AI Algorithms for Autonomous Vehicle Decision-Making in Complex Traffic Scenarios

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1. Introduction to Autonomous Vehicles

The performance of the trained models was evaluated in unknown environments, in this case a faculty connected to the testing site with a communitarian road. In a known environment, the system was capable of executing navigation passing through critical situations. Performance evaluation was relational to a set of indexes regarding requirements, for example, collision avoidance, detection of persons, and detection of static and dynamic obstacles or limitations. The two manned vehicles for validating the baseline data were the driverless vehicle communicating with the call center of the faculty and the validation of the navigation route using the GPS codes of this system. All these new would like to respond to the following question: What are the probable problems, methods, solutions, and impacts regarding the extensive use of driverless vehicles in urban traffic and some rural and highway situations? Major attention was paid to the different types of driverless vehicles that were used in real traffic that showed that there is a mismatch between the recent efforts of the research team and the real-world experiences of commuters (on the drivers' and partners' side) that moped, motorcycles, push scooter, or electric bike riders have been affected by fear and unease.

Autonomous vehicles (AVs) are self-aware and reliable transportation systems that operate with an array of sensors to observe and sense the circumstances [1]. These vehicles are mainly developed for three essential functions, such as improving road safety by avoiding or reducing human caused crashes, increasing road capacity by avoiding the effect of human interaction and passengers' practice, and effort reduction by releasing drivers from driving tasks and giving them the chance to do a secondary task while driving (eg, watching movie) [2]. The driver assistance systems, classified as conditional automation (Level 3), high automation (Level 4), and full automation (Level 5), are recognized as the 3 levels of AVs with varying dependence on their controls for the venture. In recent years, a large number of reports and data highlight the problems of significant assistance from human drivers when using the condition-based systems (Level 1) and that at least the partial assistance from the computers is a safer way of operation. Next, dependence over the automatic control systems are various, high, and full, respectively. These systems diminish the number of accidents significantly and achieve substantial fuel economy. An established V2I and V2V communication system and Internet of vehicles can reduce the CO2 emission of AVs by 33% [3]. Different levels of V2V communications improve energy efficiency because the length of on-cycle time, the exterior shape of the vehicle, and vehicle mass are reduced. On the other side, if the cruising speed of AVs is restricted, the energy consumption of AVs will increase, hence the level of service of the road is not efficiency.

1.1. Definition and History of Autonomous Vehicles

Safety concerns, accidents caused by humans, environmental problems, and the desire to make daily transportation safer and more efficient are some of the motivators to prepare new technologies for autonomous vehicles. The first most critical decision-making layer for controlling an autonomous vehicle safely is its perception system as it is required to estimate and recognize environmental objects and actors and evaluate their intentions reliably and accurately to plan and determine an efficient driving policy. Autonomous cars require large engineering investments for developing and integration of multiple sensory data combination model-based fusion, designing efficient commercial sensor hardware, and challenging sensor fusion and real-time detection, tracking, decision, and control of self-driving vehicle motion for everyday road driving on unknown roads in unpredictable traffic scenes without causing danger to the road transportation system and human drivers [4]. An autonomous vehicle requires not only local perception and long-term decision and motion planning method algorithms but also tracking non-ego-acted consent-reasonable trajectory compact representations, most likely momentum intensity and some motion certainty descriptions.

Autonomous vehicles are able to operate without a human driver utilising a combination of artificial intelligence, environment perception sensors, motion control algorithms, and vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications [5]. The development of advanced autonomy systems for unmanned aerial and ground vehicles has become a popular research direction in the last few years. The future market and demand for autonomous cars is anticipated to revolutionize public transportation, by providing cheap, safe, and efficient mobility for people and goods. The global car manufacturers anticipate that fully autonomous cars, trucks, and buses will be available for public purchase in the next nine to fifteen years at affordable costs. The current side money losing for-profit companies like OTTO Motors, Neolix, TuSimple, and Nuro with road legal testing/operation products for autonomous cars, trucks, and shuttles promises fully adoptable future for autonomous mobility.

1.2. Importance of AI in Autonomous Vehicles

[6] Autonomous vehicle (AV) technology has been extensively developed in recent years. In the field of traffic management, as a research topic for the realization of urban Automated and Connected Vehicles (ACVs), it represents one of the great scholarly challenges. Numerous cities all over the world have been promoting the spread of autonomous vehicles in these years. In many initial stages, it is expected that human-driven cars will continue to circulate in cities, and the gradual dissemination of AVs together with the conventional cars raises important safety implications that need to be deeply studied.[7] There is no certitude about the consequences that traffic will have in the urban environment, introducing AVs. In particular, the high-level and low-level decision making algorithms of AVs are based on AI; both decision making, occlusion management strategy, trajectory planning, the overall control strategy of the vehicle, and task management are based on Artificial Intelligence (AI). The perception of the environment, through the various on-board sensors, enables the lateral control function of the AV, and it is supported in the local awareness of the vehicle.setCellValueThrough the on-board sensors and the interaction with the existing infrastructure, typically through the use of wireless communication, the AV is able to handle the static and dynamic obstacles that come to interaction while navigating in the urban environment. The Smart traffic management systems will monitor and control the road network by means of a shared AI to grant the vehicle with prior art to the critical issues that could affect it.

2. Challenges in Autonomous Vehicle Decision-Making

Much effort has been dedicated to creating safe and reliable Artificial Intelligence (AI) decision-making algorithms for AVs through studies of human characteristics in complex traffic scenarios. The challenges in AV decision-making mainly focus on both vehicle control strategies and their implementations in various uncertain and complex traffic scenarios. This is particularly reflected in navigation decision-making at roadway intersections. The intersection is a spatial complex and dynamic urban scene with multiple vehicles and pedestrians, especially as influenced by traffic signs and signals, i.e., environment dynamics, i.e., the intersection is an essential part of the environmental status around the AV [8].

[9] [10]Building a safe and reliable decision-making system for autonomous vehicles (AVs) in complex traffic scenarios is a significant technical challenge. Autonomous vehicle functions are divided into four blocks, including sensors, localization, perception, and decision-making. Research on autonomous vehicle decision-making mainly focuses on the relevant decision-making level and algorithm models for safety and efficiency assurance in the complex traffic environment. The first level, known as the Global Motion Planning (GMP) Module, determines the route of the vehicle. The second level, also known as the Behavior Reasoning (BR) module, judges the urgency of vehicle behaviors. While the Global Motion Planning module and Behavior Reasoning module contribute to determining the path and destination of the vehicle, the third level, which depicts the Local Motion Planning (LMP) module, calculates the trajectory. The final level, known as the Control Module (CM), implements vehicle control strategies. Whether these modules are simple, they are very substantial for getting the vehicle as close to behavior-oriented as is possible.

2.1. Complex Traffic Scenarios

In the process of integrating them into their surrounding environments, autonomous vehicles will need to frequently make decisions in complex and dynamic scenarios that are currently nearly impossible to represent with a deterministic model [11]. Additionally, under all scenarios, autonomous vehicles need to ensure safety and preserve driving correctness. In drive-by-wire systems, it is observed that during interactions with their driving environments, autonomous vehicles must consider various physical constraints, such as comfort measures and vehicle handling dynamics, when making driving decisions. In summary, to ensure that an interaction is safe (that is, avoid collisions), legal (that is, satisfy regulatory requirements), and comfortable (that is, exhibit driver-like behavior), the decisions of autonomous vehicles should be based on their joint dynamics and uncertainty models.

Autonomous vehicles are expected to continue increasing in popularity in the coming years thanks to their potential for making transportation more efficient, reliable, and safe [12]. In particular, autonomous vehicles are expected to not only improve efficiency and convenience for our daily automobile-based activities, but also to lower delivery times for businesses. Once this technology is further matured, it is expected to have a profound impact on similar activities for vehicle automation across domains such as off-road, aerospace, and watercraft, as well as for more general automation activities.

2.2. Dynamic Environment and Uncertainty

Due to the complexity and variability of environmental information, the dynamic environment has great uncertainty. Therefore, the environmental content of the shape, color, and texture should be expressed accurately to reduce the correct rate and false alarm rate as much as possible. At the same time, the layer features include not only explicitly expressed dynamic information such as traffic lights and pedestrian light poles but also other surrounding environment features [13]. The scene content needs to be judged without input from the highest certainty priority to the complete context for consistent decision-making and execution results. The dynamic target needs to be accurately extracted only with the location information and identification context in the description of the shape texture at different observation distances.

The environment surrounding the autonomous vehicle contains extensive and diverse information. These include temporal changes in the environment, changes in the traffic signals and pedestrian crossings, environmental disturbances such as fog, rain, snow, and storms, etc. effectively cause multiple changes in the state of the intersection or the movement path of the vehicle. There are different types of traffic signals and pedestrian crossings present in a dynamic environment that are always changing due to the flow of traffic [14]. There are the same and opposite directions on the train system, usually having a right turn go straight, left, right bypass, left bypass, and U-turn six kinds of signal options. In addition, rail signal systems include stage signals such as speed and working status, station signals, and closed signals that prohibit vehicles from directly entering station platforms from the track.

3. AI Techniques in Autonomous Vehicles

In this research, all the algorithms except the unsupervised learning segment of the perception phase have been included by the authors. The paper aims at reviewing the concept, theories, main idea, and prior advances in employing the aforementioned techniques and in a large number of application scenarios [15] [13] [16].

The necessity of using robots and vehicles has been increasing rapidly in recent years due to their rapid, accurate, and unfatigued service in various daily tasks. Owning to their significant contribution, various researches such as in ground and marine vehicle, robot manipulators, and drones can be found. In the field of vehicle, many efforts have been directed to optimize fuel consumption and emissions, so autonomous taxi-sharing systems have recently been proposed. Not only reducing cost, energy, and emissions, autonomous vehicles can also improve road capacities and safety. The technology keeps developing to realize that the vehicle in not only specializing in outdoor drive but also in robotization of conventional vehicles, which is termed autonomous driving. In both employments, particularly in the case of autonomous driving, a vehicle should perceive its environment, and plan, decide, and control extra- and intra-vehicular actions to complete given missions. Various sensors like camera, lidar, ultrasonic sensors, and GPS are needed to finally perform these operations. At the current state of the art, machine and deep learning techniques, among which feedforward neural networks, convolutional neural network (CNN), long short-term memory network (LSTM), synergized residual network-based U-net are typical, and reinforcement learning methods are widely employed to perform tasks related to perception, decision, and control phases.

3.1. Machine Learning

These zones will be taken as the reference for the existing lane change decision making and planning strategy, and we can safely input the vehicle state and the status information within the communication range into the lane change choice module to obtain the vehicle dynamics and the decision-making lane-changing results. After obtaining the intention of lane change, the lane change trajectory should be planned. Here, a path optimization scheme based on multi-segment polynomial curves is proposed. A high precision and smooth lane change trajectory can be easily generated from optimization problem satisfaction.

There are several key problems in the current lane changing decision-making and planning system related to ML. First, the existing works did not consider a comprehensive strategy to connect the lane changing zones with traffic information, especially with multi-lane changes, and it will degrade the comfort of the driving and the efficiency of the traffic system. Second, the existing works do not consider the vehicle dynamics and lane change decision-making and planning separately [15]. As a result, the system is not flexible and cannot avoid the action errors effectively. This paper presents the lane change decision making and planning system for the highly connected and automated vehicle based on the graph convolutional networks (GCN). We use the lane change choice module to predict long-term timing and find the lane changing strategy. It is worth noting that a multi-segment polynomial curve optimization algorithm is designed to generate the entire lane change trajectory. In terms of different regions, miscellaneous factors such as the traffic flow, the lanes' trajectory and the vehicle state variables within the communication range, the surrounding vehicles' state variables such as the speed, acceleration, etc., are inputted into a position related module to express the corresponding intergal (internal and external) factor condition [17]. In addition, the clustering module is used to generate the status-clustering clustering for the vehicles within the communication range, and the reasoning module is used to output the lane changing zones.

Autonomous decision-making is a critical factor for artificial intelligence (AI) in the automotive industry. There are two major AI methods that are widely used in autonomous vehicle decision-making, one of which is machine learning (ML) [18]. ML divides into supervised learning, unsupervised learning, and reinforcement learning (RL). Supervised learning is a popular ML technique utilized in autonomous driving to complete perception tasks, such as segmentation, object detection, and recognition. RL has been demonstrated to be suitable for solving more complex problems, such as robotics and self-driving car controllers. Convolutional networks, small networks, and deep networks are several typical network categories used in RL for autonomous driving. Traffic comfort and safety are two important reference indicators to examine the performance of an RL algorithm in its control scheme. Learning-based algorithms require large data sets and depend on high fidelity simulators allowing novel alterations such as neural network modifications, feature augmentation, etc.

3.2. Deep Learning

The basic properties of deep learning algorithm make its training data some spaghetti-like non-linear surface embedded in high-dimensional space, which is kind of a 'black box' that is difficult to be explained [9]. In autonomous driving scenario, the decision-making made by such 'black box' is challengeable about its reliability and controllability when accidents happen. In this respect, more transparent method should be introduced to improve the controllability and trustworthiness of the decision-making algorithms. There are many Black-Box experimental methods to visualize the function of the deep learning model or interpret the decision-making process, most of which is based on similarity-based models. This type of method is efficient for instance-wise visualization or explanation.

In recent years, deep learning has achieved great success in many areas with the breakthrough of big data and computation power [19]. Deep learning can help autonomous vehicles solve problems in perception, HD mapping, prediction, and decision-making [5]. However, there also exist some limitations of deep learning in complex traffic scenarios, such as scalability, transparency, and generalization. In some complex and rare scenarios, it is challenging for deep learning to achieve satisfying generalization.

3.3. Reinforcement Learning

Research on mechanism to make decision-making and planning judgments is the basis of the research of ADAS system. There are a lot of approaches to solve this problem. Krajzewicz P /ref:5e3d2a02-9e1a-4c49-80a3-9fc5f07ccc4d' have summarized these methods into two categories, non-data-driven methods, and data-driven methods. Non-data-driven methods include finite state machine, Decision Trees, and Game Theory. While Data-driven kind approaches usually associate with several sorts of highly effective data-driven design methods, /ref:5e3d2a02-9e1a-4c49-80a3-9fc5f07ccc4d' such as deep learning methods or reinforcement learning methods. Among them, the reinforcement learning is used for sequential decision problems and model building, such as lane changing, overtaking, etc. More and more works are showed GNN is helpful for pursuing connections in the information instead, and is hard to have better performance even with more and more embedding dimensions.

Reinforcement learning (RL) uses the concept of reward to train an agent, which /ref:6e3a1137-7712-4bdc-8ecf-9fbcdb932dac' from one decision point to another, and ultimately from starting position to goal position. Deep reinforcement learning (DRL), the combination of deep learning and RL that has now been more and more used for autonomous vehicle decision-making. For example,—1[[Davis_2016]]—has used DRL to develop a lane and speed changing behavior based on vehicle, lane, and speed data. Similarly, Komorowski et al. /ref:d62d747e-3ac3-4755-b3e0-387161ee8f6a' have used DRL for car following by observing and imitating human behavior. Although DRL-based decision-making methods have successfully modeled several complex tasks, and have been widely adopted in fields of artificial intelligence (AI) and the process control, it still remains a challenging issue to combine mathematics models and machine learning method to solve the problems in the traffic flow based on the real environment and the physical world.

4. Decision-Making Process in Autonomous Vehicles

A top view of the car, showing the current speed and the driver's camera view equipped car and such synthetic vision. A top-view shows the road encoding used for each car obtained from SVL. It also shows the Dynamic Road Map that includes the current plan and trajectory planning. When the agent takes control of the car, this dynamic road map is communicated to SVL for real-car testing. The final test of the complete agent involves sending the plan to the car and reasoning about future simulation runs. [9]

We bridge the gap between commercial summers versus full implementations by designing rule-based rounding that consistently performs better than model-based rounding in multiple displacement-oriented tasks. We identify the shared and private interfaces for output rounding, modularize the turn-taking behavior when integration with collision avoidance. We provide interfaces for neural policy integration and a parameter server to inform the two modules. [20]

Autonomous vehicle decision-making requires careful and well-planned operation, encompassing high-speed perception, trajectory prediction, and diverse maneuver decisions. Previous work focuses on well-defined, individual traffic scenarios without much research on the relationship and evolvement of traffic conditions. To alleviate this gap, ramp merging with diverse times and vehicle density is examined as the primary research topic. In this paper, we extend the job-shop scheduling framework to accommodate the spatiotemporal scheduling of each merging vehicle simultaneously. [21]

4.1. Perception and Sensing

Many data sources are integrated in the vehicle perception module in this article which includes vehicle-mounted cameras, GPS perception, IMU collection, and data cleaning, point cloud data synthesis, waveform data processing, far-field data preprocessing, near-field data preprocessing, and so on. The environmental-perception system is crucial for autonomous vehicles as it provides the basis for decision-making. It impacts lane-changing decisions by providing vehicle and surrounding information. Various technologies, such as visual perception, laser perception, and microwave perception, are used for environmental perception. Sensors like on-board cameras, laser radar, and others play a key role in autonomous vehicle environmental-perception systems. The fusion of the near, middle, and far distance information is what mainly dominates the lane-changing decisions of autonomous vehicles [22].

An intelligent and safe decision for autonomous vehicle motion in complex traffic scenarios is crucial for the potential to be realized. The environmental-perception system is important because it provides the basis for decision-making. The vehicles' lane-changing decisions are impacted by the environmental-perception system, which integrates the near, middle, and far distance information around the host vehicle [23]. A well-functioning sensor that precisely senses the vehicle and the surrounding environment is an essential cornerstone. The subsystems in environmental perception can be divided into five parts: acoustic perception, magnetic perception, microwave perception, visual perception, and laser perception. The environmental stimuli include hot metal, various physical phenomena of friction, the emission of light photons, and electromagnetic radiation. However, there is still a great deal of work remaining in understanding our senses, processing and responding to dynamic environmental events.

4.2. Planning and Control

As for path planning, two major approaches can be noted: first heuristic search-based methods for global, online and offline path planning and secondly, model-based maneuver planning for near-term path planning using trajectory tracking control with generated paths as nominal points. As final remarks, it is important to consider that the so-far adopted planning and control algorithms might not be satisfactory when concerning controlled simulation-only researches and if any of the safety layers and underlying monitoring and prediction of the surrounding layer is flawed [10]. Such an immediate response requires homeomorphic motion space exploration which is not directly handled by planning and control subsystem discussed in this Sec. 4.C, but can be well handled since such improved DMS design is realized and therefore hence it was not considered any further in this chapter.

A decision-making process for autonomous vehicles always starts with understanding the intentions of other road-users in their surroundings [13]. The need to avoid obstacles arising from blocker vehicles or other pedestrians is then the next obvious drive for decision-making action. Moreover, it should be able to handle situations concerning parking and lane changes and navigate intersections, curves, and T-junctions. One of the most complex but yet still efficient form of decision-making is adopting Hierarchical Finite State Machines (FSM) [24], which encourage effective handling of complex traffic scenarios while concentrating on both safety and traffic efficiency.

5. Current State of Autonomous Vehicle Technology

According to NHTSA crash behaviour reports from 2005-2007 and 2012-2015, 93% and 95% of the car accidents happened because of the human-factor. Therefore, and in order to reduce the amount of these accidents and to perform a complete automation of vehicle driving, decision-making is one of the most important components in vehicle autonomy. To make cars completely automated and deal with different cases safely and without involving human drivers, the decision-making algorithm should be flexible and also be able to handle unstructured events and scenarios [16].

An autonomous vehicle (AV) is fundamentally a robot responsible for safely transporting people from point A to point B, without a human driver [25]. Among the many complex challenges necessary for autonomous vehicles to be safe and driving all the way autonomously, decision-making is at the core and considered as one of the most important challenges for achieving full autonomy [10]. Over the years, many different decision-making approaches have been proposed, these include rule-based systems, model predictive control, machine learning, and several optimizations. For example, a common question is: "Should I squeeze into the left lane now in order to take the next left-turn exit?" Or "In this multiple vehicle merge situation, can I trust vehicle-3 that it is giving way to me?"

5.1. Industry Players and Innovations

their runtime decision-making and vehicle navigation. Many other big corporations have recognized the need for AVs' training and decision-making processes, and therefore, they have profoundly invested in driving innovations in this industry. As a result, a significant number of AV models were developed with core functionalities of speed control, LPD, TL, and obstacle, split into multiple, specialized layers, performing dedicated tasks of real-time navigation, safety, and long-term prediction. For example, Argo AI provides self-driving vehicles to realize a safer and more flexible future of vehicle transportation, with AVs' transportation of goods and monitoring, including residences and commercial facilities anywhere and anytime. And this can use AI for speeding up, LPD, and TL identification and has become a leading vehicle and vehicle parts-sharing service.

In addition, many startups like Zoox, waar, and Nuro have presented their vehicle-oriented algorithms to boost .

Artificial Intelligence (AI) algorithms for autonomous vehicle (AV) decision-making manage the complex interactions arising in traffic scenarios by rapidly processing abundant information and making the best possible decision to deal with the situation at hand [26]. The presence of sophisticated AI algorithms and the convergence of sophisticated AI techniques with data-rich and task-oriented paradigms have been the main factor for increased rather expected deployment of AVs. As a consequence, various industry players have entered the market to drive innovations for AVs by investing high amounts of money [27]. To that end, these industrial players have channeled high amounts of investment to develop a significant number of AI models for AV decision-making in complex traffic scenarios, and many institutions and companies have played a major role in achieving this objective. AI models like CNN and DRL are now widely used to train the AVs to improve their efficiency of data processing and judgments for decision-making [25]. In Sections 3 and 4, we have discussed how these models infer "what, why, and how questions" to make efficient and safe decisions based on their acquired data and intuition. Afterward, these trained models can be used to make AV-real-time decisions, e.g., real-time path determination, relevant object deletion, and redundant sensing; and helping the dispatching of specific data flow in massive streams; and dealing with the external, locally/mildly constraint scenarios.

5.2. Regulatory Landscape

Initiatives for the regulation of autonomous vehicles also occurred in Asia and Australia. In July 2018, the National Transport Commission (NTC) of Australia proposed legislative changes under the Heavy Vehicle National Law to permit the trials of automated vehicles in Australia. The proposed regulation defines an automated vehicle as a driver-less or self-driving vehicle. The vehicles or trials must satisfy the duty of the vehicle owners in terms of safety, and the drivers' duties, among other rules. A final report is to be submitted by 2020 to permit widespread deployment and commercial usage of automated vehicles [1]. In 2016, Japan approved its first laws for the use of autonomous vehicles. The regulations are less directive when compared to the United States, allowing companies to develop their own rules of operation in a predefined location and after obtaining approval from the Japanese authorities. Also, in 2016, the United Arab Emirates presented the Smart Vehicular Structure Project in the Dubai Emirate. The project seeks a smart and sustainable infrastructure that allows for the testing of autonomous and electric vehicles. The project considered the construction of infrastructure and collaboration with car manufacturers to facilitate the testing and commercialization of autonomous vehicles.

In terms of legal regulation, in a global context, one can observe the adoption of specific regulations for autonomous vehicles in various jurisdictions and an intense debate to reconcile the regulatory framework with the fast pace of technological development in this sector [12]. One of the earliest jurisdictions to adopt a legislative framework for autonomous vehicles was the state of Nevada, in the United States. Furthermore, the State of California also adopted specific traffic laws for autonomous vehicles in 2012. More recently, the US Congress has been aligned with the state regulations and has approved laws for autonomous vehicle operation in the country. One should mention that regulations and the development of autonomous vehicles have been strongly influenced by the established protocols and regulations for connected vehicles, which can provide a better view of the main trends for autonomous vehicles. In the European Union, one of the most important regulatory developments was the approval of a new revision of the Vienna Convention on Road Traffic in 2016. This legal instrument was one of the main barriers to the development of autonomous vehicles in Europe since it prevents a machine from operating a vehicle without the need of the direct intervention of a person.

6. Ethical and Legal Considerations in Autonomous Vehicles

Regarding the ethical questions, in case of an accident, an algorithm could be designed to avoid personal injury by always preferring the safety of pedestrians. However, an ethical decision is described in such a case: Who must be protected in more uncertain traffic situations? The vehicle passenger, who has paid the service and is the direct customer of the technology, or the people in the traffic environment? For example, if avoiding a pedestrian collision would automatically direct the vehicle into oncoming traffic, it could potentially result in the self-endangerment of vehicle passengers when following a pedestrian protective principle. A common ethical opinion dictates that vehicle decisions must be in favor of reducing passenger endangerment, while obviously also minimizing the injury and fatality rates of pedestrians [26]. If technology development in the autonomous driving sector consistently tends to include a utilitarian ethical approach, on the other hand, vehicles may act in ways that might contradict common norms in an ethical-philosophical sense and – whether intended or not – increasingly reinforce the distribution of social resources predominantly in favor of the end customers. Therefore, this is considered to be a potential ethical problem that the developers of an intelligent technology must compromise when making a decision.

As artificial intelligence (AI) methods and algorithms are playing increasingly important roles in the automotive sector, ethical and legal considerations have become topics of increasing interest. Regulation becomes increasingly important with complex traffic situations if an autonomous vehicle is involved in a car accident [28]. In this case, ethical questions about legal and moral responsibility are raised, especially since the technology focus is increasingly shifting towards the end customer who will be the main beneficiary of the technology. In case of a traffic accident, it becomes necessary to determine liability within the framework of civil law. Liability and compensation claims resulting from damages are determined according to the Legal principles. Based on these legal principles, driver liability in traffic accidents are largely determined on the basis of negligence, presumption and strict liability.

6.1. Safety and Liability Issues

The question of liability for autonomous vehicles involves several distinct aspects. The denial of driver liability, when the AI driving unit makes decisions instead of a human driver, implies the shift of liability towards manufacturers, service providers, public institutions, and software engineers. Creative and efficient solutions are necessary to reveal the actual entity that will be the liable person for victims' and/or passengers' security [29]. A potential solution is connected with the proposal of an 'autonomous driving insurer' that would sell primary (i.e., obligatory) insurance and potentially other kinds of insurance (e.g., property insurance), by analogy to current traffic accident insurance systems, but adapted to the specifics of autonomous vehicles. An advocate may also be necessary to defend, during legal proceedings, the passengers' and/or victims' interests vis-à-vis insurance companies, the state, or other entities in the complex system of autonomous transportation [30].

Safety is the most significant concern with regard to autonomous vehicles. The artificial intelligence algorithms used in systems such as self-driving vehicles must guarantee high safety levels [10]. Sophisticated behavior prediction, safety-driven planning and control, and comprehensive risk assessment are desired for decision-making units of autonomous vehicles. Additionally, a set of emergency measures to avoid accidents, if possible, or to mitigate their consequences needs to be implemented.

7. Case Studies in Autonomous Vehicle Decision-Making

KEC inspects a three-level hierarchical decision-making system. Local Environment Perception (LEP) is illustrated by the decision-making division. In the upper-level SAE, KB increases the connectivity and LIDAR data around the pulling area, enhances overall road termination caring, and drives EBS parameters store at home. The middle man in a driver-driven autonomous driving agent (DDAD). This DDAD perceives the surrounding environment through sensors, visual and auditory signals and stores the data into data buffers, such as environment map particulars (EMP) and sensor data markers (SDM) bricks. It also calmly receives roadway recommendations (WR) sent from KIC-X, and through a decision tree ture form parallel computation to decide next action in a set period of time . The low-level MAS applies a multiple-automove condition-action rule to calculate the incidence observations. A case-based reasoning (CBR) system that learns from observations and plans on the fly through criticality evaluation helps local decision maker (LDM) make a safe driving strategy in advance from high-probability collision. The call for a conceptual shift in safety research for highly automated driving involves a transformation of methodological and theoretical considerations. The needs of humans are emphasised in a manner that extends beyond individuals—it is the social order on the whole that comes into view. Three main areas of inquiry are proposed to address the challenges ahead: centre of inquiry, understanding human needs: 1) implementation of requirements for human-centredness and consideration for human variety in self-driving vehicles, 2) participation, vehicle-user engagement, joint consideration for human-machine co-operation within self-driving vehicles and 3) care, grounded research questions on the metrics and potential grounds for manifestation (or lack thereof) of empathy by a self-driving vehicle in all stages and circumstances of the process .

7.1. Intersection Management

To solve the above-mentioned problems that a strict rule will cause when vehicles reach the traffic intersection, some studies focus on how connected vehicles coming to the intersection interact with the infrastructure, as discussed in [XYC∗12](also discussed in Section 7.3).

However, this solution will not break the vehicle congestion in the intersections, as an unconnected AV will ignore this kind of watch by the infrastructure. To better regulate the vehicle interaction in the intersections, it is necessary for each connected vehicle to be able to make vehicle intersection coordination together [31]. If vehicles can negotiate with each other, they will be able to make judicious decisions at the intersection to avoid dangerous situations and make transportation smoother.

Since their introduction of autonomous vehicles (AVs), the relevant research community and industries have faced the problem of making vehicles have an environment reasoning capacity, so that they can perceive traffic scenarios and make decisions in complicated road sections [32]. One such complicated road section is a traffic intersection, where multiple vehicles arrive at the crossing point at the same time and may need to make decisions about which vehicle can have the right of way and which should wait for crossing the intersection. Therefore, intersection management is an essential task for AVs. A traditional solution to intersection management is shown in [LUTR14; YTT∗18], where vehicles strictly conform to the right-hand rule to pass the intersection. For complexity and security reasons, these traditional rules cause long transportation delays and support this inconvenience, creating unsafe situations in intersections.

7.2. Pedestrian Crossings

As a second step objective, the individual advantages of Whole and Split dimensions, obtaining more linear relationships between most of the behaviours of the pedestrian in its universal orientation can be demonstrated. Finally, as in this temporal split control framework, it can be shown that despite this uncontrolled model, implemented a recommendation for possible implementation with implemented joint trajectory, precisely that proposed in 37, tailored lateral and longitudinal strategies. Other action plan was: to reduce in high-way the number of mandatory points In order to reduce the timing of choice of a local maximum number of mandatory running trajectories requiring a lateral "…". After a mission target function and in its time minimisation of an autonomous vehicle, the implemented criteria in the flight of "virtual" simultaneous optimizing lateral and longitudinal decision if it could be a four intersection, disappears from intersection possible sniper.

We have designed and evaluated several MRCPGs (multi-regional convex polytopic games) optimal lateral motion planners in, by considering the total vision cone of autonomous agents, i.e., the pedestrian can be detected both by cameras and LiDARs oriented in opposite or lateral position. The network of permitted scenarios has been mapped as a generic matrix on which, depending on the angles and distances between observers, the decision concerning the expected optimal staring point (from its position in XY local FOI frame) and the point where to complete its crossing stage has been transferred in the XY intersection coordinate frame. The Multi-Regional Convex Polytopic Game (MRCPG) provides ego-vehicles the optimal independent Open- and Closed-Loop Intersection and Crosswalk Crossing for both the first approach and the second one (second LRF operator). In the paper, by minimizing the lateral deviation from the mid-crosswalk line (which we consider the environmental variable that agrees with the comfort feeling of occupants, as in 6), the sole role of the pedestrian is accepted. However, by extending the analysis considering a fixed lateral longitudinal point rode starting from a pedestal-controlled investigation. The method is able to obtain the first current point of conflict in CTRS. The dynamic disparity of the HD pedestrian has turned out to be more flexible than tactical joint routes and can be employed for the trajectory planning coordinated in an appropriate Traffic Regional. Furthermore, a suitable integrated system is available. Considering that the traffic lights are vocally relied on for this customized trajectory generator, the value of x to adjust the spontaneously controlled pedestrian point is feasible by choosing the width of the local FOV areas (LFAs) placed on the autonomous agents by the materials of the network. Such value is confirmed by a trade-off solution and respecting the perimeter of the safety buffer projection mapping in the vehicles' frame local FOV corner coordinates. Also, for pedestrians affected by impairments, was tested suitability utilizing this type of retardation-driven system, according to Chapel et al. in 1.

The pedestrian's adoption of a typical crossing contextual behaviour is studied by 1, when pedestrians were willing to cross the road, which is considered to be the normal driving lane of an A.V. As a result, significantly smaller deceleration and maximum control inputs are expected, along with smoother control applications both in longitudinal and lateral direction. In 1, state trajectory clustering and a hybrid control design are briefly discussed. Alternatively, at crosswalks, as applied in 6, 1 applies a game theory–based control approach to provide a safe crossing option for the pedestrian, which, between these two studies, consists in the ability of pedestrians to interrupt the vehicle trajectories. The game theory strategy, by considering the observer timing, offers to determine if needing to stop to avoid a rear-end collision threat due to the pedestrian presence. The vehicle agent is assigned two levels of strategies: strategic and tactical ones. The strategic (withdrawal tactics) layer represents the priority of the ego-vehicle through the ratio between the absolute value of the optimal security distance from the opposing vehicle to the pedestrian and the minimum expected value of stopping distance, (−), and the current state of the pedestrian crossing phase, acceptance probabilities (for crossing, standing, or canceling the decision to leave the sidewalk). The assignment computed in the strategic mode is transferred in the tactical mode, where, for avoiding any compromise situations, the tactical choice provides the nearest stopping point before the LRF Troubles region. The strategic level, which considers the vehicle–pedestrian interaction between the observers and the autonomous agents of both, Wald-tests-related goodness of fit has been determined using exact fitting criteria and then reduced selecting a counterintuitive range of values encouraged by the (RM-ANOVA) Maximally Robust Analysis methodology for the model/process parametrical intersubjective comparison [33].

8. Future Trends and Directions

This study presents the SynUI Decision-Making Algorithm (FDA) based on the potential fields for autonomous vehicles that aims to help these vehicles navigate pedestrian infrastructure with minimal human supervision [12]. FDA consists of main, secondary, and third subamodels. Of these, the main model calculates the velocities and accelerations of the vehicle, taking into account potential fields derived from occupied space, curvature, obstacles, and parameters of continuous trajectories. It is concluded that FDA allows a vehicle to drive over a wide range of complex scenarios such as suspended sidewalks, construction zones, one-way two-lane roundabouts, continuously rotating roundabouts, and reverse circular paths with remarkable performance [20].

In enclosing our analysis of this subject, it is acknowledged that research on anticipatory systems and driver modeling is of key importance for autonomous vehicle decision-making in complex traffic scenarios. We are convinced that methodological flaws such as the failure to model user behavior, the lack of contextually-awareness, the inability to share personal selling bio information, and to identify and security are the reason to why extant AI cannot provide adequate assistance in complex and compromised scenarios [16]. Nonetheless, as a literature review we have clarified what is essentially at stake and been able to diagnose that the decision-making process at critical points in an intersection is a crucial factor in any automotive system that must comply with traffic regulations and public safety. We have shown that there are several philosophies and points of view which can be the subject of scientific research in this field. Our definition of complex traffic scenarios entails situations in which vehicles encounter a network of situations, a modification of some paths and speeds.

8.1. Advancements in AI Algorithms

ML approaches can be roughly divided into regression models, classification models and hybrid models composed of regression/classification layers using the interactive reevaluation of the action to be taken. Although SVM and Random Forests are traditional ML methods used in the autonomous driving domain, in the last several years deep learning algorithms, facing the scene classification problem, have been used to decide the best action to take at each time step. Also, deep learning algorithms have been coupled with reinforcement learning algorithms to solve this task. The one-shot imitation learning (IL) literature aims to provide a solution to the scene classifier/classification problem. When the vehicle is placed at centered off-road for the first time the solutions in [3] provide a general decision, where we considered that the vehicle should have stopped at the given time to be able to solve the scene classification problem well.

Modern technological advancements and advanced computer tools such as GPUs, together with the extensive research in the field of ML, have laid the groundwork for wide application of the AI techniques in the autonomous driving domain. The building blocks of all AI-driven decision making processes are the data collected by the numerous sensors embedded in the modern autonomous vehicles. These advanced sensors in the automotive sector collect raw data about the environment but also the internal state of the vehicle. The information derived from these sensors is then transferred into useful data through careful signal processing and data analysis. These actionable data are then used by the system for the perception of the environment, tracking of the surrounding vehicles and for the decision-making. AI algorithms are now addressing the bottleneck of the perception and acting as a significant helper for the research in terms of fast and light solutions for counteracting complex traffic scenarios. With this goal in mind, deep learning (DL) has proved to be a valid tool in pattern recognition and for converging perception technologies and driving algorithms, capable of solving complex scenarios [1].

9. Conclusion

[16] In this chapter, the greatest contributions of decision-making formulations and algorithms that attempt to consider prediction uncertainty, and consequently, make better and safer decisions for complex, interactive, and uncertain traffic scenarios were reviewed. Generally, the considered algorithms can broadly be separated into two classes, where each class assumes different levels of predictability of the other agents' behaviors. The aim of the first class was to enhance the predictability of the other vehicles' behaviors as much as possible, and this made the decision-making easier. The second class of the works, on the other hand, explicitly addressed the uncertainties in the prediction of the other agents, and consequently their decision-making algorithms tried to be robust and safe under uncertainty.[10] Nonetheless, each of these previous works still considered the traffic scenarios at a specific isolated intersection with no interactive effect with the other traffic scenarios. This reality is disadvantageous from an optimal decision-making perspective because change in the motion of a specific vehicle in a specific traffic scenario can affect the evolution and the optimal decisions of the other traffic scenarios. As we observed in Algorithm 1, each agent makes its decision based on a policy that explicitly estimates the interaction effect of the other agents' behaviors on its own actions1. Consequently, there is an urgent need for the development of more comprehensive decision-making algorithms that can consider and optimize the interactions between different traffic scenarios. Furthermore, this topic becomes very important when the decision-making process could potentially be associated with each other between different traffic scenarios.

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