Report

MCSINC

Summarising the main findings of work package 1: Demands and requirements for machine sensing infrastructure.

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Report No:

2023:01055 - Unrestricted

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KEYWORDS
Mobility
Digitalisation
Artificial Intelligence
Nordic conditions
Automated Transport
Machine sensing
Physical infrastructure
Digital infrastructure

VERSION
1.0

DATE
2023-11-20

AUTHORS
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CLIENT
The Research Council of Norway

CLIENT'S REFERENCE
333875

PROJECT NO.
102028030

NO. OF PAGES
41

SUMMARY
The main objective of the MCSINC project is to identify the opportunities and challenges with AI-based machine vision of road infrastructure under Nordic conditions. Work package 1 focuses specifically on "Demands and requirements for machine sensing infrastructure". This project report summarises the work done in work package 1 in the MCSINC-project: a state of the art on machine sensing under Nordic conditions, a brief presentation of the research platform for data collection and finally a discussion on the actors' requirements for machine sensible infrastructure and road environment.

The partners of the MCSINC project are SINTEF (project owner), NTNU, the Norwegian Public Road Administration (NPRA) and Troms and Finnmark County Council.

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REPORT NO.
2023:01055

ISBN
978-82-14-07871-8

CLASSIFICATION
Unrestricted

CLASSIFICATION THIS PAGE
Unrestricted

Document history

VERSION	DATE	VERSION DESCRIPTION
1.0	2023-11-20	Final version

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1 Introduction

Janne Venæs and André Bekkevold Sande

MCSINC (Machine Sensible Infrastructure under Nordic conditions) is a research project whose primary objective is to answer how improved AI methods for vehicle machine sensing of the road environment together with adjustment of winter maintenance and infrastructure can be optimised under Nordic conditions. The project seeks to identify the possibilities and challenges of machine sensing of the road environment under Nordic conditions, and improve state of the art AI vision-based localisation algorithms by AI-assisted generation of ground truth data and thereby HD-maps. MCSINC will also test and learn from AI vision-based localisation and perception of road objects under Nordic conditions to generate recommendations for and collaboration on how infrastructure design and winter maintenance procedures can be optimised towards machine sensing.

This first report from the MCSINC project is a collection of the notes produced in work package 1: “Demands and requirements for machine sensing” lead by SINTEF. These notes have generated important knowledge on the status quo for machine sensing under Nordic conditions. Hence, the purpose with this report is to address the current challenges and possibilities for machine sensing, seen from both the industry perspective and authority perspective. The actors’ requirements for machine sensing lay the foundation for the way forward and their perspectives will be decisive to improve machine sensing and succeed with automated driving under Nordic conditions. Work package 1 consists of three tasks:

- 1.1: Mapping actors’ requirements for machine sensible infrastructure and road environment in interviews
- 1.2: State of the art (SOTA) on machine sensing under Nordic conditions, GT data generation, including HD-maps
- 1.3: Requirement analysis for data collection process and database structure

First, in chapter 1.1, we shortly define relevant terms that are repeated throughout this report. In chapter 2, we present a SOTA on machine sensing under Nordic conditions discussing both current and future requirements. Chapter 3 contains a presentation of the NTNU research platform for data collection, which will be used in the MCSINC project. Finally, based on interview data, Chapter 4 will present and discuss the different actors’ requirements and reflections. Chapter 4 further concludes with a section on recommendations for future development of machine sensing in Nordic conditions.

1.1 Definitions

1.1.1 Nordic conditions

In this project we are exploring the barriers and opportunities of machine sensing under Nordic conditions. By Nordic conditions we mean the special and varying conditions one can experience in the Nordic countries. Specific Nordic conditions relate to weather such as snow, fog, heavy rain (in combination with wind) and ice on the road surface, but also relate to the road network such as tunnels and large rural areas with less developed infrastructure.

1.1.2 Physical and digital road infrastructure

The following definitions are based on a paper from Farah, Erkens, Alkim and van Arem (2018).

By "Physical Road Infrastructure" we mean the road body with its geometric design, extent, and paving, including physical road safety equipment, physically visible signs, and road markings.

By “Digital Road Infrastructure” we mean all infrastructure for digital communication, i.e., road equipment (sensors, signs and other RSUs) set up for online communication with vehicles, digital maps, traffic rules and regulations, and positioning services.

Some road equipment may be both physical and digital, e.g., visual signs set up with digital communication.

1.1.3 Levels of automation

SAE International have described six levels of driving automation and this has been the most-cited source for driving automation (SAE International, 2021). The six levels range from Level 0 (no driving automation) to Level 5 (full driving automation). The requirements for machine sensing differs between the different levels of automation. The three highest levels are considered most relevant for the MCSINC project. The latest version of the SAE levels, including a short description of each level, can be found in Figure 1 below.

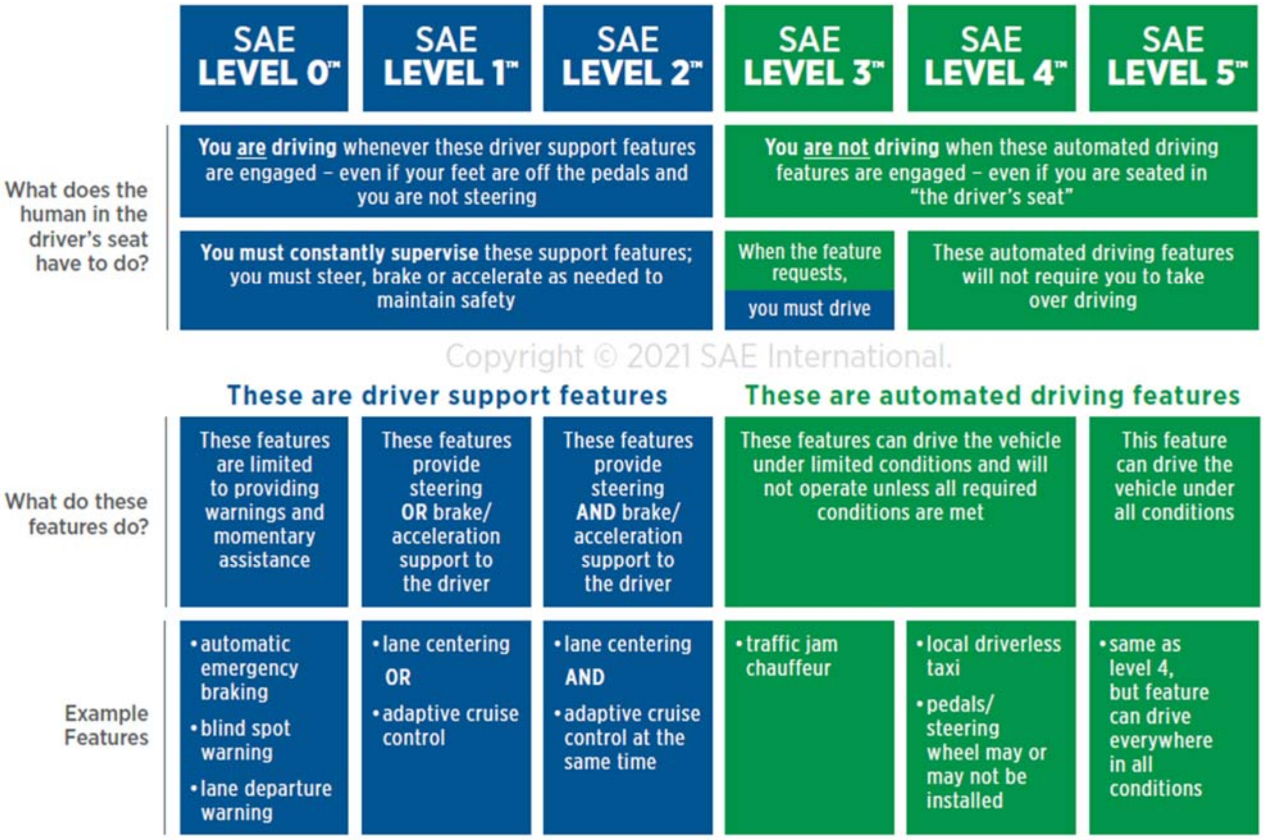

Figure 1: SAE levels **(SAE International, 2021)**

1.1.4 Technology/sensors

Machine sensing refers to the capability of a machine or system of machines to detect, identify, and assess sensory readings from the environment. Various types of sensors such as LiDAR, RADAR and cameras are used to “sense” the environment in the form of digital information. The collected information is then processed by computer algorithms to make it useful for the car’s control system.

LiDAR (Light Detection and Ranging) is a technology used to create detailed digital 3D maps of the environment. This is achieved by sending out light waves which reflect off the objects they hit. This allows on-board software to calculate the distance to nearby geometry. This is very useful to detect any physical entity close to the car (Yanase, Hirano, Aldibaja, Yoneda, & Suganuma, 2022).

RADAR (Radio Detection and Ranging) is a technology used to track fast-moving objects in the vehicle's vicinity. RADARs send out radio waves, in the non-visible (to humans) part of the electromagnetic spectrum. This allows RADAR to "see through" objects or adverse weather conditions such as rain or fog (Popov, et al., 2022).

Cameras utilise the already visible light in the environment, much like human eyes. As such, cameras are reliant on advanced algorithms to make sense of information, just how human eyes would be useless without our brains. However, with recent advances in computer vision, cameras are becoming more and more useful and relevant for automated driving (Herb, et al., 2021).

1.2 References

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2 Exploring Machine Readable Infrastructure in Nordic Environments: Research Trends, Challenges, and Opportunities in Sensing, Localisation, and Mapping

Kristoffer Tangrand

2.1 Introduction

The purpose of this state-of-the-art chapter is to provide an overview of the current research on machine readable infrastructure under Nordic conditions. The chapter focuses on the areas of sensing and perception, positioning, localisation, and mapping, as well as some of the aspects of HD map generation. The chapter aims to synthesise the existing literature and highlight the latest advancements and trends in this field, as well as identify challenges and opportunities for future research. Through a comprehensive literature review and analysis, this chapter will provide valuable insights for researchers, practitioners, and stakeholders in the field.

Automated driving has the potential to greatly benefit society in multiple aspects. It can help reduce traffic accidents and fatalities, increase fuel efficiency, reduce congestion on roads, and provide mobility to people who are unable to drive, such as the elderly and the disabled. Additionally, the widespread adoption of automated vehicles could create new job opportunities in fields such as vehicle maintenance and repair, and could also lead to the development of new technologies and industries. The benefits of automated vehicles are likely to be significant and could greatly improve the quality of life for many people (Atakishiyev et al., 2023).

Such benefits are not limited to individuals; they could also have a significant positive impact on society. For example, a reduced number of traffic accidents and fatalities could save lives and reduce the burden on healthcare systems. The increased fuel efficiency of automated vehicles could also help reduce greenhouse gas emissions, which would have a positive impact on the environment (Taiebat et al., 2018). Additionally, the increased use of automated vehicles could lead to a more efficient use of roads and other transportation infrastructure, which could help reduce congestion and improve overall transportation in cities and other densely populated areas (Bezai et al., 2021).

The current approach to automated driving involves a traditional vehicle. These vehicles were designed with the intention of a human controlling and interacting with them. The human driver controls parameters such as acceleration, steering, and deceleration (Storsæter et al., 2021). To make decisions about these controls, the human uses biological sensors such as vision, hearing, motion perception, and vibrations from the vehicle. Since humans are biological agents, they are adapted to be able to interpret weather conditions from their sensory inputs. Contrarily, agents with artificial intelligence (AI) are usually trained for a specific purpose, using a specific set of data. Hence, they are less equipped to adapt to changing conditions.

In automated driving, weather conditions that the AI agent is not trained for may have serious consequences. Inclement weather, often experienced in the Nordic region, can change rapidly. This might also change the driving properties of vehicles in the same fashion. As such, the effects of inclement weather conditions have long kept automated vehicles from achieving SAE level 4 or higher autonomy (Zhang, Y. et al., 2023). Usually, precipitation refers to rain and snow, but it also includes drizzle, sleet, ice pellets, graupel, and hail. All types of precipitation would necessitate special considerations for automated vehicles. Mixtures of precipitation types are equally important to account for. The precipitation also effectively changes the conditions of the road itself (Skjermo et al., 2020).

In the following sections of this chapter, we first provide a clarification of what we mean by positioning and localisation and the difference between the two terms. Next, we give an overview of localisation methods, and the sensors used as input, which is our primary focus in this chapter. Secondly, we examine literature relevant to the influence of weather on such sensor data, with a specific focus on challenges related to cold weather and snowy conditions. We then extend the discourse by investigating end-to-end localisation algorithms for adverse weather. Relevant to this, we highlight the importance of infrastructure such as reflective landmarks and visibility of road markings. These infrastructure entities can assist in the creation of HD maps, which we discuss in the last section. Finally, the chapter concludes with a critical discussion on the implications of these findings for future research.

2.2 Knowing where you are

2.2.1 Positioning vs. Localisation

We start with defining *positioning* and *localisation*. Clearly, the terms are related, but refer to different concepts of determining the locations of objects.

Positioning generally refers to numerical coordinates in coordinate system, e.g., latitude and longitude. Typically, this is achieved through satellite positioning, such as global navigation satellite system (GNSS), and is typically used to determine an automated vehicle's geospatial coordinates within a global reference frame, such as geodetic or map-based systems. To facilitate precise navigation and route planning in automated vehicles, it is essential for integrating global and local positioning data.

Localisation, on the other hand, typically refers to the process of determining the position of an object or device relative to a known map or environment. Localisation often involves using sensors, such as cameras or LiDAR, to detect and track features in the environment and compare them to a pre-existing map or model of the space. This allows the device or object to determine its location with respect to the surrounding environment and navigate accordingly. Since localisation is the primary focus of this chapter, a more detail introduction follows.

2.2.2 Localisation

Automated vehicles rely on precise localisation to operate successfully in environments where they have been designated to drive. In these environments, the cars can navigate from their current location to a specified goal location using maps that have been constructed with a high degree of accuracy. To do this, the cars require precise maps of the environment they are operating in, with accuracy at the level of a few centimetres. In this context, it is essential that the cars are able to solve the following problems: position tracking, global localisation, and the "kidnapped robot" problem:

1. *Position tracking* is the process of determining and monitoring the location or coordinates of an object or individual in real-time or over time, often using technologies such as GNSS, sensors, or computer vision. Inaccuracies in position tracking is usually solved through probabilistic algorithms such as Kalman filters or particle filters.
2. *Global localisation* refers to the problem of determining the location of an automated vehicle within a global coordinate frame, such as a map. This is different from localisation, which refers to the problem of determining the car's location within a local coordinate frame, such as a particular lane on a road. Global localisation typically involves the use of a map of the environment, along with the car's sensors and algorithms, to determine the car's location with respect to the global coordinate frame. This is an essential capability for automated vehicles, as it allows them to navigate accurately within a known environment and reach their destination. Usually, GNSS will solve this problem. However, GNSS can be affected by several factors, such as signal interference, which can reduce its accuracy or make it

unreliable. Additionally, GNSS is not always available in certain environments, such as tunnels or in areas with heavy tree or mountain cover, which can limit its usefulness for automated vehicles.

3. The *kidnapped robot problem* refers to the situation where an automated vehicle is suddenly moved to an unknown location without its knowledge. This requires the vehicle to use its sensors and algorithms to determine its new location and resume its mission. As such, it is a special case of the global localisation problem (Cavalcante et al., 2021).

A lightweight and low-power approach for converting 3D point clouds of LiDAR data into sparse local maps was proposed in De Paula Veronese et al. (2016). More recently, commercial robotaxis have been deployed on the streets of selected cities in the United States. These robotaxis typically rely on 3D point cloud matching to HD maps for localisation, as discussed in Qin et al. (2021). Herb et al. (2021) propose a method that aligns camera frames with semantic map information to determine the real-time position of a vehicle, without requiring specialised equipment or landmarks. This method has the potential for diverse applications, such as indoor augmented reality and outdoor automated vehicle navigation.

Safe and effective automated driving requires accurately predicting the motion of nearby actors, such as vehicles, pedestrians, and cyclists (Kamenev et al., 2021). Various deep learning approaches are commonly employed to achieve this, such as Popov et al. (2022), who present a deep neural network that detects moving and stationary obstacles, computes their orientation and size, and detects drivable free space from RADAR data alone.

2.3 Vehicle sensors

Several types of sensors used for localisation are important for automated vehicles, and the specific sensors used may vary depending on the design and intended use of the vehicle. Some of the most important sensors for automated vehicles is discussed in the following section, and an overview of their strengths and weaknesses is found in Figure 2.

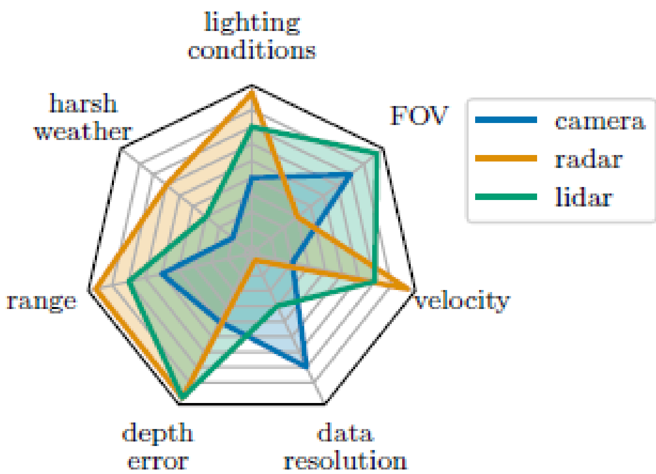

Figure 2: Strengths and weaknesses of different sensors, according to Reichert et al. (2021). FOV is short for field of view.

2.3.1 LiDAR

LiDAR sensors use lasers to create a 3D map of the vehicle's surroundings. This can be used to accurately find and avoid obstacles and make detailed maps of the surrounding area.

Snowy weather can influence how well LiDAR sensors work in automated vehicles. Snow can scatter or absorb the laser light used by LiDAR sensors, which can make it difficult for the sensors to accurately detect objects and features in the environment. Some LiDAR sensors are more resistant to snow than others, and they may be able to keep working well even when it is snowing (Abdo et al., 2021b). According to Abdo et al. (2021a), snow affected range measurements of Velodyne and Ouster LiDAR units very little. Rain and especially fog did, however, degrade performance significantly. Also, the performance of LiDAR sensors can be improved by using special algorithms and methods that are made to deal with the problems that snowy environments bring. For example, some LiDAR sensors use multiple lasers at different wavelengths, which can help reduce the effects of snow on the sensor's performance.

Overall, snowy weather can impair the functioning of LiDAR sensors, but there are strategies and technologies that can be used to reduce these effects and make sure the sensors still work well when it is snowing.

2.3.2 RADAR

Radar sensors use radio waves to detect objects and measure their range, angle, and velocity. This information is used to detect and avoid obstacles, as well as to determine the vehicle's position and orientation. It is mostly weather invariant, but not as precise as LiDAR (Yanase et al., 2022).

2.3.3 Cameras

Cameras are used to provide visual information about the vehicle's surroundings. This can be used for tasks such as identifying obstacles, traffic signs, and other objects. In snowy situations, most known picture segmentation techniques that function well in clear weather conditions fail. Due to the low gradient of colour pixels, it is difficult to identify snow-covered objects. In Vachmanus et al. (2021), a combination of RGB image and thermal map inputs is used for segmentation (classification) in snowy environments. The inputs were merged in the head module from double encoder paths. The results of the experiment indicate that employing a heat map can improve the effectiveness of human segmentation in snowy environments, particularly at night.

In poor light and harsh weather, camera vision diminishes severely. Dhananjaya et al. (2021) generated a weather and light classification dataset, that was labelled according to different weather and light levels. They found that active learning can classify large-scale object detection datasets to comprehend weather and poor light. Yellow road markings can be detected by computer vision algorithms through snow up to 0.5 centimetres deep (Storsæter et al., 2021).

2.4 Weather influence on different sensor data

Snowy weather can pose several challenges for automated vehicles, which can make it difficult for the vehicles to operate safely and effectively in these conditions (Guo et al., 2020) (Zang et al., 2019). Some of the biggest challenges for automated vehicles in snowy weather includes:

- Reduced visibility: Snow can reduce visibility and make it difficult for the vehicle's sensors to accurately perceive their surroundings. This can make it harder for the vehicle to detect and avoid obstacles, as well as accurately determining its position and orientation.

- Slippery roads: Snow and ice can make roads slippery, which can make it difficult for the vehicle to maintain control and traction. This can increase the risk of accidents and make it harder for the vehicle to execute safe and efficient manoeuvres.
- Poorly marked roads: Snow can obscure or alter the appearance of lane markings, traffic signs, and other road features that are important for navigation. This can make it harder for the vehicle to understand its surroundings and plan routes that are safe and efficient.
- Cold temperatures: Cold temperatures can affect the performance of the vehicle's sensors and other systems, potentially reducing their reliability and accuracy. This can make it more difficult for the vehicle to operate safely and effectively in snowy conditions.

The following subsections will detail computer vision methods designed to address challenges associated with sensory input impairments due to adverse weather conditions and in particular snowy conditions. Typically, this is done by "Snow Removal" procedures, but we present also here briefly an alternative "Reconstruction" procedure.

2.4.1 Snow Removal

Some of the problems described above can be alleviated through a process called snow removal. In computer vision, snow removal refers to the process of removing snow from images or videos to improve visibility and clarity (also called de-snowing). Several methods, such as image enhancement, image segmentation, and object detection, can be used to do this. The goal of snow removal is to improve the quality of the image or video so that it can be used for further analysis or decision-making. Cameras on cars, drones, or other platforms may be used to take these pictures or videos. The goal is to improve visibility and clarity of the scene, which can be challenging in snowy or snow-like weather conditions. The improved images and videos can be used to find objects, analyse images, and find your way around.

K. Zhang et al. (2021) proposes a Deep Dense Multi-Scale Network (DDMSNet) for snow removal from images by exploiting semantic and geometric priors. The method incorporates semantic and geometric maps as input and learns a semantic-aware and geometry-aware representation to remove snow. Experiments on synthetic and real-world snowy images show that the proposed method offers better results both quantitatively and qualitatively.

Hahner et al. (2022) addresses the problem of LiDAR-based 3D object detection under snowfall by proposing a physically based method to simulate the effect of snowfall on real clear-weather LiDAR point clouds. The method samples snow particles in 2D space for each LiDAR line and uses the induced geometry to modify the measurement for each LiDAR beam accordingly. It also simulates ground wetness on LiDAR point clouds. The method is used to generate partially synthetic snowy LiDAR data and then use this data to train snow-resistant 3D object detection models. The evaluation shows that the simulation consistently yields significant performance gains on the real snowy STF dataset compared to clear-weather baselines and competing simulation approaches while not sacrificing performance in clear weather.

Ding et al. (2022) address the problem of object detection in snow by first establishing a real-world snowy object detection dataset, named RSOD. The paper also develops an unsupervised training strategy with a distinctive activation function, called Peak Act, to quantitatively evaluate the effect of snow on each object. This helps grading the images in RSOD into four-difficulty levels. The paper also proposes a novel Cross Fusion (CF) block to construct a lightweight object detection network based on YOLOv5s (call CF-YOLO). CF is a plug-and-play feature aggregation module, which integrates the advantages of Feature Pyramid Network and Path Aggregation Network in a simpler yet more flexible form. Both RSOD and CF lead the CF-YOLO to possess an optimisation ability for object detection in real-world snow. The experiments show that the CF-YOLO achieves better detection results on RSOD, compared to SOTAs.

Cheng et al. (2022) propose a Snow Mask Guided Adaptive Residual Network (SMGARN) to tackle the problem of image restoration under severe weather, specifically snow. SMGARN consists of three parts: Mask-Net, GuidanceFusion Network (GF-Net), and Reconstruct-Net. The Mask-Net, is built with Self-pixel Attention (SA) and Cross-pixel Attention (CA) to capture the features of snowflakes and accurately localise the location of the snow, thus predicting an accurate snow mask. This mask is then sent into the specially designed GF-Net to adaptively guide the model to remove snow, and an efficient Reconstruct-Net is used to remove the veiling effect and correct the image to reconstruct the final snow-free image. The experiments show that the proposed method numerically outperforms all existing snow removal methods, and the reconstructed images are clearer in visual contrast.

Ye et al. (2022) develops a novel Efficient Pyramid Network with asymmetrical encoder-decoder architecture for real-time HD image de-snowing. The proposed network utilises multi-scale feature flow fully and implicitly mines clean cues from features. Compared with previous state-of-the-art de-snowing methods, this approach achieves a better complexity-performance trade-off and effectively handles the processing difficulties of HD and Ultra-HD images. The experiments on three large-scale image de-snowing datasets demonstrate that this method surpasses all state-of-the-art approaches by a large margin, both quantitatively and qualitatively, boosting the PSNR (Peak Signal-to-Noise Ratio) metric from 31.76 dB to 34.10 dB on the CSD test dataset and from 28.29 dB to 30.87 dB on the SRRS test dataset.

S. Chen et al. (2023) present a snow removal method using a parallel network architecture split along the channel based on the vision transformer to remove snow in a single image. The method includes the MSP module, which utilises multi-scale AvgPool and multi-scale projection self-attention to improve the representation ability of the model under different scale degradations and a lightweight and simple local capture module. The method outperforms the state-of-the-art methods with fewer parameters and computation, as demonstrated by the experiments on three snow scene datasets.

Bae et al. (2022) propose a novel self-supervised learning framework for removing snow points in LiDAR point clouds. The method exploits the structural characteristic of the noise points: low spatial correlation with their neighbours. Consists of two deep neural networks: Point Reconstruction Network (PR-Net) and Reconstruction Difficulty Network (RD-Net) which reconstructs each point from its neighbours and predicts point-wise difficulty of the reconstruction respectively. With simple post-processing, the method effectively detects snow points without any label and achieves state-of-the-art performance among label-free approaches and is comparable to the fully supervised method. Additionally, the method can be exploited as a pretext task to improve label-efficiency of supervised training of de-snowing.

S. Chen et al. (2022) propose a novel transformer, SnowFormer, to handle the challenging task of single image de-snowing, which is a difficult image restoration task due to various and complicated snow degradations. SnowFormer explores efficient cross-attentions to build local-global context interaction across patches and surpasses existing works that employ local operators or vanilla transformers. SnowFormer has several benefits over prior de-snowing methods and universal image restoration methods. Firstly, it incorporates the multi-head cross-attention mechanism to perform local-global context interaction between scale-aware snow queries and local-patch embeddings. Second, the snow queries in SnowFormer are generated by the query generator from aggregated scale-aware features, which are rich in potential clean cues, leading to superior restoration results. Third, SnowFormer outshines advanced state-of-the-art de-snowing networks and the prevalent universal image restoration transformers on six synthetic and real-world datasets.

Wolf et al. (2022) propose an algorithm called EBSnoR (Event-Based Snow Removal) for removing snow in event-based camera data by measuring the dwell time of snowflakes on a pixel and using it to partition the event stream into snowflake and background events. The algorithm was tested on a new dataset called UDayton22EBSnow and showed that it correctly identifies events corresponding to snowflakes and improves the performance of event-based car detection algorithms when applied to preprocess event data.

Lin et al. (2022) presents a lightweight snow removal network called Laplace Mask Query Transformer (LMQFormer) which utilises a Laplace-VQVAE (Vector Quantization Variational Autoencoder) to generate a coarse mask of snow, reducing both the information entropy of snow and computational cost. The network, called Mask Query Transformer (MQFormer), uses parallel encoders and a hybrid decoder to learn extensive snow features under lightweight requirements. A Duplicated Mask Query Attention (DMQA) converts the coarse mask into specific queries which constrains the attention areas of MQFormer with reduced parameters. The experiments show that the proposed model achieves state-of-the-art snow removal quality with significantly reduced parameters and the lowest running time.

Karavarsamis et al. (2022) present a novel model called Cross-stitched Multi-task Unified Dual Recursive Network (CMUDRN) that targets the task of unified de-raining and de-snowing in a multi-task learning setting. The model uses cross-stitch units to enable multi-task learning across two separate DRN models, each tasked for single image de-raining and de-snowing, respectively. The proposed model can enable blind image restoration for the two underlying image restoration tasks, by unifying task-specific image restoration pipelines via a naive parametric fusion scheme.

Yu et al. (2022) have developed an unsupervised de-noising algorithm, LiSnowNet, for LiDAR point clouds corrupted by snowfall that is 52x faster than existing methods and achieves superior performance in de-noising. The algorithm is based on a deep convolutional neural network and can be easily deployed to hardware accelerators. Additionally, the method can be used for mapping even with corrupted point clouds.

Vachmanus et al. (2022) describe a method for detecting snowy roads in a forest environment using an RGB camera. The method uses noise filtering and morphological operations to classify image components and assumes that all roads are covered by snow. The performance of the algorithm is evaluated using two error values, with results showing high efficiency for detecting straight roads but low performance for curved roads.

2.4.2 3D Point Cloud Reconstruction

Xiang et al. (2022) propose SnowflakeNet, a point cloud completion method that addresses the issue of discrete nature of point clouds and unstructured prediction of points in local regions. Point cloud completion is a crucial task in the field of automated driving, as it allows the car to perceive and understand the environment around it. Automated vehicles rely on a variety of sensors, including LiDAR, to create point clouds that represent the surrounding environment. However, these point clouds are often incomplete due to occlusions or other factors, which can limit the car’s ability to navigate safely. When driving in snowy weather, it can be challenging to accurately perceive the environment using LiDAR sensors, as snowflakes can scatter and absorb light, leading to incomplete or inaccurate point clouds. The use of SnowflakeNet and SPD, which are specifically designed to complete point clouds with high accuracy from partial observations, could help to mitigate these challenges and improve the car’s ability to perceive the environment even in snowy weather.

2.5 Visual Infrastructure Support

Camera-only models perform poorly under challenging conditions, but including multiple modalities (radar, LiDAR) allows much better generalisation ability, according to Almalioglu (2022). They introduced geometry-aware multimodal ego-motion estimation (GRAMME), combining multiple sensors and pre-trained models. This is done by combining DepthNet (a depth map from paired stabilised pinhole images) and VisionNet (self-motion prediction). RangeNet and MaskNet use LiDAR and radar to predict self-motion and input masks. Everything is fed into a spatial transformer that geometrically reconstructs the scene.

A lightweight, real-time fusion method was proposed in Liu et al. (2022). The fusion approach makes up for impaired vision and tracking under severe weather conditions. Elhousni et al. (2022) presents a unique approach based on LiDAR point clouds and OpenStreetMaps (OSM) via a particle filter to ensure vehicle localisation accuracy when GPS is missing. The OSM modality generates simulated point cloud images and adds geometrical restrictions (e.g., roads) to improve the particle filter's ultimate outcome. The proposed approach is deterministic and does not require labelled data. Using the KITTI dataset, it accurately tracks vehicle pose with a mean error of less than 3 m. This method is more accurate than OSM or satellite-based methods.

However, cameras and LiDAR do not necessarily work together in snowy environments. LiDAR may not be able to recognise the changed shape from snow cover. Yanase et al. (2022) propose a solution that uses radar data when rain or snow is obstructing the LiDAR data. Analysing if the road surface pattern is visible or not is critical for using this approach, which is solved through a deep learning estimation method.

2.5.1 Reflective landmarks

Reflective landmarks combined with laser range and bearing is a well-known method for localisation and map-building (Guivant et al., 2000). Compared to GNSS positioning it has limited accuracy and reliability. That is not to say it cannot be used as assistance in certain cases, for instance when GNSS signal coverage is missing. Reflective landmarks with laser range and bearing could also be used in cases with degraded quality of HD maps, i.e., because of damages to road infrastructure or markings. The recent influx of cars with advanced sensors has led to some notable research in localisation using such landmarks.

Zaganidis et al. (2017) propose a method for introducing semantic information extracted from point clouds into the Normal Distributions Transform (NDT) registration process and present a large-scale experimental evaluation of the algorithm against NDT on two publicly available benchmark datasets, showing improved accuracy, robustness, and speed, especially in unstructured environments. Zaganidis et al. (2018) extend the NDT registration pipeline by using PointNet, a deep neural network, to learn and predict per-point semantic labels, and present an ICP equivalent of the algorithm. The performance of the proposed algorithm, SE-NDT, is evaluated against the state of the art in point cloud registration on publicly available classification data set Semantic3d.net and on dynamic scenes from the KITTI dataset. The experiments demonstrate the improvement of the registration in terms of robustness, precision, and speed, across a range of initial registration errors, thanks to the inclusion of semantic information.

Z. Zhang et al. (2018) created a tutorial with methods for quantitatively evaluating the quality of an estimated trajectory from visual-inertial odometry (VIO) The methods include determining the transformation type to use in trajectory alignment based on the specific sensing modality (i.e., monocular, stereo, and visual-inertial) and describing commonly used error metrics (i.e., the absolute trajectory error and the relative error) and their strengths and weaknesses. The tutorial generalises the formulation to any given sensing modality and publicly release implementation to facilitate reproducibility of related research.

Fiducial markers are commonly used to localise robots, but existing systems using standard cameras suffer in low-light conditions and on computationally constrained processors. Davis et al. (2019) propose using 3D light detection and ranging (LiDAR) scanners to mitigate these issues by creating a custom "beacon" with reflective fiducials and designing a high-performance segmentation and localisation algorithm to find the 2D pose of a mobile robot. The experiments showed that the system achieved an average Euclidean error of less than 0.063 m at ranges of over 10 m while maintaining a runtime of under 3 ms on a basic single board computer, and it is highly occlusion resistant, as confirmed by multiple field tests.

Ghallabi et al. (2019) solve a localisation problem by matching road perceptions from a 3D LiDAR sensor with HD map elements, using a particle filtering algorithm that estimates the position of the vehicle by matching observed High Reflective Landmarks (HRL) with HD map attributes. The proposed approach extends previous work by the authors on a localisation system based on lane markings and road signs and experiments have been conducted on a highway-like test track using GNSS/INS with RTK corrections as ground truth. The obtained accuracy of the localisation system is 18 cm for the cross-track error and 32 cm for the along-track error.

Most of the SLAM approaches use natural features that are unstable over time, repetitive or insufficient for robust tracking. Munõz-Salinas et al. (2020) propose a novel SLAM approach by fusing natural and artificial landmarks for long-term robust tracking in many scenarios. The proposed method is compared to the state-of-the-art methods ORB-SLAM2, LDSO and SPM-SLAM in the public datasets Kitti, Euroc-MAV, TUM and SPM, obtaining better precision, robustness and speed. Their tests show that the combination of markers and key points achieve better accuracy than each one of them independently.

Figure 3: Road signs designed for machine readability (concept art created by Midjourney AI)

S. Wang et al. (2021) propose and implement a lightweight, ”real-time” localisation system (SORLA) with artificial landmarks (reflectors) that only uses LiDAR data for laser odometer compensation in high-speed or sharp-turning scenarios and theoretically, the feature-matching mechanism of the LiDAR, locations of multiple reflectors are not limited by geometrical relation. A series of algorithms are implemented to find and track the features of the environment, such as the reflector localization method, the motion compensation technique, and the reflector matching optimisation algorithm, which guarantee the algorithm’s precision and robustness in high speed and noisy background. Experimental results show that the SORLA algorithm has an average localisation error of 6.45 mm at a speed of 0.4 m/s, and 9.87 mm at 4.2 m/s, and still works well with the angular velocity of 1.4 rad/s at a sharp turn. The recovery mechanism in the algorithm could handle the failure cases of reflector occlusion, and the long-term stability test of 72 h firmly proves the algorithm’s robustness. The authors argue that the strategy used in the SORLA algorithm is feasible for industry-level navigation with high precision and a promising alternative solution for SLAM.

Kotilainen et al. (2019) introduce the concept of so-called “active poles”, which are snow poles equipped with ultra-wideband (UWB) beacons. The authors demonstrate that such poles at known locations, can provide localisation for vehicles. Due to the natural properties of the UWB signal, the localisation is weather invariant, and was not influenced by temperature, humidity, or snow.

2.5.2 Road markings visibility

Retro-reflectivity and daytime visibility are critical factors for both human drivers and the machine vision (MV) used by automated vehicles. Tests performed by Händel et al. (2019) investigated the influence of winter conditions on passive radar reflectors. They concluded that winter phenomena, such as blowing snow, could influence the reliability of such reflected radar signals. Increased speed of vehicles further reduced reliability.

Eight materials, varying in colour and retro-reflectivity, were tested for visibility by LiDAR and by cameras in rain, fog, and incoming vehicle glare (Burghardt et al., 2021). The response of MV equipment depends on the equipment, the road markings’ retro-reflectivity, structure, colour, and glass beads. Overall, the highest MV intensities were measured with ”premium” glass beads and white road marking tape. Orange paint’s LiDAR recognition in dry conditions was disproportionate to its retro-reflectivity. Greyish paint imitated heavily weathered marks. ‘Premium’ glass beads enhanced camera contrast ratio in rain and fog, but not LiDAR intensity. Moisture reduced the contrast ratio by 80% (range: 69–86%) and the LiDAR response intensity by 84% (range: 72–96%). The authors suggest that can be used to generate MV-recognisable road marker materials.

2.6 HD Maps

High-definition (HD) maps are digital maps that create a representation of roads as they are in real life, as accurately as possible. As such, these maps also contain rich semantic data about the road and its surroundings. The semantic data contributes traditional mapping information about lanes, roads, and traffic rules. This can be spatial or categorical information, and the accuracy can be at the level of centimetres. Thus, HD maps are a core component of applied automated. They provide the basis for the agents to self-localise in their surrounding topology. Further, urban environments are of special interest due to their complexity (Zhou et al., 2021).

The general procedure used to generate HD maps is to use 3D point clouds combined with relevant semantic information (Elhousni et al., 2020). Such 3D point clouds are usually collected using LiDAR. It is a 3D laser scanning device that is mounted on top of a vehicle. As such, the device can monitor all topologies surrounding the vehicle. Radar and cameras are also used to provide additional information. The various sensor scans are then combined to produce a visual representation of the scene. Human specialists then annotate the scene manually, creating the semantic properties. Automating the annotation process by means of AI and ML has been undertaken by models such as HDMapGen (Mi et al., 2021). This model proposes a hierarchical graph generation architecture “capable of producing high-quality and diverse HD maps through a coarse-to-fine approach”. The focus was on generating lanes represented as geometric polylines. A natural requirement would be that the control points are fine-grained enough for reconstruction on a map.

A new type of transformer network that can be used to map images and videos to a bird’s-eye-view (2D map) of the world in a single end-to-end network was introduced by Saha et al. (2022). This network is based on a 1-to-1 correspondence between a vertical scanline in an image and rays passing through the camera location on a map. This formulation allows the network to use the context of the image to interpret the role of each pixel, leading to a restricted convolutional transformer network that is efficient and effective. It achieves state-of-the-art results on three large datasets.

2.6.1 Automatic Labelling for Supervised Learning

Historically, one of the central limitations of supervised machine learning has been curating labelled training data. Automatic labelling is the process of putting labels on data as a whole or on each individual piece of data. It is a special instance of a general problem in machine learning involving the construction of a model that translates inputs into outputs. The challenge of mapping data to a fixed set of labels is known as automatic labelling. The labels are selected from a predetermined set. The issue is especially significant for the development of supervised machine learning systems, in which a model is constructed to map input to labels using a collection of labelled training data. In this instance, the challenge of automatic labelling can be viewed as the mapping of data to labels that can be utilised as training data. Naturally, this challenge persists in the quest for autonomous driving (X. Chen et al., 2022).

2.6.2 Privacy

Privacy concerns related to automated vehicles arise from the use of LiDAR and camera systems that collect information about individuals on roads and streets. While these technologies are crucial for vehicle navigation and safety, they can inadvertently capture personal details about pedestrians, cyclists, and other road users. To mitigate these risks, it is essential to implement data anonymisation techniques that strip away identifiable information before storage or processing. By anonymising the collected data, it should be possible to strike a balance between harnessing the potential of automated vehicle technology and preserving the privacy rights of individuals in public spaces. Recent research using deep learning models in the field of anonymisation has shown great promise (Hukkelås et al., 2019; Hukkelås et al., 2023).

2.6.3 Synthetic Data

Machine learning techniques benefit greatly from large amounts of labelled data. There are several fields where it is impractical and prohibitively expensive to acquire data. Because of this problem, scientists have started looking into ways to train machine learning algorithms with artificial, or synthetic data. This is data that has been generated by a process that is intended to mimic the process that generated the real data. We review the approaches established for using synthetic data in the generation of HD maps for automated driving.

While synthetic data cannot fully replace real-world data, it can be a useful tool for addressing some of the challenges posed by snowy weather for automated vehicles. For example, synthetic data can be used to:

- Increase the amount of training data available for the vehicle’s algorithms: By generating large amounts of synthetic data, it is possible to train the vehicle’s algorithms to better handle the unique challenges posed by snowy conditions. This can help to improve the performance of the algorithms in these conditions.

- Test the vehicle's algorithms in a controlled environment: Synthetic data can be used to test the vehicle's algorithms in a controlled environment, which can help identify and address any potential issues or weaknesses. This can be particularly useful for testing algorithms in challenging conditions, such as snowy weather, that may be difficult or dangerous to test in the real world.

- Generate data for scenarios that are difficult or impossible to collect in the real world: Synthetic data can be used to generate data for scenarios that are difficult or impossible to collect in the real world. For example, it may be possible to generate synthetic data for extremely rare or dangerous scenarios, such as heavy snowstorms or blizzards, that would be impossible to collect in the real world.

DeepRoad is an unsupervised DNN-based platform for testing automated driving systems online. DeepRoad synthesises driving situations without image processing rules (e.g., scale, shear, and rotation). DeepRoad can generate driving scenes with diverse weather circumstances (even extreme ones) using generative adversarial networks (GANs) and real-world weather situations. DeepRoad uses metamorphic testing to assess system consistency with generated pictures. DeepRoad validates DNN input photos by comparing them to training images using VGGNet features. DeepRoad can discover hundreds of conflicting system behaviours and evaluate input photos to improve system robustness (M. Zhang et al., 2018).

Several other studies have also sought to produce syntethic data. In Von Bernuth et al. (2019), photo-realistic snow and fog was simulated and added to existing images. The authors proposed that this approach can be used for generating training data from pre-collected image data. Synthetic training data was used to classify weather in Minhas et al. (2022). Simulated snowfall was included in the training data in Hahner et al. (2022). Another approach, involving a novel de-snowing algorithm for LiDAR images, was proposed by W. Wang et al. (2022). in 2022, researchers from MIT open-sourced their "photorealistic" simulator for automated driving called "VISTA 2.0" (Amini et al., 2022).

Particularly interesting for this report, is a dataset for semantic scene understanding in adverse weather created by Sakaridis et al. (2021). Four main categories of adverse conditions were investigated: fog, nighttime, rain, and snow. For each scene (image), a corresponding image was also taken under normal conditions. A binary mask could also tell the difference between clear and unclear semantic content within an image (See also Lei et al. 2020).

2.7 Discussion

After being foreshadowed for many years, robotaxis (a recent term that generally refers to SAE level 4 or 5) are now a reality in select parts of the city of San Francisco. The robotaxi company Cruise reported close to 3000 driverless taxi rides in the last quarter of 2022. Only one collision was reported during this period, and no human injuries (Hawkins, 2023). Even with resistance mounting from multiple angles, it appears clear that SAE level 4 and 5 is possible, and already here in limited cases. However, it is no coincidence that companies that are ahead of the competition, such as Waymo and Cruise, are testing or introducing their robotaxis in cities with favourable weather conditions, such as Phoenix and Arizona. These are among the driest cities in the US (Stumpf, 2022). Precipitation in any form is a challenge for automated vehicles, as it impacts not only their sensors, but also their driving ability. In fact, Cruise's permit from the Californian DMV regarding their automated cabs clearly states that robotaxis should not operate in weather worse than light rain or light fog. The permit specifically mentions snow, fog, black ice and wet road surfaces as conditions the automated vehicle should identify and is incapable to operate reliable under ("DMV Approves Cruise and Waymo to Use Autonomous Vehicles for Commercial Service In Designated Parts Of Bay Area" 2021).

The limitations facing automated driving in colder weather conditions presented in this state-of-the-art should give directions for future research in the area. These limitations will persist especially in the Nordic region which faces harsh winter weather during much of the year. Many current research endeavours focus on snow removal (de-snowing) from sensor or camera data. The motivation for this direction has a clear and concise rationale. Performant and efficient (computational wise) de-snowing of sensory data would let automated vehicles operate in winter conditions with algorithms that already works in clear, summer weather. To the best of the author's knowledge, end-to-end solutions that aim to learn the relationships between snowy sensory data and the subsequent image segmentation tasks are much rarer.

Reliable localisation requires not only accurate sensor hardware, but also accurate and up-to-date HD maps of the area in which the vehicle is operating. In many cases, these maps may not be available or may not be accurate enough to fully support automated driving. This can pose significant challenges for the reliable operation of automated vehicles, particularly in areas that are unfamiliar or where the environment is constantly changing.

The introduction of artificial landmarks, fiducial markers or "active poles" are promising directions for assisting automated vehicles in localisation. Especially during an introductory period, until consistent and high-performant HD-maps are established, such landmarks could provide an early boost for the introduction of automated vehicles in winter weather.

One issue with using artificial landmarks is that they may require significant infrastructure investments, and it may not be feasible or cost-effective to deploy them in all areas where automated vehicles operate. Especially in sparsely populated countries such as Norway this problem would be exacerbated. Additionally, the reliability of these markers could be impacted by factors such as weather conditions or vandalism.

Reinforcement learning from simulated worlds has also proven efficient in many fields, especially in cases where the full state space can be efficiently simulated. This approach requires large amounts of data to train the machine learning models. However, self-driving in real traffic conditions is a very complex task and there is no guarantee that the models will generalise well to new, unseen locations. It is unlikely that a simulation can capture all nuances and edge-cases that can appear in the real world (Dulac-Arnold et al., 2021). This problem persists even if the simulation is injected with real world data. The rarest edge cases are unlikely to have happened also in the real world, and as such would be unseen data for the machine learning algorithm.

Finally, the challenge of using advanced sensor data on unseen locations underscores the need for ongoing research and development in the field of automated driving. As technology continues to advance, it will be critical to develop new approaches and techniques that can support the reliable and safe operation of automated vehicles in a wide range of environments and conditions.

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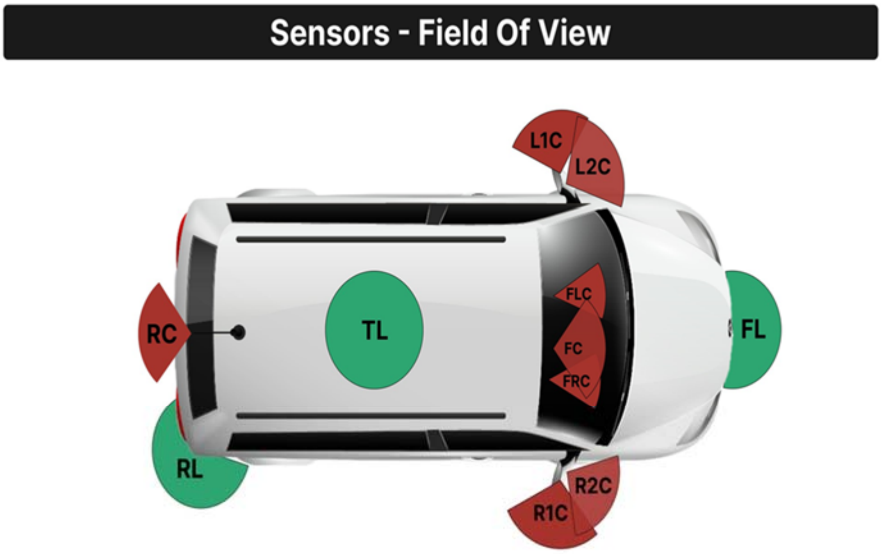
3 NTNU research platform for data collection

Kristoffer Tangrand

In the MCSINC project we address research gaps concerning automated driving (AD) under Nordic conditions by utilising a research platform for AD developed by Norwegian University of Science and Technology (NTNU). This is a dedicated vehicle equipped with both hardware and software (NVIDIA Drive), in addition to a range of different sensors, as seen in figure 4 and 5. This includes eight cameras (three forward-looking inside the car, two on each mirror (forward and backward looking to the side) as well as on backward looking), three LiDARs (one 360 degrees 128-channel at the top, one 180 degrees 16 channel in the front and one close to 270 degrees looking at the rear right side), two Radars (one forward-looking in the front and one rear backward-looking), two GNSS system with CPos corrections (highly-accurate). This will be a unique test bed to develop methodology and new knowledge for the overall project objective.



Device	Type
FL	Front lidar
TL	Top lidar
RL	Rear lidar
RC	Rear camera 120°
R1C	Right mirror side camera 120°
R2C	Right mirror front camera 120°
L1C	Left mirror side camera 120°
L2C	Left mirror front camera 120°
FC	Front camera 120°
FRC	Front right camera 60°
FLC	Front left camera 60°

Figure 4: Sensors in the NTNU research platform

Front LiDAR

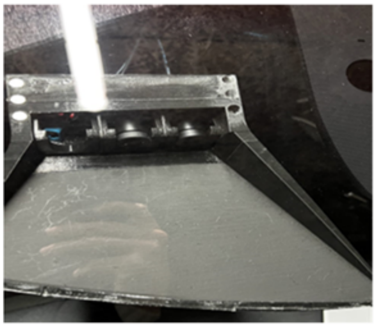
- Small, 16 beams LiDAR from Ouster
- Mounted on the front of the car
- Monitors objects and people approaching from the front
- Range up to 50 meters
- Connected to Nvidia Drive (AGX Xavier) via 100Gb switch

Rear Right LiDAR

- Small, 16 beams LiDAR from Ouster
- Mounted on the rear right side of the car
- Monitors people and cars approaching from the right side and behind the vehicle
- Range up to 50 meters
- Connected to Nvidia Drive (AGX Xavier) via 100Gb switch

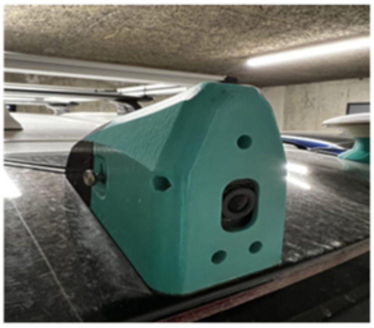
Big LiDAR

- Large, 128 beams LiDAR from Ouster
- Mounted on top of the car's roof
- Provides a comprehensive overview of surroundings
- Offers higher resolution data
- Range up to 260 meters
- Connected directly to Nvidia AGX unit



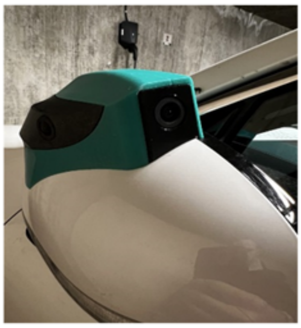
Front Cameras

- 3 front-facing cameras
- Sekonix Nvidia Drive Cameras
- Side cameras FOV of 60
- Middle camera FOV of 120



Rear Camera

- Rear-mounted camera
- FOV of 120°
- Monitors backside of car
- Assists in parking and reversing



Side Cameras

- 2 cameras on each side mirror
- Pointing in different directions
- Enhances blind spot monitoring
- 120° FOV

Figure 5: Information about the different sensors

4 Stakeholder requirements for vehicle machine sensing of the road infrastructure for automated driving

Janne Venæs and André Bekkevold Sande

4.1 Introduction

Work package 1 of the MCSINC project focuses on identifying demands and requirements for the future automated vehicle's ability to do machine sensing of the road infrastructure and environment, particularly under Nordic conditions. This chapter presents the main findings from a series of conducted interviews related to this topic. First, the methodology used for this task is explained in chapter 4.2. The main findings from the interviews are presented and discussed in chapter 4.3. Finally, recommendations for further work needed to proceed the development of vehicle machine sensing of the road infrastructure for automated driving in Nordic conditions are presented in chapter 4.4.

4.2 Methodology

To learn more about different stakeholder requirements for vehicle machine sensing of the road infrastructure for automated driving, we conducted 11 semi-structured interviews with representatives from 8 relevant actors from both the public and the private sector. In total, 14 informants were included in the interviews (See Table 1 below).

	Actor	Interview	Informants
	The Norwegian Public Roads Administration (NPRA)	2	2
	The Norwegian Mapping Authority (NMA)	1	1
	The Norwegian Data Protection Authority (DPA)	1	1
	The Norwegian Board of Technology (NBT)	1	1
	Troms and Finnmark County Council (TFFK)	2	2
	Technology provider one	1	1
	Technology provider two	1	1
	OEM	2	5
Total	**8**	**11**	**14**

Table 1: Overview of interviews

4.2.1 Sample of the study

The Norwegian Public Roads Administration (NPRA) is an important actor within this domain and is responsible for the overall strategies, but also for operation and maintenance of the highways in Norway. The two informants from the NPRA are working in the division for operation and maintenance and are experienced with controlling and analysing the road conditions using LiDAR and cameras. The informants are involved in checking the condition on the road surface during summer and investigating the quality of winter maintenance by measuring friction, road surface, temperature etc. Using artificial intelligence is one of the key innovation areas within this domain.

Troms and Finnmark County Council (TFFK) is also an actor responsible for management and is responsible for the county roads in Norway. The informants from TFFK work in the county's transport section, has experience from operation and maintenance, and has been part of innovation projects such as testing on-vehicle machine sensing using cameras, machine learning and object recognition. TFFK collects data from 4 500 kilometres of county roads every year using a vehicle with LiDAR and 360-degree camera.

The Norwegian Mapping Authority (NMA) collates, systemises, manages, and communicates public geographical information, including roads. Accordingly, they produce and manage national digital map series, operate the national registry for public property information and administrate services for determining accurate, satellite-based positions. The NMA is also a nationwide coordinator of geodata, including establishing and coordinating work with the national geographical infrastructure within Norway (Kartverket, 2021). The informant from the NMA is experienced with mobile mapping (mapping using LiDAR and camera data from a vehicle) and is involved in several research and development projects about precise positioning and maps linked to intelligent transport systems (ITS).

The Norwegian Data Protection Authority (DPA) is a public authority set up to protect the individual right to privacy, and supervise that authorities, companies, organisations, and individuals follow data protection legislation. The DPA uphold acts and regulations concerning data protection, but the Personal Data Act is the main legislation directing their work (Datatilsynet, n.d.). The informant from the DPA has long experience from the transport sector and cooperation with the NPRA and private companies within the road sector, with recent work related to ITS, smart cities and European standardisation.

The Norwegian Board of Technology (NBT) is a body for technology assessment and aims to assess impacts and options of technology and to support shaping of technological change and the political decision-making processes. The Board also monitors international technological trends and methods for technology assessment and foresight. They also use participatory methods in technology assessment to strengthen the voice of lay people and strengthen knowledge and debate on science and technology issues (Teknologirådet, n.d.). The informant from the NBT has experience from projects related to automated vehicles and other transport technologies.

The original equipment manufacturer (OEM) included in the interviews is a well-established European car manufacturer. Several informants from this OEM participated in the interviews, and they all had experience from research and development on safe vehicle automation and expertise from regulations and traffic rules relevant for automated driving functionality.

Two **technology providers** were interviewed. The first technology provider develop technology for road perception and vehicle onboard analytics. The informant has experience from working with connected services and monitoring the road and the road performance. The second technology provider is working on automated driving in all weather conditions and has been involved in several research projects.

4.2.2 Semi-structured interviews

To identify the possibilities and challenges of automated vehicle machine sensing under Nordic conditions and to learn more about different stakeholder requirements to use such solutions in the navigation system of such vehicles, e.g., for automated driving on public roads, we conducted 11 semi-structured interviews with 14 representatives from 8 relevant actors.

At the beginning of the project, we initiated discussions regarding suitable participants for the interviews, considering various criteria crucial to the recruitment process: i) we aimed to include representatives from both private and public actors, ii) it was essential for them to possess knowledge on machine sensing for automated driving, iii) we sought individuals well-versed in legal and ethical aspects concerning automated driving, and iv) we aimed to involve individuals with hands-on experience from operations and winter maintenance. This can be seen as a strategic selection of informants as we wanted actors that we knew would bring relevant reflections on vehicle machine sensing for automated driving operations under Nordic conditions into the interview (Tjora, 2012, s. 145). The final 11 informants ended up covering OEMs, technology providers and public authorities, with varying levels of knowledge to automated vehicle machine sensing and Nordic conditions. They are considered representatives for their respective organisations, but at the same time we need to remember that the interview outcomes originate from individuals and that opinions and experiences may differ within each organisation (Tjora, 2012, s. 145).

Prior to the interviews, we developed a semi-structured interview guide. However, as the different actors had various levels of knowledge and different expertise regarding vehicle machine sensing of the road infrastructure under Nordic conditions, the interviews and related questions were customised to each individual interview. The questions were separated into three main categories: i) challenges, ii) possibilities and iii) collaboration and areas of responsibility. For instance, they were asked about possible challenges with vehicle machine sensing under Nordic conditions for automated driving, with sub questions related to technology, regulations, winter conditions, road design etc. They were also prompted to discuss the requirements necessary for advancing the development of such technology. Furthermore, the informants were questioned about any ongoing collaboration with other entities involved in related topics.

All of the 11 interviews were conducted digitally, via Microsoft Teams. To succeed with this kind of interviews it is crucial to create a safe environment where the informants feel comfortable and relaxed (Tjora, 2012, s. 110). Therefore, the interviews started with some easy and general questions where the informants could share information about their background and experience with vehicle machine sensing for automated driving. These questions were also included to kick start their reflections and preparing them for the main part of the interview; i.e., questions requiring more reflection. Hence, the interview proceeded to questions related to challenges, benefits, and collaboration where the informants could share their knowledge, reflections, and experiences. The interviews were recorded and all of them were transcribed subsequently, which makes it easier to get an overview of the data material as a whole and contributes to structuring the data (Kvale & Brinkmann, 2015, s. 206). As the majority of the interviews were conducted in Norwegian the transcripts were written in Norwegian also. However, as this report is written in English, some of the quotes presented in the upcoming chapter are therefore translated from Norwegian to English.

4.3 Interview results

In this section the interview results are presented and discussed. The results are divided into three categories: *challenges and possibilities, added value* and *collaboration and areas of responsibility*. In chapter 4.4, we outline three recommendations for the future development of vehicle machine sensing of the road infrastructure for automated driving to secure operative conditions for such systems under Nordic conditions. When we refer to vehicle machine sensing we here mean both the sensor set equipment on the vehicle and the software, e.g., algorithms for sensor fusion, that process the sensor inputs.

4.3.1 Challenges and possibilities with vehicle machine sensing of road infrastructure for automated driving in Nordic conditions

In sum, this section highlights that all informants see the potential of societal benefits when vehicle machine sensing is being deployed, but there are several challenges that slow down the use of such technologies in society, ultimately slowing the realisation of these benefits of automated transport.

Vehicle machine sensing for automated driving is still under development

In the interviews, vehicle machine sensing as a part of the automated driving task is characterised as immature under Nordic conditions, and according to the interviews, most testing is executed under stable weather conditions. Machine sensing in the typical harsh Nordic conditions with snow, rain and wind is not a main focus area among the technology providers we interviewed. However, several of the interviewees point to a need for more knowledge on the performance of vehicle machine sensing under Nordic conditions. One of the technology providers stated that: "If you have snow or rain, it will affect your sensor data. And if you have not tried to compensate for that noise, then you will have that noise later in the decision making as well. And you will probably make wrong decisions."

> *The unpredictability of the world is so high.*
>
> *- Technology provider*

One technology provider said that most companies working on vehicle machine sensing base their development on so-called "vehicle centric decision making", where the vehicle must monitor what is happening around it and make decisions based on these observations. I.e., the vehicles will primarily rely on its own sensors and in-vehicle systems when making decisions. However, winter conditions are challenging for the vehicle centric decision making, for instance, lane markings may not be visible anymore, and the whole scenery in a street may change due to snow. The OEM and both the technology providers highlight the importance of redundancy and that the vehicles must use several types of sensors and data inputs to ensure that they sense the road correctly and that the systems are safe. The OEM said that "In order to achieve self-driving, we need redundancy in everything. We want sensors and various modalities."

However, the vehicle centric approach implies that external data sources, such as publicly available maps, or roadside equipment, are currently not considered as being a primary source of information for the navigation of automated vehicles, even though such external data sources could be argued to help the redundancy in conditions where the vehicles' sensors are compromised. This is a well-known technical, and organizational, challenge for the industry, that needs to be solved to develop stable solutions for vehicle machine sensing in Nordic conditions, and ultimately enable automated driving under winter conditions. Today, most effort is put into defining when and how to safely shut down the system if the limit of validity of the sensor input is reached.

> *Everything is software, which is basically making the decisions.*
>
> *- Technology provider*

Apart from the technology side, user acceptance, regulations and liability are mentioned as challenges for the implementation of automated vehicles, where Nordic conditions increases the complexity. Technology providers believe that there are some levels of acceptance among the users already, one stating that "I believe there is a general recognition already that some automated solutions are better than an average human driver". However, while also recognising that it is still a long way to go before every functionality in an automated vehicle can be deemed safe under Nordic conditions. Several aspects need to be investigated for the performance of vehicle machine sensing under such conditions, and where perhaps the most important question is to answer how to prove that an automated vehicle is safe.

According to the OEM and the technology providers the current national regulations provide enough room for development. The OEM explained that currently it is the vehicle functions rather than the regulations that limits automated driving in Nordic conditions. So far, within the current regulations on piloting and automated driving, most of the tests are performed at temperatures above zero and during daytime, according to the OEM. The testing of automated driving functions follows a step-by-step process, where the functionalities first are proven to work in the less complex contexts.

However, as the OEMs currently are in the starting phase of defining their relevant operational design domains (ODDs), within which environment and under which conditions the automated vehicle is designed to operate. Regulations might be needed to secure harmonisation of these ODDs across different OEMs and secure that they are defined also for Nordic condition. In this picture it is important that authorities facilitate testing automated solutions under more challenging conditions, such as heavy snow, low temperatures, and icy roads, and contribute to more realistic test scenarios and ultimately extending the ODDs. Today, the OEMs or technology providers in most countries in Europe have to apply to the authorities to get permission to drive automated within testing scenarios. Hence, making commercially viable products for automated driving is still in the early days, and more standardisation and harmonisation of regulations for automated vehicles are important issues for developing commercially viable products.

The liability part needs to be defined, because if you drive a commercial vehicle, it is always the human driver who takes true responsibility, but once you have automated driving, when is it the human driver that need to take the responsibility and when is it the system or when is it the car manufacturer?

- OEM

The OEM brings forward in the interview that they are responsible for the safe operation of the vehicle in the higher automation levels. As an example, the OEM used SAE level 3 driving with an Automated Lane Keeping Systems (ALKS), UN regulation 157, as an example when talking about challenges for vehicle machine sensing under Nordic conditions. There are still regulatory uncertainties regarding ALKS in countries which have signed the regulation. One country that has made it clear that vehicles with these functionalities are allowed to be driven on public roads, is Germany, which gave the first approval in Europe, where level 3 driving with ALKS is allowed on motorway under certain circumstances[1]. In Norway, there is not much discussion about how to use this specific regulation, according to the OEM. Discussion have revolved around whether it is allowed in Norway to activate the system and whether the drivers are allowed to use the functionalities as intended. Even when the vehicle is equipped with ALKS, human drivers might still be required to operate certain functionalities for instance in adverse weather.

The technology for automated driving is still under development, as well is the supply chain for vehicle machine sensing of the road infrastructure. There is uncertainty about who should have what role and who will be responsible for different areas within the field. Furthermore, smaller actors (with restricted resources) might find it especially challenging to enter this field according to the technology providers, due to the high uncertainty. This seems particularly true for infrastructure providers, who face the vehicle centric approach from most of the industry today and has to balance this with the current framework focusing on the human driver. An interviewee from the authorities highlights lack of competence and knowledge in the public sector (i.e., road authorities and road owners) as a critical barrier against realising societal benefits from vehicle machine sensing.

Physical and digital infrastructure for automated driving

The physical infrastructure such as narrow roads, narrow road shoulders, unpredictive curvature, as well as extreme events such as landslides or avalanches may represent a significant challenge to vehicle machine sensing systems for automated driving. One of the interviewees representing the authorities highlighted that the roads outside of the main network in Norway is a challenge: “County roads in Norway can be narrow. Some places, there is no room for more than one car in the width. You can simply forget about road

[1] See: https://etsc.eu/europes-first-cars-with-level-3-automated-driving-go-on-sale-in-germany/

markings, and obstacles can arise quickly." The Nordic countries also have more road wear and higher need for maintenance levels because of frost heave, ploughing, and studded tires – all of which contribute to deteriorating road conditions.

Determining the feasibility and realism of achieving increased maintenance is a major question. A backlog in terms of maintenance levels particularly on county roads would require increased funding for maintenance, but the benefit would be improved traffic safety for all travellers, including automated vehicles. This is a balancing act between many different needs in society. A respondent from the authorities stated that "One might argue that we should have wider roads and road markings, and that this would benefit everyone. But that won't happen", implicitly arguing that the costs for upgrading the physical infrastructure would be too high, despite the considerable benefits. The same goes for maintenance such as snow removal during winter season. For automated vehicles to have valid ODDs in these conditions, the maintenance requirements and contracts with entrepreneurs would need to be altered and most probably be more expensive, as a higher quality of the road infrastructure is expected to serve such vehicles, at least short term.

> *One can rather imagine more virtual signs and virtual road markings that make the vehicle aware of their whereabouts. Of course, it requires a lot of positioning accuracy, but I think it is more likely to be achieved.*
>
> *- Authorities*

A different approach to maintenance is through increased use of digital infrastructure, such as information and effective data sharing processes. This approach requires investments in solutions such as adequate positioning accuracy, securing connectivity and updating road infrastructure data base(s). Again, an obvious challenge is to uncover the requirements and needs from the vehicle centric approach. As an example, the authorities brought forward the challenge of signs getting covered by snow – making them impossible to read by cameras. A digital map with updated signs, communicated to the vehicles could provide redundancy in such Nordic conditions. The road authorities also highlight that they see high societal benefit if the vehicles could communicate back to the map when discrepancies are discovered, for instance wear and tear of traffic signs or road markings, or wrong placement of these.

The technology providers are also positive towards information exchange between the vehicles and the infrastructure. One technology provider stated that "the infrastructure must communicate with the vehicles, and the vehicles must communicate with the infrastructure, otherwise it [automated driving] will not work." From the OEM perspective it is more interesting to discuss the requirements towards the infrastructure when moving towards higher levels of automated driving. The OEM is clear on that there is an added value in communicating with the infrastructure, but such systems should be international to ensure interoperability across countries.

A point brought forward by one of the technology providers is that the data from the vehicles are currently being experienced "subjectively" by individual vehicles, while (more standardised) data provided from the digital infrastructure can be used to complement these vehicle-individual data. In particular, data from different vehicle manufacturers are difficult to compare as they use different sensors, different sensor fusion systems and so on. Hence, using information from the digital infrastructure will complement the vehicles' (individual) perception of the physical infrastructure.

Data sharing

Vehicle machine sensing involves processing sensor data capturing the road environment. Among these data sources are for instance cameras, making GDPR an important consideration, as the vehicle is filming its environment, including individuals. Sharing of such data with third parties, for instance in collective perception services, is problematic in terms of GDPR concerns since individuals have the right to get full insight into how their personal data are being used. Having the complete picture when sharing data with third parties is a major challenge, however, this is not relevant for all types of data used in automated driving systems (i.e., LiDAR, radar).

> *On the one hand, video recordings will be made of both what is outside the car, but also what is inside the car, in addition to audio recordings inside the car. It is very difficult to get the consent of everyone inside a car, and even worse if it is a small bus.*
>
> *- Authorities*

Collective perception services enable vehicles and infrastructure to exchange data and information so that each vehicle increase their perception beyond line of sight of its own sensors. For this purpose, the OEM and technology providers interviewed in this project are positive towards sharing their data. Enabling vehicles to see events further ahead on its route, providing more real time information is important, for example about the driving conditions or if there is emergency vehicles or operational vehicles along the route. Providing such information could help avoiding the so-called trolley-problem, i.e., the ethical dilemma of choosing who to save from being hit or killed by a trolley, or in this case an automated vehicle. The goal is to have enough information about the road conditions so that the vehicle would not have to deal with that dilemma at all, which ultimately will extend the ODD of the automated vehicle.

> *We are convinced that if a car is to be able to be used autonomously in a wide range of conditions, i.e. not only where the weather is very predictable, then the car must have a perception of how the road is going to behave in front of the car and ideally maybe 500 meters or 1 kilometre away.*
>
> *- Technology provider*

Collecting approvals from all drivers to share and exchange data was mentioned as a challenge by several of the interviewees, as the basis for processing of personal data is based on a voluntary consent. How to solve this challenge, both from an OEM and regulatory perspective, is something that needs further exploration. As the technology matures it is expected that the GDPR-related issues within automated driving will be handled as part of the permanent legislation. And with the current emerge of IoT (Internet of Things) systems, which the automated vehicles are a sub-component of, a cross-sectoral challenge in terms of regulation arises to cover all applications of a technology. For instance, regulations for storing and sharing vehicle data in Norway would involve at least three authorities, the national communication authority who typically covers communication protocols and internet security, the road authorities as the application owner, and the national data protection authority with particular focus on e.g., GDPR.

Also, to facilitate data sharing and management across Europe, there is a need for collaboration between the national authorities, such as the data protection authorities in European countries. One example of such a collaboration is the European Data Protection Board (EDPB), which among other seeks to harmonise the processing of personal data and the infringement fees across countries. "The

> *There is probably a lot of data that we don't know how to use. But if there had been a place, and you knew what actually is inside, then maybe someone else will find out "yes, but we can do this and that and that". But today is not like that. I think other authorities see it too, I just don't think they have the capacity to do it.*
>
> *- Authorities*

location of the main office of the OEM decides which national data protection authority is responsible for ensuring compliance to GDPR." Hence, if the main office is located in Sweden, it is the Swedish data protection authority that is given the responsibility among the European data protection authorities.

The authorities highlight the necessity for distribution of more real-time data from the infrastructure side. They want solutions where real-time information is distributed directly to the vehicles, bypassing the need for an app or a website where one have to manually verify whether the planned route has adequate driving conditions. For instance, adverse weather conditions, like heavy fog or snowy conditions, is already being detected by roadside sensors and it is envisioned as beneficial to be able to communicate data on such conditions directly to the vehicles. Technology providers agree that real-time data is needed, but they highlight the need for further standardisation of information sharing between the infrastructure and the vehicles. One example that was highlighted is the need for electronic traffic rules in English for all countries. Here, much effort is currently being spent, from standardising communication protocols for sharing of traffic information to the content of the data being shared, e.g., an open architecture for high definition maps. Relevant to this discussion, the OEMs highlighted the need for data quality and integrity. If data is provided directly to the vehicle from a multitude of sources, such as from the infrastructure, a standardised procedure for ensuring sufficient data quality and integrity is needed.

> *Thinking about higher levels of automation and more options in the functions, we can see a benefit in having the infrastructure connected digitally, so information will go to maps or cloud solutions etc. That is definitely something that will come in the future, and we will definitely facilitate.*
>
> *- OEM*

Machine sensing technologies are typically utilizing Artificial Intelligence (AI) solutions. The European AI Act is a legal framework for regulating AI by providing demands for providers, developers, and users, and was proposed by the European Commission in April 2021. The European Parliament approved its negotiating position in June 2023 and the AI Act is currently under negotiation between the European Commission and the EU member states[2]. Final approval is expected by the end of 2023. The OEM calls for greater clarity on the AI act's impact on other regulations for the automobile industry, which would serve as a guideline for how vehicle software must be developed and secured in the future. Currently, it is the vehicle manufacturer's responsibility to ensure the quality of the data provided from the vehicle.

> *What we would like is clarity on how the rules of the AI act will work alongside with the other technical and vehicle regulations for automobile industry.*
>
> *- OEM*

4.3.2 Added value of vehicle machine sensing of road infrastructure for automated driving in Nordic conditions

This chapter summarises the added value of vehicle machine sensing in Nordic conditions mentioned by the informants. The results show that they all see such technology as a potential data source to leverage from, possibility to increase societal benefits, especially increasing traffic safety and potentially solving the driver shortage.

[2] https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence

Vehicle machine sensing as data source for the transport authorities

Several of the interviewees see vehicle machine sensing as a highly useful data source already today, and highlight that benefits may be realised before higher SAE levels are reached as well. One example brought forward by the authorities is using sensors on plough trucks or operational vehicles to report road conditions. One interviewee from the authorities stated that: "The fact that we can check the entire road network with one person driving a car instead of people having to stop and get out can make it safer for those who will use the road". Even data collected and shared from private vehicles can be used as a source of information to detect road conditions. Another benefit is that vehicles with machine sensing capabilities could verify digital maps. Data from the vehicle could also be used for detecting the condition of for instance signs, railings, and snow poles, and with this reduce the need for manual labour (i.e., drive and check physically).

> *Having a LiDAR scanner on a plough truck that drives continuously on the stretch to have a look at the road conditions can be useful. But then it is extremely important with these back-end systems to get this information flowing. This information quickly becomes obsolete in wintertime.*
>
> *- Authorities*

The utilization of vehicle sensor data could increase reliability of data in national databases, and it could contribute to enhancing traffic safety for all road users and for workers along the road. However, for this to work, the authorities highlight the need for a well-developed backend system to have efficient data flow for these services, especially to provide real-time data where needed. For instance, authorities envision such data as a means to increase the quality of operation and maintenance of roads and for instance for LiDAR scanning on plough trucks used for reporting on driving conditions, needs to be as real-time as possible, even though the data processing of such a data source typically is massive.

The authorities recognise advantages with using vehicle machine sensing as a data source but are in many instances dependent on agreements with the OEMs and technology providers that owns the data. For this to become a reality, a business model that serves the needs of authorities, while given added value to the OEMs and technology providers is required.

> *You must have some data to interpret. [...] The challenge for the authorities is to obtain data quickly enough or often enough for them to be relevant. Or getting a business model that allows us to collaborate with those who have access to data.*
>
> *- Authorities*

Enhanced traffic safety by data sharing

The informants referred to several safety benefits associated with a data sharing platform, including information about the position of emergency vehicles and road work vehicles, or analysing emergency break information to identify hot spots for possible incident sites. Such services require data sharing between different actors in the transport ecosystem. The OEMs have the impression that the authorities' attitudes towards who should be responsible for operating a joint data sharing service also differ between different countries.

> *My understanding is that the authorities in Norway can imagine taking responsibility for a data sharing service. It looks like we can get a service where e.g. road workers and ambulances can share their position and OEMs can convey this to our drivers.*
>
> *- OEM*

4.3.3 Collaboration and areas of responsibility

This chapter presents the informants' thoughts on collaboration and areas of responsibility. There is a common perception across the stakeholder groups that more collaboration will be needed in the future for further developing and leveraging on vehicle machine sensing technology. As the supply chains for automated driving are not established yet, the actors need to think outside the established practices to obtain success in their collaboration.

Need for more collaboration

A challenge that is brought up during several of the interviews is the sharing of knowledge and data between the different stakeholders, and in particular utilising their strength collectively to achieve societal benefits. Most of the interviewees point towards the road authorities for a facilitating role, which could be natural due to their responsibilities in terms of regulation, procurement and possibly as a coordinator for sharing of data and making data publicly available. The public sector is often considered a reliable source and are experienced with these types of roles. However, at the same time securing the creation of viable business models are a real challenge.

> *There are private companies that make HD-maps, map bases and position services. But it is this with support for free competition, and that not only the largest global companies become competitive. If the public and private sector manage to cooperate and work together to keep the map base up to date for everyone and manage to find a business model that is acceptable to everyone, where everyone gets their benefit, then society as a whole will be better off.*
>
> *- Authorities*

Collaboration with the OEMs and technology providers is important for authorities. Both because they want to utilise the data collected by private actors, and because they want knowledge on what that future looks like and what needs to be considered when planning for a long-time perspective. One uncertainty for the authorities is the potential costs with operating and maintaining roads for automated vehicles as compared to conventional vehicles, and the authorities want input from and dialogue with the OEMs.

> *A future with automated driving should be taken into account when planning the transport sector, but I don't think that those who work with planning, operation and maintenance think about it. It probably has a lot to do with people's competence and knowledge.*
>
> *- Authorities*

In their collaboration with the authorities, some of the technology providers and OEMs say that they experience the public sector as bureaucratic. Particularly, this relates to tender processes for procurement of innovative transport technologies. One of the international technology providers say that: "In one way, it is always a challenge when business meets government, and almost all countries have laws on public procurements that can have a more or less of a pragmatic approach. […] It is not certain that whoever has the best technology will win. It is very frustrating". It is highlighted that the tender process could be quite different depending on the country, which is difficult to handle for smaller companies. Openness in dialogue with public entities is also a challenge, as the private actors do not want to disclose business sensitive information. This is a challenge that the actors work on by developing contracts or agreements that ensure the data is used according to the contractual agreement, which contributes to increased trust and better collaborating among the actors.

Technology providers also want to collaborate more with OEMs. Regulations from the authorities is also brought forward as key to realise the ambition of automated transport. For instance, it would be useful if the authorities could promise service levels for the roads or provide information if the road condition is beyond a limit, e.g., if there is more than two centimetres of snow on the road or if the road is slippery, so that technology can be developed to meet these given requirements and establish viable business models.

The OEM describes that collaboration with other OEMs is in many ways easier than collaborating with a public actor as both parties share an understanding that their respective businesses need to collaborate to meet their mutual needs. At the same time, in such collaborations, there is a greater risk of secrecy and withholding information. The OEM want collaborations that can lead to a federated system for data sharing that could easily be implemented in several European countries, with possible the authorities in a coordinating role as mentioned above.

As also stated earlier, collaboration between different national authorities is crucial in today's cross sectoral technological development, not only to understand the technologies and their possibilities, limits and challenges, but also to secure full benefits across public sectors, e.g., when collecting data that might be relevant and useful for more than one sector. As an example, collecting and sharing of georeferenced point clouds, where a national collaboration is established, however, still in its infant stage. Especially, understanding of each other's needs and procedures for collection and sharing of these types of data is not yet in place. For instance, Troms and Finnmark County Council has a LiDAR scanner mounted on the side of their multi-purpose measuring vehicle, which covers the terrain beside the road. However, the quality or usefulness of these data are not known and established. One solution could be to compare these data to the needs of the NMA in terms of collecting LiDAR scans of the whole nation for mapping purposes, or to set the procedures for how to share these data in a seamless way.

If we are to become good enough at this, I don't think we will be able to do everything ourselves or develop everything ourselves. It is completely impossible.

- Authorities

Innovative roles and responsibilities

In the interviews, the OEM highlights that vehicle machine sensing can more easily be achieved if innovative roles and responsibilities start to develop in the value chain of automated driving. However, it can be a challenge for stakeholders to dedicate resources to responsibilities that are beyond the scope or mandate of their organisation. The benefits of vehicle machine sensing for automated driving can in some cases materialise many years from now, so actors may need a long-term perspective to see the possible gains. At the same time, the authorities experience that the rapid development of technology forces short contracts and solutions because there can be different market leaders from one year to another. Thus, the process of establishing viable roles and responsibilities long-term is challenging.

The OEM perceive that collaboration with authorities and other OEMs on vehicle machine sensing has been fruitful in the past. However, occasional disparities between the stakeholders can lead to a sense of mutual misunderstanding, often related to expectations on responsibilities and roles. For instance, the OEM have experienced that the authorities focus primarily on their day-to-day operations, and that they could be reluctant to go beyond their area of responsibility, which then becomes a barrier. Nonetheless, there is a prevalent willingness to comprehend each other's challenges and work together toward solutions. When it comes to innovation processes like a research project, it is necessary for all actors to be able to discuss possible solutions for the challenges that is not within their original area of responsibility, here the research organisations have a particular important role in facilitating the discussions and being part of the technological development with the perspective and future responsibilities of all stakeholders in mind.

There must be a willingness to invest in this. So, we have to see a specific need, which I myself may not have yet, or be able to put numbers or words to.

- Authorities

4.4 Recommendations

Based on the interview results we have outlined three recommendations for the further development of vehicle machine sensing in Nordic conditions:

Recommendations

1) Stronger collaboration between the stakeholders involved in vehicle machine sensing under Nordic conditions.

2) Explore how a common data sharing service for vehicle and infrastructure data could be operated.

3) Explore how physical and digital infrastructure could be used to enable and support machine sensing under Nordic conditions.

Recommendation 1 – Stronger collaboration

The first recommendation is highlighting the importance of collaboration between authorities, the OEMs, and other industry stakeholders. To accelerate the development of vehicle machine sensing in Nordic conditions, the in-vehicle technologies and the physical and digital infrastructure should work together. Understanding the complex relationship between the stakeholders is important for gaining insight into the ecosystem, including both the ongoing innovations and developments in the industry as well as regulatory aspects. This was clearly highlighted in the interviews, both the importance of collaboration but also the different actors' desire for more collaboration across stakeholders. A deeper collaboration, sharing knowledge and utilising competence across stakeholders, will have several positive impacts. Firstly, this will build trust between different stakeholders with different roles and responsibilities, which is essential for proceeding the development of vehicle machine sensing in Nordic conditions. Secondly, when collaborating with the industry, the authorities (regulators and road owners) will gain insight into how, for instance, maintenance levels may need to change due to automated transport, such as whether winter maintenance need to change for supporting vehicle machine sensing technologies to cope with the Nordic conditions. Thirdly, a closer collaboration with the industry will provide the authorities with insight into the development of the technology, which will be important for the authorities when developing reasonable regulatory solutions. Finally, more collaboration can lead to more data sharing across actors in a safe and efficient way.

Recommendation 2 – A joint data sharing service

The second recommendation concerns the actors' desire for a joint data sharing service. As clearly shown in our interview results, all stakeholders want collaboration that can lead to a system for data sharing. The stakeholders are generating data (from vehicle, digital or physical infrastructure) and express interest in providing updated information about the road conditions and road environment, but as of today, the data sharing between stakeholders is limited. However, the different actors interviewed in this project, are positive towards contributing with data. Several positive benefits with data sharing were mentioned in the interviews: utilising existing data, also data that was collected for different purposes, and provide more real time information. To succeed with a data sharing service, this requires that someone takes responsibility for operating this service. In several of the interviews it was argued that the best solution for organising a data sharing service might be if a public stakeholder operated the service, as it would create more stability and a less competitive situation than if a commercial actor where appointed this responsibility. A data sharing service for vehicle machine sensing would require close collaboration across different sectors. In a long-term perspective with higher levels of automated driving, a federated system for data sharing is probably necessary, for instance for European countries, but this will require an established collaboration and trust between the different stakeholders across countries, as presented in recommendation one.

Recommendation 3 – Explore infrastructure for automated driving

The last recommendation concerns the importance of exploring the physical and digital infrastructure for automated driving. Infrastructure might be particularly important under Nordic conditions as sensors used for vehicle machine sensing might be impaired under these conditions. There are several challenges in the Nordic countries that have to be handled: narrow roads, bad road conditions, narrow road shoulders and road wear because of frost heave and ploughing, to name a few. In addition, there is a lot of harsh weather conditions, such as rain, heavy snow, ice and storms. The infrastructure is not built and operated for vehicle machine sensing. The technology and the infrastructure might need to be customised to enable machine sensing, but more testing under Nordic conditions is needed to explore these challenges. This can be most effectively done by collaborations (recommendation 1) and data sharing (recommendation 2) between the different stakeholders. Such an approach will enable the road authorities to be better prepared for the uncertain future ahead.

4.5 References

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