AI-Driven Approaches for Autonomous Vehicle Adaptive Cruise Control

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1. Introduction

AI technology and edge computing are going to play key roles in the future of autonomous vehicles, facilitating comprehensive software and hardware co-development. As a result, the automotive industry has been witnessing considerable AI-driven initiatives to reach smart lateral-conducive and longitudinal-regulating systems that are amended to suite the sky-reaching requirements of autonomous vehicles. The communication between vehicles and the cloud server will be a bottleneck for advanced intelligent control of autonomous vehicles that can be solved through deploying AI and edge computing support. Consequently, the following research questions should be carefully addressed: how can edge-AI engine be designed and deployed to approximate critical interactive features among AV-only networks and also among mixed AV- CV networks. Furthermore, being an integral part of the future automotive industry, the technology is expected to be applicable to a series of performance tests under real traffic scenarios. Consequently, the communication between vehicles and the cloud server will set to be a bottleneck for advanced intelligent control of autonomous vehicles that can be greatly solved by deploying AI and edge computing support. [1]

Intelligent transportation systems are essential for the sustainability of modern societies, [2] and the research and manufacturing communities have focused their efforts on developing smart vehicles and intelligent driving systems. In particular, the development of autonomous vehicles has attracted significant attention in the automotive industry over the past few years. As an important approach for improving the safety, reliability, and energy consumption of autonomous vehicles, adaptive cruise control (ACC) systems have been widely investigated for a series of driving scenarios. Adaptive cruise control systems are developed to help drivers maintain safe distances to cars ahead of them at appropriate speeds by capitalizing on vehicle-to-vehicle communication, environmental sensors, and actuator systems. Although numerous significant breakthroughs have been made in ACC development, the system still confronts serious challenges when coping with complex and uncertain traffic scenarios characterized by frequent cut-ins and cut-outs.

1.1. Background and Significance

Existing literature provides a wide-suggested range of approaches to optimize the ACC settings, yet most of these strategies are largely driven by off-line optimization and do not effectively adapt to the dynamically changing traffic condition. To counter this weakness, this research seeks to introduce a novel AI-based approach driven through a model sharing the name AI-based Multiple Model Predictive Control (M2PC). In the M2PC, a limit model Kalman filter and linear Interception model predictive control was used to generate the shortest, optimal sub-goal to observe the predefined reference speed in real-time. M2PC based driving decision making architecture with fully self-sufficient vehicle system ensures environmentally friendly and smart drivers decision compared to rule-based and machine learning models. The main contribution of this research is the proposed AI-driven M2PC control strategy which is able to conceptually result in decreased amount of energy and CO2 emissions compared to standard machine learning algorithms, by considering the human reference speed; then, it may contribute to improving traffic-related issues in the complex traffic environment.

Adaptive Cruise Control (ACC) is a constantly evolving technology integrated in autonomous vehicles (AVs) to allow user-defined speed, which is further adjusted by laser or radar sensing and real-time measurements of the distance to preceding vehicles [3]; ACC assists in maintaining a user-defined safe headway to front vehicles. During cut-in and cut-out maneuvers, safety, comfort, and economy are the main objective functions when developing ACC. ACC has been considered as one of the most recently developed functionalities (besides the lane-keeping assist and automatic parking) for Advanced Driver Assistance Systems and increasingly in Autonomous Vehicles, as well [4]. In Autonomous Vehicles, ACC is considered a significant tool to optimize fuel economy and safety, particularly as a first step to automation. Indeed, most of the vehicles deployed on the roads are human-driven vehicles, which leads to many traffic jams and collisions, mainly due to delayed and/or irrational driving decisions. Adding communication and sensing to the ACC controller is expected to optimize traffic flows, avoiding these unwanted scenarios on the road.

1.2. Research Objectives

In the Authority, the major of highly practical performance problems have been analyzed and solved by using the value method to design action policy and the intensive test items. The last worth to be mentioned is that the general control policy network has the potential capability for robustly and adaptively controlling the leading target vehicle at a proper and safe longitudinal distance. The management of the shortened or even cancelled lane must ensure traffic order and safety. In this chapter, the lane-cancelled rewarding environment is simulated and subsequently tens of car following scenarios were directed. The results have been analyzed from the following several aspects: u-turn situation was analyzed from simulation and test track.

research into autonomous vehicles following and obstacle avoidance based on deep reinforcement learning method under map constraints [5]. Open areas described in maps are divided into two parts— on lane and off lane. The action policy of the control policy network is assigned different extend ratio of throttle and brake outputs acts in both on-lane and off-lane areas, and the first reward is used to complete the following job. The observation states selected from the environment space are mainly variables composing the longitudinal and lateral distance and velocity, and the input states of the control policy network are mainly longitudinal and lateral distance and velocity of several state vehicles compositions and the velocity, acceleration of ego vehicle. The main problems solved by our method are Adaptive Cruise Control (ACC) and merging—providing favorable models for controlling the leading vehicle at a safe longitudinal distance with stable and comfortable states avoiding obstacle and ensuring the possible road of it to decrease driving risk [6]. The simulation results show that the method has excellent dependability and promising performance. Last but not least, the method controlled by optimizer is an effective controller that allows for minimized fuel consumption based on the safety conditions mentioned before. The environmental modelions, an Adaptive Cruise Control (ACC) algorithm, and an experimental test track are described, and an energy consumption measure was used to validate the performances while differing from maximum acceleration output to idle [7].

1.3. Scope and Limitations

In order to wed teach, three concerns we embarked with various optimization, simulation models and algorithms have been developed. In the section that follows, under sub section

2.0, vi discussed modality and MFD we will be using while designing a controller and the type two model. Further, we conclude our manuscript with a comprehensive discussion about the future work and conclusion supported by the macroscopic MFD simulations .

As said before, planned work falls under the domain of designing the controller within type 2 macroscopic traffic flow model (MFD). Further, we intend to develop a Lane Adaptive Cruise Control (LACC) protocol especially suited for autonomous L4 and L5 vehicles wherein the existing traffic is a mix of manually driven L1 to L5 vehicles. The Controller design perspective is the prime motivation behind choosing the MFD, in the next section we discourse further about vehicular and network constraints. In all, we outline following constraints and preliminary obstacles which the adaptive vehicular cruise control (AVCC) aught to be designed robustly with: (i) Time variant vehicular demand and source select at various duration (Δ W); (ii) RfC at the origin and destination stations (Δ W);(iii) ELLs at the origin stations of the communicating pairs traffic stations.

2. Fundamentals of Adaptive Cruise Control

Constrained quadrotor, nonlinearities, and external disturbances are the major issues in controller design of quadrotor, but more importantly fast switching from one mode to another is the main issue, which restricts the aircraft' autonomy. In essence, the hybrid nature is the main reason why nonlinear model predictive control cannot work in order to control the UAV. In order to enhance the autonomous flying control of quadrotor, the feasible controller design for each cruising mode will be simulate. [8]

An adaptive cruise control (ACC) system is an indispensable intelligent vehicle system that can effectively maintain a safe headway distance to a front vehicle automatically. An adaptive cruise control system consists of perception, decision, and control modules. The perception module is designed to acquire and identify the road conditions and environmental information. The decision module is responsible to make the most appropriate driving decisions under complex situations based on the perception results.

2.1. Basic Principles

[9] Auto- mated driving technology, such as cruise control, has a been a key area of development for auto manufacturers in their efforts to create comfort- able journeys. Many vehicles are equipped with a proprietary feature called adaptive cruise control (ACC). The

Basic inputs to an ACC controller system from real-time vehicle data include information about the traffic speed of the vehicles within the vicinity, their longitudinal distances, the traffic sign limit of the preceding vehicle, the traffic speed limit, traffic sign input and road topography. At this juncture, this study proposes a novel technical architecture, in which adaptive cruise control (ACC) and regenerative braking algorithm are integrated.[10]The road travel experience should be greatly modified by multiple technological advancements. With the continuous evolution of modern electronics, radar technology, sensor units and microcomputer, ADAS has further developed state-of-the-art intelligent features that have improved the safety of highways. For instance, adaptive cruise control (ACC) has contributed to reduced accident probabilities, lessened the load of the driver and provided a comfy and stress-free atmosphere for riding over lengthy distances. As the data is being gathered at a frequency of 100 Hz, max, by the sampling signal by each sensor, the real time system could be implemented with the assistance of the data and should move forward effortlessly so that perception and decision making, control architecture could be anticipated accordingly.

2.2. Types of ACC Systems

Autonomous Vehicle Adaptive Cruise Control (ACC) plays a significant role in the traffic jam's avoidance, which leads to increase the fuel consumption, maintain a safety vehicle following distance and the operating conditions and ensures the power plant to perform near to the optimal control and less noisy, etc. Whenever a driver is either carefully driving the vehicle or that vehicle is equipped with cruise control bad to maintain the pre-defined speed. The automatic gain fuzzy PID based robust ACC is located at the lower level. Also, from the literature, one witness that many adaptive cruise control work related to Fuzzy logic controllers (FLCs) where the major influences of the systematic error and the spurt of the Tc^% were not implemented or incorporated in the fuzzy control law with variable gain. [11] The fuzzy control laws may not adapt their gains at dynamic road condition which may alter the vehicle intervals. It is clearly shown for a typical car-following scenario environments such as asset, a single line in which a major number of drivers are interacted, the percentage of the CO_2 boosts to 4,5% and the fuel consumption augmented by over a 2.5% under certain conditions.

ADAS applications such as ACC provide a strong base for autonomous vehicle developments. It is examined as a system that assists drivers to control vehicles and ensures good traffic flow.

These systems target various tests such as enhancing the energy output of fuel cells in serial hybrid electric vehicle (HEV) and a powerful communication between vehicles to improve the activeness of server in sensor networks. [12] This chapter will mainly concentrate on the ACC systems to analyze their effectiveness on fuel cell lifetime by controlling the Variable geometry Turbo Charger (VTC) and engine power assistance. It is also intended to increase the energy output of the FC-HEV, which results in saving fuel consumption and decreasing the emissions.

3. Artificial Intelligence in Autonomous Vehicles

Moreover, the speed of the vehicle must comply with speed consistency of road traffic. Otherwise commuting drivers will get irritated and autonomous vehicle will be forced to withdraw to be overtaken by another vehicle. As a run-out driver in streetcar analogy, many manual vehicle drivers may believe, an autonomous car could not provide quick decisions in complicated and steadily changing traffic flow. So a lot of bad decisions can be made by organism of another cognitive ability. In case of game theory which creates a theoretical platform for dealing with conflicts, not only illusions of provided security and robotics are dealt with, but also theoretical concepts are placed in a practical application. Seeing the criteria of determining the decision phase of the autonomous vehicle placed in front of us at this stage from the lens of game theory can produce an interesting message [10].

Today, the concept of transportation is changing all around the world [7]. One of the most significant challenges encountered in implementing connected and autonomous vehicle technologies pertains to forming an adaptive cruise control using a fuzzy supervisor that ensures the fulfillment of given performance requirements taking into account mutual interaction of vehicles. Over the years, a multi-directional development can be noticed in smart transportation systems also in the field of autonomous vehicles. The researchers began to implement fuzzy logic and neural networks to derive replacement control of vehicles with stability as well as capacity of coping with the unstructured environment. Additionally, fuzzy logic is a practical decision-making methodology in changing environment. Currently, to facilitate communication between vehicles, the Long Term Evolution (LTE) network and its advanced modifications are used. Due to their limitations of the maximum capacity and the need to keep low latency of telecommunication links, in the future the 5G, as well as the 6G networks are planned to be used. Sensors provide information to the controller that gives orders to the actuator [13]. Similarly to the phase of perception edging car to reality, the control step in the form of task management by autonomous vehicle must be conducted in a right way with the participation of the artificial intelligence. Managing a vehicle that comes into contact with an autonomous car requires extraordinary skills to be able to make appropriate decisions.

3.1. Machine Learning in AVs

The state of the art for controlling distributed systems predominantly uses physics-based modeling methodologies. While these models are an important part of safety-critical systems and allow for rigorous and verifiable system designs, recently data-driven approaches utilizing machine learning (ML) have become popular. Reinforcement Learning (RL) is a branch of machine learning that has the potential to entirely negate the need for utilizing hand-crafted rule bases and is especially advantageous for making decisions in situations that have many possible (perhaps unknown) meaningful actions which cannot be explicitly enumerated [14]. The design and synthesis of adaptive cruise control (ACC) strategies for AVs using reinforced learning is a part of the adaptive cruise controller module in the AV's software stack. In the rest of this section, we are going to look at what RL is and how has it been used in several relevant smart car systems.

Over the decades, integral components have been incorporated into modern car models which make the driving experience more convenient for the user. From an automotive-perspective, one of the most important of these components is a form of control termed Adaptive Cruise Control (ACC) [15]. Similar to passive cruise control, ACC is an advanced driver assistance system (ADAS) that adjusts vehicles' speed automatically based on the environment, thus ensuring both safe and optimum vehicle spacing from other vehicles. Utilizing various sensors and actuators, ACC allows drivers to fix a desired speed and headway, resulting in a semi-automated (level 2 in the driving automation scale) driving experience. It is conceivable that public roads in the near future be occupied by fully autonomous vehicles (AVs). The emergence of AVs mandates that fundamental passive safety systems receive major updates and active safety systems become more sophisticated in order to coexist with humans in mixed traffic conditions.

3.2. Deep Learning for ACC

Despite considerable caveats, AI-based autonomous vehicle control is achieving noticeable progress. In order to narrow the gap between model-based and AI-based approaches, it is recommended that a future AI-dominated robotic car architecture should integrate knowledge-based systems inside and a standard set of a team settlement to simplify control synthesis verification and generate mixed reactive AI and model-based systems. Besides integrating more and more abundant bi-level feature vectors, developing all possible fusion schemes for information recognition and exploiting new DL paradigms, such as Transformer models, should be explored [16].

Stanley fared better than Aurora and Junior in the race to the Del Mar Marine Corps Base with a time of 6:53 compared to 7:14 and 8:14, respectively. The robot cars earned $2 million, $1 million, and $500,000 for their respective creators. The secret behind Stanley's victory was deep learning. The field of deep learning, which relies on multi-layered neural networks for automated tasks such as AI-based reasoning and decision making, has recently expanded revolutionary areas such as media analysis and resource management systems. Connected to this booming development in intelligent vehicles, the number of accidents should be dramatically curtailed, whether they are caused by human errors or system errors. However, this vision seems to be overlooked in the current mark.

4. Challenges and Solutions in ACC Systems

However, to further promote the development and practical use of the platoon-driving and intelligent vehicle industry, it is necessary to extend simultaneously the operation mode and the route environment adaptability. Consequently, the proposed ACC here can handle the overtaken vehicle caused by the platoon operation and implement the real-time environment synchronization according to the surrounding traffic lights (PTLC). Currently, the intelligent vehicle industry is pushing the application of the autonomous navigation system, and it is required by the CC. In other words, how to merge the basic ACC, PTLC, and CACC (cooperative adaptive cruise control) adaptively and develop in a more compatible V2X environment represents an important issue in the future intelligent vehicle industry.

Adaptive cruise control (ACC) systems are widely used in intelligent vehicles [17]. They not only facilitate the following vehicles to keep a safe following distance from the preceding vehicle but can also accelerate and brake jointly as the preceding vehicle does [5]. The interconnected self-driving vehicle platoons can be constructed only by adapting the ACC system with the vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. As the safety distance between each connected vehicle in the platoon can be much shorter than that between the nonconnected vehicles, interruptible platoon driving makes the traffic much smoother and the road capacity is put into better use. Furthermore, vehicle congestion and undesirable traffic control can be eliminated by adopting the path-planning-controlled ACC (PACC) [12].

4.1. Environmental Factors

Predictable maneuvers are used in regular intersections, open traversals and followings while decision are made by SAS. When uncertainty increases, DDMI(s) interference begins in order to bring extra safety. Therefore, DDMI(s) are always used simultaneously with SAS. When DDMI(s) are activating, some special conditions, like the intersections without traffic lights, open traversals, followings and the centers of horizon intersections, are structured in order to keep the system's reliability and improvement.FDDMI follows a human-like cognitive decision tree to make the decision and the last decision-maker which uses reinforcement learning method, is driven by network control policy. The used cognitive pattern in FDDMI module has a human-like kind and a method, called CogSim, which maps a subjective ratio of noise added to the normal vehicle control system's inputs [18].

The environment perceptron is an important part of an autonomous vehicle. The decision-planning system can plan better and make the car more auxiliary by analyzing the environment variable, so as to ensure driving safety and traffic fluidity [5]. In order to simulate the influence of environmental factors on the AGV, different complexities, such as lineup velocity, intersection, and curve, were set in the virtual simulation environment of the AGV [3]. The speed and bearing angle are the most important Information for this system. Therefore, researchers utilize two sensors to feed environmental information to the system: cameras and Light Detection and Ranging sensors.

4.2. Sensor Fusion Techniques

For instance, approaches based on particular sort of sensors, such as data fusion plays an increasingly important role in autonomous vehicles, self-driving cars, that relies on data furnished by multiple sensors to get a reliable information about the world surrounding them. They are thus used in sensor networks combining data from cameras, ultrasonic sensors, lidar sensors, vehicle-to-everything (V2X) networks, GPS, and memory on the cloud, among others. It is to be noted that such sensor networks are used in self-driving cars and other vehicular ad hoc networks (VANETs), where typically similar data is shared among all the participating vehicles [17].

[7] [19]In single-sensor systems, the limitations of a single sensor including noise, measurement errors, and geospatial biases can result in unreliable data and uncertain decisions. Therefore, single sensor data fusion may be used to resolve these concerns. By combining data from a variety of sensors, data fusion techniques may enhance the accuracy, reliability, and robustness of the information. However, the implementation of data coordination strategies are technologies that differ with regard to computation, dimension, and location. Moreover, data coordination also includes navigation and data calibration. The data is also at the sensor levels, the data at the generic configuration, and the global coordination of the data.

5. Case Studies and Applications

The neural network of DDPG-ACC-AEB is configured as follows. The structure of the actor network is designed such that it consists of three hidden layers with 64 hidden neurons and ReLU activation functions. The last layer has only a single output (the acceleration/braking control command). The critic network consists of three hidden layers with 128, 64, and 32 hidden neurons. The last layer has only a single output and uses ReLU activation functions [20]. Critics have two separate inputs: state inputs (which considers the states for feedback) and action inputs (which considers the control input for feedback). The state input flows through a network structure, which combines “partially observed” or latent state information w.r.t. an employed method for handling the unknown and uncertain dynamics during learning.

Integrated control logic for multi-objective autonomous driving systems State-of-the-art commercially viable adaptive cruise control (ACC) and advanced emergency braking (AEB) systems are two separate functions: ACC primarily focuses on longitudinal dynamics and AEB mainly on driving safety [21]. They are designed to control a vehicle within certain boundaries either by the driver or by automation. However, the performance of an integrated ACC-AEB system is much better than either an ACC or AEB as they can use each other’s information. An integrated system changes the longitudinal vehicle response according to the surrounding environment and provides the driver with a secure, comfortable, and smooth driving experience, regardless of the other vehicles' driving behaviors and traffic incidents. In this study, a machine learning-based integrated adaptive cruise control and advanced emergency braking system is designed for intelligent vehicles. A set of longitudinal driving states and control inputs are defined to both capture the vehicle's dynamic behavior and to receive the driver's inputs and/or automation's outputs.

5.1. Industry Examples

The ai-driven systems are now also more intelligent in learning the driving style than the conventional library models. Using AI models for improved system response and accuracy is essentially the aim of the current study. The ai-driven Isfahan IFCR (iIFCR) system has about 92.0% capability to predict the possibilities of the vehicle moving-out from its point of moving, while time-to-collision (TTC) (67%). Also, the authors estimate that, in a reduced speed rear-end collision, the dsTrainedA model has 4.9(4.7) times institutes higher accuracy than that of the library trained A model. The intelligent-FCR (i-IFCR) model, in the safe zone, has a been able to estimate the predicted saviors (AE (2/2/4)) with a 100% certainty rate. The accuracy of the proposed models is almost near 100%; accordingly, there will be no or very low false positives in B mode of i-IFCR with a 100% F1 score.

Currently, the automotive industry is changing to meet the needs of sustainable mobility based on renewable energy [7]. Advanced Driving Assistance Systems (ADAS) and autonomous driving technology are being developed to meet consumer demands that are based on reduced CO2 emissions created by traffic, digital services and safety. Adaptive Cruise Control technology (ACC) is an essential part of the autonomous vehicle technology as it can optimize the vehicle's speed and braking strategy by allowing the vehicle to adapt to different traffic conditions as well as for the driving comfort and energy use [22]. In-Front Collision Report (IFCR) technology is developed that prevents a vehcile collision to a moving or/and static object by the vehicle in front, especially at low speeds. The system has two steps for automated preventive manuever: performing a simple lane change as the first stpe and performing vehicle decelaration, if required, as the second step. Every year, many people suffer from the car crash injuries while a lot of the damages are caused by the rear-end collision with the vehicle in front. Rear-end car crash has the biggest percentage of all types of car crash types while rear-end crash is big enough to show the importance of the IFCR and

FCW technologies.ện an LIDAR OS-1 with a maximum range of 120 m and a frequency of 20 Hz is fixed to the vehicle, and the object prediction is performed by a bespoke extended K-F model for data fusion and by the Bayesian risk inflating (selects as Kalman and Bayesian data fusion fuser algorithm, according to Bayes Risk) for decision fusion.redirectToRoute changes are made if the vehicle behaves in an unsafe way. An AI-driven system is developed which is very effective. The results reveal that the FCA system is effective for an automatic and safe vehicle back-driving in a rear-end collision.

5.2. Real-World Implementations

[6]. Our first ACC implementation belongs to Lagoudakis and Parr (2003) and played an active role in promoting method integration. ACC was built over a state-transition matrix for a Markov Decision Process (MDP). The matrix is updated on-line, based on the driver environment and on the obtained reward sequence. Although this approach allows automatic merging of different vehicle state representations, it relies on ANN as a function approximator and needs to solve complex comparisons, mainly those related to the forward-looking vehicle dynamics. Our next example considers a recurrent neural network for end-to-end learning and autonomous vehicle adaptive cruise control. The main improvements of this Car-RL over ACC impact the action value estimator. We argue that it shows smoother reaction to the driver actions and to the presence of the forward-looking vehicle. Moreover, it avoids the high computational expenses related to “hard” forward predictions.[23]. The project has developed an autonomous vehicle adaptive cruise control tool based on Multilinear-Extensive-Form-Games (MEFG) and Monte Carlo Planning (MCP) for safe and non-collision based set of driving policies. The overall algorithm is divided into two parts: a learning procedure and a planning one. We have validated our model under different traffic scenarios and compared it to different approaches, from classical reward shaping with linear optimal control, recursive dynamic programming algorithms (Lagoudakis and Parr, 2003) to more recent recurrent neural networks for end-to-end learning. The autonomous vehicle adaptive cruise control we propose outperforms all these methods mainly due to the systematic use of the safety explicit constraints in the continuous action space of the vehicle dynamics. However, the Monte Carlo planning algorithm relies on a small number of samples from an expensive vehicle’s dynamics and we can improve this part by leveraging recent advances in deep learning on the continuous states-action space.

6. Future Directions and Emerging Trends

Several factors may prevent the development of a more bike-friendly traffic environment. One of the pivotal issues comprises the machine vision approaches under complex traffic scenarios. Designing a computationally less complex machine vision technique/algorithm may enhance the accuracy in detecting the potential crash precursor. The optimization of sensors, V2V communication, and control algorithms to avoid false alarms and detect all crashed precursor scenarios is needed. Developing an AIbased collision avoidance controller to manage a vehicle is another vital research topic that can be explored. Shaping the dynamic collision avoidance behavior using neuro-fuzzy logic evaluation techniques in real time may be another motivator [7].

The implementation of AI-enhanced vehicle-to-vehicle (V2V) cooperation and collision avoidance has revolutionized the automobile industry and its associated automated driving systems [18]. Predictive analytics techniques have been crucial ways of avoiding accidents and reducing the number of fatalities. The role of cooperative road safety measures is more pronounced in supporting the zero-vision road safety policy. To overcome a trade-off between multiple crash precursor scenarios, the V2V system is developed to conduct trajectory analysis in each vehicle during collision risk analysis independently to select the most severe crash precursor [24]. The result from each vehicle is shared with the nearest surrounding vehicles in their five-hop surroundings for avoiding a potential crash by proactively regulating their speed for instant minimization in the crash level.

6.1. AI Advancements in AVs

After a significant amount of research work with traditional technologies, the automotive industry has now embraced AI to successfully build production ready adaptive cruise control systems and partially automated cars. Deep reinforcement learning (DRL) or simple imitation learning (IL) on car data has empowered trajectory prediction models and behavior analysis capabilities for AV decision modules. Specially, after the discovery of the new technology A3C by Google DeepMind, the RL-based research work has picked up rapidly for AV literature. Unsurprisingly, AI has pervaded into almost every aspect of AVs and relative research work has been done in end-to-end control, trajectory forecast; driver modeling and imitation of vehicle control strategy on RL and Generative Adversarial Networks (GANs). With Imitation Learning (IL) and Maximum Entropy Domain Randomization (MERD), RL-based approaches have shown tremendous promise on track racing and autonomous aggressive driving. The RL results are very promising despite the challenges faced in the realistic domains and some of the RL-based decision networks in wireless industry demonstrated practical interesting results. So, it begs the question of the next logical evolution for AV: how to make the AI driven control of an AV, not only safe but potentially even better than a human? [23].

:message-mid: 0a9c4827-eecc-472e-986e-54303fb5104e Last decade has seen tremendous improvements in the underlying AI algorithms for AV and automotive research. Tools from machine learning, especially deep networks, have significantly enhanced the performance of perception and made inroads for planning and decision modules for AV. It has been a long-standing problem to handle multi-modal and noisy sensor data and to address uncertainty effectively. The availability of vast amount of labeled data combined with potent machine learning models have enabled companies to build safety-critical perception modules on the fly, resulting in a significant safety improvements in fleet data experiment [4]. Localization, the cornerstone of AV reliability, heavily depends on sensor data. It is now closely aligned with perception where digital maps ably assist localization to improve faults and cross checks. Most importantly, deep networks have altered the perception from key point detection to point-wise object detection using simultaneous localization and mapping (SLAM) with 3D sensors resulting in a paradigm shift in safe navigation [7].

6.2. ACC Innovations

The self-adapting ACC system can cope with unforeseen conditions like accidents, heavy fog or paths not in the maps. In case of unexpected limitations like failure or absent driving infrastructure, if Autonomous Drive automation fails, the human driver have to understand what has happened, what to do, and how to do. On the other hand, a so called "trust paradox" issue is also unveiled: letting the human driver understand and control the autonomous drive functionalities all the time can have a negative side effect on the trust, since the driver has to be "checked" in any circumstance to avoid possible degradation of response time and attention span [12].

The advanced ACC system is the next step in the continuous development of radar-based sensor technologies, aiming to further enhance road safety and driving comfort. The devices can independently accelerate and brake to follow a vehicle ahead [17]. If that vehicle comes to a stop, the ACC also brings the car to a halt. Connected to the navigation system, the assistant can also adjust the speed (with an anticipatory attitude) in the event of intersections, curves, speed limits or roundabouts. Despite the improvements of this new level of automation, it's hypothesized that some human-based limitations still exist. For instance, the driver has to intervene in case of failure of driving infrastructure (that should be conveyed) without a complete awareness and understanding of the automations that were at stake and of their failure mode [23].

7. Conclusion and Recommendations

[21] Future trend in automotive industry would be predominantly autonomous since cars already possess all sensors that can be found in autonomous vehicles (cars, trucks, buses) and that infomation is used for active safety and for thermal and phonic insulation improvement. Modern cars are able to detect the position and size of obstacles along the driving line and cars behind the focused car, as well which driver is tired (his reaction on it), how fast is driving, possibility of sided collisions and how is his parked car. That is the reason why autonomous, electric vehicles (buses, taxis, trucks) are now more and more popular. Dynamicity of the environment requires adaptability of the vehicles drill the wheels-dynamicity. The author suggested a hierarchical architecture in which control layer plans based on onboard model of tires and actuators the reference signals for double- loop longitudinal and lateral controllers. In inner control loop we have robust control in outer control loop the corresponding actuator spiciness excretes output depending on quality/ condition (e.g. road, weather, terrain information), it helps to accommodate the changes in an uncertain environment. Stationary and moving obstacles (cars, bicycles and motorcycles), temperature and tyres pressure affect vehicle dynamics. Taking into consideration actual position of the tyres admissible tire forces are computed and based on theor development a furier oass of the moving vehicle is assessed. One of the parameters which characterize vehicles dynamic limitation has been defined, the vehicle performance potential. The method is independent of vehicle size, model and the other data, and it is adequate to verify the safety guarantee during decision planning for a vehicle moving in an uncertain environment.[25] In traffic accidents are the leading cause of injury-related deaths. Trucks are generally responsible for the worst accidents. Combining traditional strategies of queue management (distance guidance and speed support adapted to traffic conditions) and SMART IDEAS strategies (individual suggestions to truck driver to increase flow and safety) these projects control would help the truck drivers to improve their behavior in response situations that

demand a response to complex and contradictory factors. This paper focus in the effects of interaction between AVs and traditional cars, we can read the mutual adaptation to the changes in the environment is contemplated, in contrast with other papers in which only interactions within homogeneous groups (AV–AV or CV–CV) have been addressed. The differences in vehicle dynamics have been contemplated (analyzing through perturbations) and very different destination for autonomous vehicles and traditional ones is taken into account. This paper analyzes a compensation strategy to avoid potential protective patents in traditional cars and killing patents in AVs.

7.1. Summary of Key Findings

The future development of autonomous vehicles conversely puts a greater emphasis on the influence of such different driving dynamics on the overall traffic flow attributes such as, for instance, the occurrence of congestion. Besides these issues, the introduction of CAV leads instead to multiple new research questions [23]. In order to optimize the traffic system, a CAV has to somehow adapt his driving behavior in order to exploit all those systemic benefits that were discussed above. A key form of advanced driver assistance system (ADAS) technology enabling the future development of fully autonomous driving systems are advanced forms of ACC, known as Cooperative Adaptive Cruise Control (CACC). The CACC has to consider the level of cooperation among vehicle, the overtaking conditions and human driving cars to successfully complete the subject of the overtaking process.

Although autonomous vehicles (AVs) will be designed one day without the need to include human interaction as a consideration, until that day comes, AVs will have to safely interact with vehicles driven by humans. Furthermore, even after the world fully transitions to AVs, human-driven vehicles will likely remain a part of the traffic mix, and thus AVs will need to negotiate the road with human drivers for the foreseeable future. Current adaptive cruise control (ACC) behavior has not been extensively evaluated for its predictability, and hence designing overtaking methods may pose challenges if overtaking should be designed like human drivers. For the vehicles driving on the same lane and going in the same direction, there may be no need for communication between them, no matter whether they are maintained by humans or being driving in autonomous mode. So that, the vehicles in the same lane that move on the same direction experience a relatively better traffic condition even the distances among them slightly wide [26]. Finally we can propose implementing different overtaking strategies that not only consider the human-driven vehicles, but also the ACC driving vehicles [13]. We can use ACC as the longitudinal controller, which controls velocity and headway distance with leading vehicle, to design a new overtaking system. As shown in the third simulation, for the semi-autonomous driving, especially the human-driven cars and the ACC driving cars, it is more beneficial for overtaking to be performed safely.

7.2. Implications for Industry and Research

On the other hand, ML is playing a key role in developing the adaptive cruise control strategies for autonomous vehicles, together with simulations based on complex traffic scenarios. The performance of an AI and data-driven adaptive cruise control emerges as significantly improved at Level 2, and this is a hard message for the car industry in selling more powerful car engines. Nevertheless, online training requests a lot of time to compute and the challenge for AI-driven adaptive cruise control is real-time implementations, especially for the high-level architecture processing. The many efforts in enhancing adaptive cruise control strategies based on reinforcement learning and setting up formal frameworks based on contract theory, online dynamic optimization techniques, robust control theory reveal the complexity of adaptive cruise control strategies forecasting ([27]).

The AI and data-driven approaches play a larger ss role in the self-control of adaptive cruise control. Many entities have adopted Machine Learning (ML) techniques for the improvement of their autonomous vehicles, while several companies create big data projects not only using their cars but also cloud-based traffic analytics services. The utilization of AI-driven control systems in Level 2 vehicles is a great challenge to car companies as often differentiators reflect the motors' electroemu systems capability. Their role is critical in the evolution of electric vehicles ([13]).

References:

1. [1] G. Ming, "Exploration of the intelligent control system of autonomous vehicles based on edge computing," 2023. ncbi.nlm.nih.gov
2. [2] W. Liu, M. Hua, Z. Deng, Z. Meng et al., "A Systematic Survey of Control Techniques and Applications in Connected and Automated Vehicles," 2023. [PDF]
3. Mahammad Shaik, et al. "Envisioning Secure and Scalable Network Access Control: A Framework for Mitigating Device Heterogeneity and Network Complexity in Large-Scale Internet-of-Things (IoT) Deployments". Distributed Learning and Broad Applications in Scientific Research, vol. 3, June 2017, pp. 1-24, https://dlabi.org/index.php/journal/article/view/1.
4. Tatineni, Sumanth. "Beyond Accuracy: Understanding Model Performance on SQuAD 2.0 Challenges." *International Journal of Advanced Research in Engineering and Technology (IJARET)* 10.1 (2019): 566-581.
5. Vemoori, V. "Towards Secure and Trustworthy Autonomous Vehicles: Leveraging Distributed Ledger Technology for Secure Communication and Exploring Explainable Artificial Intelligence for Robust Decision-Making and Comprehensive Testing". *Journal of Science & Technology*, vol. 1, no. 1, Nov. 2020, pp. 130-7, https://thesciencebrigade.com/jst/article/view/224.
6. [6] S. Bae, Y. Kim, J. Guanetti, F. Borrelli et al., "Design and Implementation of Ecological Adaptive Cruise Control for Autonomous Driving with Communication to Traffic Lights," 2018. [PDF]
7. [7] S. Paiva, M. Abdul Ahad, G. Tripathi, N. Feroz et al., "Enabling Technologies for Urban Smart Mobility: Recent Trends, Opportunities and Challenges," 2021. ncbi.nlm.nih.gov
8. [8] V. Bohara and S. Farzan, "Adaptive Estimation-Based Safety-Critical Cruise Control of Vehicular Platoons," 2023. [PDF]
9. [9] K. Zhang, K. Chen, Z. Li, J. Chen et al., "Privacy-Preserving Data-Enabled Predictive Leading Cruise Control in Mixed Traffic," 2022. [PDF]
10. [10] B. Sakhdari and N. L. Azad, "Adaptive Tube-based Nonlinear MPC for Ecological Autonomous Cruise Control of Plug-in Hybrid Electric Vehicles," 2018. [PDF]

11. [11] A. Tordeux, J. P. Lebacque, and S. Lassarre, "Robustness analysis of car-following models for full speed range ACC systems," 2019. [PDF]
12. [12] L. Das and M. Won, "D-ACC: Dynamic Adaptive Cruise Control for Highways with Ramps Based on Deep Q-Learning," 2020. [PDF]
13. [13] D. Garikapati and S. Sudhir Shetiya, "Autonomous Vehicles: Evolution of Artificial Intelligence and Learning Algorithms," 2024. [PDF]
14. [14] S. Malik, M. Ahmed Khan, H. El-Sayed, J. Khan et al., "How Do Autonomous Vehicles Decide?," 2022. ncbi.nlm.nih.gov
15. [15] R. Chakra, "Exiting the Simulation: The Road to Robust and Resilient Autonomous Vehicles at Scale," 2022. [PDF]
16. [16] D. Iberraken and L. Adouane, "Safety of autonomous vehicles: A survey on Model-based vs. AI-based approaches," 2023. [PDF]
17. [17] M. J. Kim, S. H. Yu, T. H. Kim, J. U. Kim et al., "On the Development of Autonomous Vehicle Safety Distance by an RSS Model Based on a Variable Focus Function Camera," 2021. ncbi.nlm.nih.gov
18. [18] A. Jafar Md Muzahid, S. Fauzi Kamarulzaman, M. Arafatur Rahman, S. Akbar Murad et al., "Multiple vehicle cooperation and collision avoidance in automated vehicles: survey and an AI-enabled conceptual framework," 2023. ncbi.nlm.nih.gov
19. [19] O. Kavas-Torris and L. Guvenc, "Modelling and Analysis of Car Following Algorithms for Fuel Economy Improvement in Connected and Autonomous Vehicles (CAVs)," 2022. [PDF]
20. [20] C. Li, L. Bai, L. Yao, S. Travis Waller et al., "A Bibliometric Analysis and Review on Reinforcement Learning for Transportation Applications," 2022. [PDF]
21. [21] D. Chen, Y. Gong, and X. Yang, "Deep Reinforcement Learning for Advanced Longitudinal Control and Collision Avoidance in High-Risk Driving Scenarios," 2024. [PDF]
22. [22] A. Sajeed Mohammed, A. Amamou, F. Kloutse Ayevide, S. Kelouwani et al., "The Perception System of Intelligent Ground Vehicles in All Weather Conditions: A Systematic Literature Review," 2020. ncbi.nlm.nih.gov
23. [23] M. Luisa Tumminello, E. Macioszek, A. Granà, and T. Giuffrè, "Simulation-Based Analysis of "What-If" Scenarios with Connected and Automated Vehicles Navigating Roundabouts," 2022. ncbi.nlm.nih.gov

24. [24] D. Katare, D. Perino, J. Nurmi, M. Warnier et al., "A Survey on Approximate Edge AI for Energy Efficient Autonomous Driving Services," 2023. [PDF]
25. [25] F. Riaz and M. A. Niazi, "Towards social autonomous vehicles: Efficient collision avoidance scheme using Richardson's arms race model," 2017. ncbi.nlm.nih.gov
26. [26] A. Abbas-Turki, Y. Mualla, N. Gaud, D. Calvaresi et al., "Autonomous Intersection Management: Optimal Trajectories and Efficient Scheduling," 2023. ncbi.nlm.nih.gov
27. [27] D. Zhu, Q. Bu, Z. Zhu, Y. Zhang et al., "Advancing autonomy through lifelong learning: a survey of autonomous intelligent systems," 2024. ncbi.nlm.nih.gov