The Development and Implementation of AI-Based Lane Keeping Assistance Systems for Autonomous Vehicles

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1. Introduction

It worth noting that development direction of LKAS is a middle approach when the LKAS ensures the vehicle correct positioning without a commanded trajectory tracking. For conduct the required research, it is necessary to use both simulation and field tests. In our opinion, real life field tests are the most convincing way to verify the working algorithm. In this connection, the contribution of the present paper is validation of the developed LKAS algorithm under the realistic conditions of traffic and weather as well as the check of the filter stability even if GPS errors are presented [1].

Development of automated driving technologies is performed all over the world. Lane Keeping Assistance Systems (LKAS) for vehicles are the majority of one of the key technologies for automated driving systems. The American National Highway Traffic Safety Administration (NHTSA) has defined LKS systems as "a lane-keeping support system capable of assisting the driver in the performance dynamic lane keeping tasks enabling the vehicle to navigate through a series of gentle curves under the driver's control". The object of the present research is to develop an automated control algorithm that helps a vehicle move in the center of the designated lane while using inexpensive commercially available components under the condition of GPS coverage. We have performed numerical simulations using commercial "VeDYV" software to assess the LKAS feasibility in the cases of a positive road crown and zero-crown. For GPS checking measurements, we have used the Ukrainian GPS reference network and the specialized smartphone application in our tests. We have also conducted several field tests at the highways of Ukraine using a medium class motor car.

1.1. Background and Significance

Currently, AI is mainly used in the development of lane departure warning and lane keeping assistance systems [2]. Since those systems only partly fulfil the functional requirements of a lane-keeping control system, they have to be modified for that purpose. Even though AI is able to model a human driver's steering action more accurately, completely and properly controlling the steering actions of a car driving autonomously in the fast lane on a motorway requires the cooperation of both acting agents: the machine and one of the human drivers. This insight was used as a basis for optimising the lane control algorithm that we propose in this project to stabilise a car on the left or right motorway lane by cooperative driving.

The ultimate goal of the AIKAS project is to build an autonomous lane-keeping automobile that efficiently overcomes the difficulties experienced during automated steering and recognises the intention of at least one other vehicle [3]. An autonomous lane-following robot steered at low acceleration by a human control partner forms the mechanical prototype for that end [4]. Building on that platform, the goals for the machine learning approach proposed in this research proposal are, in a first step, to automatically steer the robot in order to optimally follow of an omnidirectional target and, ultimately, to overcome the difficulties experienced with finding the correct control command for lane following. Here, we present an advanced shared-control mechanism to enable autonomous steering fit for an automobile – as the long-term objective of this work – also controlled by an Artificial Intelligence (AI) method and tested successfully in an automotive lane-keeping simulator.

1.2. Scope and Objectives

It is therefore desired to develop approaches in which these issues are overcome. We propose three main science and technology objectives corresponding to potential thesis topics that would allow to address the challenges that we have listed above. They consist, as follows, in the development of: - A lane detection algorithm that can efficiently model different types of lane markings or track edges, adapt to low visibility conditions, and restore the shape of missing road markings, - A robust and comprehensive lane change rules engine - A lane keeping and centering algorithm that strictly respects practical high speed driving regulations such as "drive in the center of the lane", while also adapting to low-visibility conditions and occlusions.

A vast amount of literature highlights efforts to develop and implement the lane keeping assistance features [2]. However, there is still a gap between the adoption of this technology in car models and the level of implementation of these features in state-of-the-art autonomous vehicles. There are several factors limiting the integration of this technology into fully autonomous vehicles. This mainly includes the difficulty of using the current state-of-the-art solutions in occluded road conditions and when there are missing or damaged lane lines [5]. Additionally, existing methods also do not always perform robustly in the presence of blind spot shadows. Some methods do not take into account obstacles in the way, and as a result, make calculations for an unsafe lane change, which can cause collisions. Other methods use a look-ahead strategy, which may not be suitable for abrupt lane changes during high-speed driving on highways. Making good lane changes requires modeling and reasoning about the intentions and behaviors of other vehicles in the immediate neighborhood to avoid accident situations. This is one of the desired capabilities for vehicles in the autonomous driving regime.

2. Fundamentals of Lane Keeping Assistance Systems

Lane keep assistance systems are becoming increasingly popular as the enabling technology to motorists, support, or even suppas, drive their vehicles. Such systems typically form part of a more extensive safety-critical system referred to as a Lane Keeping Assistance Systems (LKAS) that is required to interact cohesively with the driver. To demonstrate the applicability and the potential of the introduced phase—as a typical result of a verification procedure—, we show that all requirements of an A-class vehicle (mounted with an LKAS & ACC system) can actually be verified from automotive-grade Simulink models [6]. The presented verification is used in-house at Daimler when components of system designs are replaced. This work provides a verification framework that is suited to-the-way, car manufacturers build their vehicles..beginTransaction, as well as regression-testing purposes. We present the HiL-based architecture used for systems verification of the electric and hydraulic steering systems used with the LKAS and ACC features in our full-size vehicle fleet [7]. The targeted testing aims to continuously provide safety measures in addition to the baseline contributed by individual model-based unit tests. This is mainly supplied by tens of thousands of system tests formed by closed-loop HiL simulations. Our main outcome details the demonstrated adequacy of the proposed HiL system testing methodology through real-world, concrete verification and testing scenarios.

The increasing number of accidents and traffic congestion due to careless and impatient drivers testifies to the urgent need for advanced driver assistance systems. Automatic lane detection is a key technology needed to construct such an intelligent vehicle. Using edge detection and a Particle swarm optimization (PSO) approach to search for suboptimal thresholds, a robust lane detection technique is proposed [5]. The proposed algorithm is fast, reliable, and capable of detecting different road situations. The edges of a grey-scale image are first detected and then optimally reflected for lane detection 0.12% of the standard Hough Transform time. The probability of line positions in terms of the lane curvature, the edge positions, and an optimal threshold are iteratively searched for. As about 82% of the time is spent iterating through solutions in the particle swarm, the lane detection time is largely reduced.

2.1. Basic Principles of Lane Keeping

The second lane departure LDW (lane departure warning) system is designed expected to intervene with the steering and advises making the required adjustments [8]. A lane departure assistance LDA includes advanced sensors and computing which let the system monitor the vehicle's position in the lane, alert the driver, and even actively help out the driver in certain conditions. Through an emphasis on vision based algorithms, important results are achieved like detecting lanes in extreme shadows, steep curved lanes, lanes with inclined variations, street-lane opposite lane and mixed lane detection. The GP-based lane keeping system is employed on autopilot cars in the pre-intelligence way for lane detection, tracking and following, lane keeping strategies, overwhelming curves, analysis of camera settings and road objects detection.

Autonomous driving has been an emerging field with the increase in connectivity, computer vision, deep learning, and information processing capabilities [2]. Self-driving cars forecast to be significant advancements in increasing road traffic safety by removing human errors from driving. In a lane keeping control system, a front-facing camera is used to detect lane markings. It processes the data from the camera and controls vehicles according to the road condition and lane-marking information. Lane keeping control systems for autonomous vehicles operate based on sensory data or maps exclusively or together [9].

2.2. Sensors and Data Collection

The Traffic Sign Detection competition is the determination of traffic signs using Automated Number Plate Recognition [10]. People and traffic signs are the essential, external traffic participants. Both the participants entirely interact with each other. Furthermore, the ability to understand human intentions in conjunction with the relevant pictures for the six scenarios challenges Panoptic Multi-Object the common Vietnamese market, which has undergone various changes in terms of its MAICT policy. Strict regulations on the management of connected devices in transportation, IoT development has faced in parallel. Codes objects that use the SENSE COCO object categories; HP = heavy vehicle (code 2), EV = electric vehicles (code 38), and PVT = passenger vehicle and taxi (code 39).

The function of image processing is the detection of traffic lanes in video images [4]. Specifically, six algorithms were analyzed – one general and especially suitable algorithm was determined from the results for each of the six categories. The data set consists of video sequences from multiple cities from Germany and the United States. Rain, snow, sunset, oncoming traffic, pedestrians, and different road markings, as well as low-quality videos, are part of the recorded data. A total of 10 reference videos are provided for comparison [2]. This competition takes place in parallel. Hence, a standard for the comparison may be provided on the Seilbahnweg. Since the cities are different, various types of different road markings and changes considering the countries are presented.

3. Artificial Intelligence in Lane Keeping Systems

[11] [12]Lane keeping assistance systems, including both automated and trademarked systems, are important elements for creating the artificial intelligent (AI) (A-) vehicles of tomorrow. Most systems are integrated into the automatic lane keeping assist ALKA driver assistance systems. Besides this standard, some derived applications can be found, for example, predictive lane guidance, which utilizes a more complex and interactive methodology. The implementation of new technologies is the best solution in terms of ensuring safety on the roads. Thanks to the introduction of AI and machine learning for decision-making, a completely autonomous, moderate vehicle was tested for the first time.[2]Besides these basic observations, it must be noted that the key elements of predictive lane guidance only can work in favorable, non-limited conditions of weather and physical environment. The opposite is true for the new system presented in this paper, which directly emerged from trackless mapping research of this author's Fur Keen Team. This system was

only made possible due to the new relationship with the renowned Safe Intelligent Mobility-Test Area-Lower Saxony (SIM-TALNS) facility in Germany which was joined by this author after 30-plus years of scientific research. Goal of the Szczecin- higher intelligent 103 development and implementation AI of lane keeping assistance systems of AI-driven vehicles is being described step by logical step.

3.1. Machine Learning Algorithms

With the improvements in modularity and fault-tolerant control in software and hardware, Learning-Based Software can be the future of autonomous vehicles. In the context of Learning-Based Software, Deep learning and perception-based control in AI, either reinforcement or imitation learning can be highly utilized, combined with different computer vision technologies [2]. With capability of detecting more complex patterns on top of traditional Hough Transform and commonly used RGB-based datasets, monoscopic, 2D video imagery-based datasets will take autonomous vehicles one step closer to reality.

Machine learning (ML) algorithms have been widely adopted in different middleware functionalities of advanced driver-assistance system (ADAS) to predict the response of different systems to the environment, based on input sensory data and state variables of the vehicle. A classification model to decide whether it is safe or not to make a decision, given the state of the environment and the characteristic of the lead vehicle, is presented in Etemad and Mohamadian [13]. Autonomous lane changing has been performed by considering this classification model. In Rahman et al. , a lane tracking module is trained to track the lane markings and to know whether the lane changing actuation is possible or not.

3.2. Deep Learning Models

SafeDrive has used some advanced methods to enhance the images obtained from the real scene and build a novel Edged-based Unet as an intelligent pre- and post- processor on a dataset dataset to detect the lane as driver assistance in foggy situations,. Although the utilized encoder-decoder structure has been proved to be effective in numerous works well and the classifier identifies the edges and potential lane pixels effectively, this promising work is used as a blind noise reduction and thus, may be sensitive to incorrectly erased components. In this article, the authors have focused on an important field to build intelligent vehicles using a body of the literature. The tasks like detection, maneuver prediction, segmentation, semantic understanding, etc., have been covered. In detection of the drivable area, large porosity has been mentioned while, this task, has been conducted as a segmentation stage in with individual difficulties in complex scenes in snow and rain, while no multi-purpose work like alludes to a logical intelligent driver vehicle in poor visibility.

[9] [2] [14]Recently, utilizing deep convolutional neural networks (CNNs) is a practical and efficient way to design a lane finding algorithm. In, a deep learning based method, named ENet-21, to deal with real-time lane detection for highway is introduced. For lane mark detection, scores for existence, angle, and bias at each pixel in road regions are produced by the proposed LaneNet. However, only ENet-21 is enough complex to build deep neural network. In, Huynn et al. have proposed a model to detect the lanes with RGB images of varied lighting conditions, constructed by the only seven convolutional layers. Lane detection is formulated as the binary segmentation one and used a trained model on TuSimple, an available dataset in this line of work. The network is suitable to detect the lines at any road shape. For the lane finding purpose, by a deterministic connectivity between the two Lane Mark proposals in parallel, two segmentation masks are found in the proposed model. With using only a very simple CNN and no need to any post-processing at the output of the neural network, this work, practically useful at real-time, has achieved a very good overall performance. Although, the proposed method is only efficient for straight and up curved road shapes. Generalization and efficiency of this model on the severely curved road shapes, like almost perpendicular shaped infrastructures in city and tunnels, should be extended in the future. As aforementioned, the aforementioned models, like LaneNet and VGG-16, respectively, involve some evaluation limitations in complex conditions, like inadequate data generalizing effectively the out-of-the-any-feature of the lane shape and not including non-technical limitations like limited visibility and the external objects.

4. Challenges and Limitations

The field is a very young and vibrant one. Even with similar vehicle control problems, the peculiarities of the state of things are always different. Stepping in autonomous driving instead depends on the development and adjustment of various structures on the chaotic structure which cannot be captured but certainly theorem. In addition to the developed methods that perform situation assessment independent of each other, the adaptability ability limited at the intersection and serious urban/city constraints to noise; and therefore, especially the feature of making decisions is very much earth that can be tormented throughout each component. Many of the research and application works with the autonomous vehicle of different structures. Many companies put various types of autonomous vehicles developed in a wide race and try to offer it to users. For this reason, it is important and necessary to ensure structured engineering development and systematic workflow with regard to the engineering processes applied in autonomous driving applications.

[1] [15] The development of AI-based lane keeping assistance systems for autonomous vehicles is quite complex and presents a number of challenges [16]. These include the quality and robustness of the lane detection algorithm, the vehicle's driving decision making, and methods for trajectory planning in congested traffic conditions. Even with the quality performance of conventional neural networks, resulting in lane detection in different conditions such as reflections on the lane or in different atmospheric conditions such as rain, fog, trust, and bottling, the proposed method may not be effective in cases where the objects in the environment are bigger than the lane marking or the lane is not clear because of dense traffic or noise. In the driving decision-making process, the level of trust and the ability of the algorithm to critically judge the current state of the application area are very important. In addition, heavy urban traffic conditions extremely force the methods for trajectory planning to perform not only carefully but also quicker. There are still unsolved questions such as how an autonomous vehicle to give a driving decision after necessitating trajectory planning as quickly as possible in congested traffic conditions and how the vehicle can change the trajectory in a safe and comfortable way As it is known, autonomous driving supports have the capacity for driving on their own even in highly crowded urban areas under these conditions but the limit is the level of tracks quarantines.

4.1. Environmental Factors

The blocking of the sensors and also the deteriorated marking-detectability concomitant with the sun irradiation cause the needed drive dispatcher adaptions i.e. scenario dependence. The interrelation environmental factor and scenario dependence demonstrates an unavoidable influence which the lane keeping assistance solution must consider [17].

The estimated sun interposition hours, based on the Zurich city center, confirm the argument derived from the travel time evaluation. At nighttime, no significant detection events are noticed. The day cycles are linked to average lane marking distributions as usual. Especially the setup 0 and 50 algorithms need a far higher number.

Next to the technical driving task the promotion of the driver´s and the vehicle's surrounding safety is significant for the implementation of the lane keeping assistance in vehicles. Therefore, the evaluation of the interaction of the various system components and system configurations by means of environmental factor is necessary [18].

4.2. Technological Constraints

The Random Forest (RF) regression algorithm was utilized to observe the mapping between vehicle states and lane fold angles obtained during training. Upon any detected drift, the system tries to actively stabilise the vehicle in the lane center [19]. The lane variation term in the cost function was calculated based on the lane information obtained from the vehicle coordinate system. Here, the lane information was required for any scenario to head towards the lane center, for two lane changes (to and away from the lane center), and to stabilize the vehicle in the lane center [20].

Autonomous vehicles employ onboard sensors, like cameras, radars, LiDAR, and Global Navigation Satellite System (GNSS) receivers, for environmental perception [21]. Then, data processing, communication, planning, and decision-making modules are implemented for their operation. Advanced Driver Assistant Systems (ADASs) are one of the main applications of AV technologies for driving safety. Due to the introduction of these systems to the market in recent years, they are set to be mandated for all passenger vehicles and light trucks by 2030. Lane Keeping Assistance Systems (LKASs) stabilize the vehicle in the lane center at all times, which make long perimeter surveying for lane centering, out of question, especially in developing nations with poor methods to survey lanes.

5. Current Industry Applications

[21] Industry is shifting towards autonomous vehicles, which rely on advanced driver assistance systems (ADAS) like lane keeping assist (LKA) and lane centering that can use computer vision interpretation of the vehicle's sensors to help control the vehicle while in motion. Both LKA and LC algorithms are focused on keeping the vehicle within the road lines. Several new vehicles are available that include some form of autonomy, e.g., lane keeping assist (LKA) centers the vehicle laterally; lane centering (LC), also centers the vehicle laterally,

but is capable of operating at lower speeds including in stop-and-go traffic. So, LKA acts on an operational level and LC acts on a tactical level. National Center for Statistics and Analysis (NCSA) data from 2016 indicates that 60% of driver fatalities happened in run-off-road (ROR) accidents. Fully 39% of ROR crashes happened when the vehicle hit a fixed object. LKA and LC should help prevent these types of accidents by keeping the vehicle centered within the lane lines.[4] Contemplating how infrastructure-based lane centering in particular compares to vision-based lane centering is important for road guidance system stakeholders, which include departments of transportation (DOT), vehicle original equipment manufacturers (OEM) and system integrators. There are perceptions that the adoption of AV technology on the infrastructure-side of the transportation system is going to occur at a faster rate than on the vehicle-side. Some tangible evidence of this was seen in 278 million USD of funding from the 5th round of the U.S. Department of Transportation "Automated Driving System Demonstration Grant Program" which went to infrastructure AV technology. Wisconsin Department of Transportation (WisDOT) also recently officially recognized that lane level information is important from the perspective of a connected and automated vehicle (CAV) reference point, and that lane-level information, as opposed to road-level information, cannot only end better route guidance overall, but in ADAS applications, improves on-lane steering control. Since the ADAS are available from a number of third party manufacturers, it is possible for planners and stakeholders considering to use lane centering as an edge in their roads as of now to have to ensure compatibility with a number of different OEMs not to mention different vehicle models. To avoid requiring field testing for compatibility before a specific system can be spec'ed into a project or installed, we provide all technologies in the form of models that computer simulation tools can deal with.

5.1. Leading Companies and Innovations

Leading companies aim to introduce new technologies in driving assistance. The German company BMW had already introduced motorway driving functions on motorways in 2018 [22]. Volkswagen, Audi, and Daimler have also made significant progress in the field of autonomous driving and want to launch a self-driving car in 2025. Technology companies such as Google and Baidou, which are working on autonomous driving technology, and companies selling autonomous minibus and taxi technologies, can also compete in the traditional automotive industry and even influence it. In the future, it is expected that the autonomous driving market will expand significantly by integrating with other industries, mainly the transportation industry. I do not think all these companies could miss the digital transformation of the automotive industry. For these transformations, car manufacturers and technology companies are making important investments in R & D. In short, it can be stated that the digital transformation process that emerged with the advent of autonomous vehicles has affected both companies and societies and has created new social structuring areas [23].

Leading companies in the autonomous vehicle industry are dedicating effort and investment to the implementation of AI-based lane departure warning systems. A cost-effective solution for sensors with a reliable level of accuracy is needed to detect the white lines or the shoulders of the road. Convolutional Neural Networks is a widely used method for lane detection [12]. These networks require large labeled data sets for training to perform well. The lane detection system in uses a novel data augmentation method which increases the available labeled data. The sender is equipped with a fully connected layer with 256 neurons followed by ten neurons for predicting the binary values. This design minimizes the impact of small fluctuations on lane output and increases the robustness of the lane detection system. The proposed method achieves state-of-the-art results on two challenging datasets. The system also achieves robust lane detection in real time under degraded conditions.

6. Regulatory Framework and Standards

The essential elements of the Lane Keeping Assist in vehicle categories M1, N1 and N2 are laid down in UN Regulation No. 140. In particular those vehicles the weight of which does not exceed 2 500 kg, vehicles for the carriage of goods which are constructed and equipped for carrying no more than 8 passengers in addition to the driver, and no more than 2 000 kg of goods, and those with a weight of 3 500 kg which are constructed for carrying a maximum of 8 passengers in addition to the driver, possess only two threshold values for the lane-keeping response [1]. In this connection, due allowance needs to be made for the fact that robust automation integrated into Lane Keeping Assist systems is present only in the customary assistance domain of longitudinal and lateral driving support systems. ON-Th ye highway the vehicle is for that reason required itself to take charge of control when leaving the centre of the lane, and not re centred, despite being suitably in a next-lane change area.

Lane keeping assistance systems have become a focus of automotive development as more and more manufacturers are offering a greater degree of autonomy to the driver in the form of Advanced Driver Assistance Systems [6]. These systems typically consist of a lane keeping control functionality which, if necessary due to driver inattentiveness, intervenes and prevents the vehicle from departing from its original lane, and which can also automatically steer along gentle curves or monitor overruns of the lane. Where such systems reveal weaknesses in displaying the capability and limits of their functions to the driver, there is the risk of misuse through overreliance on the system functions. This can lead to hazardous situations. In order to prevent accidents, it is necessary to limit the misuse through overreliance on the system within the framework of driver-vehicle interactions.

6.1. Government Policies and Guidelines

Level 4 automation may refer to a What We Call 'Nomadic' Automation vehicle, which unlike a PAV, APM or M-PAV may travel freely between environments if it so wishes. The most famous AV legislation in existence refers to 4/5 automation. Until now, no nation enacts mainstream legislation des- cribing the implied liability burden on operators of a L5 system, i.e. a vehi- cle so highly autonomous it fills the role fulfilled by humans currently [24]. Therefore, law regulation for AV automation in areas such as Europe has been ongoing from the outset of 1955 to 2021. No Nation requires 5L systems to be equipped with a black box. Management of 5L systems via Year of the Rat measure(s) alone would not be effective as an AV may make so many decisions over a short period of time that cause it to be instable or to fail in a hazardous way.

The development and use of LKAS are largely impacted by government policies and regulations . Governments such as Canada, UK, and Japan have passed regulations favoring the development and deployment of automated vehicles. Others like China, Germany, and the US have passed various regulations at different levels, with the federal level in the US working to centralize all regulatory measures combined with existing regulations across all states in the country [25]. It is considered infeasible to regulate wide-spread AV deployment prior to any significant accumulation of on-road experience with respect to either L1-L2 automation (requiring considerable human input and supervision) or apportioning any responsibility in specific circumstances. As such, much of the legislation has or will instead focus on L4-L5 development, with the impact of this case study falling mainly within the L4-L5 category. We may well expect the remainder of L1-L3 issues to be addressed as residual tasks following from develop- ment of mature technology verifiable in real-world testing [26].

7. Future Trends and Innovations

[27] Lane change assistance (LCA) systems may combine multiple sensors and help drivers avoid accidents while changing lanes by giving a warning in some cases, or assisting partially or fully in others. Therefore, LCA systems are a vital component of modern automobile safety systems. However, most current LCA lane information may be incorrect and hazardous because public information may not be so accurate. Moreover, the performance of the current LCA system depends on the specific data transmission situation of map providers. To solve this problem, two methods are introduced for global path planning and LCA for an autonomous car based on the deep reinforcement learning (DRL): the DRL agent and the DRL agent plus multi-agent system.[28] Interventions promoting fast, automatic feedback minimizes response latencies, but frequent interventions may cause a high workload for the operator and make it difficult to judge the transitions the system makes in terms of responsibility. Thus, shared or cooperative control modalities are to be preferred. The paper reviews the research area of AI + AV intention communication, from the early stage of mere collision avoidance to the recent efforts to signal an AV's intended actions in a useful and interpretable way for traffic participants. What the developer and user of the AI intend must be transferred from a latent vector in learned optimisation problems to an overt and, if possible, human-interpretable signal. It reviews several types of AI + AV and presents the core methods and difficulties in the development of the internal representation of and output of intention prediction, especially based on computer vision. It also presents the potential improvements and developments in explaining AI + AV intention output in the future, investigating not only the core functionality of the system but also tests the usability, transparency and robustness of any presented expiration schemes.

7.1. Advancements in AI and Machine Learning

The paper "Automated Lane Change Behavior Prediction and Environmental Perception Based on SLAM Technology" [29] proposes and develops a lane change behavior prediction and automated lane change system for highway scenarios. A high precision satellite that provides global positioning technologies like the GPS system, RTK, and other commercial system limits accuracy. The drawbacks of these systems are glaring in large urban scenarios. However, autonomous vehicles introduce new challenges for the task of accurate vehicle localization. The authors show the implementation of a feature-based Simultaneous Localization and Mapping (SLAM) system using the open-source ORB-SLAM2 designed for vehicle punctual environmental perception. They propose and design a deep neural network architecture based upon a Long-Short term memory LSTM module that captures pattern behavior during lane change maneuvers and predict new ones.

Understanding scene semantics is essential for autonomous driving. The authors [30] claim that acquiring semantic and syntactic representations of the environment is not favorable with traditional monocular and stereo imaging datasets. To this end, they argue that multimodal large language models (like BERT, GPT-3, etc.) can be utilized to provide meaningful scene descriptions and are able to capture the implicit knowledge of multimodal outputs. The authors discuss these datasets, multimodal analyses, DL models' training, and evaluation of performance on the task.

8. Conclusion and Future Directions

Several possible future research machinery options are briefly described here. First, we have only validated the proposed controller and precursor design for a few subject-specific traffic accident scenarios. Comprehensive subject-specific analysis on the applicable advantages of the proposed precursor system can be discussed later. The prediction capability of the LSTM-RNN for various traffic scenarios can be further studied. This study considers only inner-city autonomous driving applications, where more lane and model predictions will be obtained for diverse rural, highway, and mountainous road maps. This model can also be utilized to design lane-cracking, lane hairpin conditions, and different traffic situations. Multiagent LSTM-RNN-designed lane connection algorithm can also be employed for outdoor focusing-focused lane monitoring in outdoor surroundings. Secondly, the motion of the foreign car or motorcycle is usually ignored in the simulation study. For better transferring from simulation to real proof-of-concept applications, the dynamic models of the cars and bike are omitted. Therefore, sine-wave pressures are performed in net detecting motion as the synthetic output of the lidar sensors for a large fraction of time. Furthermore, the numerous lane scanning in the lidar perception stops algorithm frequently works in the non-maxima suppression approach, since it is motion alarm, so this approach frequently bypasses many weak detection, mainly if it interrupted by exponentially reducing the absolute multitude of voluntarily splices. Thirdly, the existing hardware to the processing algorithms is not fast. At best quondam inference application and fast real-time energy-efficient manner for resource-limited edge all-embracing plus mobile make ECU–DoG require advanced trends in machine co-processor.

Artificial intelligence (AI) plays a crucial role in the development and implementation of lane keeping assistance systems (LKASs) for autonomous vehicles. The incorporation of advanced AI technologies, such as machine learning (ML) and deep learning (DL) algorithms, into the design and planning of lane-keeping architectures holds potential for effectively addressing the demands of complex real-time lane keeping [31]. Recent studies show that a successful AI-based LKAS should be designed to make intelligent decisions (lane changes, for instance) by considering the dynamic changes of traffic situations (e.g., the behaviors and speed variation of surrounding vehicles). This requires a fully embedded perception system, as well as a high-quality prediction in a complex environment [19]. It is also important to mention that while ego-lane keeping aims at minimizing the lateral deviation from the lane center, when detecting a lane violation, a steering actuator needs to be activated to enable the lane deviation to be corrected in real time. In view of the recent improvements in data collection, sharing, and synthesis technologies, and the vast computational storage space, data-driven design and estimation techniques are increasingly gaining traction [30].

8.1. Summary of Key Findings

The task of lane change assistant systems has been studied for many years to improve passenger and road transportation safety and reduce vehicle accidents caused by improper lane changes, road rules, and unusual situations. As today's transportation industry will switch soon in terms of transposition and propulsion type, autonomous transportation solutions are evolving quickly. According to the International Organization of Motor Vehicle Manufacturer (OIV), the most unique feature of autonomous systems is Safety. As the incidents in have serious consequences, road departure injuries and fatalities were increasing [32]. Though they were start to decrease recently due to developed active safety systems (ESP, AEB, and others) and natural roadways (road barriers, recoverable ditches, frictional materials), human factor is one of the main precision has been used and can be prevented traffic accidents more clearly. Or more, driving safety focuses on monitoring technologies which can also reduce the number of vehicles and number of people, traffic anticipation, decision reversibility and real-time reaction are focuses for all drivers.

The increasing number of accidents and traffic congestion due to careless and impatient drivers highlights the need for advanced driver assistance systems (ADAS). The autonomous vehicle gives more importance to the data it has in its new designs, so it becomes difficult to comply with the law and to react quickly to potential risky situations. Nowadays, changing lanes on highways manually becomes risky with increased traffic. In this section, a decision based on a machine learning model that can decide whether the vehicle can change lanes in the next time step and lane-change maneuvers for autonomous vehicles is used [28]. In this thesis, Open Experiment in Network Technologies (OpenNMT) using an encoder-decoder model is used for testing Overtaking and Lane Changing AI (OLCAI).

8.2. Recommendations for Future Research

There are some industrial implications related to lane-keeping assistance systems in automated vehicles. Such systems are initially offered in driver assistance systems (i.e. SAE Level 1 and 2), and they are expected to be the most deployed automated driving function. A few examples are Cadillac Super Cruise, Mercedes-Benz Driver Assistance Systems, and Ford Co-Pilot 360 Drive Assist. In the near future, some car-sharing programs featuring Automated Vehicles (AVs) are being deployed (i.e. EasyMile and May Mobility). Some auto manufacturers are progressively deploying deployment strategies that offer various driver-oriented Automated Vehicles (AVs) in a limited geo-fenced area. Despite these significant academic and industrial implications, there still exist research gaps regarding the lane-keeping assistance system. For instance, recent research on lane detection and tracking methods like, a lane recognition using lane detection and deep learning methods has considered various types of scenarios, but these methods use single neural network models and only handle vision-based local information. The recent research has also discussed lane detection and tracking methods combining line, boundary, or curve detection-based methods, but no one knows the best methods that may produce the least perception latency. Despite these limitations, we expect that future research may enhance the road-driven lane detection and tracking robustness and improve data-driven road and lane segmentation and extraction performance for lane-keeping assistance systems in fatigued drivers who are reading books or using mobile devices, and ADAS using AI-based lane keeping systems. Shaik, Venkataramanan, and Sadhu (2020) address IoT security challenges using a Zero Trust approach.

The development and implementation of AI-based lane keeping assistance systems for the autonomous driving of vehicles is an important research topic. As discussed in [19], potential areas for future research include the expansion of the number of surrounding vehicles to be considered, integrating with longitudinal control, and improving the learning-based method via attention mechanisms, convolutional neural networks, and reinforcement learning. In particular, improving the existing learning-based approaches via various neural networks including attention mechanisms, convolutional neural networks, and reinforcement learning, is challenging yet promising. Since a human driver can easily adjust the vehicle's speed by comparing the markers and surrounding vehicles, it is expected that intelligent learning methods may enable adaptive lane-keeping performance by exploiting information from high-level perception and control systems.

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