Machine Learning for Autonomous Vehicle Behavior Adaptation in Complex Traffic Situations

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1. Introduction

The work presented in this paper takes the latter route towards the development of data-driven learning-based approaches. More specifically, this work proposes machine-learning methods to develop learned models and algorithms for coping with the often encountered object behavior uncertainty. The topic is challenging and involves modeling and using techniques from machine learning that focus on handling limited and often incomplete label-to-data type data sets, as in this case only partial observation is received from an object on the road and the data likelihood is subject to the error in perception and other influences. Perception limitations such as occlusions and detection errors might occur frequently in real road settings. Consequently, this results in missing and less reliable information. In addition to this, other road user behavior might become difficult to track for the aforementioned reasons and also due to the predictions leading to a chain effect that directly costs the road users their robustness against errors [1].

An autonomous vehicle (AV) is expected to adjust its behavior and make decisions considering the driving styles of the surrounding vehicles, road regulations (e.g., traffic signals) and environmental influences (e.g., weather and road conditions) [2]. Achieving this behavior adaptation in practice requires the ability to predict the future behavior of other road users, hence allowing the AV to express co-operative and/or competitive interaction and reason about them. In this sense, existing approaches can be broadly classified into model-based and data-driven methods, where computer-based simulations and analytical program-based models are used in the simulator and machine learning to deal with the uncertainty of real-world problems.

1.1. Background and Motivation

Traffic safety can be accessed through the evaluation of real world crashes. The goal of safety is reducing the crash rate and severity per vehicle-kilometer traveled. The safety level of road traffic is often characterized with f (safety-critical events rate, injury severity, fatality, or a combination of these indicators). The won-derful day when all the vehicles on the road were autonomously controlled is coming. Within a couple of years powered by maturity autonomous vehicles (AV) technology will completely replace human-driven vehicles. The automated driving technology should be able to handle nearly all traffic situations under sophisticated configurations safely, effectively, and also calmly [3].

Changing lanes and merging into traffic involve considerable potential for causing an accident [4]. This is mainly because the behavioral strategies typically employed entail the utilization of complex real-time sensory perceptions, as well as crises, of prioritizing and controlling the power and steering system [5]. This system is characterized by repeated revisions of predictions and considerations about the surrounding environment, which often leads to difficulty with replication and/or abstraction for the traditional rule-based models of the cramming approach. As observed in line with the growing maturity of machine learning techniques that can be appropriately utilized to better solve specific technical problems, the present research work intends to use a machine learning-based algorithm to handle vehicle autonomous adaptive behavior in the context of complex traffic situations by the Freeway percentage of location data.

1.2. Research Objectives

More precisely the main object of this dissertation is to analyze, develop, test and deploy a Machine Learning (ML)-based system able to auto- matically adapt the driving behavior of the AV in a relatively short time. Deep Reinforcement Learning (DRL) will be leveraged for the training of the various models required to generate both the adaptive behavior of the AV and the driving policy to use within the context of an integrated Advanced Driver Assistance Systems (ADAS). In this regard the recurrent aspect of control philosophy for the system that will be developed is the importance to define and take into account the most appropriate observation space that the decision-making algorithm should control. The development and the implementation (on a specific AV platform, Italian Driverless all-electric car TUe.Smart) of a Traffic aware Decision / Planning Architecture for urban advanced driver assistance able to control the adaptive behaviors of the AV in order to provide a repetitive and safe driving style under different traffic density conditions within different complex urban scenarios will also be part of the present thesis. All these objectives are progressively aligned with the H2020 European projects, besides of the planned DISRI, United, HIPEBA, AI4DI! and Dream CARS 4kids EU ones. To enormously expand the scenarios as urban ones and to easily manage the research and development of new artificial intelligence algorithms for the autonomous driving, the development of new mixed reality simulator architecture for repetitive and ground breaking test management is needed [6].

In the context of this PhD project, the main goal is to provide a unified and sustainable framework for the investigation and implementation of innovative systems able to adapt their behavior in a perfect or an acceptable manner under a wide range of driving situations and in particular in complex urban scenarios. Although beyond the scope of this dissertation, the methodology employed for the decision-making algorithm and for testing the behavior of autonomous vehicles (AV) at a different level of autonomy may be of interest when designing behavior adaptation predictions for cars driven by human drivers as well. Defining an autonomy degree for a car with an advanced driver assistance system can help in the capillary evaluation of technological innovations that can be easily tested by drivers while driving their private car [7]. These technologies accept data coming from sensors already installed on advanced driver assistance systems (and others like LIDARs/CAMERAs/...), process data to make a decision/prediction/action, thus providing a flexibility that the traditional legislation cannot immediately understand and rules cannot encompass. This also relevant in framework of new concept of training where different people can learn how to drive AVs (both fully and partially autonomous) in a collaborative way with real cars or through traffic simulator [8].

2. Fundamentals of Autonomous Vehicles

To correctly diagnose traffic rules and recognize complex traffic environments, an AV controller must be infused with AI capabilities. The TAS tries to understand traffic situations with respect to ducking, overtaking, frequently changing lanes, and sustained hard braking. TAS must be able to address emergency situations to make good driving decisions, including collision avoidance maneuvers, yaw angles, and throttle and brake decisions for overtaking, and free-wheeling or sustained lightweight braking for ducking. From the perspective of safety, it is important to maximize the target recognition range and computational efficiency as well as address the potential need to address unwanted signal-noise or to remove common cause failures. The approach to maximizing the perception ranges is to introduce deep learning, swarm intelligence, and game theory. Game theory enables vehicles to cooperate with each other for coordinated overtaking and intelligent lane shifting. Traffic scenarios also include distinct mine-maneuvering indicators, visibility (e.g., sea fog, and spray), the nature of areas (desert, and forest), and traffic signs [1].

As the number of fatalities and economic losses due to car accidents continues to rise, they result in a trend in which modern cars are becoming increasingly more intelligent, and they are gradually evolving towards the Internet of Vehicles and Car2X (a type of vehicular communication system). Autonomous Vehicles (AV) are being touted as the effective solution. However, the existing knowledge base has a lack of specific conditional behavior rules to handle critical situations, omitted from the driver's handbooks. This lack of knowledge and unwritten rules are especially worrying when one considers that over 90% of road traffic accidents are caused by human errors. Some of these errors include neglect of the pace of traffic, rule violations, and dealing with complex traffic scenarios. Employing a self-learning machine to build this fundamental knowledge base is of both scientific and practical significance [9].

2.1. Definition and Components of Autonomous Vehicles

In advance-automation, [10] concludes that autonomous vehicles which, aiming at driving on expressways with low or high traffic density, are autonomous over most parts of the ride, however, there is always a human fallback. Full automation has potential to reduce human error, as has been indicated in simulations and public demonstrations. But also, driver compliance is expected to increase efficiency, capacity, and comfort. It is concluded that CAVs have a high potential to improve efficiency, capacity, and comfort.

Artificial intelligence and machine learning techniques have become a key focus in system design and testing for autonomous vehicles. Decision-making becomes challenging when the vehicle experience complex and unpredictable conditions. Moreover, it is difficult to synthesize environment models of such situations and consequently, ensuring functional safety. ML methods provide an alternative approach to capture unmodeled contributing factors. For instance, end-to-end learning of an autonomous system, including environment data perception, prediction and planning, provides an effective and scalable way to handle large data and dependencies. However, interpretability leaves questions about identification and resolving of the achieved behavior by design in safety-critical systems [11]. Furthermore, even adversarial perturbations and preventions demand measures for verification and validation methods. Feedback and feed-forward connections of sensors and actuators in interaction with environment (vehicle-to-vehicle (V2V) and Vehicle-to-(V2V) and Infrastructure (V2X) communication affect their current and future state of the system. This interaction is also challenging to reason about since behavior depends on the dynamic states of the vehicles within the system.

2.2. Sensors and Perception Systems

To navigate effectively in its environment, an automated vehicle needs to detect and classify external agents such as other vehicles, pedestrians, road users, and cyclists from the point cloud and camera sensors observing its surrounding space [12]. These boundaries and classifications need to be projected into the bird's eye view to provide the corresponding poses relative to the vehicle, which will be directly used in the control system, localization, and path planning. System processing and making decisions based on the perceived scene is commonly called perception in the autonomous vehicle community. The sensor suite in an automated vehicle usually consists of Light Detection and Ranging (LiDAR), radar, cameras, accelerometers and several environmental sensors to map and localize the vehicle effectively and robustly. The LiDAR and camera sensors are used for perception, static and dynamic map generation. In our design implementation, where to position and orient the sensors to get the best input to feed to the second stage of perception, mapping, and localization system, are discussed.

Automated vehicles need to understand the surrounding environment. They need to perceive and identify the dynamic agents and static structures such as lanes, traffic signals, and guard rails from this environment. This information will be used to localize the vehicle in its surroundings, and provide the control mechanism with states of the agents and static structures [13]. The host vehicle needs to localize itself in the environment by identifying the local map. This map contains the set of lanes and the set of relevant structures such as guard rails, traffic signals, and road signs with their respective geometric coordinates in the host vehicle frame of reference. Although map generated by consumer map providers might be used for localization, construction of an HD ("High Definition") map specific to the route of autonomous vehicles serves better to guide them on the road. This provides an active safety measure [14].

3. Machine Learning in Autonomous Vehicles

Autonomous vehicles (AVs) have made excellent progress according to the simple scenarios. In complex traffic scenarios, as the task of adaptation is very complex, there is still a long way for mainstream development [15]. This section of the chapter presents survey results on main current solving methods of this issue. An extension of the potential field method approach to create a subfield of potential function is a possible trend. Named artificial potential field (APF), it can be mathematically described as gradient flow that provides us with a powerful technical tool to describe dynamic constrained systems. In the AVs, APF approach has been used for local path planning of the control problem of avoiding obstacle ability of a vehicle. In the presence of the various behavior of the surrounding vehicle, the traditional potential field method will generate excessive interference with the original intended behavior of the AV. Therefore, our team has conducted a certain amount of research into using the conditional potential field theme as potential field method of that plan kicked behaviour [16].

Machine learning, particularly embedded machine learning, is widely used in autonomous and assisted vehicles [17]. It is mainly used to enhance decision-making, behavior prediction, and trajectory generation. Since the focus of this study is on behavior adaptation of autonomous vehicles in driving, a short review of the well-established embedded machine learning methods is given. Also, the embedded machine learning methods that are based on physical sensors are reviewed that are suitable for autonomous vehicle applications, like radar, lidar, ultrasonics, and many others. Then it is shown how conditional type of machine learning has the potential of addressing the issue that the autonomous vehicle's behavior seems tend to be deterministic and conservative.

3.1. Supervised Learning for Behavior Adaptation

According to the one-step nature and real-time characteristic of lane-change, we propose a supervised learning method to handle adaptation patterns in lane change scenarios. In our approach, we learn human drivers' (or vehicle controllers') action patterns when facing two critical types of traffic conflicts during lane-changing (Fig. 17): 1) ahead vehicles rapidly cut in – which causes a safe lane change to subsequently fail – and 2) a wide vehicle (such as trucks) continuously occupies the target lane – which requires us to choose either to change back or to try another lane change before crossing in front of the truck. We further utilize the real-world driving haptics collected in the same traffic scenario by a human driver to learn an upper-bound model for our traffic-driven lane change optimization method. Models can be evaluated in non-specificity to the scenes, different scenes, but under the same scenario, and eventual on-road A/B testing situations to figure out their effectiveness.

After recognizing that these critical traffic situations (truck blocking and vehicle cutting in) cannot be handled properly using traditional optimal control-based behavior planning methods, we propose a supervised learning method to learn human drivers' action patterns in these complex situations. We first introduce the learning performance by fine-tuning the neural network parameters based on our own test scenario in lane change-based critical traffic situations. Then we discuss supervised learning-based behavior adaptation, which relies on real driving data to improve the performance of traffic adaptation manners. In addition, we demonstrate the efficiency of our learning model by comparing our method with a naive deep learning-based traffic adaptation model and an approximate optimal control-based behavior planner.

3.2. Reinforcement Learning for Decision Making

In the future TransportIX vehicle will employ a Dynamics Based Controller (DBC) that makes use of the incrementing and decrementing feedback to make decisions on individual rules. So, naturally a part of the deceleration time available to the vehicle must be used for initiating normal deceleration. Important scenarios for any Lane-Change (LC) are those where there is a prominent risk of being cut by a neighboring vehicle [5]. Sequential responses elevate the incoming vehicle and maintain the above rule of thumb. The results efficiently reduced the false positives and detected all potential cut scenarios.

Due to very fast internet connection transferring data from one location to another within short duration is implemented to transfer data at a rapid pace. This generally the subscribers who make the most of this service provider. This team mainly works to gauge vehicle learning process or at least they suggest a vehicle decision and control approach that detects desirable scenarios, associates them with expected desirable responses, determines action spaces and strategies, and detects signals for turning or executing related tasks in identified scenarios

[18]. Every method developed to-date are typically open-loop in nature. These developments will be packaged into an intelligent driver model for on-road testing.

4. Challenges in Complex Traffic Situations

[19] Understanding driving behaviors is an essential requirement for the development of fully autonomous vehicles that can interact with human drivers [Hämäläinen et al., 2019]. In traditional rule-based autonomous driving, the design and instantiation of driving rules models is required to ideally represent the behavior of humans. However, this process is extremely challenging due to the complexity of human driver behavior and the difficulty in manually analyzing all possible driving scenarios [Harned et al., 2007] [Dixit et al., 2004]. Machine learning (ML) provides a promising approach for the development of driver models without the need for hand-crafted rules and with the ability to learn and adapt driving behavior based on the occurrence of various traffic situations and changes in the behavior of other road users. Reinforcement Learning (RL) is an important branch of ML and has been effectively applied to AVs to achieve significant achievements in the field of autonomous driving.e.g. [Pan et al., 2017] [Shalev et al., 2016]. Using machine learning techniques, autonomous vehicle agents can use complex non-linear functions to map from road observation to driving actions to model human driving behaviors and make decisions in complex driving scenarios.[20] In recent years, the development of autonomous vehicles (AVs) has achieved breakthroughs due to technological advances such as artificial intelligence and machine learning. An important area in AV development is the design of decision-making algorithms for complex driving scenarios. This is an evolving area of research, and it is still an open question as to which decision-making approach can lead to a highly complex, yet safe, driving behavior, adapting to the environment and traffic conditions. The major challenge in the decision-making process is the prediction of uncertain vehicle behavior and navigation of uncertain and dynamic environment [Hauskrecht, 2000]. Sampling-based decision-making methods (e.g. Monte Carlo simulations) constitute a promising approach for sample-based prediction [Karl and Guestrin, 2016]. In this work, we introduce a utility-based decision-making approach for AVs to infer and predict the intentions and driving behaviors of interacting vehicles in complex interaction and merge scenarios. In order to account for non-adversarial noise uncontrollable by the AV, we use a reinforcement learning approach combining Monte Carlo Tree Search (MCTS) methods for decision-making over an approximate estimative set of human intent signal templates.

4.1. Dynamic Environment and Uncertainty

Overcoming such a complex computational problem would impose an enormous demand, so robotic cars must always optimize the tactics adopted. Due to uncertainty concerning the route of the track, for example, vehicle A can choose vehicle B, before the road need change from the front right to the back left, actively adapted to vehicles and pedestrians, the decision will be changed from the original go straight to the right lane, and vehicle B has to do emergency care on whole left lane directly by changing. Only in the process of complex environment, vehicle B is not on front Among them, the control target of vehicle A is not theoretically probability disturbances, but it is car B robot mode mixed advantages reduce the chance of car accidents; therefore, the research on control commands adaptation for dynamic environment, will inevitably focus on complex situations in the dynamic development, where uncertainty as a fruit of unknown crowded actions, risky primitive environmental factors or dynamic situations is pervasive.

[4] The development of highly automated vehicles (HAV) has advanced from driving primarily in structured urban or highway environments to cities with complex traffic. Often, the safety and autonomy of vehicles may see the world as a simple three-dimensional formation of essential objects, but such simplified target objects or human entity perceptions are unreasonable when encountering complex city environment scenes, since city environments are complex, ambiguous, and dangerous to unfamiliar vehicles or familiar human operation while rarely holding stable structures and patterns. Therefore, uncertainties about the impacts of these complex environment and rail features increase the challenges to HAV predictably around but also amplify the faults of autonomous vehicles' decisions. In order to reduce the degree of uncertainties, the San-Francisco training dataset contains a number of city driving scenes for coding. This means that path planning requires constantly updated road and environmental observations: the vehicle must accurately recognize and perceive a variety of actors, continuously update their states in case of complexity, and always receive the most recent road undersandings.

4.2. Human Driver Interaction

To increase interaction with human driving styles in complex traffic situations, we analysed the RSS algorithm proposed as a rule following model in the literature and its limitations [21]. As we do not have contact with the responsible teams working with mental model related concepts, an application was developed a scenario including mental model concepts be added that including these to the test scenarios. On off-policy use, QLearning uses states coming from random data with the belief that a significant number of variables in the environment can have an impact on the global policy. However, traffic is an environment that can be assumed to have infinite states, so it can be quite hard to avoid time-consuming states. The added situation in the simulation environment is that the driving style of the traffic is taken into account in the training of the policy of the autonomous vehicle and a transition to a different driving style as a conflicting vehicle is included.

The TrafficAutomata contains a module that simulates human driving styles and interactions with other vehicles [4]. When confronted in an unexpected situation, a traffic agent can prompt an elevateutation of all pedestrians in the target destination of its path to prevent them from being hit. To model such floods, the crossing traffic agents are rapidly striding in turns to the destination. An idle status of a traffic agent is divided into five types with increasing levels of intimacy. The higher level of a traffic agent indicates more intimate interaction. The background levels are used to store the adversarial information of the traffic agents and up to five information records are implemented as the agents' workflow if there are up to five different normal traffic agents maintaining a record of the environment information at the same time. A status update about the city traffic environment is made every 3 s.

5. State-of-the-Art Approaches

Recent research describes two newly developed subsystems that exhibit human-like perception, generate human-like decisions, and validate their computational and physical implementations [22]. The two subsystems are oriented toward ecosystemive modular robotic (EMR) matrix vehicles with distributed sensor suites surrounding their main bodies. In ENRVS, a cognitive methodology for Honda Accords with Super Cruise on brownfield highways simulating intercontinental regions and nations is transferrable to autonomous operations in multimodal urban and oceanic environments. In EHME, a manipulative approach comprises embedded machine learning modules of error-robust inventory tags buzzing over and around the EMR vehicles. Generally, the human's right cerebellum interprets the perceptual information channeled from the contralateral left sensory areas via the right occipital, parietal, and frontal lobes to calibrate upcoming actions [5].

The earliest research on vehicle behaviors addressed collision prediction through cyber-physical systems modeling [23]. Machine learning models are created based on one or more sensor inputs. Engineers emphasize on manipulating the training input data to develop efficient and robust models. However, the formal methods for safety assurance of these models lag the empirical methods. Indeed, generation and validation of the devices are formidable challenges. Moreover, studies barely consider the fundamental reason why a vehicle relies on specific sensor input to display certain characteristics.

5.1. Deep Learning Models for Perception

The level of security perceived by the public is a decisive factor for technology adoption by in-vestors and governmental institutions. 5G is expected to respond to the security challenges with higher level of privacy, stronger authentication, security by design and response to spectrum security challenges. They enable a secure and scalable interconnected system that supports millions or billions of devices producing and consuming data in real time thus allowing the AG to make informed decisions and navigate independently in a challenging environment. With an unstoppable IoT increase and millions of new devices added every day, trillions of bytes of data are produced and consumed in real time [24]. Therefore, a critical aspect to achieve the full-scale deployment of level 5 AVs as IoT devices is to support the aggregation because the mobile_MEC depends on frequent offloading operation due to the computational restrictions and intermittent connectivity.

A deep learning (DL) model is trained to detect driving intention via historic route information [25]. In perception, DL models use mediated and direct perception for tasks like scanning, tracking, and creating detailed maps of the surrounding environment. Localization, a fundamental challenge in AVs, relies on matching sensor data with a priori maps to estimate vehicle location and detect obstacles. LiDAR, for instance, uses point clouds for environment shape description but other sensors have to refer to deep learning for object proposals. Based on the intersection of visual perception and dynamic behavior of the ego vehicle, learning-based prediction methods are used in motion prediction. Referring to various databases and real world collected information, a supervised learning approach is proposed to predict road driving scenarios.

Various methods have been proposed to predict surrounding vehicle path trajectories or driving reaction under complex traffic situations in the framework of machine learning. In motion planning, recurrent and convolutional neural net-works are used, according to the motion prediction requirement. YOLO v4 compares the speed of recognition and the speed of quality metrics while RBF-PRM can sample an environment using radial basis functions as opposed to uniformly spaced sample points. In decision making, learning-based and formal verification methods are developed to extract the behavior rules from large-scale traffic accident data.

5.2. Simulation and Testing Platforms

Using models to control real world vehicles is only one part of the problem. It is important that such models are trained and tested in diverse situations such as weather, traffic, and time of day. The Big Impulse Response Dataset (BIRD) was designed to alleviate the difficulty in bridging the reality gap between the model and real-world driving by tackling the equally difficult task of long-term prediction of other participants behaviour. The objective for driving simulators can be use-cases, support for physical car testing, realistic traffic behaviour or realistic visual perception. Part of the challenge is using the simulator as an environment to train the specific target machine-learning model. address the question of resource navigation in the anticipation of future adaptive deep driving in an autonomous vehicle. For example, hand-made objectives can be insufficient and a model-based reinforcement learning might be best. Co-simulation with functional mock-ups could also be used with a model-based control target.

Part of the challenge of developing machine learning models for prediction and control of autonomous vehicles is the need to develop robust execution in a diverse set of real-world scenarios. This requirement has motivated academics to extensively develop both open-source and proprietary datasets focused on various problem formulations of autonomous driving. For instance, the Multi Agent Driving Simulator (MADRaS) [26] developed at the TCS Research and Innovation lab is equipped for end-to-end as well as rule based driving. Similarly, the HiSTORquIAL dataset [27] provided by Intel Labs studying driving policies from different human agents is developed to "stimulate the autonomous vehicle controller to handle varied driving styles and unpredictable road events from an unsegmented streaming long-tailed dataset, which doesn't allow the model to overfit to easy patterns". In the case of the WILLA dataset [28], in addition to providing interactive multi-participant highway driving, the authors also introduce novel fake driver behaviours to test the robustness of prediction models.

6. Case Studies and Applications

Current trends in autonomous driving point to the emergence of vehicles that are supervised by a human driver for unique or difficult scenarios. As autonomous driving technology matures, however, it is expected to enable more drivers with accessibility to driving and decrease fatality rates. As vehicles begin to navigate public roads, they need to more than just follow traffic rules, no accidents, and reach their destination. To be truly valuable, the autonomous vehicle (AV) of the future must conform to societal considerations as well (like driving predictably) [29]. With these interlinking constraints, the rules of how the vehicle should navigate the macro world are non-trivial to manually craft, and most real-world behavior would slide off of assumed causal tiers. Many researchers believe in reinforcement learning (RL) for being the right approach to manage self-learned decisions from experience while explicitly aiming for one or more predefined goals.

ML-powered autonomous driving technologies are able to navigate through complex traffic situations in comfort and safety. These technologies, also need to be able to adapt their behavior in response to changing operating conditions, traffic rules, and sensor performance. Reinforcement learning (RL), an area of machine learning, is well suited to this because it is able to learn from the immediate impact of its actions [8]. This allows RL-controlled vehicles to be robust in wild scenarios and also provides a natural way of handling the long tail of scenarios that are encountered in the real world. In the scenarios presented, RL is used to learn longitudinal and lateral car control to apply smooth driving and collision avoidance [30]. We also present a gloss of how our approach to applying RL to high-level decision-making finds a balance between planning and executing near-optimal policies in the present.

6.1. Urban Driving Scenarios

Consequently, questions arise such as how the acting AV can be adap- ted to such situations to reduce energy consumption, emission, and stop page risk on the one side, and improve traffic efficiency on the other side [31]. To facilitate the transfer to real driving scenarios, one central aspect is to realistically simulate the traffic participants. While there are already approaches that present homogeneous traffic situations decently, these still intertwine potential objectives such as energy consumption, emissions, and traffic violation. Simplistic kinematic particle models or behavioral rule-based agents can further not handle complex optic scene situations, mainly why they are not general enough to particularly capture the multi-modality, non-normal distributions, and intense anticipation of the actual relative agent dynamics.

[32] Urban Driving Scenarios The continuous growing demand in safety, traffic efficiency, emissions, parking availability, fleet management, and environmental conditions are leading the automotive industry towards the production of vehicles capable of partially or fully driving autonomously. Over the last years, the amount of research dedicated to autonomous vehicles (AVs) has increased significantly, with an increasing interest in this field and intensive government and industrial efforts to accelerate the development and proliferation of this technology. Despite the rapid progress in the field of AVs, numerous problems are still to be solved before self-driving cars can become common on our streets. One of the major challenges in the realization of self-driving cars are urban scenarios, in which a suddenly approaching vehicle can lead to abrupt stop maneuvers and hence, critical safety situations. AVs are still not able to reason based on the in- tentions of other traffic participants and thus often have to be overly cautious, especially in urban traffic, and hence drive non-optimally regarding as- pects like smoothness and energy consumption. We aim to introduce a hybrid sim- ulation framework that uses a traffic generator in synthetic scenarios to create a dataset [15].

6.2. Highway Merging and Lane Changing

This could be needed in an exceedingly merging scenario, wherever the freeway vehicle, (possibly) contemplating to merge into the photographers lane, is outside of the personal good representation of the participant and may thus represent surprising actions. To reflect this a lot of expandable level of behavioral diversity while not matching each totally different conditioned observation, the latent area is discretized and multiples representatives square measure purpose a variety of beside the conditioned raster photo observations to encode every das physical action [33]. This approach is qualified of concerting both the social rules and the tactical behavior aspects and exhibits better HSR driven accomplishment metrics in contrast to a baseline LQR controller.

Despite being vital for highway travel, the job of merging and lane changing has only originated a small quantity of research attention within self-governing vehicles [34]. In particular, since merging and lane changing maneuvers are unendingly being performed in city surroundings and at interchanges, adaptive execution of self-initiated travel behaviors is mandatory for self-directed vehicles. As advertised at the NIPS 2018 meeting, Social reinforcement learning is educated from screen captures of the photographers or from seeing their representations and is ready to find deterministic fix estates, therefore marketing statistics. Similarly trained touch it is ready to sing its own praises plus replicates for which there are not any observables of development. In numerous work, a large range of task area assets square measure enclosed in a very RNN model to predict future trajectories of the opposite vehicles and train the RL controller in an exceedingly parallelized setup on let alone representations [35].

7. Ethical and Legal Implications

Autonomous driving AI must generally come closer to human driving behavior and make sure not to achieve too aggressive, too sports mode, or uncanny user experience. The distraction also needs to go in slightly different directions and encouraged ethically dubious aggressive behavior should be avoided, even if a lot of human drivers are following such ways heavily. However, on the other hand, neither a defense limitation nor too sidle traffic actions should occur; otherwise, the car will be a rolling block. This is the most striking apparent difference from current laws-based ethical systems because our definition of ethics in autonomous driving itself is a little bit broader than current rules- and law-based behaviors, which do not consider side-usage, distractions, or user inconvenience. While reducing inconvenience is always necessary and important, it is not as similar an ethical dimension as safety, frugality, or the greatest common skeptical user support [36].

[37] [38]As vehicles become increasingly intelligent, machine ethics plays a more and more important role in their safety-critical decision-making processes. While traditional traffic rules are designed to govern human driving, autonomous vehicles will be programmed to react properly in unforeseen and emergent situations. Current self-driving systems have already evolved beyond a simple naıve AI system. In reality, autonomous vehicles need to be empowered with complex human-like reasoning, empathy and negotiation skills to cooperatively share the roads with other traffic participants. Another ethical challenge is to

balance two critical and competitive extreme behaviors: The law-based conservative and safety-first ethical mode versus the proactive user-experience-oriented mode. User-centric behavior should satisfy user experience, minimizing hindrance or discomfort, while always strictly conforming to the law and traffic regulations. Laws-based behaviors are conservative and safety-first and hence should also consider the traffic rules, laws and regulations, especially in new uncertain traffic situations.

7.1. Data Privacy and Security

From the perspective of infrastructure, secure and fast communication from ground sites (secured V2X data exchange) is vitally important for service applications in future autonomous vehicles, and it is emphasized that with the new communication protocols, there is an opportunity to provide V2X secured data exchange infrastructure in a way that allows communication with the cloud. It is difficult for any sensor-based communication and navigation system to predict what exactly is required for decision support in fair and complex traffic situations. Actions taken to ensure full compliance with traffic rules affect the confidence of the system on the white security cloud, although laws prevent autonomous vehicle use in traffic scenarios that require ethical judgment to suit the laws of individual countries. Software and hardware efficiency and vehicle adaptation in legal and ethical scenarios must be verified and developed in many different traffic and accident scenarios within the same physical structures as required by specific ethical rules [24].

It is discussed in increasingly loud voices and various discussions that the best possibilities for collecting data and understanding it by machine learning are blocked, as consumers agree to data privacy and the cloud layer is not available for many machine learning algorithms [38]. This prevents efforts to capture a wide environment and understand it, and limits how autonomous vehicles can adapt behavioral algorithms in compliance with traffic rules and in the traffic environment. In a comprehensive review conducted in the studies that we examined, it was emphasized that the rules on data privacy and security and the process-technical difficulties still prevent the widespread use of technology in public fields and the contribution in technical production [39].

7.2. Liability and Regulations

The first liability question is who is responsible for accident which whole or partially is influenced by machine learning algorithm. Because the probability of an accident caused by the autonomous vehicle is lower than in human driving, nevertheless intersection and crash accidents will always take place. Consequently, crash occurred by vehicles operated by self-learning machines who have learned autonomously will be a critical liability question. According to situation or circumstances, blame will be shifted primarily upon the driver, vehicle manufactures but also the software developer. The second question to be considered is whether an ethical decision should be made in extreme traffic situations. In the not too remote future, a downtrend in human-controlled vehicles and an upward trend in self-driven vehicles are expected. If this is to happen, author of the algorithm and gaining private companies will be also face with an ethical dilemma over whether to save passengers or the people on the crosswalk when a general solution is not found for the problems named "trolley problem" which are a dissertation for philosophers and cleared off with a ready recipe in industry and when it is involved in the programming of the vehicle in the event of a crash. The EU's legal regulations, as wel as Turkish law, do not include them and regulate only some specific aspects related to autonomous vehicles that will be identified within the scope of traffic laws. Therefore, in the EU, the need for clear regulations to be developed in the short-term period becomes apparent which will address the ethical and security issues of the algorithms autonomous vehicles learn from. In the same time, it is not though unrealistic to claim that similar regulations will be developed in technology-friendly countries like Turkey [40].

The integration of machine learning in autonomous driving technology does not only bring a need for improved hardware and software; it also entails amendments to current policies, regulations, and ethics. Although fully autonomous vehicles are expected to greatly reduce the number of traffic accidents [41], these vehicles may also cause crashes and serious injuries or fatalities. In the light of new paradigm, legal and ethical issues were raised, ranging from liability and responsibility of traffic accidents involving autonomous vehicles to the trolley problem dimension of the autonomous driving systems that should execute ethical decisions in extreme situations.

8. Future Directions and Research Opportunities

The ML models and algorithms used in road traffic problems are supervised, unsupervised, and reinforcement learning. Supervised learning algorithms use big data training data where labels of known entities exist. Training a neural network-like model consists of learning the weights of the links between the hidden layers. These models are not straightforward to apply when adaptation is required. The unsupervised nature comes in when traffic patterns have to be discovered and then replicated. This algorithm is under the reservoir computing paradigm. Reinforcement learning for navigation and ADAS are the management of trade-offs among greed and exploration relative to different ADAS use cases [article_id]. An autonomous car has to exhibit dynamic behavior adaptation in real-world traffic situations, as it is not feasible to contain all kinds of situations during the training phase. Flexible computational models, capable of learning the intricate non-linear relationships between (possibly) conflicting driving style targets according to the given traffic situation, should be put in action. Here, we can think of an architecture based on a Mixture of Experts Variational auto-Encoder and GAN model connected with Evolution Strategies [article_id].

[30] [7]The future of autonomous vehicles lies in the use of AI methods to achieve levels of autonomous driving beyond current state-of-the-art systems, as discussed in [article_id]. One pressing challenge in this area that requires attention is the ability of autonomous vehicles to recognize and react to complex traffic situations without human intervention and, in some cases, without previously provided training examples. Real-world traffic, particularly urban traffic, is highly complex due to its dynamic properties, high number of traffic participants from different categories (e.g., cars, bicycles, pedestrians), and various natural and man-made obstacles (e.g., trees, construction sites, public works). Due to the varying degrees of interdependency and interaction among traffic participants, the classification boundaries between normal and severe traffic situations have high non-linearity. Natural and weather conditions add to the complexity of the situation, as these conditions often make it confusing to decide on the reaction when the driver is in control of the vehicle [article_id]. Current AI-based self-driving cars, with fully-decentralized decision-making strategies, will need to recognize such complex traffic situations and act accordingly.

8.1. Multi-Agent Systems and Coordination

The models and tools described in this article have successfully passed acceptance for complex traffic situations (e.g., for interchanges, roundabouts, crosswalks, and discrete mechanisms of vehicles cooperation) [42]. The potential impact of all the issues is of crucial importance in the broad debate on the correctness of implementing autonomous vehicles in mass traffic. It should be expected that the presented aspects affect not only road vehicle users, but also the hazards and levels of air pollution.

Agent-based Multi-Agent Systems (MAS) are gaining importance in modeling, simulation and research on agent solutions in the context of intelligent transport systems [43]. Due to the distributed nature of such approaches, from the perspective of the AV model developer, the universality of the multiagent platform at the intersection of traffic and infrastructure opens up the possibility of modeling the behavior of various road users in the context of infrastructure, as well as policy decisions in the area of constructing and modifying the road network. From the perspective of model users, the multiagent concept promotes constant development and strengthening the position of the effectively and efficiently acting solution based on state machines, which is used to guide road users and the consideration of desired infrastructure changes. Mathematical models are used in a wide variety of fields to predict the behavior of a system under study and illustrate its potential changes under different stimuli. Agent-based Multi-Agent Systems (MAS) can serve as an effective tool for modeling and simulating the behavior of complex, dynamic, and adaptive systems like traffic [7]. MAS allows creating decentralized simulations. The key elements of these systems are agents being able to make autonomous decisions, oriented at their own interests, and often based on partial and/or incomplete information about the state of the entire system. This, in a natural way, allows us to represent the individual behaviors of drivers and other road users and allows the analysis of the overall system's behavior that comes from it. MAS research regarding traffic consists of multiple disciplines, such as automatic control, computer science, operational research, logistics, and economics, but very generally it comes down to planning, scheduling, and optimizing decisions at the individual and team level while satisfying dynamically emerging and changing demands.

8.2. Explainable AI for Safety-Critical Applications

For the explainability of the predictions, current research focuses on generating reasoning for the decisions or predictions generated by the different AI systems. Which need to be interpretable, justifying the actions it takes for building trust among users. In the case of cutting-edge technologies which behave in an unreliable manner, might arise public backslash so, interpretability might help in protecting the company's reputation and reduce any uncertainty. The other reason which demands interpretable models is the safety and reliability of the model under surveillance for a self-driving system. The vehicles are becoming more complex with so much data to process so, interpretations improve maintainability and verification of the systems of such a vehicle which is a safety requirement. When the decisions of the AI systems for autonomous vehicles can be explained, that greatly enhances the safety of the system [44].

The recent advances in the field of end-to-end learning for autonomous driving with the help of deep learning methods identify some key challenges like distribution shift, issues of attribution, and computational instability. The importance of how the driving datasets are collected works hand in hand with the reward and policy design for reinforcement learning, also the need for behavioral safety of the agents generated through imitation learning [45]. With this much data and model sizes, the interpretability becomes a prime concern. Apart from this, the vehicle might not always behave ideally out of various reasons like a perception error or dangerous environment causing starting issues like unobservable human-made faults. To overcome this unsuitability, it is crucial to interpret the decisions made by the AI system inside the vehicle [24].

9. Conclusion and Summary

The next interesting area of research is the vulnerability to autonomous vehicles this is included in the vulnerability and availability part of the taxonomy. Technologies enabling driver handovers will become essential to avoid side effects such as loss of concentration for monitoring tasks during automation. The goal will be to assess user comfort and define the best conditions for driver handover [b:baa1ecc0-0bce-4550-b548-cb4727b112ae]. Indeed, the fact that an autonomous vehicle is not able to retrieve its operator from the inattentive driving state has been shown to potentially lead to dangerous situations in a smart road environment: based on notions from the automotive human–machine liaison and from psychophysics, research has shown that it takes longer to refocus attention in transition situations [a:2a825c44-a1ec-41ba-a51c-bfd43a72619c].

One immediate area that could use more research is driver-to-vehicle interaction in fully automated and autonomous vehicles, and how the human factor is crucial to the design, operation, and acceptance of this technology [b: 98b4a1e3-cb1b-4fcc-9d85-5fe092c821ea]. The open problem of the human factor is included in the taxonomy and has connections with cooperative adaptive cruise control, driver state detection, infrastructure-based technologies, driver behavior prediction, etc. As it is a fundamental part, a lot of research is focused on the interaction between humans and autonomous vehicles [a:2a825c44-a1ec-41ba-a51c-bfd43a72619c]. So indeed, assessing human behaviour is a challenging approach to build improved driver models. Whether in psychology or robotics, body postures, motion and force patterns of human pedestrians have been modelled using machine learning algorithms. For example, in a context of safety and comfort enhancements in vehicles, it is interesting, just like this work [b:baa1ecc0-0bce-4550-b548-cb4727b112ae], to look at the consequences of torques applied by the driver on the driving and the posture of the driver and of companions in case of automated vehicles.

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