two-lane road, edge line	solid	-	0.10, 0.15	white
Two-lane road, centre line	broken	3+9	0.10, 0.15	yellow



Table 17. Road marking types in Sweden.

Road marking	Туре	Mark + gap (m)	Width (m)	Colour
Motorway, right edge line	solid	-	0.3	white
Motorway, left edge line	solid	-	0.3	white
Motorway, lane line	broken	3+9	0.15	white
2+1 road*, right edge line	solid	-	0.2	white
2+1 road*, left edge line	solid	-	0.3	white
2+1 road*, lane line	broken	3+9	0.15	white
Two-lane road, edge line	broken	1+2	0.10, 0.15	white
Two-lane road, centre line	broken	3+9	0.10, 0.15	white

^{*) &}quot;2+1 road" is a common road type in Sweden. It has three lanes, with two lanes in one direction and one lane in the other direction, alternating every few kilometers. Opposite lanes are usually separated by a steel cable barrier.

In 2021, 61.5% of the road marking length in Sweden fulfilled the requirement on retroreflectivity of 150 mcd/m²/lx. The corresponding results for Norway were 64.9% for white markings where the requirement is 150 mcd/m²/lx and 75.2% for yellow markings where the requirement is 100 mcd/m²/lx (NordFoU, 2022b). The wear of road markings in Norway and Sweden is relatively high, due to winter maintenance and use of studded tyres. Most road markings consist of thermoplastics.

5.2.2 Method

5.2.2.1 Data collection

As mentioned above, the data collection was carried out within the ROMA project, which was finished before the present study was initiated. Road objects in six different categories, ranging from motorways with AADT > 50 000 to two-lane roads with AADT 250–2500, were randomly selected from all roads governed by the respective national road authority. Roads with road lighting or with newly installed asphalt were not included in the sample. Further information about the selection of objects can be found in the ROMA 2021 report (NordFoU, 2022b). A subset of the data collected in 2021 included machine-readability data (in addition to conventional performance parameter data). All available machine-readability data was used in the present study, and it included data from the southern part of Norway and from the middle part of Sweden, Figure 15.

In total, data from 242 road objects were used – 78 in Norway and 164 in Sweden. Each road object consisted of a road segment of approximately 10 km and included three road marking objects. For multilane roads, one right and one left edge line and one lane line were assessed. For two-lane roads, both edge lines and the centre line were assessed. The total number of road marking objects was 609 (193 in Norway and 416 in Sweden).

All data was collected in daylight on dry roads, in June-September.



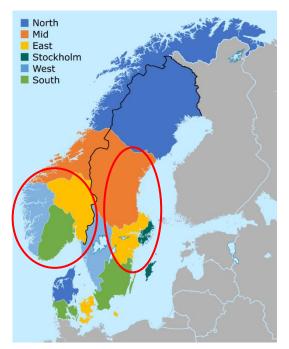


Figure 15. Data was collected in the southern part of Norway and in the middle part of Sweden (red rings).

Equipment

The data was collected by Ramboll's tailor-made vehicle for road marking assessment, *Ramboll Road Marking Tester* (RMT). Retroreflectivity and luminance coefficient *Qd* (and some other parameters that were not used in the analyses below) were sampled every 100 m. Retroreflectivity was measured by a conventional off-the-shelf device from Delta (Denmark), while the luminance coefficient was predicted from a laser instrument used for surface texture measurements (Lundkvist, Johansen, & Nielsen, 2008). A MobilEye system 630 collected machine-readability data from both the left and the right line every 0.1 m.

Data analysis

The machine-readability parameter analysed from the MobilEye system is called *lane confidence*, which ranges from 0 to 3. 0 and 1 mean *not detectable* and 2 and 3 mean *detectable*.

Machine-readability was defined as the percentage of (the total length of) the road marking objects that was machine-readable, i.e. where the lane confidence parameter was 2 or 3.

The analysis included right and left edge lines on multilane roads and edge lines and centre line on two-lane roads. Data from lane lines were not included in the analysis as it would be time-consuming and complicated to extract that data¹². The first and the last 100 m of data of all objects were discarded to avoid any effects of the system being started or shut down. No other data was excluded, i.e. the analysed road marking data includes sections with crossings, interchanges, roundabouts, bus stops etc that were present along the road.

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¹² In short, when the retroreflectivity of the lane line is measured, it is not known from the data whether the vehicle is driving to the right or to the left of the line. Thus, it is not known whether it is the right or the left line registered by MobilEye that corresponds to the lane line. It would be possible to get that information from pictures, but that is expected to be too time-consuming for this study as the dataset is very large.



The data analysis was carried out in Python, Matlab and Excel.

5.2.3 Results

5.2.3.1 Percentage of machine-readable road markings

Table 18 and Table 19 show the percentage of machine-readable road markings per road type (multilane road, two-lane road) and per road marking type (edge line, centre line), in Norway and in Sweden, respectively. The machine-readability was approximately 99% on multilane roads and 93% on two-lane roads, in both Norway and Sweden.

The total length of the road markings included in the study was 5 796 km (1 791 km in Norway and 4 005 km in Sweden). The total number of road marking objects was 609 (193 in Norway and 416 in Sweden).

Table 18. Percentage of machine-readable road markings in daylight on dry roads, in Norway.

Type of road and road marking	Number of road marking objects	Total length (km)	Machine- readable (%)
Multilane road Right edge line (white)	17	166	99.3 %
Multilane road Left edge line (yellow)	17	166	98.9 %
Two-lane road Edge line (white)	114	1052	93.6 %
Two-lane road Centre line (yellow)	45	407	92.4 %

Table 19. Percentage of machine-readable road markings in daylight on dry roads, in Sweden.

Type of road and road marking	Number of road marking objects	Total length (km)	Machine- readable (%)
Multilane road Right edge line (white)	54	530	99.3 %
Multilane road Left edge line (white)	55	539	99.2 %
Two-lane road Edge line (white)	212	2035	92.0 %
Two-lane road Centre line (white)	95	901	93.8 %

Table 20–Table 21 show the distribution of machine-readability, per road type and road marking type, in Norway and in Sweden. For multilane roads, around 90% of all road marking objects had a machine-readability of 98% or higher. For two-lane roads, the distributions are shifted towards lower values. In Norway, 76% of the edge lines and 78% of the centre lines on two-lane roads had a machine-readability of 90% or higher. The corresponding figures for Sweden are 79% and 85%, respectively. In



total, 10 out of the 466 road marking objects (2,1%) on two-lane roads in Norway and in Sweden had a machine-readability of less than 50%.

 $\textbf{Table 20. Distribution of machine-readability, i.e.\ number\ \textit{n}\ of\ road\ marking\ objects\ per\ machine-readability\ range,\ in }$

Norway.

norway.								
	Multilane	Multilane	Multilane	Multilane	Two-	Two-	Two-	Two-
	road	road	road	road	lane	lane	lane	lane
Machine-					road	road	road	road
readable	Right	Right	Left	Left				
(%)	edge	edge	edge	edge	Edge	Edge	Centre	Centre
(70)	line	line	line	line	line	line	line	line
		0/		0/		0/		0/
	n	%	n	%	n	%	n	%
98–100	16	94.1	15	88.2	44	38.6	22	48.9
95–98	1	5.9	1	5.9	26	22.8	7	15.6
90–95	0	0.0	1	5.9	17	14.9	6	13.3
80–90	0	0.0	0	0.0	22	19.3	6	13.3
50–80	0	0.0	0	0.0	5	4.4	2	4.4
<50	0	0.0	0	0.0	0	0.0	2	4.4
Total	17	100.0	17	100.0	114	100.0	45	100.0

Table 21. Distribution of machine-readability, i.e. number n of road marking objects per machine-readability range, in

Sweden.

Sweden.	Multilane	Multilane	Multilane	Multilane	Two-	Two-	Two-	Two-
	road	road	road	road	lane	lane	lane	lane
Machine-	5	51.1.			road	road	road	road
readable	Right	Right	Left	Left	- 1	- 1	0 - 11 -	0
(%)	edge	edge	edge	edge	Edge	Edge	Centre	Centre
	line	line	line	line	line	line	line	line
	n	%	n	%	n	%	n	%
98–100	48	88.9	51	92.7	97	45.8	64	67.4
95–98	5	9.3	3	5.5	43	20.3	12	12.6
90–95	1	1.9	0	0.0	27	12.7	5	5.3
80–90	0	0.0	1	1.8	21	9.9	7	7.4
50–80	0	0.0	0	0.0	20	9.4	3	3.2
<50	0	0.0	0	0.0	4	1.9	4	4.2
Total	54	100.0	54	100.0	212	100.0	95	100.0



5.2.3.2 Lengths of not machine-readable segments

Figure 16–Figure 17 show the lengths of not machine-readable segments as percentages of the total not machine-readable length, per road marking type and country.

For multilane roads, most not readable road marking segments are shorter than 200 m. The same is observed for edge lines on two-lane roads in Norway. For centre lines on two-lane roads in both Norway and Sweden, and for edge lines on two-lane roads in Sweden, the not readable segments tend to be longer than on multilane roads. Out of the total not readable road marking length of centre lines in Norway, about 50% consists of segments longer than 200 m. The corresponding figure for centre lines in Sweden is 68%.

The total percentages of not machine-readable road marking lengths are approximately the same in Norway and in Sweden (Table 18–Table 19), but the not readable segments are in general shorter in Norway than in Sweden (Figure 16–Figure 17). The number of not machine-readable segments is however higher in Norway than in Sweden: 3.6 per 10 km on multilane roads in Norway versus 2.4 in Sweden, and 20.0 per 10 km on two-lane roads in Norway versus 13.7 in Sweden.

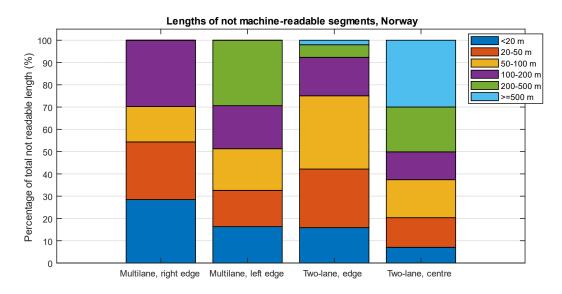


Figure 16. Lengths of not machine-readable segment as percentages of total length of not machine-readable road markings, Norway.



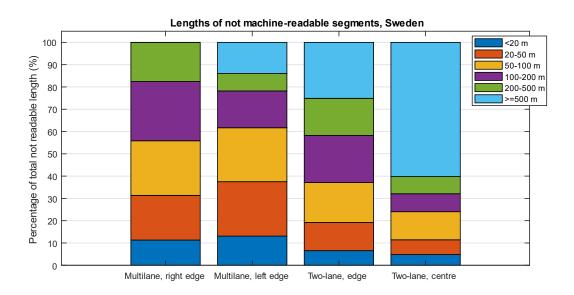


Figure 17. Lengths of not machine-readable segment as percentages of total length of not machine-readable road markings, Sweden.

5.2.3.3 Solid versus broken lines

The machine-readability of solid versus broken lines were assessed using data from edge lines (white) on two-lane roads in Norway and Sweden. Line widths of 0.1 m and 0.15 m were analysed separately. Table 22 shows the total road marking length, the average retroreflectivity and the machine-readability per type of road marking.

Table 22. Machine-readability of solid and broken edge lines on two-lane roads, in Norway and Sweden.

Type of road marking	Total length (km)	Retroreflectivity (mcd/m²/lx)	Machine- readable (%)
Solid line, 0.1 m	649	183	96.6
Solid line, 0.15 m	298	174	98.4
Broken line, 0.1 m	1109	175	86.6
Broken line, 0.15 m	1031	168	94.7

The machine-readability of broken lines is somewhat worse than that of solid lines, especially when the line width is 0.1 m. From this study, it cannot be concluded whether the worse machine-readability of 0.1 m broken lines is related to the line itself or to other factors. Broken lines with a width of 0.1 m are typically used on minor roads, which tend to be narrow, curvy, hilly and with vegetation close to the road (which may cause shadows).

The retroreflectivity values show that any differences in machine-readability between the categories most likely are not related to differences in road marking condition, at least not on the aggregate level, as the retroreflectivity is similar in the four categories.



5.2.3.4 Relationship between machine-readability and conventional performance parameters Figure 18–Figure 19 show the relationship between retroreflectivity and machine-readability on an aggregate level, per road type and country. Each datapoint in the charts corresponds to one road marking object (i.e. approximately 10 km, see also the section *Data collection* above). For Norway, white and yellow road markings are presented separately.

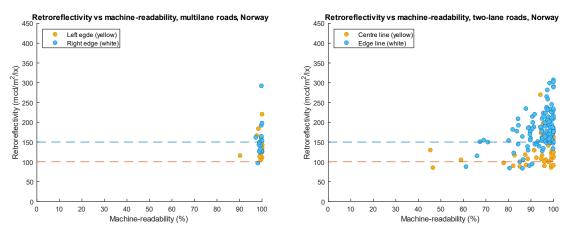


Figure 18. Retroreflectivity versus machine-readability in Norway. Left panel: left and right edge lines on multilane roads. Right panel: centre lines and edge lines on two-lane roads. The horizontal lines show the Norwegian performance requirements on retroreflectivity for white (blue line) and yellow (yellow line) markings (respectively).

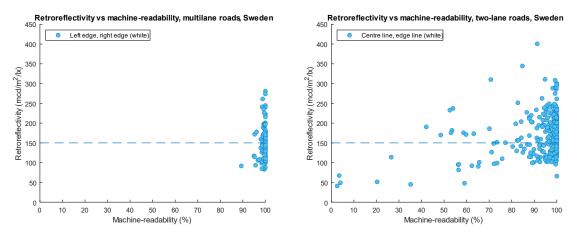


Figure 19. Retroreflectivity versus machine-readability in Sweden. Left panel: left and right edge lines on multilane roads. Right panel: centre lines and edge lines on two-lane roads. The horizontal blue lines show the Swedish performance requirements on retroreflectivity for white markings.

No clear relationships between retroreflectivity and machine-readability can be observed. For multilane roads, almost all road marking objects have a very high machine-readability (>95%) for the entire range of retroreflectivity values present in the dataset (83–281 mcd/m²/lx). For two-lane roads, there is a tendency that road markings with poor machine-readability (<75%) also have low retroreflectivity (<150 mcd/m²/lx), but about 2/5 of the road marking objects with machine-readability <75% have a retroreflectivity of >150 mcd/m²/lx. For white road markings on two-lane roads that have a retroreflectivity of <100 mcd/m²/lx, 17 out of 22 road marking objects have a machine-readability of <90%.



Figure 20–Figure 21 show the relationship between luminance coefficient *Qd* and machine-readability, per road type and country. Each datapoint in the charts corresponds to one road marking object. For Norway, white and yellow road markings are presented separately.

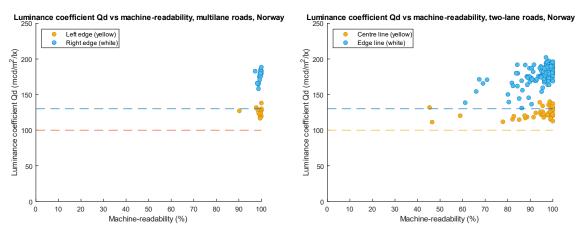


Figure 20. Luminance coefficient *Qd* versus machine-readability in Norway. Left panel: left and right edge lines on multilane roads. Right panel: centre lines and edge lines on two-lane roads. The horizontal lines show the Norwegian performance requirements on luminance coefficient for white (blue line) and yellow (yellow line) markings (respectively).

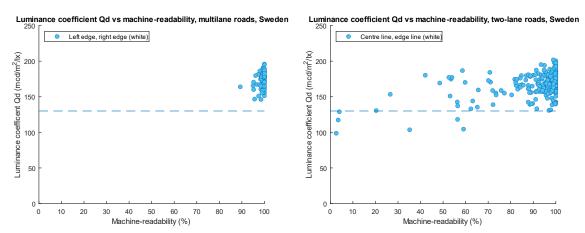


Figure 21. Luminance coefficient *Qd* versus machine-readability in Sweden. Left panel: left and right edge lines on multilane roads. Right panel: centre lines and edge lines on two-lane roads. The horizontal blue lines show the Swedish performance requirements on luminance coefficient for white markings.

The relationship between luminance coefficient *Qd* and machine-readability tend to be even weaker than that between retroreflectivity and machine-readability. For multilane roads, no relationship can be determined as almost all road marking objects have a very high machine-readability. For white road markings on two-lane roads, a luminance coefficient *Qd* of <130 mcd/m²/lx often means that the machine-readability is low (<75%). However, low machine-readability does not necessarily imply that the luminance coefficient is low.

It should be emphasized that the retroreflectivity and luminance coefficient values presented above refer to the average values of approximately 10 km of road marking. There might be large variations in the performance parameters within the objects, in particular with respect to retroreflectivity, that could



provide further insights in the relationships between machine-readability and the conventional performance parameters. Therefore, a more detailed analysis was carried out on retroreflectivity, where not machine-readable segments longer than 50 m were matched to machine-readable segments of the same length and in the same road marking object. Segments shorter than 50 m were excluded from this analysis as retroreflectivity is provided per 100 m. The retroreflectivity of the matched pairs were compared, Table 23.

Table 23. Retroreflectivity (mean ± standard deviation) of the matched pairs, per type of road marking.

	Number of	Not machine-readable	Machine-readable
Type of road marking	matched pairs	Retroreflectivity, m±sd (mcd/m²/lx)	Retroreflectivity, m±sd (mcd/m²/lx)
Multilane roads, white road markings	35	121 ± 48	117 ± 51
Multilane roads, yellow road markings	7	116 ± 34	128 ± 9
Two-lane roads, white road markings	755	141 ± 67	176 ± 70
Two-lane roads, yellow road markings	53	103 ± 47	122 ± 35

For white road markings on multilane roads, the mean retroreflectivity was actually somewhat higher for the not machine-readable segments than for the machine-readable segments. The opposite was found for yellow markings on multilane roads, but the number of matched pairs was few. Thus, no conclusions could be drawn regarding the possible relationship between retroreflectivity and machine-readability of road markings on multilane roads.

For two-lane roads, the average retroreflectivity of machine-readable segments was higher than that of not machine-readable segments, both for white and for yellow markings. However, when the data is shown in violin¹³ plots, it is obvious that there is a large overlap between the two groups, Figure 22– Figure 23. In other words, it is not possible to predict whether a road marking is machine-readable or not, from its retroreflectivity.

One could argue that the base of the violin of not machine-readable segments is much wider than that of machine-readable segments and that low retroreflectivity values thus are associated with poor machine-readability. However, it must be kept in mind that out of the total length of road markings investigated, the overall probability that a randomly selected segment is machine-readable is much larger than that it is not (see Table 18–Table 19). Thus, for the entire sample of road markings, the number of segments where retroreflectivity is very low, e.g. 50 mcd/m²/lx, and at the same time are machine-readable could actually be higher than the number of segments with low retroreflectivity that are not machine-readable. No analysis of probablitites have been carried out – the main point here is to illustrate the fact that it is not possible to identify a certain level of retroreflectivity that can distinguish between machine-readable and not machine-readable road markings.

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¹³ Violin plots are a way of visualizing distributions of data. They include markers for the median value and the interquartile range and usually also all datapoints. Figure 22–Figure 23 are created in Matlab, using code from: Bechtold, B. (2016). *Violin Plots for Matlab, Github Project.* https://github.com/bastibe/Violinplot-Matlab, DOI: 10.5281/zenodo.4559847



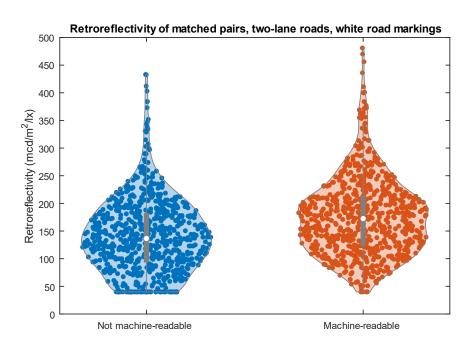


Figure 22. Violin plot of retroreflectivity of not machine-readable versus machine-readable segments. White road markings on two-lane roads, Norway (edge lines) and Sweden (edge lines and centre line). For further information about violin plots, see footnote 13.

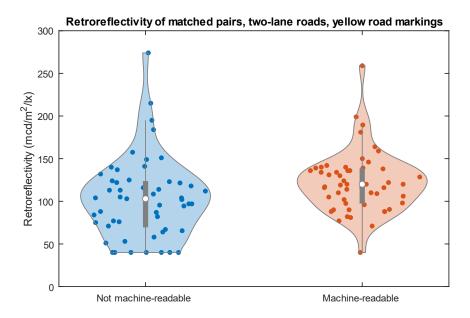


Figure 23. Violin plot of retroreflectivity of not machine-readable versus machine-readable segments. Yellow road markings on two-lane roads, Norway (centre line). For further information about violin plots, see footnote 13.

5.2.4 Discussion

The machine-readability in daylight on dry roads was investigated on approximately 5 800 km of road markings in Norway and Sweden. The main findings were:



- Approximately 99% of the edge lines on multilane roads were machine-readable.
- Approximately 93% of the edge lines and centre lines on two-lane roads were machine-readable.
- Overall, the machine-readability was approximately the same in Norway and in Sweden. The
 number of not readable segments was higher in Norway than in Sweden, but the not readable
 segments were shorter in Norway.
- The lengths of not machine-readable segments were in general shorter on multilane roads than on two-lane roads.
- The machine-readability of broken lines was somewhat worse than that of solid lines, especially when the line width is 0.1 m.
- The relationships between machine-readability and retroreflectivity, and between machine-readability and luminance coefficient *Qd*, were weak.

The results regarding machine-readability were in line with those found in other studies. In an Australian study on road markings on highways and two-lane roads, the machine-readability in daylight was 98.7–99.3% (Marr et al., 2020). In a study carried out on primary roads in southern Europe, the machine-readability in daylight was 95.8% (Konstantinopolou et al., 2020). The results imply that ADAS that read road markings in general work well on multilane roads and two-lane roads in daylight on dry roads.

On multilane roads, most not readable segments are shorter than 200 m. Many of these segments are probably found on entrances and exits, where the wear of the road markings is high. On two-lane roads, a substantial part of the not readable road markings consists of segments longer than 200 m, particularly on centre lines. With such long segments, LDW/LKA will be inactivated for relatively long times which impairs the safety effects.

The machine-readability of broken lines was somewhat worse than that of solid lines, especially when the line width was 0.1 m. It should however be noted that broken lines with a width of 0.1 m typically are used on the smallest roads, which tend to be narrow, curvy, hilly and with vegetation close to the road (which may cause shadows). It can thus not be concluded whether the worse machine-readability of 0.1 m broken lines are related to the line itself or to the road characteristics. In other studies, the machine-readability of solid lines tended to be somewhat better than that of broken lines, but the differences were small (Marr et al., 2020; Pike et al., 2018). The exact effects on machine-readability of replacing broken lines with solid lines is not known – this could probably only be determined from controlled before-after studies – but based on available knowledge the effects can be expected to be relatively small.

The relationships between machine-readability and the conventional performance parameters retrore-flectivity *RL* and luminance coefficient *Qd* were weak. For multilane roads, no relationships could be determined as almost all road marking objects had a very high machine-readability. For two-lane roads that had road markings with low retroreflectivity or luminance coefficient (average of 10 km), the machine-readability (percentage of readable road marking of 10 km) tended to be low. Low machine-readability was however not necessarily associated with low retroreflectivity or luminance coefficient. When comparing not readable segments with readable segments (of the same length and on the same road), it was found that the retroreflectivity on average was lower for the not readable segments, but that there was a large overlap in retroreflectivity between the groups. Thus, it can be concluded that retroreflectivity can not be used to predict whether a road marking is machine-readable or not, in daylight. This is not an unexpected result, for two reasons:



- 1) retroreflectivity is a measure of visibility at night-time, and
- 2) ADAS does not primarily read the markings from their retroreflectivity.

The finding that road marking objects with a low retroreflectivity (average of 10 km) tended to have low machine-readability is thus probably not related directly to the retroreflectivity but to the general condition of the road marking. If the average retroreflectivity of 10 km is <100 mcd/m²/lx, the road marking can be expected to be in a poor condition, probably with segments where the road marking is missing or very faded.



5.3 Main study

The main data collection within the project depended on the results from the literature study as well as from the pilot study. From the literature study, it was concluded that:

- If a road marking is detectable for humans, then it can also be detected by LDW or LKA systems.
- More knowledge on detection in challenging weather conditions is needed.
- A field study is recommended to focus on wet weather conditions, with the aim to relate LDW or LKA performance to road marking functionality.

From the pilot study, it was concluded that:

 Many parameters unrelated to road markings, such as glare, weather, shadows, reflections in the road surface, other longitudinal structures etc., affect LDW detectability.

The original aim of the main study, at the start of the project, was to find minimum requirements for road markings to be machine-readable. However, the literature study implied that current requirements on road markings are good enough, and the pilot study resulted in that minimum requirements are impossible to find, because they depend on so many other parameters. This was also supported by findings in the study on machine-readability of dry road markings in daylight. In addition, it was found that there is not much knowledge about ADAS detection in challenging weather conditions. Hence, based on knowledge achieved within the project, the aim of the main study was reformed to answer the following research questions:

- What is the share of detectability, i.e., machine-readability, in wet conditions, for different roads and road markings?
- How is machine-readability in wet conditions at night-time affected by whether the road markings are flat or profiled?

The ambition was further, *if considered possible*, to analyse how different types of profiles affect machine-readability in wet night-time conditions.

5.3.1 Method

5.3.1.1 Routes

Two routes were selected – one in southern Sweden and one in Denmark, close to Copenhagen. The Danish route was 100 km and consisted of nine road objects, Figure 24 and Table 24. The Swedish route was 74 km and consisted of twelve road objects, Figure 25 and Table 25. For example photos of the Danish and Swedish road objects at the time of measurement, see Appendix 1 and Appendix 2.

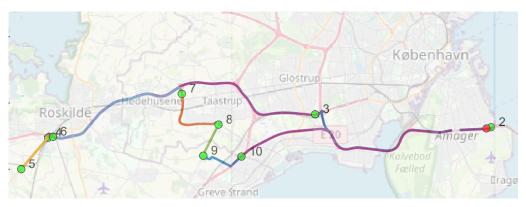


Figure 24. The Danish route, with nine road objects (numbered from 2 to 10). Map: OpenStreetMap contributors.



Table 24. The nine road objects in Denmark.

Table 24. I	ne nine road objects in Denmark.			
Dood		Longth	Type of road marking*:	Type of road marking*:
Road	Type of road	Length	Right line	Left line
object		(km)	(edge line)	(lane line, centre line, edge line)
2	Motorway	17.9	Solid 0.3 m, profiled	Broken 0.15 m, profiled
3	Motorway	25.9	Solid 0.3 m, profiled	Broken 0.15 m, profiled
4	Four-lane, two-lane (rural)	3.7	Solid 0.1 m, flat and profiled	Solid 0.1 m, flat
5	Four-lane, two-lane (rural)	4.1	Solid 0.1 m, flat and profiled	Solid 0.1 m, flat
6	Motorway	12.6	Solid 0.3 m, profiled	Broken 0.15 m, profiled
7	Two-lane (rural)	5.9	Solid 0.1 m, profiled	Solid/broken 0.1 m, flat
8	Two-lane (suburban)	3.0	Solid 0.1 m, flat	Solid/broken 0.1 m, flat
9	Two-lane (suburban), mo-	4.0	-	Broken 0.1 m, flat
	torway		Solid 0.3 m, profiled	Broken 0.15 m, profiled
10	Motorway	22.9	Solid 0.3 m, profiled	Broken 0.15 m, profiled

^{*)} The table shows the main road marking type per object. Other types (warning lines, double lines etc) may be present.

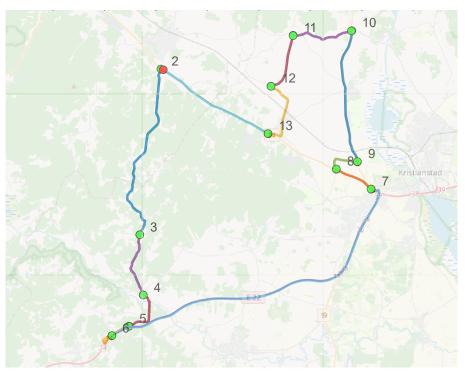


Figure 25. The Swedish route, with twelve road objects (numbered from 2 to 13). Map: OpenStreetMap contributors.



Table 25. The 12 road objects in Sweden.

	he 12 road objects in Sweden.		Type of road marking*:	Type of road marking*:
Road object	Type of road	Length (km)	Right line (edge line)	Left line (lane line, centre line, edge line)
2	Road without centre line	11.4	Broken 0.1 m, flat	Broken 0.1 m, flat
3	Road without centre line	4.0	Broken 0.1 m, flat	Broken 0.1 m, flat
4	Road without centre line	3.1	Broken 0.1 m, flat	Broken 0.1 m, flat
5	Two-lane road	2.7	Broken 0.15 m, flat and profiled	Various 0.15 m, flat and profiled
6	Motorway	20.7	Solid 0.3 m, profiled	Broken 0.15 m, flat
7	2+1 road	2.5	Solid 0.2 m, profiled	Lane line: broken 0.15 m, flat Left edge: solid 0.3 m, profiled
8	Road without centre line	2.1	Broken 0.1 m, flat	Broken 0.1 m, flat
9	Two-lane road	8.2	Various 0.1 m and 0.15 m, profiled	Various 0.15 m, profiled
10	Two-lane road	3.8	Broken 0.1 m	Various 0.1 m
11	Road without centre line	3.6	Broken 0.1 m, flat	Broken 0.1 m, flat
12	Two-lane road	4.5	Broken 0.1 m, flat or no edge line	Various 0.1 m
13	2+1 road	7.5	Solid 0.2 m, profiled	Lane line: broken 0.15 m, flat Left edge: solid 0.3 m, profiled

^{*)} The table shows the main road marking type per object. Other types (warning lines, double lines etc) may be present.

The routes were selected so that they would include different types of roads and road markings, to be able to obtain results that are representative for the types of roads and road markings that are common in Denmark and Sweden. Several types of profiled markings were included: longflex, longdot, stairs, and rilled (see also Chapter 2). For the comparison of machine-readability of flat and profiled road markings, certain objects were selected: 1) Objects 4 and 5 in Denmark had edge lines that alternated between flat and profiled markings, 2) The motorway objects in Denmark had profiled lane lines, while the motorway objects in Sweden had flat lane lines.

5.3.1.2 Equipment

Data was collected by Ramboll's tailor-made vehicle for road marking assessment, *Ramboll Road Marking Tester* (RMT). Retroreflectivity on dry and wet roads, daylight contrast¹⁴, luminance coefficient *Qd* and cover index were sampled every 25 m. Retroreflectivity (dry) and daylight contrast were measured by a conventional off-the-shelf device from Delta (Denmark). Retroreflectivity in wet condition was

¹⁴ Daylight contrast = (ambient luminance of road marking)/(ambient luminance of road surface)



predicted from the retroreflectivity (dry) and mean profile depth (*MPD*) which is a measure of the texture, while the luminance coefficient was predicted from the laser instrument used for the texture measurements (Lundkvist et al., 2008). Predicted parameters are less accurate than data obtained from hand-held reference instruments, in particular when assessing single objects. The results of predicted parameters should thus be interpreted with care. Cover index, which is defined as the part of the road marking area that remains at the time of measurement relative to the area within the prescribed outer dimensions of the marking, was obtained by a camera and digital image processing. The RMT system measures one road marking line at a time. A MobilEye system model 630 collected machine-readability data from both the left and the right line every 0.1 m.

5.3.1.3 Data collection

Data was collected in four conditions: dry roads in daylight, wet roads in daylight, dry roads at night and wet roads at night. Machine-readability data was collected in all four conditions, while conventional performance parameters only were collected on dry roads in daylight. All wet conditions were run twice, to increase the accuracy of the data. Also, the collections of conventional performance parameters were done twice, which resulted in a total of four runs on dry roads in daylight, since only one line can be measured at a time (see also the Equipment section above). The total number of measurements per condition is shown in Table 26. In one of the runs on dry roads in daylight in Denmark, the machine-readability equipment failed and there is thus data from only three runs.

Table 26. Number of measurements per condition

Condition	Number of measurements in Denmark	Number of measurements in Sweden
Day, dry	3 (4)*	4
Day, wet	2	2
Night, dry	1	1
Night, wet	2	2

^{*)} Conventional performance parameters available from four runs, machine-readability data available from three runs.

In the wet conditions, data was collected either on wet roads after a rain or on wet roads while it was raining. The measurements were conducted out of rush-hours, in order to try to avoid biased results due to vehicles obstructing the view, low speeds or constant glare from oncoming vehicles. High beam was used where appropriate. The data collection was carried out in August-October.

5.3.1.4 Data analysis

The machine-readability parameter analysed from the MobilEye system is called *lane confidence*, which ranges from 0 to 3. 0 and 1 mean *not detectable* and 2 and 3 mean *detectable*. Machine-readability was defined as the percentage of detectable road marking within an object.

The analysis included right edge lines and lane lines on multilane roads, edge lines and centre line on two-lane roads, edge lines on roads without centre line and centre line of roads without edge lines. The datafiles, which consisted of all data from the entire routes, were divided into objects according to Table 24–Table 25. In one of the datafiles from Denmark, 1 300 m of data was excluded from the analysis because of a road work. In addition, road object 9 in Denmark was excluded because it



consisted both of a narrow suburban road mainly without edge lines and a motorway, which makes the results difficult to interpret. No other data was excluded from the routes, i.e., the analysed road marking data includes sections with intersections, interchanges, roundabouts, motorway entrances/exits, bus stops etc that were present along the road. Objects that were located just before or after a motorway object included the motorway entrance/exit ramp.

The data processing was carried out in Python, Matlab and Excel. No statistical analyses were done because the number of samples per category was too few.

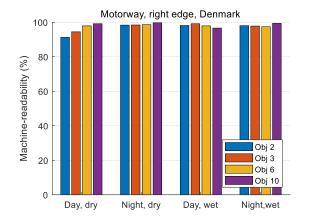
5.3.2 Results

5.3.2.1 Machine-readability under wet conditions

In this section, the machine-readability per object, road marking type, road type, country and conditions is presented. For conditions where more than one measurement was carried out, the mean values are presented.

Figure 26–Figure 27 show the machine-readability on motorways. Regarding the right edge line (Figure 26), which is profiled and has a width of 0.3 m, the machine-readability is very good in all four conditions. At night, the machine-readability is somewhat worse on wet roads than on dry roads (98.2% vs 98.8% in Denmark and 97.6% vs 99.5% in Sweden), but the differences are small. In Denmark, the machine-readability is the lowest on dry roads in daylight (95.7%) and the highest on dry roads at night-time (98.8%).

The lane line (Figure 27) on motorways has a high machine-readability in all four conditions in Denmark. As with the edge lines, the machine-readability is the lowest on dry roads in daylight (97.3%) and the highest on dry roads at night-time (98.9%). In Sweden, the machine-readability is approximately the same as in Denmark in the daylight conditions and in the dry night-time condition, but somewhat lower in the wet night-time condition. This is probably related to the fact that the lane lines are profiled in Denmark and flat in Sweden. However, the machine-readability is still high on the Swedish lane line (92.9%), which implies that the difference in readability between profiled and flat lines is relatively small on motorways.



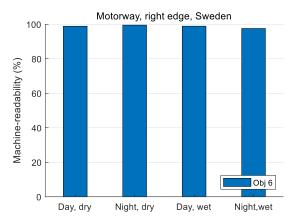
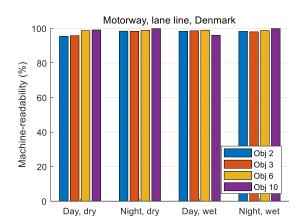


Figure 26. Machine-readability of right edge line (width: 0.3 m) on motorways. Left panel: Denmark (profiled marking). Right panel: Sweden (profiled marking).





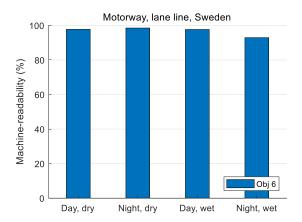
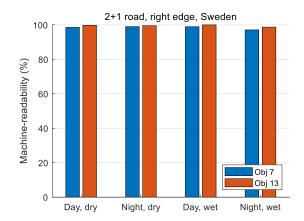


Figure 27. Machine-readability of lane line (width: 0.15 m) on motorways. Left panel: Denmark (profiled marking). Right panel: Sweden (flat marking).

Figure 28 shows the machine-readability on 2+1 roads in Sweden. The machine-readability of the right edge line, which is a 0.2 m wide profiled marking, is approximately the same as for the right edge line on motorways. The left line alternates between left edge line (profiled, width: 0.3 m) and lane line (flat, width: 0.15 m) as the number of lanes alternates between one and two. At daytime and in the dry night-time condition, the machine-readability of the left line is very high (≥97.0%) and any differences between the two line types are thus expected to be small. In the wet night-time condition, the machine-readability is lower, in particular for object 7. A detailed assessment of that object shows that the result is explained by very poor machine-readability of the lane line, while the result of the left edge line is in line with that of the right edge line.



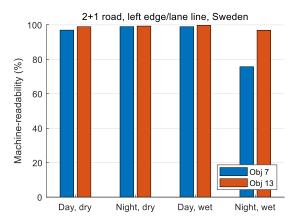
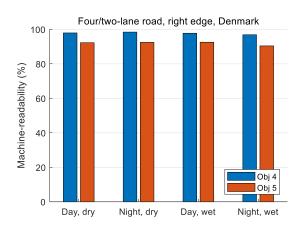


Figure 28. Machine-readability of road markings on 2+1 roads in Sweden. Left panel: Right edge line (profiled marking, width: 0.2 m). Right panel: Lane line (flat marking, width: 0.15 m), left edge line (profiled marking, width: 0.3 m).

Figure 29 shows the machine-readability on roads with two or four lanes in Denmark. The line widths are 0.1 and 0.15 m, and the marking alternates between profiled and flat. The machine-readability is high (>90%) in all four conditions and for both the right edge line and the lane line/centre line. The machine-readability is the lowest in the wet night condition, but the differences between the conditions are small.





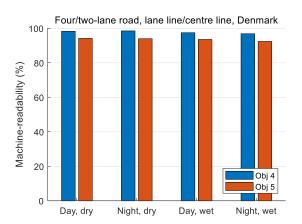
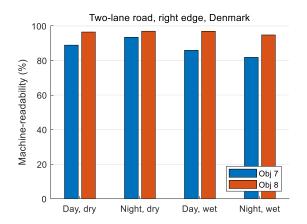


Figure 29. Machine-readability of road markings on four/two-lane roads in Denmark. Left panel: Right edge line (profiled marking, flat marking, width: 0.1 m). Right panel: Lane line (flat marking, width: 0.1 m), centre line (profiled marking, width: 0.1 m).

Figure 30–Figure 31 show the machine-readability of road markings on two-lane roads. For most objects and lines, the machine-readability is about 80–95%. In the two daytime conditions and in the dry night-time condition, the machine-readability is approximately the same (average 87.7%), while it is somewhat lower in the wet night-time condition (average 79.4%). The road markings are sometimes flat and sometimes profiled on two-lane roads.

Object 12 has a poor machine-readability in all four conditions. The road markings are in a bad condition and are missing on some parts of the road.



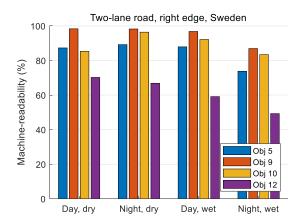
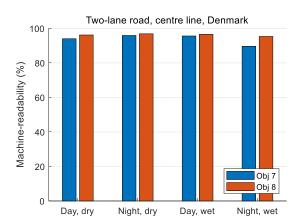


Figure 30. Machine-readability of right edge line on two-lane roads. Left panel: Denmark. Right panel: Sweden.





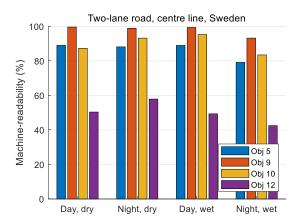
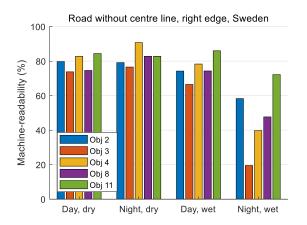


Figure 31. Machine-readability of centre line on two-lane roads. Left panel: Denmark. Right panel: Sweden.

Figure 32 shows the machine-readability on roads without centre line, in Sweden. The machine-readability (average of right and left edge line) is the highest in the dry night-time condition (75.1%) followed by the dry daytime condition (69.8%) and the wet daytime condition (67.7%). The machine-readability was the lowest in the wet night-time condition (35.9%). All road markings in this road category were broken lines with flat surface and a width of 0.1 m.

The machine-readability is in general worse on the left edge line than on the right edge line, which probably is explained by the fact that the right line usually is closer to the vehicle than the left line, maybe in combination with sunken and cracked road edges.



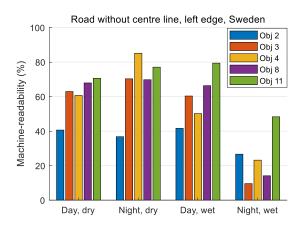


Figure 32. Machine-readability of road markings on roads without centre line in Sweden. Left panel: Right edge line (flat marking, width: 0.1 m). Right panel: Left edge line (flat marking, width: 0.1 m).

5.3.2.2 Flat versus profiled road markings

No very exact comparison of flat versus profiled markings could be carried out because this would require that all other factors that could have an influence on machine-readability were identical in the two cases. This includes road characteristics (curvature, width), road marking characteristics (solid/broken, width, condition with respect to conventional performance parameters) and weather conditions. In an attempt to reduce the influence from other factors, data were selected from motorways (which are all relatively wide and flat) and from objects 4 and 5 in Denmark (which were located on the same road and which had alternating flat and profiled edge markings).



For motorways, there was one object with flat lane line (in Sweden) and four objects with profiled lanes (in Denmark). The profiled lane line that was most similar to the flat lane line with respect to road marking condition was selected for a comparison, Table 27.

Table 27. The two lane line object selected for comparison between flat and profiled marking.

	Object	RL	04	Doublight	Cover
Line type	length (km)	(mcd/m²/lx)	Qd (mcd/m²/lx)	Daylight contrast	index (%)
Flat (object 6-SE)	20.7	138	169	2.7	94
Profiled (object 2-DK)	17.9	137	156	2.2	92

Figure 33 shows the machine-readability of the flat and the profiled lane lines. In the dry daylight condition the machine-readability of the flat marking is somewhat better than that of the profiled marking, while the machine-readability is approximately the same for the flat and the profiled marking in the dry night-time condition and in the wet daylight condition. In the wet night-time condition, the machine-readability is higher for the profiled than for the flat marking (98.3% vs 92.9), but the machine-readability is still relatively high for the flat marking.

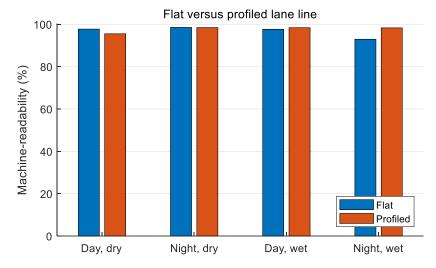


Figure 33. Machine-readability of flat versus profiled lane line.

Regarding object 4 and 5 in Denmark, all segments with either solid flat or solid profiled right edge line (width: 0.1 m) were selected for analysis. There was no road lighting or crossings in the selected segments. The road was straight and flat. The selected segments were grouped into "Flat" and "Profiled". The characteristics of the two groups are shown in Table 28.



Table 28. The characteristics of the segments included in the comparison of flat and profiled marking.

Line type	Total object length (km)	RL (mcd/m²/lx)	Qd (mcd/m²/lx)	Daylight contrast	Cover index (%)
Flat (segments from object 4-DK and 5-DK)	1.3	161	152	2.0	91
Profiled (segments from object 4-DK and 5-DK)	2.0	129	160	2.0	58

Table 29 show the machine-readability of the flat and the profiled markings. The machine-readability was 100% in the two daytime conditions and in the dry night-time condition. The profiled marking had 99.9% machine-readability in the wet night-time condition while the flat marking had slightly lower: 99.5%.

The overall machine-readability was very high in this case, which probably can be explained by the fact that the road was straight and flat and that segments including crossings etc had been excluded from the data.

Table 29. Machine-readability (%) for flat and profiled markings in the four conditions.

Line type	Day, dry machine-	Night, dry machine-	Day, wet	Night, wet
· ·	readability (%)	readability (%)	readability (%)	readability (%)
Flat (segments from object 4-DK and 5-DK)	100	100	100	99.5
Profiled (segments from object 4-DK and 5-DK)	100	100	100	99.9

In the two cases presented above, the machine-readability was high both for flat and for profiled markings in the wet night condition. The road markings were in acceptable conditions (RL was approximately 130-160 mcd/m²/lx and Qd was approximately 150-170 mcd/m²/lx). Figure 28 shows an example of a flat lane line that has poor machine-readability in the wet night condition. In the graph the result consists of data both from the lane line and from the left edge line, but if the two lines are separated, it was found that the poor machine-readability was related mainly to the lane line. In the first wet night condition, the machine-readability (of the lane line) was 73.8% and in the second wet night condition it was 38.2%. Also in this case, the road marking (lane line) was in an acceptable condition (RL: 154, Qd: 156, cover index: 94). An assessment of images from the data collection showed that the poor results probably are explained by several factors. Some parts of the road marking were in a rather poor condition with a high degree of wear, even though the average RL and Qd values were acceptable. Furthermore, there were some oncoming vehicles that caused glare and reflections in the wet road surface. There was also a longitudinal joint in the asphalt along the lane line, which possibly could have caused pooling of water. In addition to the results presented above, the results in the preceding chapter regarding roads without centre line showed that the machine-readability of flat broken edge lines with a width of 0.1 m were poor in the wet night condition. In conclusion, flat markings may have high machine-readability if the circumstances are favourable (markings in a good condition on a straight and flat road with a minimum of glare from oncoming vehicles). In less favourable circumstances, the machine-readability may be poor.



Because of the relatively few objects (which had different characteristics with respect to road type and road marking condition) and the overall high machine-readability, it was not possible to compare different types of profiles with respect to machine-readability.

5.3.3 Discussion

The machine-readability of road markings in daylight and at night-time on dry and on wet roads was investigated in Denmark and Sweden. The main findings were:

- The machine-readability of the right edge line (profiled, width: 0.2–0.3 m) on motorways and 2+1 roads was very high (average 98.2%) and approximately the same in all four conditions (day/night, dry/wet).
- The machine-readability of road markings on two-lane roads (flat and profiled markings) was relatively high (average 87.7%) in the two daytime conditions and in the dry night-time condition, while it was somewhat lower in the wet night-time condition (average 79.4%).
- On roads without centre line, where all road markings were flat broken lines with a width of 0.1 m, the machine-readability was 67.7%-75.1% in the two daytime conditions and in the dry night-time condition. In the wet night-time condition, the machine-readability was very poor – 35.9%.
- In favourable conditions (i.e. road markings in a good condition on a straight and flat road with
 a minimum of glare from oncoming vehicles), flat markings had almost the same machinereadability as profiled markings in the wet night condition. In less favourable conditions (such
 as narrow and curvy roads and/or road markings in a poor condition), the machine-readability
 of flat markings on wet roads at night may be poor.

The results regarding machine-readability were in general somewhat lower than those presented in the chapter *Machine-readability of dry road markings in* daylight where data from the ROMA study was used. This could probably be explained by the fact that fewer intersections, interchanges, roundabouts, and motorway entrances/exits were present in the ROMA study, because the objects typically started and ended at e.g. the motorway, while in the present study, they started and ended in interchanges etc. It could be discussed how the data should be processed and categorized to get interpretable and representative results. In the present study, machine-readability was compared in four conditions (day/night, dry/wet) for the same set of road objects. The presence of intersections etc was assumed to have similar influence on the results in all four conditions and thus, in combination with the fact that it would be very time-consuming, it was decided not to exclude segments containing intersections etc. This implies that the machine-readability cannot be expected to be 100%, as there, for example, are no lines to detect when the vehicle is turning in an intersection.

The machine-readability was similar in the two daytime conditions and in the dry night-time condition, and worse in the wet night-time condition (except for the right edge lines on motorways where the machine-readability was high in all four conditions). This is reasonable, since the visual conditions are expected to be the worst on wet roads at night, where light from the own vehicle is reflected forward and not back to the driver and where light from oncoming vehicles causes reflections and glare.

The investigation of flat versus profiled road marking showed that the machine-readability was almost the same for flat as for profiled markings for lane lines on motorways and for the right edge line on a flat and straight two-lane road in the wet night condition. In both these cases, there will be little reflections/glare from oncoming vehicles. Motorways usually have some kind of barrier between opposite



lanes and the location of the right edge line makes it less sensitive to the lights of oncoming vehicles. For one of the objects on a 2+1 road, on the other hand, the machine-readability of the (flat) lane line was rather poor in the wet night condition. On this type of road, the barrier consists of steel cables, which do not block glare from oncoming vehicles.

The machine-readability was the worst on small roads without centre line (where the road marking always was a flat broken line with a width of 0.1 m), particularly in the wet night condition. This agrees with the results of the study by Lundkvist and Fors (2010). In that study, the poor machine-readability was assumed to be related to the non-profiled (flat) markings and in some cases be caused by sunken road edges or curves. Figure 34 shows two examples from the present study that illustrates the influence from external factors in the dry daylight condition. In the left picture (object 11-SE), where the road marking is in a poor condition with an average RL of 82 mcd/m²/lx, but the road is straight and flat and located in an open landscape, the machine-readability is higher (87.8% vs 54.2%, average of the two runs where conventional performance parameters were measured on the right line) than for the road in the picture to the right (last 4 km of object 2-SE). In the latter case, the road marking is in an acceptable condition (except for a high degree of wear in some curves) with an average RL of 158 mcd/m²/lx, but the road is curvy and surrounded by vegetation that causes shadows on the road. Thus, as concluded in the literature study, the machine-readability is influenced by many factors and not only by the properties of the road marking.



Figure 34. Left panel: Right edge line with RL=82 mcd/m²/lx and machine-readability of 87.8% (over 3.6 km). Right panel: Right edge line with RL=158 mcd/m²/lx and machine-readability of 54.2% (over 4.0 km).

In this study, machine-readability has been investigated with respect to what percentage of the longitudinal road markings an LDW/LKA system detects. The investigation has been based on the assumption that all detected road markings actually are road markings. To what extent this assumption is true is not known, as no images that illustrate what the LDW/LKA system classifies as road markings were available. For one of the objects in Denmark (object 9-DK, which was excluded because the road type varied) it was observed that the machine-readability of the edge lines was unexpectedly high, given the fact that edge lines were missing on a substantial part of that road. An inspection of images taken by the RMT system revealed that there were curbstones along the road where the LDW/LKA system had detected road markings (but where no road markings were present), Figure 35. Thus, the LDW/LKA system had probably classified the curbstones as road markings in this case. To our knowledge, false detections are not much discussed in the literature so far and this could thus be of relevance to investigate further in future studies.





Figure 35. Example of a road where the LDW/LKA system has detected a road marking to the right, but where no road marking is present. The system probably classifies the curbstones as road markings in this case.



6 General discussion

This NordFoU project has contributed to increased knowledge of machine-readability of road markings, considering different aspects.

The literature study revealed that many parameters are reported to affect machine-readability, such as those related to road environment, road maintenance, weather and light conditions. Of parameters related to road markings, contrast ratio was reported to be the most important parameter for machine-readability, and this parameter in turn is affected by many external factors, for instance weather, glare and ambient light. From the interview survey, it was found that exact performance properties of road markings do not directly correspond to machine-readability. A combination of data collection technologies is often used, and machine learning is applied for processing the data. Both the literature and the interview study concluded that if the human eye can detect the road marking, then the road marking is machine-readable. However, only a few studies have been conducted in wet conditions relating machine-readability to road marking functionality.

The pilot study conducted within the project focused on the contrast ratio between the road marking and the road surface in both dry and wet weather conditions. The pilot study uncovered some practical problems, but also further evidenced that in the field, i.e., on real roads, there are many parameters affecting machine-readability that are not related to road marking functionality. Hence, contrast ratio alone could not infer machine-readability. Results from both the literature study and the pilot study pointed out that wear and lack of road markings were the parameters related to road markings per se that contributed to bad machine-readability. Therefore, it was of interest to see how machine-readable road markings on real Nordic roads were, and how machine-readability was affected by weather and light conditions.

The project had the opportunity to use data collected within the NordFoU project *State assessment of road markings in the Nordic countries* (ROMA), where a large data material on conventional road marking performance parameters had been collected for several years in three of the Nordic countries. Within the present project, a large and unique set of daylight data collected by a measurement vehicle equipped with a MobilEye system (around 5 800 km length of road markings in Norway and Sweden) was analysed. The analysis showed that in daylight, there was no strong relationship between machine-readability and conventional road marking performance parameters. For example, retroreflectivity levels of road markings that were machine-readable and those that were not machine-readable in daylight had a large overlap. This is logical since retroreflectivity is a measure of visibility at night-time, not in daylight, and because ADAS does not primarily read road markings from their retroreflectivity. In addition, machine-readability was higher on multilane roads (99%) compared to on two-lane roads (93%), which may be explained for example by fewer curves on larger roads. Although data showed that machine-readability of broken lines was somewhat worse than that of solid lines of line width 0.1 m, this could be an effect of factors related to the (minor) roads where broken lines with 0.1 m width are commonly used.

The main study data collection within this project was carried out on various types of roads with different types of road markings in both Sweden and Denmark. Data was collected for all roads under both dry and wet weather conditions and during daytime as well as night-time. Overall, the machine-



readability on edge lines was high (average 98%) on motorways and 2+1 roads, irrespective of weather and light conditions. In the wet night-time condition, there was some difference between the flat Swedish lane lines and the profiled Danish lane lines on motorways but machine-readability was still high, 93%. The lowest machine-readability, 36%, was achieved on small roads without centre line, where the road marking was always the same (a flat broken line with a width of 0.1 m). However, it is reasonable to believe that the road type had a large impact on machine-readability. Flat road markings did not differ much from profiled markings in the wet night-time condition on a straight and flat road without glare.

The European Commission has decided that from July 2022, emergency lane-keeping systems (ELKS) are required for type-approval of all new passenger cars and light commercial vehicles on the EU market (European Commission, 2021). It is stated that ELKS should be required to operate on straight, flat and dry roads at vehicle speeds between 65 and 130 km/h, in all illumination conditions without blinding the sensors, for markings in good condition and of a material conforming to the standard for visible lane markings. The results from this project have revealed that for the Nordic countries of Denmark, Norway, and Sweden, at least, road marking quality does not seem to be a problem for machine-readability in dry weather and hence not for ELKS. Aspects related to road markings that have been pinpointed to decrease machine-readability within this project are missing or very worn road markings. These aspects are not part of the requirements from a car manufacturing perspective, however, since the European Commission further states that the ELKS should not be required to operate in the absence of lane markings and that it should operate on markings in good condition (European Commission, 2021).

Since missing and very worn road markings seem to be the road marking related problem for machine-readability, these markings should be remedied in agreement with current requirements. Finally, it should be kept in mind that machine-readability for LKA or LDW systems can never be expected to be 100%, because there are not, and should not be, road markings everywhere along the road network, due to the existence of intersections, crossings, etc.

6.1 Project conclusions

Summing up the project results, the following conclusions can be drawn:

- It is not possible to find minimum values of performance parameters for machine-readability due to complex relationships.
- There are many factors unrelated to road markings that influence machine-readability.
- There are no clear relationships between machine-readability and conventional performance parameters.
- Machine-readability was very good in daylight on dry roads, 99% for multilane roads and 93% for two-lane roads.
- Machine-readability was mostly similar in daylight, for dry and wet roads, and on dry roads at night-time, and worse in the wet night-time condition.
- Worst machine-readability was found for wet night-time conditions on narrow and curvy roads with road markings in a poor condition.
- As long as the road markings are visible for the human eye, they can be expected to be machine-readable as well.



6.2 Research questions for future studies

The following research questions could be of interest to investigate in future studies:

- How can machine-readability from ordinary vehicles be used to assess road marking condition?
- Do the results hold for other manufacturers than MobilEye?
- The results on machine-readability presented in this report and in other studies may include false detections. What is the share of false detections and do they constitute a problem?
- How does the state of the asphalt influence machine-readability?
- How does road maintenance affect detection of road edge and road markings?
- What will the role of road markings be for future lane positioning systems?



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Appendix 1 – example photos from road objects in Denmark

































Appendix 2 – example photos from road objects in Sweden



























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