AI/ML-based Services and Applications for 6G-connected and Autonomous Vehicles

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Abstract

AI and ML emerge as pivotal in overcoming the limitations of traditional network optimization techniques and conventional control loop designs, particularly in addressing the challenges of high mobility and dynamic vehicular communications inherent in the domain of connected and autonomous vehicles (CAVs). The survey explores the contributions of novel AI/ML techniques in the field of CAVs, also in the context of innovative deployment of multilevel cloud systems and edge computing as strategic solutions to meet the requirements of high traffic density and mobility in CAV networks. These technologies are instrumental in curbing latency and alleviating network congestion by facilitating proximal computing resources to CAVs, thereby enhancing operational efficiency also when AI-based applications require computationally-heavy tasks. A significant focus of this survey is the anticipated impact of 6G technology, which promises to revolutionize the mobility industry. 6G is envisaged to foster intelligent, cooperative, and sustainable mobility environments, heralding a new era in vehicular communication and network management. This survey comprehensively reviews the latest advancements and potential applications of AI/ML for CAVs, including sensory perception enhancement, real-time traffic management, and personalised navigation.

Keywords: 5G, 6G, connected autonomous vehicles, intelligent services, machine learning

1. Introduction

Vehicular communication technology has been around for almost two decades, and yet the integration of Artificial Intelligence (AI) and Machine Learning (ML) with the next-generation wireless networks, 5G and forthcoming 6G, figures to transform the way in which research, industry and regulators alike look at Connected and Autonomous Vehicles (CAVs). By leveraging AI and ML, and their potential to significantly enhance the operational efficiency, vehicles can make smarter decisions, predict and adapt to dynamic road conditions in real-time, and optimize vehicular communication.

However, the application of AI/ML in CAVs is not without its challenges. Strengths such as the ability to process and analyze in real-time vast amounts of data coming from on-board and road-side sensors, learn from past experiences, and adapt to new situations, are offset by weaknesses including the need for extensive data for training, potential biases in decision-making processes, and the vulnerability to adversarial attacks. Additionally, the reliance on high-quality, diverse datasets for training ML models poses a significant challenge, especially in scenarios that have not been encountered during the training phase.

Another challenge is the interoperability among different communication systems and technologies, which is crucial for the successful deployment of CAVs. CAVs must communicate seamlessly with each other (V2V, Vehicle-to-Vehicle) and with infrastructure (V2I, Vehicle-to-Infrastructure), requiring the development and adoption of universal communication standards [1]. The European Telecommunications Standards Institute (ETSI), 3GPP and other international bodies like the Institute of Electrical and Electronics Engineers (IEEE) and the Society of Automotive Engineers (SAE) are working towards harmonizing these standards to ensure global interoperability. However, achieving this on a global scale remains a formidable challenge due to the varying technological and regulatory landscapes (particularly as regards spectrum sharing issues) across different regions.

The advent of 5G and the outlook to 6G technologies offer a promising solution by providing ultra-reliable, low-latency communication essential for the seamless operation of CAVs. These technologies facilitate the real-time exchange of vast amounts of data between vehicles and infrastructure, enabling advanced applications such as cooperative driving, enhanced sensory perception, and real-time traffic management. The enhanced bandwidth and reduced latency of 5G and 6G networks are crucial for supporting the computationally intensive tasks required by AI applications, from sensory data processing to decision-making algorithms.

As technology transitions from 5G to 6G, one must consider the evolving use cases and their unique demands on vehicular networks. The integration of AI/ML in this context not only promises to enhance the capabilities of CAVs but also introduces new challenges in terms of net-

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work design, data management, and security. The journey towards fully autonomous and intelligently connected vehicles is complex and multifaceted, requiring a concerted effort from researchers, engineers, and policymakers to realize the full potential of AI and ML in the context of 5G and 6G technologies.

Finally, although beyond the scope of this paper, there are economic implications. The initial investment required for research and development, infrastructure upgrades, and the integration of advanced technologies for CAVs is substantial [2]. Additionally, ongoing operational costs, such as maintenance of the infrastructure, must be considered. However, the long-term benefits of CAVs, including reduced accidents, lower fuel consumption, and improved traffic efficiency, are expected to outweigh these initial expenses. From a market perspective, the introduction of CAVs will disrupt existing automotive and transportation industries [3]. Traditional automotive manufacturers will need to adapt to new technologies and business models, while new players specializing in AI and ML may gain prominence. Furthermore, the employment landscape will shift, with new job opportunities emerging in the development and maintenance of CAV technologies, while traditional driving jobs may decline. A thorough cost-benefit analysis is crucial for stakeholders to understand the economic impact and to develop strategies that maximize the benefits while mitigating the costs.

In this survey paper, we critically evaluate the integration of Artificial Intelligence and Machine Learning technologies in enhancing sensing operations, cooperative maneuvering and enabling beyond-Day-2 Applications for Connected and Autonomous Vehicles within the emerging 5G and 6G network infrastructures.

The rest of the paper is organized as follows: in Section 2 we explore how AI and ML enhance vehicle sensor data interpretation. Section 3 discusses ML applications in autonomous driving tasks like adaptive cruise control and cooperative lane changing, underlining the significance of AI in vehicular decision-making processes. Section 4 introduces the concept of vehicular microclouds, detailing their role in resource management and mobility prediction to enhance vehicular network efficiency. Section 5 highlights the hurdles in applying AI/ML for vehicular technologies, focusing on scalability, security, and adaptability in diverse driving conditions. Section 6 concludes the paper with future research directions, emphasizing the need for interdisciplinary collaboration to fully realize AI/ML's potential in advancing CAV technologies.

2. Sensory Perception Enhancement

Autonomous vehicles are designed to leverage sensor perception to collect information from the external world. Environment perception data can be generated by different sources, such as LiDAR scanners, radars, GPS, inertial measurements, video cameras or a combination of any of them.

2.1. Sensor fusion

To achieve a vision as complete as possible of the environment around the vehicle, it is necessary to merge the different features extracted from the sensors. This procedure, known as sensor fusion, strives to generate a comprehensive perspective of the world surrounding the vehicle. Its objective is to optimize the control system's decision-making processes, ensuring precise, effective actions for the vehicle. Namely, the procedure involved in constructing a map of the surrounding environment and determining the positions of elements within it is referred to as simultaneous localization and mapping (SLAM).

The overview in [4] presents different approaches for the processing of data generated by sensors. All the inputs are crucial in sensor fusion since they bring different kinds of information that can then be combined. The camera can clone human vision, but, in order to know the distance between obstacles, a radar or LiDAR is fundamental. The different sources are complementary to each other and their fusion provides a complete, more precise vision of the environment. Often sensor fusion is divided into two groups, the so-called "low-level" fusion, and the "high-level" fusion. The former is used to get localization and mapping of the different objects, while the feature extraction and the consequent detection and classification are done by the latter.

Sensor fusion can be done with different techniques, based on fixed rules, particular data structures, or Artificial Intelligence and Machine Learning models.

In their paper, Zacchi and Trapp [5] focus on improving the perception of vehicle surroundings in urban environments. Challenges such as occlusions, appearances, and disappearances often impede the performance of traditional tracking algorithms in urban settings. Additionally, methods addressing the data association problem are constrained by the limited viewpoint of the ego vehicle. To tackle these challenges, they propose a framework that integrates various perspectives to enable collaborative perception. In this framework, both automated vehicles and infrastructure contribute to their perception results. The developed framework includes the usage of a particular data structure, the Bayesian Occupancy Filter (BOF). A BOF combines sensor measurements with prior knowledge about the environment, iteratively updating their knowledge about the occupancy of different locations. These filters are based on Bayesian inference principles, allowing them to handle uncertainty and integrate sensor data in a principled manner. BOFs provide probabilistic object positions and enhance the prediction of future object trajectories. [5] involves specific infrastructures that can merge different BOFs, coming from vehicles, to obtain an overall probabilistic view of the covered area. This result is then provided to all vehicles, making them aware of what is around them.

One of the main challenges in sensor fusion involves the exact positions of nearby objects within 3D space and across time. Within this challenge, LiDAR excels at detecting and tracking targets but within a confined sensing range due to signal sparsity, whereas cameras offer a rich visual signal limited to the image domain. Once again, the integration of diverse sensor inputs is crucial for gaining a comprehensive understanding of scene dynamics. EagerMOT [6] stands as a framework developed to fuse data from all available sensors, ensuring a precise picture of the environment's dynamics. The first stage aims to associate object detections originating from different sensor modalities (2D observations from images and 3D from LiDAR). After that, the system employs a tracking formulation that updates track states even when only partial (i.e. under LiDAR and camera limitations). This formulation is based on the overlapping performed with intersection over union (IoU), between the 2D projection of LiDAR objects and camera objects. After this process, the fused instances contain information from both input types: each object has its 3D location and its 2D bounding box. The model illustrates the feasibility of integrating various space-based inputs, emphasizing the necessity of considering the distinct limitations inherent to each sensor technology, which vary depending on the circumstances and surroundings. Therefore, it is crucial to design resilient solutions that are modeled upon these insights.

2.2. The role of Artificial Intelligence

While the works presented above are not related to any Artificial Intelligence (AI) model, recent years have seen a strong evolution of advanced machine learning techniques. These technologies are crucial to developing new sensor fusion systems based on advanced mathematical models.

One of the main problems nowadays in sensor fusion is the corruption or the lack of data, as a consequence of adverse weather conditions, sensor obstructions, low light, etc. The traditional solutions (i.e., the ones that do not leverage Machine Learning techniques) are hampered by hurdles and issues because they follow a rigid scheme. A framework, called HyndraFusion, proposed by [7] brokers a more flexible approach to solve these problems. Its main functionality is to recognize the current driving context and, based on this information, select the best combination of sensors to maximize both the robustness and the efficiency of the fusion task. In particular, a Convolutional Neural Network (CNN) extracts a set of features coming from input sources (i.e., sensors). The features extracted are then processed by a specific module, containing information about the external context (e.g., the weather conditions). This step is fundamental for selecting a subset of branches that receive the features as input. Each branch is a deep-learning model that can convert features from a certain set of sensors into a set of outputs useful for a specific task, such as object detection or semantic segmentation. These outputs are eventually merged to obtain a final detection for the task. HyndraFusion was trained with the RADIATE dataset [8] that contains data from various sensor inputs, such as Radar, LiDAR, and video cameras. The tested task, which was evaluated and compared against other sensor fusion models, focused on Object Detection. A noteworthy result indicates that when the model utilizes all available branches, the results are worse than scenarios where the model accurately selects specific branches. This outcome demonstrates that using less sensor data can improve robustness. In general, HyndraFusion outperforms older, less flexible approaches by about 14%, demonstrating that Machine Learning offers effective tools to enhance the knowledge about environmental conditions that become a crucial part of the sensor fusion chain.

One of the key aspects for the accuracy of Machine Learning and especially of the Deep Learning models, is the need for a huge amount of data to train the algorithms, extending the model background knowledge in the desired domain. The framework presented in [9] highlights how the combination of real-world observations and simulated data can be a valid solution to add a source of information and allow models to have more data to work on. The integration between the two data sources is divided into two different layers, the data layer and the model layer. In the first one, a merging process fuses the observation and simulation data. The model trained on this mixed dataset can leverage real-world data enriched with simulation data so that the model has a huge amount of information to learn data patterns. The technique, called Feature Engineering, involves converting raw data into features that offer an enhanced representation of the underlying problem in machine learning models. This results in improved model accuracy by exploiting data patterns and correlations through various operations, such as feature extraction, transformation, selection, evaluation, etc. The huge amount of data provided to the data layer permits obtaining a more complete and refined features analysis of the investigated problem. On the other hand, the model layer facilitates the separate utilization of simulation and sensor data for training distinct models, which can later be integrated to generate predictions. The paper's results make clear that the enrichment of features significantly enhances the model performance.

While the abundance of data is crucial, an exceedingly high amount of information to share could hinder the whole process: more advanced systems must select the main features to submit to the sensor fusion process. This feature map selection can be executed by exploiting of Convolutional Neural Network (CNN) as reported in [10]. The output of this selection permits a better transmission in terms of wireless channel condition, interference level, distance, and link duration. As a consequence of that, the entire network results less stressed by traffic overload. The feature map selection through CNN can be done at different vehicle layers. Intermediate feature maps may take a longer time to process when received by the other vehicles within the network (the maps need to pass through all other filters inside the vehicles). For this reason, fusing the last-layer feature map turned out to be the best decision to generate a more efficient feature map compression, compliant with the strict time constraints of cooperative perception.

A tool that can be effectively used to support the testing and development of CAVs in deep learning and sensor fusion scenarios is the open-source simulator CARLA (Car Learning to Act) [11]. It provides a highly customizable, realistic urban environment where developers can generate diverse, complex traffic situations, essential for training robust deep learning models. By simulating various sensor inputs, such as cameras, LiDAR, and radar, CARLA enables comprehensive sensor fusion testing, allowing for the integration and validation of multi-sensor data processing algorithms. As an example, in [12] a level 4 CAV is implemented through the CARLA simulator to train and test a self-driving car agent using a Deep Q Neural Network. Sensor fusion is achieved by integrating hood-mounted cameras and radars, rearview mirrors, and a GPS. CARLA can also be used as an effective testing tool for CAVs using V2X communication to improve behavior planning and AI-aided decisions, such as lane-changing and lane-keeping [13].

Due to the huge amount of data that AI models require to be trained and tested, the collection of information is a point as crucial as it is critical in Machine Learning pipelines. Problems related to data manipulation and the lack of human control are significant concerns. As decision-making increasingly relies on autonomous systems, the opacity of these systems can lead to unpredictable outcomes and biases that are difficult to identify and correct. Moreover, the reliance on large datasets and complex algorithms makes AI systems vulnerable to attacks and manipulation, such as adversarial attacks and data poisoning. In [14], authors underline the important role that a Regulation and Policy Framework can have on CAV systems, but they also specify that it is fundamental to balance the trade-off between protecting CAV users' privacy and freedom, ensuring operational and data accessibility to maintain state regulators' command and control thresholds. The research conducted in [15] and [16] highlights the increasing importance of security policies in emerging 6G and new transportation systems. Specifically, [16] describes a privacy-preserving framework for vehicular pseudonym issuance. This tool employs a blockchain structure to mitigate security risks associated with the data handling of autonomous vehicles. Many articles [17][18][19] address the theme of machine ethics, often referred to as the Moral Machine. In this field, numerous problems arise (e.g., the Trolley Dilemma), and resolving and regulating these issues will require extensive input from legal and philosophical committees. In particular, it will be especially challenging to integrate human values into the system design of CAV solutions [20], ensuring that autonomous vehicles can make ethical decisions that align with societal norms and expectations. Moreover, biases in training data pose significant challenges, as these biases can lead to unfair or unethical decision-making by autonomous systems, further complicating the development of trustworthy and equitable CAV technologies.

2.3. V2X paradigms in 5G and 6G ecosystems

In sensor fusion applications, the integration of data gathered by individual vehicles with information sourced from other vehicles or infrastructure is fundamental. Swift and accurate data exchange ensures timely updates of the surrounding environment for enhanced situational awareness and effective decision-making. The advent of cutting-edge telecommunication paradigms such as 5G and 6G is pivotal in this regard, transforming computer networks into dynamic ecosystems characterized by ultra-fast speeds, minimal latency, and huge reliability. Consequently, the realm of networking technologies for connected vehicles stands as a primary beneficiary of these advancements [21].

According to the research conducted in [22], the 6G infrastructures have the potential to introduce disruptive services compared to 5G, thanks to advancements in processing performance, network design, and electronic technologies. The research demonstrates that many Key Performance Indicators (KPIs) of Quality of Service (QoS), currently challenging to achieve, would be within grasp with the implementation of 6G.

The newest developments of the vehicle to everything (V2X) technologies allowed the exchange of information between vehicles to pass from an ego approach (i.e., the machine perception is related only to its sensors) to a cooperative solution (i.e., the machine perception is related not only to its sensors but also to the perception that the other vehicles share with it). The ultimate goal of this new paradigm is to "also see with the eyes of other," and to have a more precise, complete representation of the environment. This paradigm is fundamental in facilitating what is commonly referred to as *Day-2 Services*, supporting real-time information sharing among vehicles. The communication systems transporting such sensory information must guarantee minimal delay, sterling robustness and unparalleled availability, features that are at the core of 5G [23] and 6G [22] architectures.

However, fast network infrastructure alone cannot guarantee the success of V2X communications without a well-designed set of messages exchanged among vehicles. ETSI, the European Telecommunications Standards Institute, plays a crucial role in standardizing these messages to ensure interoperability and efficiency in V2X communication systems. The most commonly used types of messages are the Cooperative Awareness Message (CAM), the Decentralized Environmental Notification Message (DENM), the Collective Perception Message (CPM), and the Vulnerable Road User (VRU) Awareness Messages (VAM).

Particularly, CAM and CPM messages hold significant importance in the realm of sensory perception. CAM messages are periodically transmitted by vehicles to share data regarding the vehicle's state, such as position, speed, acceleration, etc. These messages are designed to be the workhorse of road safety systems, providing vital location information to other vehicles and traffic control systems. Conversely, CPM messages are designed for collective perception, as they enable vehicles to share collected sensor information from different sources, such as LiDAR and video cameras. This data exchange allows vehicles to have a more comprehensive, accurate understanding of the surrounding environment, enhancing traffic safety and flow. In addition to CAM and CPM messages, the exchange of Vulnerable Road User Awareness Messages (VAM) can also significantly contribute to enhancing road safety in the context of sensory perception. These kinds of messages are designed to alert vehicles to the presence of nearby vulnerable road users, such as pedestrians, cyclists, and motorcyclists.

Both CAM, CPM, and VAM can be used by vehicles to build a Local Dynamic Map (LDM), a construct envisioned by ETSI [24], which plays a crucial role in V2X communications. The LDM represents a real-time environment map that provides vehicles with localized information about road conditions, traffic updates, and other relevant data within their immediate vicinity. Vehicles can access up-to-date and detailed environmental information, facilitating proactive decision-making and further improving overall road safety and efficiency.

A recent study [25] exploits the Multi-Access Edge Computing (MEC) paradigm to merge information into a centralized dynamic map of the road (the Server-LDM, or S-LDM) that can be shared efficiently among services. In keeping with the MEC paradigm, computing power can be made available at the edge, without crossing the entire network to reach a far-away server. Thus implemented, the LDM becomes a valuable centralised asset for vehicles and infrastructures that provide data to create and update it, yielding a more precise, real-time representation of the road. The S-LDM is capable of detecting when a certain triggering event occurs and, following that, computing a context around a reference vehicle or object. This output is then shared with other MEC services. Experiments, conducted both in lab settings and real-world conditions, demonstrated the effectiveness of this technology as a facilitator for advanced automation, supported by the innovative 5G architecture. In most cases, individual message decoding and map updates occurred in under 50 microseconds. Furthermore, within a mere 70 milliseconds following the previous update, the entire map could be refreshed in 95% of instances.

The solutions described above show how sensor perception is pivotal for vehicles to have complete knowledge and secure navigation within their surroundings. Indeed, the convergence of sensor fusion, machine learning, 5G and 6G telecommunication standards, and V2X protocols will play crucial roles in shaping the future of transportation.

In particular, the integration of Artificial Intelligence models within CAV systems is closely linked to the introduction of the 6G paradigm. While 5G technologies were not initially designed to include Machine Learning strategies, they can nevertheless be integrated with these technologies to some extent. However, 6G technology could provide several advantages and novel solutions for data transfer, which can enhance algorithms such as Reinforcement Learning and Federated Learning, commonly employed in these scenarios. To achieve ultra-low latency and ultra-fast speeds, recent studies [26][27][28] utilize Millimeter-Wave technologies. These technologies involve utilizing frequency bands, typically above 30GHz, which have been largely unused for telecommunications traffic until now. However, the two main side effects of Millimeter-Wave technology are that, due to the ability to transmit at higher frequencies, communication distances are reduced, and the Line-of-Sight (LoS) issue is accentuated. One of the latest advancements in cutting-edge technology is the development of Non-Terrestrial Networks (NTN). By employing drones, satellites, high-altitude platform stations (HAPS), and unmanned aircraft systems (UASs), the coverage of solutions utilizing millimeter waves can be extended [29]. This results in a network coverage, often referred to as “spotty”, which ensures high availability and low latency even in isolated places where the possibilities to interact through classical transmission channels are limited. Another innovative solution brought forth by the evolution of 6G are the Reconfigurable Intelligent Surfaces (RISs), which enhance transmission efficiency and strengthen information security [30]. RISs consist of numerous adjustable elements that reflect electromagnetic waves. By controlling the phases and amplitudes of these elements, RIS technology increases the Degrees of Freedom (DoF) of wireless channels, thereby improving signal transmission and enabling advanced capabilities. RISs mitigate issues such as signal blockage and deep fading, significantly enhancing wireless connectivity through signal enhancement, interference suppression, reliable reception, and precise positioning. In [31] and [27], authors emphasize that RIS could become a standard for modern networks, as radio signal propagation between transmitters and receivers can be flexibly reconfigured to achieve the desired realization and distribution. This approach is expected to facilitate a more flexible, reliable exchange of information.

3. Cooperative Manoeuvering and beyond-Day-2 Applications

AI/ML solutions play a critical role in autonomous and automated driving and have become an essential component of a plethora of applications that require an intelligent decision-making process [32, 33, 34]. This Section examines the integration of AI in enabling vehicles to perform complex driving manoeuvers collaboratively, enhancing road safety and traffic efficiency by leveraging the advanced capabilities of 5G and 6G networks for improved communication and data sharing among vehicles. Beyond-Day-2 Applications suggest several use cases for CAV solutions that can be grouped into four main categories, as done in [35]: Vehicle Coordination, Intersection Crossing Assist, Partial and High automation, and Advanced Warning and Information. Table 1 lists application examples for each category, and references to work that investigates them through the usage of AI/ML and 6G-based technologies.

Below, we delve into two categories listed in Table 1: Vehicle Coordination and Partial and High Automation. Specifically, we focus on ML-based solutions for adaptive

Table 1: Use cases defined by Car2Car Communication Consortium

Car2Car use case	Application examples	AI/ML solutions	6G-based solutions
Vehicles Coordination	Cooperative Lane Merging (CLM) Cooperative Transition of Control	[36, 37, 38]	[39, 40]
Intersection Crossing Assist	Advanced GLOSA (A-GLOSA) Optimized Traffic Lights via V2I Automated GLOSA with negotiation	[41, 42]	[43, 44]
Partial and High Automation	Hazardous Location Notification Cooperative EBS (C-AEBS) Advanced Pre-crash sensing Advanced Cooperative ACC (AC-ACC)	[45, 46]	[47, 48]
Advanced Warning and Information	Advanced Slow Vehicle Warning (ASVW) Advanced ICW (AICW) Overtaking motorcycle VRU presence awareness VRU collision warning VRU brake intervention	[49, 50, 51, 52]	[53, 54]

Acronyms used in Table 1:

Green light optimum speed advisory (GLOSA)
Adaptive cruise control (ACC)
Emergency brake system (EBS)
Intersection collision warning (ICW)
Vulnerable road user (VRU)

cruise control and trajectory prediction (Section 3.1) and cooperative lane changing (Section 3.2).

3.1. Adaptive cruise control

Adaptive cruise control (ACC) aims to determine in an automated way the acceleration/deceleration that a vehicle should adopt, so that it can maintain a safe following distance (or, equivalently, time headway) and obey to speed limits. Among the various possible approaches that have been proposed in the literature for ACC, Reinforcement Learning (RL) and Deep RL (DRL) are among the most popular ones, since they proved to be very effective in handling acceleration control in time- and space-varying environments, while requiring a limited amount of input information. A comprehensive survey on RL and DRL-based mechanisms can be found in [34], which underlines the effectiveness of such techniques whenever one has to control the linear movement of a vehicle. Importantly, RL and DRL models can exploit the variety of scenarios that typically characterize complex road scenarios.

A crucial role in an RL or DRL mechanism is played by the reward function, as it characterizes the objective of the learning process and the policy that will be output, thus determining a vehicle's behavior. Furthermore, the choice of the reward function affects the convergence of the learning process and whether or not it will converge to the optimal solution [55]. We argue here that using a continuous reward function can significantly help to provide convergence and often allows finding a better trade-off among the different needs of an ACC application.

In the case of connected autonomous (or automated) vehicles, ACC has been enhanced by leveraging the additional information that a vehicle's application can collect about its surroundings as well as its neighboring vehicles. Such enhanced ACC is known as Cooperative ACC (C-ACC). The work in [56] is one of the first to propose C-ACC, combining RADAR and vehicle-to-vehicle communication as sources of information to control the time headway of an ego vehicle with respect to a leading vehicle. The mechanism proposed in [56], however, defines an action space that includes discrete values of (positive/negative) acceleration, which may lead to an oscillating, often far from reality, behavior. Additionally, [56], as most of the traditional solutions for ACC, focuses on headway as a unique objective of the proposed DRL, thus failing to address vehicle stability and passengers' comfort. We underline that this is a significant shortcoming since providing safety implies accounting not only for time headway but also for the vehicle's stability under different pavement conditions as the vehicle acceleration varies.

This serious concern is partially tackled in [57, 58, 59, 60], which introduce DRL-based solutions that enable a multi-objective optimization by defining reward function that includes different factors like time-to-collision, headway, and jerk. Nevertheless, even the above solutions neglect the vehicle dynamics, thus leading to selected actions that may be unsuitable for real-world vehicle behavior.

Conversely, a study that considers vehicle stability only is [61], which focuses on electric vehicles and, specifically, on controlling the torque vectoring to improve stability. As far as passenger comfort is concerned, it is worth mentioning that an extensive empirical study on the factors that mainly impact such a performance metric has been presented in [62].

All of the above issues are tackled in [63], which additionally considers the different driving conditions that a vehicle may face. To do so, [63] defines a C-ACC solution based on DRL with a continuous action space, which accounts for the time headway, the passengers' comfort and safety, and the vehicle stability under critical road pavement conditions.

Although RL and DRL models have proved to be mostly effective for ACC, it is important to mention that other approaches have been proposed. An interesting comparison between DRL and Model Predictive Control (MPC) in ACC can be found in [64]. Interestingly, the study underlines that, since MPC is model-based, it requires online optimization, thus implying a non-negligible computational complexity, which may be hardly feasible for real-world ACC applications. Being instead model free, DRL has much lower complexity and, hence, can determine the vehicle's acceleration in real time. Moreover, a DRL approach accounts for the environment in which the vehicle operates, thus enabling a better control of the vehicle. On the other hand, DRL requires proper training to be able to effectively address different situations (a.k.a. generalization error). To overcome this critical aspect, simulation tools can be effectively used to generate extensive datasets that can capture a high number of scenarios and situations. Through these simulators, one can also represent the environment and the effect of actions on it, thus obtaining a virtual validation of the performance of RL and DRL mechanisms. Relevant examples of these tools include the VISSIM commercial traffic simulator, the open-source CoMoVe [65] simulator for virtual validation of driving applications, ADAS sensors, communications, and vehicle dynamics, and the open-source VeinsGym [66] that integrates the popular Veins vehicular networking simulation toolkit [67] with Open AI Gym [68], which has become the de facto standard for realizing reinforcement learning solutions.

3.1.1. AI/ML for trajectory estimation and prediction

Vehicle trajectory prediction is a fundamental task that builds upon AI/ML approaches and is at the basis of several other applications in autonomous and automated driving, such as collision avoidance and lane changing. A comprehensive survey on this topic can be found in [69].

A large body of work on vehicle trajectory prediction addresses rather simple environments such as highways or straight stretches [70, 71], or it focuses on specific road sections [72]. Such approaches cannot typically cope with larger and more complex road scenarios. For instance, [73] presents a solution based on a classification of drivers' driving style without accounting for the fact that this may change over time, depending, e.g., on the traffic conditions or the road layout. Thus, while such an approach may work well in straight stretches of road, it cannot adapt to, e.g., road intersections or roundabouts. [74], instead, defines a discrete set of manoeuvers on a highway scenario and computes the probability thereof. It then leverages Gaussian processes to characterize the predicted trajectory, along with the related uncertainty. Although interesting, such an approach hardly scales with the number of different road scenarios and the high number of manoeuvers that a driver can execute therein.

More complex scenarios, such as road intersections, have been analyzed much more rarely in the literature. Among the studies concerning road intersections, [75, 76] focus on a simpler problem than trajectory prediction, i.e., they only predict whether a vehicle turns or proceeds straight. From the methodology point of view, the former exploits non-parametric regression, while the latter leverages Long Short-Term Memory (LSTM) networks – an approach that has then been widely used for trajectory prediction. Enhanced predictions are provided, instead, in [77, 78], using Graphical Neural Networks models. Interestingly, such models also take into account the interaction between vehicles and between vehicles and the road infrastructure elements. A deep convolutional neural network (CNN) has been introduced in [79], which, importantly, also accounts for the fact that an ego vehicle can receive information on the manoeuvers of its neighboring vehicles through vehicular communication technologies. The method in [79], however, exhibits high complexity, since it requires to compute the likelihood of the possible trajectories of each ego vehicle. Although exploiting a different methodology based on temporal CNNs and a Kalman filter, the work in [80] has a similar goal and flavour, thus still exhibiting exceedingly high complexity.

A more scalable method is introduced in [81], which assumes that the network infrastructure can monitor and gather data on a given geographical area. Such information is then used by an edge server to create a hybrid convolutional and recurrent neural network model for trajectory prediction that is delivered to the vehicles. Importantly, such a model enables transfer learning, and the vehicles can customize the model they receive from the network using their local data on the driver's driving style. In [82], multiple data sources, such as sensors and IoT devices, are used to produce trajectory predictions, using each of them as a different data source. The final prediction is selected using the uncertainty affecting the different trajectory predictions. However, this study fails to adopt a multi-modal approach and, since the prediction uncertainty is computed as a confidence score, the approach may not be accurate enough to identify the most reliable prediction. Finally, it is worth mentioning [83], which integrates an LSTM-based model for trajectory prediction with a collision-forecasting mechanism, thus tailoring the former to the highly demanding latency requirements of the latter.

3.2. Cooperative lane changing

The recent advancements in autonomous driving technologies must consider vehicles' capability to coordinate manoeuvers with one another in a cooperative manner. Lane changing maneuvers constitute one of the most important sets of actions that have an important impact on relationships and traffic management between vehicles. The survey [84] explains the critical impact of AI solutions for vehicle motion planning. Specifically, DRL models are particularly suitable to model and solve these kinds of problems. The work also emphasizes the evolution of DRL techniques for motion planning tasks. An interesting branch of RL is Multi-Agent RL (MARL), where the agents are not seen as separate entities to be trained. Still, they are considered a common source of information for building a unique intelligent system.

A recent study [85] applies the MARL concept to develop a cooperative lane-changing framework. This latter is based on an exchange of states, actions, parameters, and rewards among all vehicles in the analyzed area. The degree of success of a given action is evaluated according to some parameters that constitute the final reward of that action, such as safety (i.e., the vehicles should operate without collisions), the distance between vehicles, speed, and the newest one, the driving comfort (i.e., avoid brutal manoeuvres that can hurt the passengers). This shared state representation permits the building of accurate motion planning strategies that outperform the solutions based on separate actor networks.

The study in [86] addresses decision-making challenges in lane change for autonomous vehicles, focusing on handling observation uncertainties and adversarial perturbations. Primarily, it introduces an Observation Adversarial RL (OARL) approach, utilizing a Constrained Observation-Robust Markov Decision Process (COR-MDP) to model lane change behaviors under policy constraints and uncertainties. By employing a black-box attack technique and a Constrained Observation-Robust Actor-Critic (COR-AC) algorithm, the authors advance lane change policies while ensuring robustness against adversarial observations. Evaluation in three traffic flow scenarios showed OARL's improvements over baseline methods, enhancing performance, collision safety, and robustness.

The work in [87] tackles safety challenges arising from blocked views and lack of cooperation among autonomous vehicles during lane changes and overtaking maneuvers. They introduce the Cooperative Collision Avoidance scheme for autonomous vehicles during overtaking and lane changing (CCAV-OLC) to mitigate safety risks. The CCAV-OLC scheme employs Inverse RL (IRL) to mimic human driving strategies, addressing challenges in high-dimensional AV environments. To enhance learning efficiency, they propose IRL-GP, leveraging Gaussian Process regression for Bayesian prediction with limited demonstrations. Additionally, the authors integrate cooperative communication among autonomous vehicles using 6G V2X technology, improving decision accuracy and speed. Their results demonstrate risk reduction in collisions during manoeuvers. Comparative analysis highlights the effectiveness of CCAV-OLC in information delivery, collision probability, and computational efficiency.

An alternative approach to RL techniques is the Monte Carlo method, which involves using random sampling to approximate solutions to problems. In particular, lane-changing can be modelled as a search tree by simulation multiple trajectories from the current state. The Monte Carlo Tree Search (MCTS) leverages this data structure to explore the space of possible random simulations for the Monte Carlo method. The research conducted in [88] combines the MCTS with some heuristic rules to divide the problem into two levels, the upper-layer, and the lower-layer. The first one optimizes the passing order through the MCTS for a critical conflict zone, while the second one, according to the plan established by the upper-layer, aims to solve the potential problems during the lane change action. The strategy of employing a bi-level strategy integrating MCTS coupled with heuristic rules shows a notable improvement in its effectiveness w.r.t. conventional cooperative driving methodologies.

A network of connected autonomous vehicles can be defined as a spatial scope or environment where information is shared among the actors inside this area. Within this scope, connected vehicles can cooperate in order to define an enhanced and safe mobility plan. The information fusion can be done by exploiting different techniques, such as traditional rule-based, LSTM [89], and Convolutional Graph Neural Network (CGNN). This latter is a valuable representation of the scope, since each node of the graph can be interpreted as a vehicle, and the edges are the connections between them. As reported in [90], the CGNN has great potential in aggregating information for a clique of nodes. Starting from these considerations, [91] has developed a solution to aggregate both information coming from the local perspective of the vehicles and the one from the connected environment. The step forward of this work is to couple the CGNN with a DRL network to plan future actions. The framework uses CGNN as the encoder to learn abstract relational representations between agents and then feeds these representations into a policy network for actions. The proposed model outperforms the baseline methods both in terms of parameter number (this new technique is more lightweight) and performance.

Cooperative vehicle motion planning is a fundamental aspect of autonomous driving systems, but optimizing and solving it with the sole usage of the described solutions. In December 2023, ETSI released the standard for the last version of the manoeuver Coordination Message (MCM). This type of message aims to establish a specific protocol for vehicles to cooperate when executing particular maneuvers, such as lane changes, with precision. More in detail, the protocol provides two kinds of messages. The first is used by the vehicle that wants to execute an action, to communicate its intention to the neighbors. The other vehicles can answer the request with a set of proposals (i.e.

possible manoeuvers) to help the vehicle in bringing the action to an end. Each proposal is assigned a score, based on how much the vehicle deems convenient to carry out that specific action. The first vehicle must assess which combination would optimize both the successful execution of the manoeuver and the score. Although some parts of the standard still need to be defined, such as the method for assigning a score to an action, this type of message has the potential to emerge as a crucial tool for efficiently organizing vehicle motion planning, which encompasses activities like lane-changing.

4. Vehicular Microclouds

4.1. Motivation

CAVs are equipped with many computing, sensing, storage, and communication resources. All the previously discussed applications require processing of collected sensor data locally or shared between cooperatively acting cars. Much of the computational effort is related to machine learning. Conceptually, all this processing could be done in a backend cloud server. However, both the sheer amount of sensor data and the real-time requirements render this approach ineffective. 5G conceptualized and later standardized MEC to overcome these issues. Given the unclear business perspective, we still see only few such MEC edge servers.

An alternative would be to opportunistically use computational resources in the local vicinity of the car. With the move towards automated driving, cars turn into high-end compute servers. These resources, when clustered together in the form of a vehicular microcloud [92], can enable the provision of intelligent applications and services on the edge. In the following, we discuss vehicular microclouds, their role in enabling intelligent services at the edge of the network.

The microcloud concept is currently being pushed forward to be generalized in the form of 6G virtualized edge computing [93]. This way, 6G edge computing will enable distributed sharing of resources and processing of computationally expensive tasks – not only in the context of cooperative driving but also for, e.g., distributed learning tasks in smartphone apps.

4.2. Concepts

In essence, a vehicular microcloud consists of a small cluster of CAVs that offer their hardware resources, including computing, communication, and storage, for use by other vehicles, pedestrians, or services. The key technology that enables the formation of vehicular microclouds is V2X, as the vehicles need to communicate among each other (and with infrastructure) using ultra-reliable and highly efficient links in order to share their resources reliably in a common pool. This way, much like traditional microclouds, vehicular microlcouds can provide the necessary infrastructure to facilitate multi-access edge computing (MEC), therefore extending this paradigm into the vehicular domain.

In terms of geographic location, a vehicular microcloud can be mobile, formed by vehicles moving in the same direction, or stationary, in the vicinity of a specific geographic region (e.g., vehicles parking or queuing in front of a traffic light) [94, 95]. Furthermore, an individual vehicular microcloud, can be connected to a larger network of distributed microclouds and be managed independently or in centralized fashion.

The possibility to utilize the resources of the connected and autonomous vehicles (CAVs) as servers at the edge of the network effectively brings storage and processing capabilities closer to the data source. This can reduce latency and improve reliability, offering a responsive and agile computing environment tailored to the evolving needs of (different applications and services). Particularly parked cars can help overcoming both communication and resource management issues [96].

4.3. Resource Management

An important characteristic of vehicular microclouds that requires particular attention is resource variability. Namely, in contrast to traditional microclouds, which have a fixed set of computing resources with predictable availability, the formation of the vehicular microcloud, and therefore the availability of its computing resources is directly dependent on the presence of the participating vehicles. As such, the dynamic nature of the vehicular traffic imposes that in a vehicular microlcoud architecture there are not only dynamic users, but also dynamic/fluctuating resources, therefore their allocation needs to be handled accordingly. This presents a set of challenges, in particular with respect to user management and resource discovery. The vehicular microcloud needs to be able to effectively balance the varying demand for resources and their availability to preserve the system's scalability and flexibility.

In this regard, AI and ML-based techniques can provide an adaptive and agile solution to address these challenges. Mobility prediction [97], computation task offloading decisions [98, 99, 100], resource allocation and content caching [101] are some of the topics that can benefit from AI and ML-based methods [102].

The delivery of the content within strict time constraints in the vehicular environment, which has high mobility presents a major challenge. One potential solution to overcome this challenge is to use content caching closer to the end-user, e.g., vehicles within a microcloud in the edge of the network. This allows access to the content at lower latency, as opposed to loading the desired content from the cloud. Aung et al. [101] exploit this idea by proposing a vehicular edge framework where some vehicles act as content providers by caching the relevant content, whereas the other vehicles consume it. The core idea behind this approach is to exploit traffic information and dynamically align the routes of provider and consumer vehicles. A graph pruning search algorithm is used to reduce the search space for consumer path planning, where the goal is to maximize the number of content providers along a vehicles journey. On the other hand, the content providing vehicles determine their routes by taking decisions at the intersection based on deep reinforcement learning (DRL) approach that rewards content delivery, more specifically, the primary objective is to optimize the revenue generated from advertisements delivered to consumers.

Guo et al. [98] consider a vehicular microcloud architecture where vehicles have limited computing capacity and they offload computationally-intensive tasks to the servers in the infrastructure for more efficient computation. This scheme uses Deep Q-learning methods for task offloading decisions, optimizing for minimal processing time within execution delay constraints, while accounting for frequent handovers and fluctuating resource availability at the servers. The Q-learning algorithm is a reinforcement learning method that iteratively learns about the best offloading decisions until an optimal policy for task offloading is determined. The approach additionally introduces two neural networks to reduce the correlation between current Q value and the target Q value and thereby improve the stability of the Deep Q Network (DQN). Additionally, an experience replay mechanism is adopted to enhance training efficiency.

4.4. Mobility Prediction

Mobility prediction can help to improve the allocation efficiency of the resources, as the system can forecast future resource demand and availability, thereby manage the available resources more effectively. This can be more beneficial than on-demand resource allocation, as long as the mobility prediction is accurate [103].

Pannu et al. [103] followed an empirical approach to investigate the so-called Dwell time of car at an intersection. Using the popular Luxembourg SUMO mobility data [104], the authors collected a huge set of mobility data, and performed statistical techniques to derive the best fitting probability distribution. The resulting Johnson S_U distribution turned out to fit very accurately for 80% of all intersections in Luxembourg. However, it turned out that the distribution is not generalizable. In a follow-up study, Schettler et al. [97] used a simple RL scheme that significantly outperformed the empirical approach.

Wu et al. [105] present a mobility prediction model and Deep Reinforcement Learning (DRL) framework for mobile service provision in a multi-user setup. This framework follows a comprehensive approach that jointly addresses mobility prediction, resource allocation, and offloading decisions. At the first stage, a Long-Short-Term Memory (LSTM)- based mobility prediction model is used to predict the future locations of mobile users based on their current position. Then, the offloading decisions and the resource allocation are considered together, as these can engage each other. A Deep Q-Network (DQN) handles the offloading decisions, whereas a Deep Deterministic Policy Gradient (DDPG) manages computing resource allocation. The reward function is designed to encourage low latency by maximising the number of successfully executed requests. As users move and seek services from edge servers, the model makes decisions regarding edge server selection and service migration based on factors such as service status, user locations, and the availability of computing resources.

5. Research Challenges

Existing proposals for cooperative manoeuvers in connected and autonomous vehicles often concentrate on specific scenarios that, for instance, consider intersection crossing [106] or lane changes [107]. Yet, they frequently overlook the vast array of potential real-world driving circumstances. These proposals are typically tailored to specific cases and rely on predefined spatial assumptions, which may not fully encompass the complexities of real-world driving dynamics. Consequently, there is an urgent need to develop cooperative driving strategies that are flexible and applicable across diverse scenarios. This necessitates formulating methods leveraging AI/ML approaches to systematically identify suitable conditions for cooperative manoeuvers on various road segments, ensuring automated driving technologies' safe and efficient deployment.

One of the most promising approaches in distributed learning for 6G-enabled cooperative autonomous driving is federated learning. Initially particularly interesting because of its privacy preserving nature, we now know that both privacy [108] as well as security [109] are not fully solved yet. At the same time, federated learning is one of the most efficient approaches for cloud and edge computing. Novel 6G virtualized edge computing concepts [93] need further research to overcome mobility-related issues and to advance the efficiency of resource allocation.

Scalability presents another significant concern [110]. Current solutions often focus on a limited number of vehicles and fail to account for cascading scenarios. For instance, concurrent lane changes by multiple vehicles may not be adequately addressed [111]. While enforcing restrictions to allow only one lane change at a time might seem plausible, such artificial constraints can severely impact traffic throughput and hinder the prompt exit of vehicles from highways. In the context of 5G and 6G technologies, scalability concerns extend to utilizing the infrastructure resources required for executing these manoeuvers efficiently. Specifically, in the context of 6G, we expect more decisions to be offloaded back to the vehicles. For example, using distributed uniform consensus algorithms [112], one could implement virtual traffic lights since 6G nodes can support low-latency, high-bandwidth communications.

Although no such approaches have been taken to the best of our knowledge, we believe that some of the results reviewed in this paper can facilitate answers to this challenge. Specifically, we believe that S-LDMs [25] can consolidate collective perception information and increase the scalability of collective perception services. We believe that such an improvement to perception services could facilitate the generalization of maneuver control and management.

Yet another set of challenges arises from the need to ensure resilience in the face of failures [113] and cyber-attacks [114, 115]. Among others, resilience to Byzantine attacks against message transmissions [116] or physical layer resilience [117] play pivotal roles. Many existing implementations involve the exchange of privacy-sensitive information, potentially compromising the privacy of road users beyond just the drivers involved in the cooperative maneuver. Recent developments in the area of *Automotive Digital Forensics* (ADF) [118] can facilitate solutions for determining the source and liability of failures and cyber-attacks. We note that in ADF, early attempts for generalization exist [119].

6. Conclusions

Our survey underscores the impact of AI/ML in advancing CAV technologies within the 5G and 6G ecosystems. While we have identified significant advancements, our work also highlights the complex challenges ahead, including data privacy, security, and the need for robust, scalable ML models that can operate effectively across diverse and dynamic vehicular environments. Looking forward, it is clear that realizing the full potential of AI/ML in CAVs will require an interdisciplinary approach, blending insights from telecommunications, computer science, automotive engineering, and beyond. Collaborative efforts will be essential in dealing with the intricacies of next-generation vehicular networks, ensuring that the vehicles of the future are not only autonomous and connected but also safe, reliable, and efficient.

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