Deep Science Publishing
https://doi.org/10.70593/978-93-49307-21-6_9

Chapter 9: Applying machine learning for driver assistance systems and autonomous vehicle technologies

9.1. Introduction

As the number of vehicles increases worldwide, the traffic situation becomes increasingly complicated in terms of safety. The automotive industry has been developing various safety technologies, and driver assistance systems, such as headway distance control, automatic braking system and evasive steering system, have become one of the major features of a vehicle for the safety of the driver and passengers. The advanced driver assistance system (ADAS) has been developed to assist the driver for improved safety and better vehicle control. The ADAS equipped with advanced sensors and intelligent video systems is designed to alert the driver to potential traffic hazards or to take over control of the vehicle to avoid impending collisions and accidents. The ADAS is activated when the predetermined conditions for the driver's operation and the state of the vehicle are met. In conventional ADAS, a threshold is set for driver's control input. If the driver's control input is greater than the predetermined threshold, the ADAS is activated. Correct prediction of driver's intention is an essential part to determine whether the ADAS should engage to override the driver's control inputs. The lane change maneuver is one of the main causes of road traffic accidents. ADAS technologies, such as Lane Support Systems and Lane Keeping Assistance System (LKAS), enable automated lane control. The lane change control of the ADAS is based on the driver's control input and surrounding traffic situation. With the current technologies of the ADAS, there are possibilities of unwanted lane change against the driver's intention. To alleviate the risk of misjudging the driver's intention, many studies have attempted to incorporate machine learning techniques to identify the driver's intention for lane change control with the ADAS. Machine learning has proven its utility in estimation, classification and prediction of system behaviors. For identification of the driver's intention, many researchers have investigated classification techniques, such as Hidden

Markov Model (HMM) and Support Vector Machine (SVM). By observing their environment, humans are enabled to drive road vehicles safely. Vehicle passengers perceive a notable difference between inexperienced and experienced drivers. The latter ones anticipate what will happen in the next few moments and consider these foresights in their driving behavior. To make the driving style of automated vehicles comparable to human drivers, anticipation skills need to become a built-in feature of self-driving vehicles. This provides a comparison of methods and strategies to generate this intention for self-driving cars using machine learning techniques. They use a large data set collected over more than 30000 km of highway driving and containing approximately 40000 real-world driving situations. They show that it is possible to classify driving maneuvers upcoming within the next 5s with an Area Under the Curve above 0.92 for all defined maneuver classes. This enables them to predict the lateral position with a prediction horizon of 5s with a median lateral error of less than 0.21m.

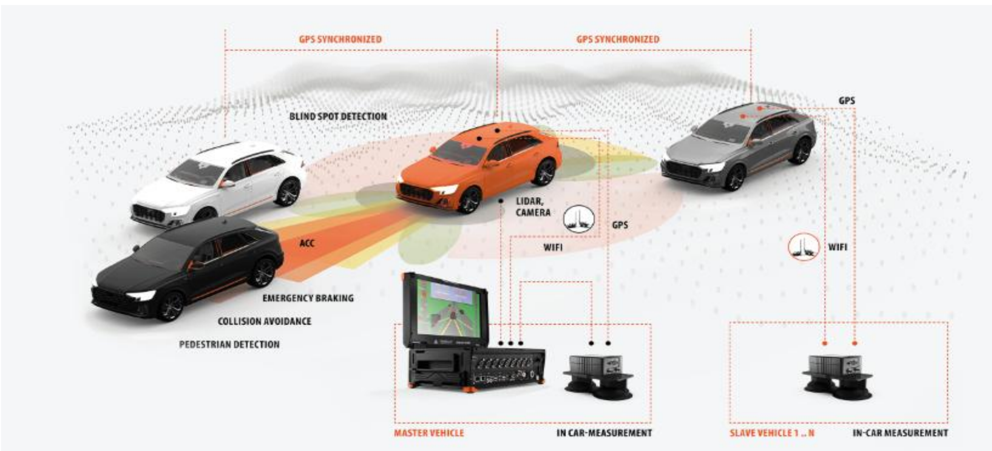

Fig 9.1: Advanced Driver Assistance Systems (ADAS)

9.1.1. Background and significance

A driver assistance system utilizes belonged sensor information from a vehicle for monitoring the driving situation. It also may have utilized a high-level driver input such as the lane change to project a predicted driving situation. Thus, one application area of driver assistance systems is aimed at supporting the driver decision by indicating the most probable lane change for driver intentions. In this point of view, one interesting research task is the driver intention recognition in which a driver’s intention of lane change can be predicted for pre-determined lanes of a decision-making area. In this area, by detecting a driver's intention sooner, a better anticipation of a vehicle trajectory can be achieved, since the driver input for a predicted maneuver would be known.

Further, the estimation of the complex motion state of the vehicle is an important issue for understanding and modeling the driving behavior of cars, which can be utilized for intelligent transportation systems. On-board sensors measure the vehicle's speed and yaw rate, and IMU measures the vehicle's tri-axial accelerations and angular motion. Some state variables which can provide a comprehensive index for the vehicle's motion characteristics can be detectable by processing the measurements from the on-board sensors and combination with vehicle characteristics. Thus, such estimated state variables can be the input for modeling analysis respectively to instantaneous or short-time motion of the vehicle. So far, the research that focuses on the construction of vehicle state estimation algorithms by integrating the information from the on-board sensors still has been continued actively, and recently lots of methods have been introduced.

By employing a motion state estimator which can provide a comprehensive index, the modeling of the driving behavior can be extended to a fusing model. The fusing model which goes well with different driving maneuvers including cornering is proposed. The applicability of the model is illustrated by analyzing the modeling results with the driver conducted data, which includes various speed and driving situations. To the best of the authors' knowledge, such a motion state estimation algorithm together with a modeling for driver behavior has not yet applied an advanced intelligent vehicle, which should be one of the future works. Additionally, many advanced features for ADAS and IT'S such as lane change intention prediction are based on the modeling and design of various methods.

9.2. Overview of Driver Assistance Systems

The development of automated driving (AD) is to meet the driving assistant demands in real-world situations. The architecture of automated driving can be categorized as environment perception, behavior planning and motion control. Based on the implementation of automated driving and the responsibility of driving behaviors, automated driving is classified from level 0 (fully human control) to level 5 (fully automated driving). In reference to the classification, ADAS merely reaches up to level 2, which assumes duties such as detecting the surroundings of vehicles, warning drivers for emergencies and carrying out simple control functions including speed control and adaptation, emergency brake execution. Currently, most commercial vehicles only support self-driving up to level 2 to assist human driving. The existing implementation of automated driving mainly reaches up to the class of ADAS. For this reason, it is worthwhile to summarize current applied ADAS functions and implementations. ADAS focuses on reducing human-related errors and avoiding potential traffic accidents. Transportation safety improvements, eliminating distractions, a comprehensive strategy to reduce speeding-related crashes, collision avoidance systems in all new highway vehicles and reducing fatigue-related accidents are all in the top recommendations. All the above requirements can be components of ADAS. ADAS was first introduced in the commercial vehicle market with the feature of ABS in the late 1980s. These kinds of ADAS functions were initially provided as luxury features for upscale brands. However, ADAS has developed rapidly since 2000, thanks to related automated driving competitions. It is now a complex and well-developed system composed of both hardware architecture for perception and software design for post processing. It improves driving comfort by helping or reshaping driving behaviors and avoids traffic crashes to ensure driving safety.

9.2.1. Definition and Purpose

With the rapid growth of the automotive industry and an increasing number of vehicles on the road, the safety and efficiency of traffic systems have become increasingly important. While there have been spectacular changes in the automotive design aspect due to modern industrial production technology, traffic situations are becoming more complicated and intertwined with vehicles than ever before. In order to keep up with this shift, the automotive industry has been developing various safety technologies. Over the years, driver assistance systems such as headway distance control, lane change support, automatic braking system, evasive steering system, and speed limit control have become one of the major features of a vehicle. Among many reasons, safety of the driver's vehicle and its surrounding vehicles from car accidents or collisions is the most important and essential purpose of such systems. Based on this purpose, many advanced driver assistance system (ADAS) technologies have been developed and equipped in commercial vehicles.

The ADAS equipped with advanced sensors and intelligent video systems is designed to alert the driver to potential traffic hazards or to take over control of the vehicle to avoid impending collisions and accidents. The ADAS using various technologies has been introduced for many kinds of purposes such as headway distance control, lane change assistance, adaptive cruise control, automatic parking system, and so on. These ADAS are classified into two categories: Systems that assist the driver to enhance safety and improve vehicle control (such as Lane Support Systems, Forward Collision Warning System, Blind Spot Detection System, Reverse Parking Assist System, etc.) and Systems that are capable of taking control of the vehicle (such as Automatic Parking System and Collision Avoidance Control). The main objective of input prediction is the prediction of future inputs. As there are many nonlinear and dynamic factors which affect the driver's control input, input prediction is very important. However, in previous studies, this component has been dealt with extensively in some specific cases such as modelling or approximation techniques.

9.3. Fundamentals of Machine Learning

Machine learning (ML) is a subset of artificial intelligence which focuses on the development of algorithms that automatically learn from data. In the broadest sense, the data could be any form of information that can be numerically encoded. This could be images, sound, text, telemetric data, etc. The range of algorithms that can be classified as ML is growing enormously. Some typical applications of ML are currently found in a variety of domains such as (i) computer vision (face detection, object detection, image recognition); (ii) speech recognition, transcription and synthesis; (iii) text processing (news intrusion detection, spam filtering, machine translation); (iv) medical diagnosis (patient classification, disease risk estimation, drug design); or (v) game AI (playing go or chess). Speed and memory improvements, largely due to improved computer chip technology, make it feasible to apply ML for answering more complex problems. Current research tends to focus on semantic segmentation or instance segmentation for improving the ego-vehicle's environment perception. However, mapping a three-dimensional environment is a challenging task especially in a knowledge scarce environment. Improving road occupancy grid maps through a highly automated learning process is proposed.

For highly automated driving, accurate models of other traffic participants are essential for assessing the safety of an automated driving system and for predicting the future behaviour of other traffic participants. As roadside and vehicular sensors are limited to line-of-sight detection, alleviating the knowledge scarcity dilemma of automated vehicles using learning based approaches is critical to improve the modelling of vulnerable road users (VRUs) such as pedestrians and bicycles . Each approach is then tested in a simulation framework. The coding procedure is optimized based on automatically generated scenarios. A suitable semi-virtual environment to incorporate diverse traffic scenarios for online further model refinement is introduced. Adding to the initial learning based model updating framework, the integration of episodes and heuristics ensures continuous, highly automated learning even under diverse, highly dynamic traffic conditions.

9.3.1. Introduction to Machine Learning

While the term ML was first introduced in 1957, this notion has grown significantly over the past decades. In recent years, however, the widespread availability of optimized embedded platforms, sensors, and data has led to extraordinary growth in this area. While traditional programming attempts to produce algorithms to process data, ML instead focuses on producing algorithms that can learn models for that data. As such, a system is trained on a dataset to learn a model that can then make predictions on new data. It can be expressed simply as $M = t(D)$, where M is the learned model, t is the learning algorithm, and D is the training dataset. A model is typically the definition of a function: f(θ, x), where θ are the parameters learned by the training process and x is the input to the model. This equation describes one of the most popular models: the feed-forward neural network.

Deep learning nowadays uses several layers of simple computations to extract features from large data and produce high-level abstractions of the input information. Deep learning is the most popular ML paradigm. For self-driving cars, ML is expected to have an enormous impact by being applied to path planning, detection of objects in the vicinity, and estimation and tracking of the dynamic state of the surrounding roadmap. While ML promises to replace tedious, manually designed and programmed algorithms, they also incur serious challenges in reliability. In the Automotive domain, where safety is a key concern, the introduction of ML in the control remains a key challenge in the assurance of the performance of these algorithms and in designing reliable fail-safe mechanisms. The self-driving car promises to increase the efficiency of the transport system and reduce traffic accidents. The design of a self-driving car is, however, a very difficult task. An efficient, cognitive architecture is needed, where each component has to work efficiently and safely while handling uncertainty. It is also difficult to ensure that the design is safe.

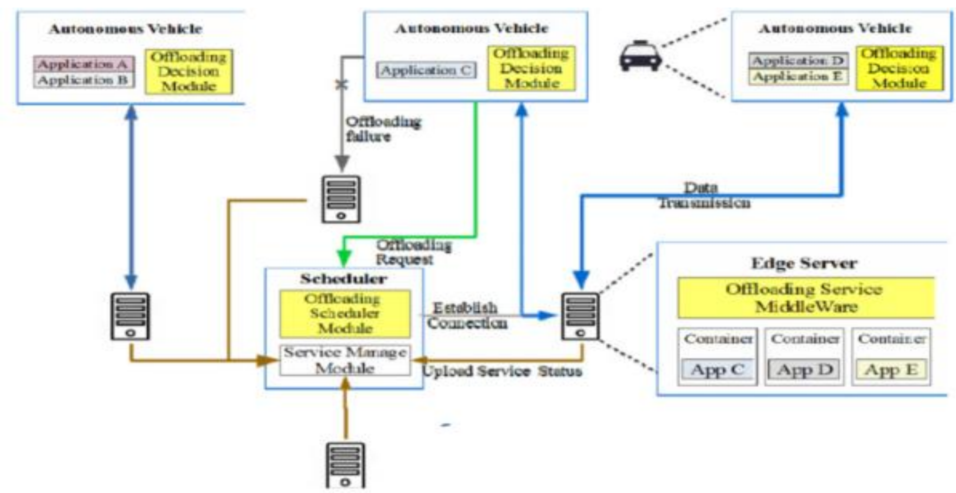

Fig 9.2: Autonomous Driving Architectures Machine Learning

9.4. Machine Learning Techniques in Driver Assistance Systems

The process of driver assistance and autonomous driving is primarily based on driving scene perception. A driving scene consists of static and surrounding objects, for example, vehicles, pedestrians, and roadside environment information. Estimation of the ego vehicle state (position, velocity, yaw angle, etc.) is also important in driving scene perception. Therefore, there is a growing demand for highly accurate driving scene perception. To solve the limitations of conventional perception techniques that use physical laws of perception, a number of deep learning techniques are expected to be the future of driving scene perception. Various driving scene perception techniques using machine learning, deep learning, and traditional perception methods are summarized in this section.

With the rapid increase of vehicles worldwide, road safety has become a large concern. An advanced driver assistance system (ADAS) is a new technology designed to improve road safety by supporting safe driving and avoiding accidents. To provide advanced features, vehicles are equipped with sensors like cameras, LIDARs, or radars. However, control of the vehicle based on available information such as sensor readings is a non-linear, high-dimensionality problem. Therefore, machine learning (ML) techniques are considered for the development of features such as collision warning and detection, lane departure warning, pedestrian detection, and driver intention prediction. Transporting the input data into a target with a complex non-linear shape is called a regression problem, while partitioning the input space into distinct regions to distinguish the class is called a classification problem. A classification technique derives a hyperplane to partition the input space. To model a probability distribution of the complex system behavior, a number of generative modeling techniques are employed. These models are widely used owing to their flexibility and intuitive nature.

9.4.1. Computer Vision Applications

Computer Vision (CV) based technologies are one of the key technologies used in Advanced Driver Assistance Systems (ADAS). Computer Vision technologies are becoming the focus of many ADAS systems. They are intensively used in order to track the position of the vehicle, detect obstacles for automatic lane change, monitor the surrounding environment of the vehicle, and provide near real time information needed to make a decision. Exterior applications are included that surround a vehicle with driving assistance functions to avoid accidents (Patel et al., 2023; Smith et al., 2024; Davis et al., 2025). Research is on-going on how to extract useful information from the driving environment.

Some applications under investigation include traffic light detection, traffic sign recognition, vehicle identification (including presence, position and orientation), vehicle speed detection, pedestrian recognition, overtaking detection, and parking assistance. The issues of lane marking detection include complex road conditions such as worn or occluded lane markings, occlusion by other vehicles or road furniture, varying width of lane markings, sensitivity to dynamic scenes including moving objects and tracking lost, and changing illumination such as shadow or light poles. The robustness and real-time performance are key indicators of the algorithm design and system implementation.

For template match-based detection, the 3D lane model has to be constructed first and then discussed. Planning and control of the vehicle motion state, especially lateral motion, is a challenging issue to control systems. Lane marking detection uses top and bottom-hat filters to find candidate lines. The detected lanes are grouped using road curvatures based on the road model. Pivots are used to rotate lane coordinates into the forms compatible with the road model which separates all lanes from any irrelevant lines and noise. After digitised simulation, rules-based decisions check the mutual connection among the two lanes found. The lane states are then tracked using a Kalman Filter. Road boundary extraction detects spikes and forms spines that are confirmed using a grammar rule. In the last stage, a more advanced bottom-up method fuses the extracted boundaries to create the lane topology which is then modelled for detection. Robustness is enhanced by model matching. The extracted lane scenery includes white lanes, yellow lanes, and non-lane objects. The scaling shows the results of segmentation stage and the corresponding lane edges detected optically and without perceptual distortions.

9.5. Autonomous Vehicle Technologies

An autonomous vehicle can operate on its own, without requiring a human driver, to navigate specific environments and road conditions (Wang et al., 2022; Thompson et al., 2023). It actively perceives its surroundings by itself using onboard sensors, understands the scene to make decisions and reason about the safety of control actions, and then operates its actuation systems to perform vehicle motion planning and closed-loop control like brakes or steering.

Aviation and maritime ship industries adopted early automated technology to allow an aircraft or ship to get from one airport or port to another with no assistance from human pilots or captains. Concerning land transport, however, fully autonomous operation of road vehicles for passenger transport between cities has never been achieved. People still uninhibitedly drive themselves to go shopping and commute every day. Road traffic is complex and variable in many regards compared with air and sea travel. Many enabling technologies for automated road vehicles are considered but are still in the nascent stages, such as technology for an environment-perception system that can see the environment like human eyes and robustly estimate the surrounding-object motion paths.

An approaching integration of several technologies and systems advanced within the车
-course is opening the way for the final step to the first fully autonomous operation of road vehicles in set environments. On board, along with active environment perception and reasoning systems and accuracy equipment installed in moving vehicles and

infrastructure, are globally accurate reference and traffic-management systems that support traffic-equilibrium and -coordination applications.

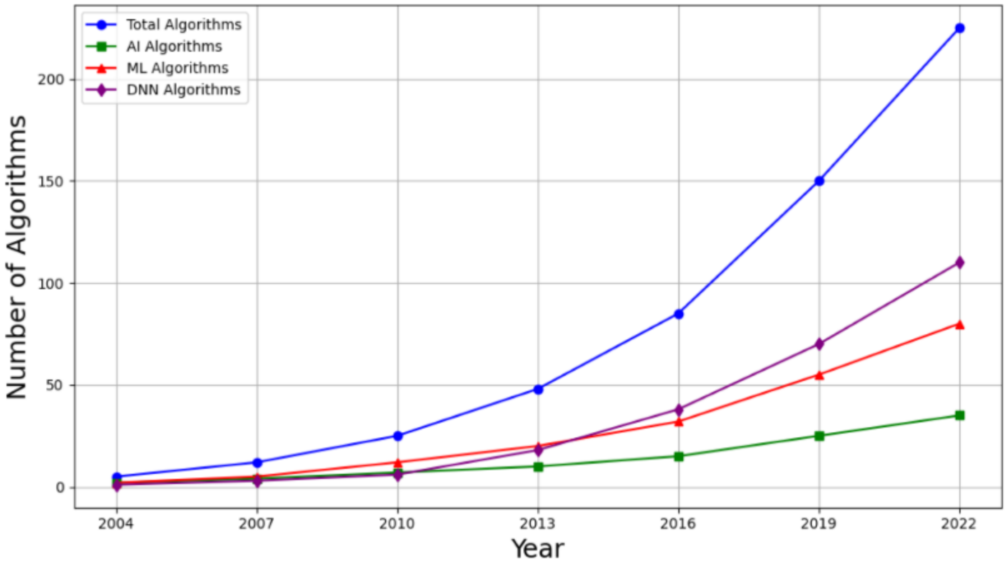

Fig : Autonomous Vehicles

9.5.1. Levels of Automation

The SAE levels of automated driving are often referred to as a hierarchy of automation, where the lowest level (0) is completely manual driving with no automation applied, while the highest level (5) requires no driver attention whatsoever on road conditions, weather conditions, or other potential risks. Several definitions will be presented based on the levels of automation, where it is important to note that L0–L2 vehicles are not defined as automated vehicles since they require permanent supervision by the human driver. However, current trends show that driving assist and driverless technologies L2–L5 are in high demand, particularly for vehicle manufacturers in China and the USA. It is expected that L3 technologies will be available in Europe within the next five years and L4 technologies within the next decade. Hence, this thesis is focused on the levels of automation L2–L5. L2–L5 levels are described according to standardized definitions from the Society of Automotive Engineers (SAE) and other statements on definitions and potential use cases.

Level 2 is defined as “Partial Automation,” where a vehicle may manage both steering and acceleration/deceleration using information from both the driving environment and the vehicle’s internal status. It is also defined as “Level 2 Condition-based Automation.” In this case, a car is able to perform the entire driving task in specific environments, but the task can be terminated at any time. Hence, human input is always necessary.

Nevertheless, level 2 increases the number of vehicles with partial automation greatly. Currently, the fully autonomous vehicle driving through road intersections has been achieved in blocks of downtowns/runways of airports. It will be possible to do it in restricted environments such as towns/suburbs. At the same time, level 3 and 4 driving alone will happen in these places, since highways are more structured than roads in towns. Currently, L2 and L3 are vehicle models offered by many manufacturers, and the number of L2 vehicles manufactured will soon exceed the number of L3 vehicles.

9.6. Conclusion

The innovation of Autonomous Vehicle Technologies and the expansion of related research are increasing due to the rapid development of driver assistance systems. To make those systems more intelligent and incorporate the latest machine learning technologies while maintaining safety and trustworthiness, works are under way to adapt the existing safety standards. One of the most common and complex issues is the adaptation of ISO 26262 to interpretable machine learning and deep learning-based technologies in Automated Driving (AD) systems, especially in their use case of Longitudinal Control (LC). Some of the hurdles that arise due to the use of machine learning and their solutions are examined, especially in the field of sensor object detection and tracking, which is usually the first function of Automated Driving (AD), hence, influencing the safety and reliability of high-level functions. The evaluation results utilizing public datasets are discussed next.

The innovative developments of driver assistance systems and the increasing research in this area trigger the interest in the innovation of Autonomous Vehicle Technologies. More intelligent systems with the latest machine learning technologies are promised for the future. At the same time, systems that are more trusted and can deploy the machine learning technologies in a more reliable and safe way are required. Various works are undertaken toward adapting the existing safety standards to machine learning technologies. One of the most common and also the most complex topics is the adaptation of ISO 26262 to machine learning technologies in automated driving systems (ADS). The topic of attention here is specifically the AD sensors, which are the first and usually the most critical assistant functions of the underlying intelligent technologies relevant to safety and reliability.

9.6.1. Future Trends

Autonomous driving technology contains many components and subcomponents that require different types of machine learning for their realization and deployment. Key areas of application are listed and explained in detail in the subsections that follow, along with the future trends and expected impacts of advancing machine learning capabilities on the wider adoption of driver assistance systems and autonomous vehicle technologies in the automotive market. All described trends are currently at different levels of maturity, with some already expected to be widely used in the market in a few years and others expected to take much longer to mature and to be brought to use in real production vehicles. Succeeding in this competition is crucial for the competitive position of all affected companies and organizations and even entire countries, as disrupting technology will create enormous opportunities in markets with revenues surpassing hundreds of billions of Euro. Pedestrian detection has made rapid progress in the last five years and is expected to continue to do so for the foreseeable future. Deep learning-based approaches have outperformed traditional techniques and have established the state of the art. Meta learning, one-shot learning, and few-shot object detection will allow drone and robot-like vehicles to detect unfamiliar objects with a single image or less. This area is likely to continue to converge with computer vision used outside car applications. Research is still needed to improve robustness and reliability in challenging environmental conditions and properly benchmark pedestrian detection systems in a standardized way. Most researchers agree on the relevance of novel concepts such as refinement networks, attention-based networks, and fewer bounding boxes, and there is some degree of consensus among the participants in the benchmarks. On-the-road scenarios for autonomous vehicles can be highly variable and complex, which are difficult to train on and are expensive to collect. Simulation-based approaches allow for unobtrusive ways to explore corner-case scenarios desirable for safety validations, allowing for richer environments and interactions. Adversarially trained generative networks and virtual-world training will have an enormous impact on developing and validating many components of fully automated driving in a safer and less costly way. More advanced algorithms, including environmental interaction algorithms and a few-shot scenario generation, will have a strong impact on the field as well.

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