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A Comprehensive Survey on the Application of Deep and Reinforcement Learning Approaches in Autonomous Driving

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ABSTRACT

Recent advances in Intelligent Transport Systems (ITS) and Artificial Intelligence (AI) have stimulated and paved the way toward the widespread introduction of Autonomous Vehicles (AVs). This has opened new opportunities for smart roads, intelligent traffic safety, and traveler comfort. Autonomous Vehicles have become a highly popular research topic in recent years because of their significant capability to reduce road accidents and human injuries. This paper is an attempt to survey all recent AI based techniques used to deal with major functions in AVs, namely scene understanding, motion planning, decision making, vehicle control, social behavior, and communication. Our survey focuses solely on deep learning and reinforcement learning based approaches; it does not include conventional (shallow) shallow based techniques, a subject that has been extensively investigated in the past. Our survey builds a taxonomy of DL and RL algorithms that have been used so far to bring solutions to the four main issues in autonomous driving. Finally, this survey highlights the open challenges and points out possible future research directions.

Contents

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1. Introduction

Road injuries are one of the main causes of mortality in the world. Latest reports of the World Health Organization (WHO) show that approximately 1.3 million people die each year as a result of road accidents (Be, 2021). More than half of this alarming number is among Vulnerable Road Users (VRUs), namely pedestrians, bicycles and motorcycles. Other studies show that pedestrians remain the large majority of sufferers among all VRU victims (El Hamdani et al., 2020). A recent study of the Focus Group on AI for Autonomous and Assisted Driving (FG-AI4AD) highlights that road injuries are already the leading cause for children death, exceeding by far the deaths caused by HIV and Tuberculosis (Vellinga and O'Kelly, 2021).

In an attempt to reduce road injuries and to address these challenges, vehicular networks (VANETs) and autonomous vehicles (AVs) have gained an increasing interest from both academia and industry. These technologies are anticipated to effectively reduce automobility related deaths and injuries and address various long-standing transportation challenges, namely, road congestion, travel delay, parking, and safety. In Singh (2015), it is reported that 90 % of all car accidents are estimated to be a consequence of human errors. Recent advances in Intelligent Transport Systems (ITS), computational systems, and Artificial Intelligence (AI) have stimulated and paved the way toward the widespread introduction of AVs. This has opened new opportunities for smart roads, intelligent traffic safety, and traveler comfort. Researchers estimate that 8 millions of AVs will hit the roads by 2025 (Bay, 2021). However, because of some previous incidents in the past, the popularity of AVs has been impeded. Although researchers and car manufacturers are still investigating different ways to address the relevant issues and the remaining challenges (Hussain and Zeadally, 2018).

An Autonomous Vehicle, often used interchangeably with self-driving vehicle, is capable of sensing its environment and making decisions without human involvement. Autonomous vehicles cooperatively collect and share information with each other, with road-side infrastructure, and with VRUs (Lamssaggad et al., 2021). Relying on vehicular communications, AVs exchange safety messages, traffic conditions, and warning messages in case of traffic jams or accidents. Driverless vehicles rely primarily on a bench of sensors, actuators, complex algorithms, artificial intelligence techniques, and powerful computing resources to run the software. As such, AVs are able to deal with complex road situations leading to significant improvement of user safety, comfort, and convenience.

The Society of Automotive Engineers (SAE) has defined 6 levels of driving automation ranging from fully manual to fully autonomous (Autonomous car, 2021). While levels 0 and 1 are characterized by no driving assistance, level 2 is defined by a partial driving assistance. A Level 3 vehicle has "environmental detection" capabilities and can make few informed decisions without human intervention, such as accelerating past a slow-moving vehicle, while in level 4 (high driving automation) the driver still has the option to manually override in case of a system failure. Finally, level 5 is the full driving automation where there is no need of a driver under all circumstances (Ma et al., 2020).

To make a level 5 vehicle possible, it requires that the vehicle has the capability of "thinking", "perceiving", and "reacting" like a human driver. The recent achievements of AI in different fields, especially in image classification, object detection, and speech recognition have led to an increasing use of AI techniques such as deep learning (DL) and reinforcement learning (RL) to realize level5 vehicles. DL based approaches have enabled many studies to tackle different challenging issues in AVs, such as accurately recognizing and locating obstacles on roads, appropriate vehicular control, and motion planning.

This paper is an attempt to survey recent AI based techniques used to deal with major functions in AVS, namely scene understanding, motion planning, decision making, vehicle control, social behavior, and communication. Our survey focuses solely on DL and RL based approaches, thus omitting the inclusion of shallow machine learning (ML) based techniques, a subject that has been extensively investigated in the past (Qayyum et al., 2019; Elassad et al., 2020). Traditional ML approaches showed their limitations in realizing the main functions of AVs (e.g., scene understanding and motion planning). This has motivated us to limit our survey to DL and RL methods showing their potential in realizing these functions.

DL and RL techniques are well-known for their capability to improve the tasks of AVs. For example, DL showed promising results in object detection, which makes it suitable for scene understanding in autonomous driving. RL has been successfully used in other fields such as gaming and robotics, where there is a need to learn from the environment. Recently, RL techniques have gained increasing interest from AV research community as result of many promising results.

The review is organized as follows. Section I discusses existing surveys and highlights the gap we aim to fill with the current survey; it also presents the scope of our survey and the research methodology. Section II presents a brief introduction to DL and RL methods applied to AVs. Section III describes the different sensors of AVs. Section IV presents recent DL based approaches applied to AVs. Section V covers existing RL-based methods that aim to solve problems of autonomous driving. Section VI presents open research issues and future research directions. Finally, Section VII concludes the paper. The acronyms are summarized in Fig. 7.

1.1. Existing surveys

Several surveys exist in the literature that have investigated different aspects of autonomous vehicle technology (Ohn-Bar and Trivedi, 2016; Xue et al., 2018; Elassad et al., 2020; Qayyum et al., 2019; Hussain and Zeadally, 2018; Kuutti et al., 2020; Rasouli and Tsotsos, 2019; Ma et al., 2020; Claussmann et al., 2019; Grigorescu et al., 2020; Tong et al., 2019; Deb et al., 2018; Feng et al., 2020; Ning et al., 2021; Severino et al., 2021). However, most of these surveys did not discuss in detail the use of AI techniques, and less so the use of DL and RL, in different applications of autonomous vehicles. Ohn-Bar and Trivedi (2016) discussed the understanding, modeling, and the prediction of human behavior in the next generation of intelligent vehicles such as interactions between the humans and vehicles inside or around autonomous vehicles.

Xue et al. (2018) surveyed the function of traffic scene understanding in autonomous vehicles and how this function can help in event detection and intention prediction. Elassad et al. (2020) compared the estimation accuracy between Machine Learning (ML) models and non-ML models; they identified the strengths and weaknesses of ML techniques for assessing driving behavior. Qayyum et al. Qayyum et al. (2019) discussed the challenges associated with the application of ML in vehicular networks and highlighted the different security issues resulting from the adoption of ML methods.

Hussain and Zeadally (2018) presented a comprehensive review of autonomous car technologies and described design and implementation issues in autonomous cars such as technical and non-technical challenges addressed by the autonomous car industry. In addition, they introduced the latest developments in ML and DL optimized for autonomous vehicle technology. However, this work covers few DL techniques restricted to few aspects, namely perception, communication, and control, and left out completely RL techniques.

Kuutti et al. (2020) discussed DL methods for controlling AVs and its promising performance in complex scenarios. Authors presented the strengths and limitations of existing DL methods applied to autonomous vehicle control. However, they did not cover other major aspects of autonomous driving.

Rasouli and Tsotsos (2019) reviewed different pedestrian behaviors based on demographics of pedestrians, traffic dynamics, and environmental conditions. Then, they studied different methods to analyze pedestrian behavior at intersections. However, the authors did not cover DL and RL techniques to improve communication between pedestrians and AVs.

Ma et al. (2020) analyzed current practices using AI techniques for AVs and discussed the challenges and issues associated with their implementation. However, they did not focus on DL and RL based approaches.

Claussmann et al. (2019) presented a review of motion planning techniques; their focus was on highway planning. They discussed the main algorithms in motion planning and their applications in highway driving. However, they did not showcase specifically the role of DL and RL in this area of AVs.

Grigorescu et al. (2020) studied DL technologies used in autonomous driving and highlighted the strengths and limitations of this technique in scene perception, path planning, behavior arbitration, and motion control. They highlighted the main current challenges regarding the design of AI architectures for autonomous driving.

Tong et al. (2019) discussed AI methods for Vehicle-to-Everything (V2X) applications and the performance of these methods over traditional algorithms; they did also cover the role of AI in acquiring information from diverse sources. However, they only focused on the issue of sharing information in Vehicle-to-Vehicle (V2V) and V2X.

Deb et al. (2018) reviewed pedestrian interactions with fully autonomous cars; they highlighted the new behavior of pedestrians, which may lead to potential risks that need to be identified before autonomous cars hit the roads. However, they did not investigate the role of DL and RL methods for accurately detecting the intention of pedestrians in real-time. Feng et al. (2020) presented object detection and segmentation systems applied to autonomous driving. They provided challenges and open questions related to these detection methods.

Arnold et al. (2019) surveyed 3D object detection methods, as well as sensors and datasets commonly used in AVs. Moreover, the authors discussed the latest contributions based on sensor modalities and classified them into three main classes: monocular, based on point clouds, and fusion methods. However, this survey did not cover DL methods.

Ning et al. (2021) presented existing AI architectures used in autonomous driving. They summarized the limitations of these architectures and introduced the concept of human-artificial intelligence (H-AI); H-AI is considered a new perspective for future autonomous driving development. They also presented open research challenges to be addressed in the future. However, they did not cover AI-based solutions that may improve H-AI in the future.

Severino et al. (2021) discussed the impact of road markings, intersections, and pavement on AVs operations, especially detecting the environment when driving. They also presented some technical problems that are caused by implementing AVs systems.

1.2. The current survey

We conclude that existing surveys do not provide a comprehensive coverage of the use of DL and RL techniques to solve the main issues in AVs related to scene understanding, motion planning, decision making, vehicle control, social behavior, and communication. This has motivated us to fill this gap in the literature by presenting a new survey dedicated to the plethora of DL and RL techniques that have been applied to the field of autonomous driving so far. Table 1 summarizes coverage of exiting surveys. The current survey sheds light on the potential of DL and RL methods in different aspects of autonomous vehicles and showcases the goals that can be achieved in this field. Unlike to existing surveys on autonomous driving, this paper is the first to focus solely on DL and RL techniques in realizing the main functions in AVs. Compared to other surveys, the current work discusses the improvements brought by DL and RL in autonomous driving that allow overcoming the limitations of traditional ML techniques.

1.3. Review procedure

In order to collect relevant academic papers and resources, we used most digital libraries (e.g., IEEE Xplore Digital Library, Science Direct, and Springer Link), and popular search engines for bibliographic databases (e.g., Google Scholar).

Table 1
Comparison of related survey papers.

Year	Paper	Papers cited	Topic(s) of the survey	Scene Understanding	Motion Planning	Decision Making	Vehicle Control	Social Behavior	Communication	Limitations of traditional techniques	Focus on DL and RL techniques
2016	Ohn-Bar and Trivedi (2016)	174	Looking at Humans in the Age of Self-Driving and Highly Automated Vehicles	✓	×	×	×	✓	×	×	✓
2018	Xue et al. (2018)	128	Survey of scene understanding by event reasoning in autonomous driving	✓	×	×	×	✓	×	×	✓
2018	Hussain and Zeadally (2018)	230	Autonomous cars: Research results, issues, and future challenges	✓	×	✓	✓	✓	✓	×	✓
2018	Deb et al. (2018)	96	Pedestrians' receptivity toward fully automated vehicles: Research review and roadmap for future research	×	×	×	×	✓	×	×	×
2019	Qayyum et al. (2019)	239	Securing connected autonomous vehicles: Challenges posed by adversarial machine learning and the way forward	×	×	×	×	×	✓	✓	✓
2019	Claussmann et al. (2019)	200	A Review of motion planning for highway autonomous driving	×	✓	✓	×	×	×	×	×
2019	Tong et al. (2019)	151	Artificial Intelligence for Vehicle-to-Everything: a Survey	×	×	×	×	×	✓	✓	×
2019	Arnold et al. (2019)	70	A Survey on 3D Object Detection Methods for Autonomous Driving Applications	✓	×	×	×	×	×	✓	✓
2020	Elassad et al. (2020)	106	The application of machine learning techniques for driving behavior analysis: A conceptual framework and a systematic literature review	×	×	×	×	✓	×	✓	×
2020	Rasouli and Tsotsos (2019)	156	Autonomous vehicles that interact with pedestrians: A survey of theory and practice	✓	×	×	×	✓	✓	×	×
2020	Kuutti et al. (2020)	230	A Survey of Deep Learning Applications to Autonomous Vehicle Control	×	×	×	✓	×	×	×	✓
2020	Ma et al. (2020)	117	Artificial intelligence applications in the development of autonomous Vehicles: A survey	✓	✓	✓	×	×	✓	×	✓
2020	Grigorescu et al. (2020)	168	A survey of deep learning techniques for autonomous driving	✓	✓	×	✓	×	×	×	✓
2020	Feng et al. (2020)	253	Deep Multi-modal Object Detection and Semantic Segmentation for Autonomous Driving: Datasets,Methods, and Challenges	✓	×	×	×	×	×	×	✓
2021	Ning et al. (2021)	154	A Survey on Hybrid Human-Artificial Intelligence for Autonomous Driving	×	✓	×	×	×	×	✓	×
2021	Severino et al. (2021)	48	Autonomous Vehicles: An Analysis Both on Their Distinctiveness and the Potential Impact on Urban Transport Systems	×	✓	×	×	×	×	✓	×
Our				✓	✓	✓	✓	✓	✓	✓	✓

We selected the papers, we did cover on this survey, following these criteria:

1) The paper must involve using DL or RL techniques in AVs.
2) The paper proposes a solution to the issues faced by AVs in at least one of the six aspect mentioned earlier. Thus, for example, papers dealing with security and attacks on AVs were excluded.

1.4. Scope of this survey

In this paper, we present a comprehensive survey of the state-of-the-art studies of AI techniques applied in the autonomous vehicle field. We focus exclusively on DL and RL techniques by identifying their strengths and limitations. Additionally, we discuss the issues and challenges of DL and RL algorithms that need further investigation to approach Level 5 autonomy. We summarize the main contributions of this paper as follows:

1) We present an overview of DL and RL techniques.
2) We present a detailed taxonomy of autonomous vehicles including their components, design and implementation.
3) We describe in detail the DL and RL techniques used to solve the problems in AVs.
4) We identify the strength and weaknesses of DL and RL techniques in the context of AVs.
5) We present and discuss the challenges and open issues, related to DL and RL techniques in the context of AVs, that need further investigation.

2. Deep learning and reinforcement learning: a brief introduction

In this section, we briefly describe the fundamentals of deep learning techniques used in AVs and show the capabilities of each paradigm. We focus on Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and RL, which are the most common DL methods applied to autonomous driving.

2.1. Deep learning

Deep neural networks are a connectionist approach to imitating human intelligence and are capable of learning from huge amounts of data. They have a wide range of applications, from fraud detection and visual recognition to self-driving cars; however, they have limitations that are becoming increasingly evident. These include a vulnerability to adversarial examples, where data are presented with the intent to cause the learnt model to make mistakes.

DL models are successfully applied in various autonomous driving application areas (see Fig. .2). In the past few years, they have become a key component of computer vision applications. Among the key problems neural networks can solve, is detecting and localizing objects in images and videos allowing AV to identify its environment. Among the DL methods used in object detection are CNNs. They provide AVs with actionable information i.e., detecting and classifying objects (e.g., lanes, traffic lights, pedestrians, crossing lines, and traffic signs.) (Shrestha and Mahmood, 2019). CNNs have shown promising results in image classification, object detection, and semantic segmentation. They always contain three basic characteristics, namely convolution, pooling, and fully connected layers. The convolutional layer consists of filters to extract the main visual features in images or videos. These filters transform the size of the image into small multi-arrays that feed into fully connected layers, and the output layer predicts image category (Gupta et al., 2021).

Another DL model that is suitable for processing sequences of data is LSTM; networks are a kind of an Recurrent Neural Networks (RNNs). LSTM networks use feedback connections for sequence and pattern recognition, and uses input, output, and forget gates. Thus, it remembers the output calculated from the previous time step and provides the output based on the current input (Chung et al., 2014). LSTM networks have been applied in different autonomous driving tasks such as motion planning, decision making, and vehicle control. This Neural Networks (NN) architecture is therefore capable of predicting the current action based on past actions of AVs (Yu et al., 2019).

The main strength of DL is its ability to work with unstructured data (e.g., images) coming from cameras attached to AVs. A DL network can learn over time, from large examples of images and videos. These huge data could take up to 10 days to train on a single computer. However, given the nature of DF, GPUs can be used to significantly reduce the training process.

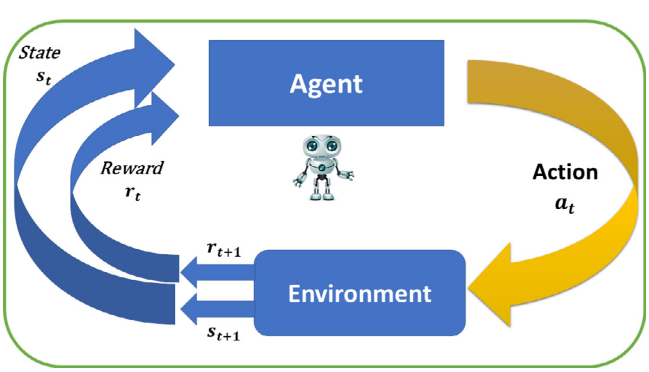

Fig. 1. The interaction of an intelligent agent with its environment based on a Markov Decision Process.

2.2. Reinforcement learning

RL is a subfield of machine learning that addresses the problem of automatic learning and optimal decisions over time. While DL methods focus on the development of computer programs that use data for learning autonomously, RL methods allow an intelligent agent to learn from its errors and experiences. The RL agent receives a reward by acting in the environment; its objective is to choose the action that maximizes the expected cumulative reward over time (Mousavi et al., 2016).

An RL agent can be modeled as a Markov Decision Process (MDP) as follows: the agent interacts with the environment by executing actions and receiving observations and rewards. As shown in Fig. 1, at each time step t, the agent receives some representation of the environment state $s_t \in S$. Based on this state, the agent selects an action $a_t \in A$. Selecting any action is based on the agent's behavior also called the policy. It tells the agent which actions should be selected for each possible state. As a consequence of each action, the agent receives reward $r_t \in R$ and observes the next state $s_{t+1} \in S$ (Winder, 2020). We can express the process of receiving a reward as an arbitrary function f. At each time t, we have:

$$f(s_t, a_t) = r_t$$

The main objective of RL is to find the action that maximizes the policy for each state. The Q-Learning (Watkins and Dayan, 1992) is used to achieve this goal by choosing the optimal policy through learning the optimal Q-values for each state-action pair. The Q-learning algorithm iteratively updates the Q-values for each state-action pair using the Bellman equation until the Q-function converges to the optimal Q-function q_*:

$$q_*(s,a) = E\left[r_{t+1} + \gamma \max_{a'} q_*(s',a')\right]$$

In Q-learning, the selection of action is based on the ϵ greedy strategy which has an exploration rate ϵ. ϵ is the probability to choose random action and $1-\epsilon$ is the probability to select the action with a high Q-value. This Q-value is iteratively updated in each selected action with the given expression:

$$q(s,a) \leftarrow q(s,a) + \alpha\left[r + \gamma \max_{a'} q(s',a') - q(s,a)\right]$$

Where γ is the discount rate that reflects the importance of current rewards relative to future rewards. α is the learning rate and s' is the next state. It can be seen that the key of the Q-learning algorithm is to maintain a Q table, which stores the Q value of the state-action pair.

3. The autonomous vehicle

The population growth has led to an increase in the number of vehicles causing a heavy load on current transportation infrastructure (e.g., parking space, charging and fuel stations). This continuous increase in the number of vehicles is the major cause of transportation issues including air pollution, noise pollution, road crashes, and traffic congestion. To address these issues, researchers have been developing AVs; the objective is to eliminate, or at least reduce, issues caused by human drivers.

AVs are defined as intelligent agents which can sense their environments by different sensors mounted on vehicles (Fig. 3). While humans use their senses (e.g., sight and hearing) to drive, AVs use sensors (e.g., cameras and radars). The quality of sensors plays a key role in building successful AVs. For example, the best perception algorithms can perform poorly if the data, collected from the corresponding sensors are not reliable.

The role of the sensors is to measure or to detect some properties of the environment or changes in these properties over time. Sensors are broadly categorized into two types: (a) exteroceptive

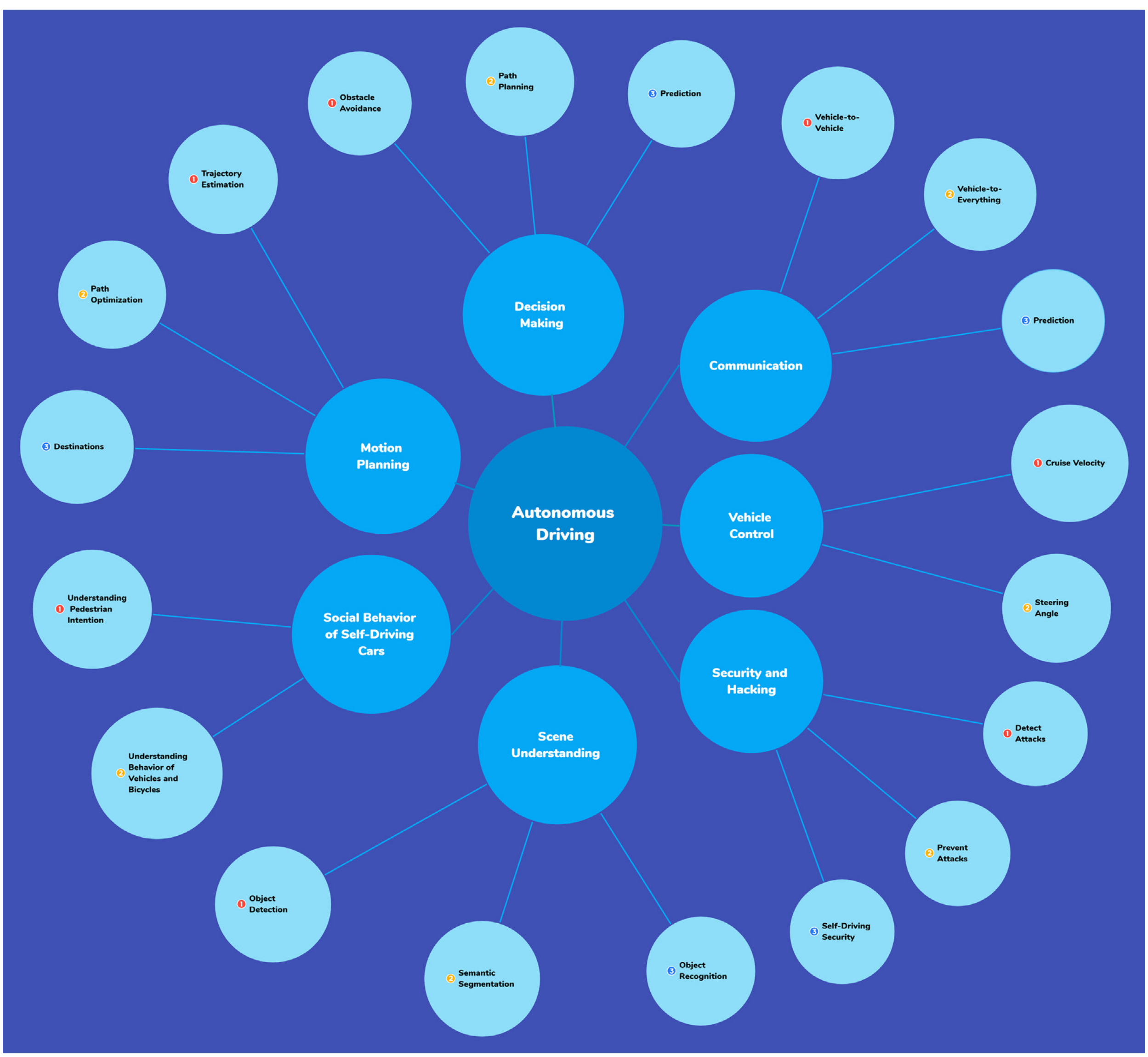

Fig. 2. Taxonomy of the main applications of DL and RL techniques in Autonomous Driving.

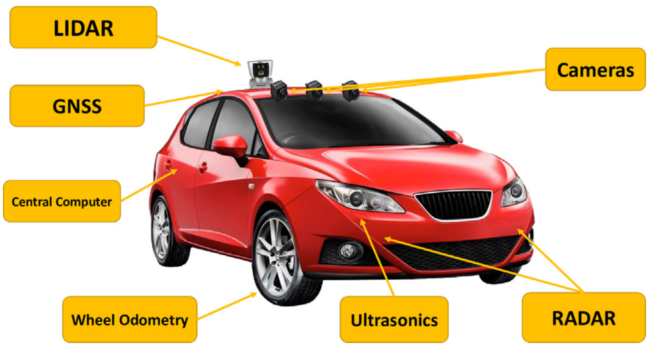

Fig. 3. Sensors used in Autonomous Vehicles.

Fig. 4. Object Detection and Classification for Autonomous Vehicles.

sensors: they record a property of the environment surrounding the vehicle (e.g., cameras and Light Detection And Ranging (LIDAR)); (b) proprioceptive sensors: they record a property of the vehicle itself (e.g., Global Navigation Satellite System (GNSS) location and wheel odometer).

The most common and widely used sensor in autonomous driving is the camera. A camera is a passive and light-collecting sensor that captures rich and detailed information about a scene. The quality of a camera is determined by various metrics such as the resolution and the field of view. The resolution is the number of pixels that create the image and impacts its quality. The field of view is defined by the horizontal and vertical angular extent that is visible to the camera and can be varied through lens selection and zoom. The dynamic range of the camera is defined by the difference between the darkest and the lightest tones in an image. High dynamic range is critical for self-driving vehicles due to the highly variable lighting conditions encountered while driving especially at night. The combination of two cameras with overlapping fields of view and aligned image planes is called stereo cameras; they produce a disparity map of the scene that is used to estimate the depth at each pixel (Thakur, 2018).

The second critical sensor in AVs is LIDAR. It shoots light beams. By measuring the amount of the returned light and the time of flight of the beam, the dept of reflecting objects can be estimated. LIDAR produces a three-dimensional point cloud map, which is useful for assessing scene geometry. LIDAR is generally governed by some critical metrics such as the number of sources, the points per second it can collect, and the field of view (Bussemaker, 2014).

Radio Detection And Ranging (RADAR) sensors have been used longer than LIDAR. They robustly detect large objects in the environment and are particularly useful in adverse weather as they are mostly unaffected by rain. A RADAR sensor is characterized by its detection range, field of view, and the position and speed measurement accuracy (Curry, 2005).

Ultrasonic sensors are also important in AVs; they measure the range using sound waves. They are particularly suitable for parking scenarios, where the vehicle needs to make movements very close to other cars (Curry, 2005).

One of the main proprioceptive sensors in the vehicular industry is GNSS, such as GPS or Galileo. GNSS allows to measure the vehicle position, velocity and sometimes heading. Inertial Measurement Unit (IMU) measures the angular rotation rate and accelerations of the vehicle. Another important proprioceptive sensor is the wheel odometer; it tracks the wheel rate of rotation and uses this information to estimate the speed and heading rate of change of the vehicle (Reinholtz et al, 2007).

Generally, after identifying their environment, AVs perform a number of tasks including object detection, planning, making decisions, controlling speed, and driving without any human intervention.

4. Deep learning based approaches in autonomous vehicles

In this section, we survey existing DL based approaches that are used to address the main tasks of AVs namely (1) scene understanding, (2) motion planning, (3) decision making, (4) vehicle control, (5) social behavior of self-driving cars, and (6) communication (See Fig. 7).

4.1. Scene understanding

In the last two decades, the scene understanding field has seen significant progress using effective DL techniques. This progress made it possible to provide AVs with crucial and precise information on the driving environment by using different sensors such as LIDAR, cameras, and RADAR. Indeed, deep CNNs have shown remarkable results in image classification and detection in real time (Fernandes et al., 2021). As shown in Fig. 4, the use of DL techniques in scene understanding provides AVs with actionable information such as the detection of lanes, traffic lights, pedestrians, crossing lines, traffic signs, etc. Cordts et al. (2016).

This said, perception remains one of the main prerequisites for vehicles to recognize road geometry and to identify road users such as pedestrians, bicycles, and other vehicles. Perception is divided into two groups: road scenes and object detection.

4.1.1. Road scenes

Recognizing and extracting the main road information accurately is critical for AVs to identify elements of the road (e.g., pavements, ditches, guardrails, and fences). Thanks to the power of DL, it is possible to achieve high accuracy in recognizing the road elements. For example, Balado et al. (2019) use the information obtained by Mobile Laser Scanning (MLS) to identify the main elements of the road environment. Their proposal is based on PointNet (Qi et al., 2017) and Semantic Segmentation (SS) methodologies to recognize road elements; it gives good vision to AVs in urban areas.

Identifying the geometric structure of the road provides AVs with more information about its environment. Laddha et al. (2016) used a hybrid algorithm based on both supervised and unsupervised learning to identify the road geometry using CNNs. Although, this algorithm reduces the human labeling efforts and makes training more scalable, it still needs to be assessed in different scenarios with critical weather conditions.

Comprehensive understanding of the surrounding environment and road area (e.g., occlusion, 3D geometry, and types of road topology) facilitates practical applications in autonomous driving. To this end, Yan et al. (2020) developed a multi-task road perception network (LMRoadNet) method based on LIDAR data. LMRoadNet aims to detect and estimate the road measurements such as length and shape of the road in order to identify its topology.

Road corners are considered one of the challenging regions to identify. A study by Bolte et al. (2019) introduced the formal definition of a road corner and detect them in video signals from AVs cameras. Therefore, the CNNs-based system enables AVs to sense better roads in critical situations.

Tümen and Ergen (2020) developed an image processing method and a DL based approach to detect intersections, separations, and crosswalks on highways using CNNs. Such a detection is crucial in improving road safety given the high incidence of accidents in these places.

Di et al. (2017) investigated the problem of traffic scene understanding to identify road objects from images with illumination conditions. They considered Dense Correspondence-based Transfer Learning approach based on CNNs to extract deep representations of urban environment images. However, this approach did not take into consideration different and complex driving scenarios.

Successful detection and classification of traffic signs are one of the major challenges to overcome for fully self-driving cars. For example, Sajjad et al. (2020) developed a method for detection and avoidance of obstacles. The model recognizes various traffic signs based on visual sensors; it allows to avoid obstacles using ultrasonic sensors. The authors implemented their prototype to facilitate vehicular perception by using only a monocular vision sensor.

4.1.2. Object detection

Detecting surrounding objects accurately and in real-time, including other road users, is critical and of most importance for AVs. Wang et al. (2020b) proposed an end-to-end 3D object detection method based on DL techniques. Specifically, their technique uses CNNs and Fusion Network (FoFNet), to predict the bounding boxes and classes of objects such as cars, pedestrians, and cyclists.

Prabhakar et al. (2017) proposed an approach to improve the effectiveness of detection by taking into account weather conditions. More specifically, they used Region Convolution Neural Network (R-CNNs) to recognize and classify obstacles such as vehicles, pedestrians, and animals. They used bounding boxes with class names on top of each detected object during a rainy day. However, more tests on other road image datasets are needed to assess the accuracy and suitability of this model.

In addition to object detection, other key parameters (e.g., distance) need to be estimated to help in autonomous driving. Chen et al. (2018b) proposed multi-task combination strategy (CP-MTL) algorithm that aims to improve detection by estimating the distance between vehicle and other road users during detection.

Li et al. (2021) address the problem of detection at night using CNNs to improve low-light image identification. They report that their proposal can help AVs identifying roads especially in rural areas without street lights.

Dinh et al. (2020) propose an approach based on CNNs for better object detection in urban traffic; they assume that AVs are equipped with two cameras with different focal lengths. They show that their proposal allows for detecting small objects (e.g., small and far away vehicles).

Several of the existing approaches (Wang et al., 2020b; Prabhakar et al., 2017; Chen et al., 2018b; Li et al., 2021; Dinh et al., 2020) rely on video for object detection; they classify objects in consecutive frames over time. However, this does not take into consideration spatial and temporal correlations between image frames leading to a loss of information. To fill this gap, Liu et al. (2020) identified vehicles in two situations, namely occlusion and truncation, based on Motion-aid Feature Calibration Network (MFCN). Compared to Ren et al. (2017), Song et al. (2018b), and Zhang et al. (2017), the evaluation of their proposal (Liu et al., 2020) did show a better detection accuracy under different object appearance.

Due to the huge amount of data that comes from sensors, decreasing the quantity of data during training can enhance the performance of detection models. Basically, using only significant data can shorten the training duration of DL-based approaches. Time is critical during driving, especially in emergency situations; thus, the detection must be in real-time (Das et al., 2020).

3D object detection reveals more accurate object size and location information for autonomous driving. Many important aspects of autonomous driving such as motion planning and vehicle control generally require a faithful representation of the 3D space around the vehicle. Existing 3D object detection contributions fundamentally differ in the way they use sensors for detection. Several contributions (Ma et al., 2019; Peng et al., 2020) use only a monocular camera. For example, Zhang et al. (2020b) propose a novel monocular framework for 3D detection in autonomous driving scenarios; the objective is to detect and locate objects with 3D boxes.

Several other approaches propose to fusion both camera images and LIDAR data. Chen et al. (2017a) tried to improve detection performance by developing 3D object detection approach based on Multi-View 3D networks (MV3D). Their proposal uses both LIDAR point cloud and RGB images to predict 3D bounding boxes; it outperforms approaches that rely only on sensors. Hong et al. (2020) propose a 3D detection approach that makes use of both LIDAR point clouds and RGB images as inputs to the CrossFusion Net method. They show, via simulations, that their proposal allows to detect objects that are usually hard to detect using sensors only.

The safety of Vulnerable Road Users (VRUs) remains one of the major challenging issues. Thus, the detection of pedestrians is of most importance as they are considered the major vulnerable road users. In this context, Zhao et al. (2020) propose an approach called Pedestrian Location Perception Network (P-LPN); it is based on Inner Cascade Network (InCNet). P-LPN categorizes pedestrians into two groups: those who are moving in vehicular lanes and those moving on sidewalks. It provides the position of each pedestrian on semantic maps using Region Proposal Network (RPN). However, P-LPN does not take into account the pedestrians' intentions, which are important for AVs to understand the movement of pedestrians.

Table 2 compares the scene understanding contributions we did cover in this section.

Based on reviewed works, it is fair to conclude that detection and recognition have reached a considerable level of reliability in terms of accuracy and detection latency, especially when involving the fusion of two or more sensor modalities. Some of these methods focus on identifying traffic signs, the structure of the road, etc. Other approaches address the problem of road user detection in corners and intersections in real-time. For example, Zhao et al. (2020) studied the detection of pedestrians in both vehicular lanes and sidewalks. However, such an approach requires more details to specifically identify each area where a pedestrian is moving in a vehicular lane, which may improve the detection accuracy. According to Table 2, most of these approaches did not take into consideration the weather and illumination conditions. Therefore, future work should investigate further these issues.

Table 2
Comparison of scene understanding techniques.

Papers	Publication year	Sensor Input	Dataset	Image size Pixels	Proposed Method	Neural Network Architecture	DL Framework	Learning Strategies	Hardware	Language	Traffic condition	Weather condition	Illumination condition
Laddha et al. (2016)	2016	Camera	KITTI	1392×512	Map-supervised Detection	CNNs	Keras	Supervised & unsupervised	Not Reported	Python	Urban	No	No
Di et al. (2017)	2017	Camera	1130 images 698 images	856×270 640×360	DCTL	CNNs	Caffe	Supervised	Nvidia EVGA GeForce GTX TITAN X GPU	Python	Urban Highway	Yes	Yes
Prabhakar et al. (2017)	2017	Camera	KITTI iRoads Bangalore road Chennai road Animal road	1392×512 640×360 1920×1080 1920×1080 (1025×680,1001×680)	Obstacle detection and classification	R-CNNs	Caffe	Supervised	NVIDIA GeForce GTX 980 Ti GPU	Python	Urban	Yes	Yes
Chen et al. (2017a)	2017	Camera LIDAR	KITTI	1392×512	MV3D	CNNs	Tensorflow	Supervised	Titan X GPU	Python	Urban	No	No
Chen et al. (2018b)	2018	Camera	KITTI	1392×512	MTL	CNNs	MXNET	Supervised	Nvidia Titan X GPU	Not Reported	Urban	No	No
Balado et al. (2019)	2019	MLS	113.6 million points Vigo city	-	SS	PointNet	Not Reported	Supervised	GPU NVidia Tesla K80	Python	Urban	No	No
Bolte et al. (2019)	2019	Camera	Cityscapes	700 ×700	Towards Corner Case Detection	CNNs	Not Reported	Supervised	Nvidia Geforce GTX 1080 Ti	Python	Urban	No	No
Zhao et al. (2020)	2020	Camera	CityScapes	1024×2048	P-LPN	InCNet RPN	Tensorflow	Supervised	GPU NVidia GTX 1080 Ti	Python	Urban	No	No
Das et al. (2020)	2020	Camera	Camvid data CARLA Data	256×256	SS	DeepLabv3+	Keras	Supervised	Not Reported	Python	Urban	No	No
Wang et al. (2020b)	2020	LIDAR	KITTI	1392×512	3D object detection	CNNs FoFNet	Not Reported	Supervised	NVIDIA Titan XP GPU	Python	Urban	No	No
Sajjad et al. (2020)	2020	Camera	10000 images	80×60	Detect traffic sign	DNN	Tensorflow	Supervised	Raspberry Pi	Python	-	No	No
Liu et al. (2020)	2020	Camera	KITTI ImageNet	1392×512	MFCN	CNNs ResNet FlowNet2 R-FCN	Not Reported	Supervised	NVIDIA GTX 1080Ti GPUs	Not Reported	Urban	No	No
Tümen and Ergen (2020)	2020	Camera	836 images	458×640	Intersection and crosswalk detection	CNNs	Not Reported	Supervised	Not Reported	Python	Highway	No	No
Hong et al. (2020)	2020	Camera LIDAR	KITTI	1392×512	CrossFusion Net	CNNs	Not Reported	Supervised	NVIDIA GTX1080 Ti GPU	Not Reported	Urban	No	No

Table 2 (*continued*)

Papers	Publication year	Sensor Input	Dataset	Image size Pixels	Proposed Method	Neural Network Architecture	DL Framework	Learning Strategies	Hardware	Language	Traffic condition	Weather condition	Illumination condition
Zhang et al. (2020b)	2020	Camera	KITTI	1392×512	MCK-NET	CNNs	TensorFlow	Supervised	GPU NVIDIA GeForce GTX 870 M	Not Reported	Urban	No	No
Dinh et al. (2020)	2020	Two cameras	10,000 images	1280×720	Vehicle detection	CNNs	Not Reported	Supervised	Not Reported	Not Reported	Urban	No	No
Yan et al. (2020)	2020	LIDAR	MultiRoad	460×300	LMRoadNet	CNNs	PyTorch	Supervised	NVIDIA GTX-1080 Ti GPU	Python	Urban	No	No
Li et al. (2021)	2021	Camera	BDD100K	1280×720	LE-Net	CNNs	Not Reported	Supervised	NVIDIA TITAN RTX.	Python	Urban& rural	No	Yes

4.2. Motion planning

After scene understanding (or perception of the environment), motion planning is the next main task for AVs to navigate both safely and smoothly by avoiding collisions in diverse environments. To deal with motion planning issues, traditional approaches (e.g., Dijkstra Algorithm, A-Star Algorithm (A^*), and State lattice algorithms) rely on optimization models. These algorithms are slow in vast areas making them not suitable for real-time applications. Thus, many researchers propose alternative approaches, such as DL based techniques. These approaches analyze perception information in order to recognize obstacles and then predict the right action (see Fig. 5). This allows AVs to navigate safely by finding efficient paths in terms of time and distance.

We classify motion planning into two categories: motion command prediction and trajectory prediction. Motion command prediction consists mainly in calculating the steering angle, acceleration, and/or braking, while trajectory prediction consists in calculating short-term trajectories for all road participants, including the ego-vehicle, as well as their future states.

4.2.1. Motion command prediction

Due to the complexity of traffic situations, it is hard to build a general motion planning system, especially in real-time. Indeed, the behavior of road users remains unpredictable and hard to model. For example, Bai et al. (2018) combined CNNs and LSTM to extract the Spatio-temporal information with the objective to predict the steering angle in real-time based on real data. Song et al. (2018a) used a similar approach to estimate the steering angle using data collected from a driving simulator.

Chen et al. (2018a) proposed to combine CNNs and LSTM to make planning decisions. They report that using simulated and real traffic allows AVs to better imitate human driving in many situations. However, we believe that their proposal should be tested more extensively to assess and improve its performance.

Some contributions (Bai et al., 2018; Song et al., 2018a; Chen et al., 2018a) did focus only on steering angle estimation; others did address more than one motion command. For example, Hu et al. (2020) proposed a deep cascaded neural network based on CNNs and LSTM to predict multiple motion commands (i.e., steering angle, acceleration, and braking), simultaneously.

4.2.2. Trajectory prediction

AVs need to analyze data, collected by sensors, to detect obstacles for safe navigation to destination. Zhao et al. (2019) propose Learning Kalman Network (LKN) to estimate the trajectory of vehicle from data collected by camera using DL. Banzhaf et al. (2019) propose a CNNs based approach that uses collected data to predict the future motion of the vehicle taking into account static obstacles and unstructured roads. Thus, bidirectional RRT^* is used in their proposal to reduce the computation time.

Grigorescu et al. (2019) propose an approach to improve trajectory prediction for an optimal path for AVs. They fusion both LIDAR and RADAR data to estimate an optimal trajectory. Cui et al. (2019) propose a method to estimate trajectories of other vehicles and pedestrians; They use CNNs to process the data coming from LIDAR or RADAR. Djuric et al. (2020) use a similar approach to predict short-term vehicle trajectories and the future state of road participant (e.g., surrounding vehicles). Deo and Trivedi (2018) propose CNNs and LSTM to predict future trajectories of surrounding vehicles in various traffic scenarios. Zhang et al. (2020c) use Imitation Learning (IL) by exploring characteristics of experience of human drivers in the environment. They utilize CNNs to process 3D environment information and provide state of surrounding vehicles.

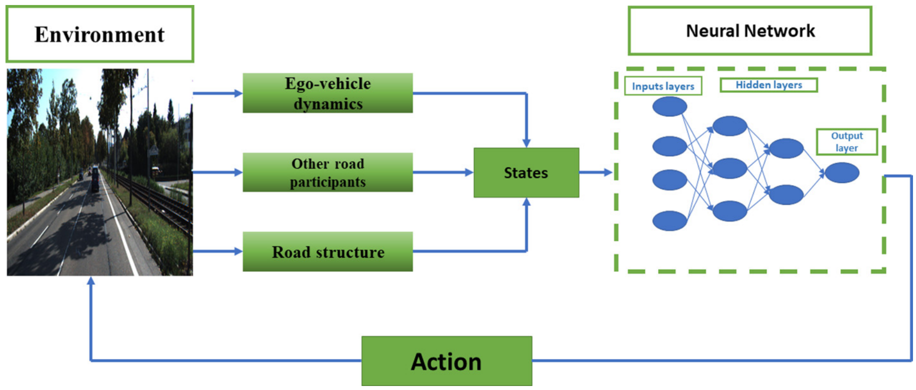

Fig. 5. An illustration of DL architecture for the motion planning process.

Table 3
Comparison of motion planning techniques.

Papers	Publication year	Sensor Input	Dataset	Output	Neural Network Architecture	DL Framework	Hardware	Experiments	Simulator
Song et al. (2018a)	2018	Camera	Eight hours of driving data	Steering angle	CNNs & LSTM	Caffe	NVIDIA GTX 1080Ti GPU	Simulation	European Truck
Bai et al. (2018)	2018	Camera	80 GB raw image data	Steering	CNNs & LSTM	Keras	NVIDIA GTX 980 GPU	Real	-
Rehder et al. (2018)	2018	Camera	Real world data	Pedestrian destinations	CNNs & LSTM & RMDN	Not Reported	Not Reported	Real	-
Chen et al. (2018a)	2018	Camera	Simulator data	Steering angle & accelerator	CNNs & LSTM	Not Reported	-	Simulation	GTA5& ETS2
Deo and Trivedi (2018)	2018	Camera	NGSIM US-101 I-80	Future trajectories of surrounding AVs	CS-LSTM	PyTorch	Not Reported	Real	-
Cui et al. (2019)	2019	Camera LIDAR RADAR	240 h of data RGB images	trajectories of AVs and pedestrians	CNNs	TensorFlow	Nvidia Titan X GPU	Real	-
Grigorescu et al. (2019)	2019	LIDAR RADAR	50 km highway 50 km inner-city driving	Trajectory estimation	CNNs & LSTM	Not Reported	Not Reported	Real	-
Banzhaf et al. (2019)	2019	LIDAR	13418 trajectories from the simulator	Future vehicle poses	CNNs	TensorFlow	Nvidia TitanX	Simulation	Gazebo & ROS
Zhao et al. (2019)	2019	Camera	KITTI	trajectory of ego-vehicle	CNNs & LSTM	Tensorflow	NVIDIA Titan GPU	Real	-
Zhang et al. (2020c)	2020	Camera & LIDAR	NGSIM US	State of surrounding AVs	CNNs & LSTM	Not Reported	Not Reported	Real	-
Hu et al. (2020)	2020	Camera	ImageNet & ten hours from Euro Tuck	Steering angle & acceleration & braking	CNNs & LSTM	Caffe	NVIDIA GTX1080Ti GPU	Simulation & Real	Euro Tuck
Djuric et al. (2020)	2020	Camera & LIDAR & RADAR	240 h of data by manually driving AVs in Pittsburgh	AVs trajectories	CNNs & LSTM	TensorFlow	16 Nvidia Titan X GPU	Real	-
Jeong et al. (2020)	2020	LIDAR & Camera & low cost GPS	4,312 trajectories of vehicles driving	Target state of surrounding AVs	LSTM & RNNs	Not Reported	Motion Planning Pc	Real	-
Leordeanu and Paraicu (2021)	2020	Camera	UED	Current location & Future trajectory	CNNs	Not Reported	NVidia	Real	-

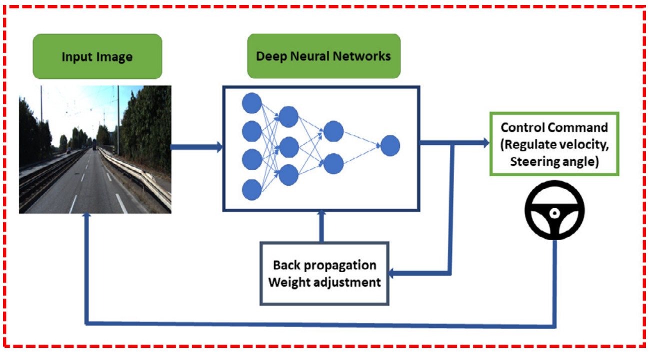

Fig. 6. Diagram of the Control System in AVs.

Leordeanu and Paraicu (2021) develop a method that predicts the current location and future trajectory of AVs based only on video and final destination. This method can adapt to short and long-term navigation under different weather conditions.

Jeong et al. (2020) propose a motion prediction algorithm, based on LSTM and RNNs; the objective is to reduce crashes at intersections. The algorithm takes the state information of surrounding vehicles as the input and predicts the sequences of the target states.

Rehder et al. (2018) use Fully Convolutional Networks (FCNs) for operating maps of the environment in order to infer all possible pedestrian destinations. The simulation results show the ability of the system to predict destinations and trajectories accurately.

In Table 3, we compare existing approaches in terms of the tools used in the task of motion planning.

4.3. Decision making

Decision making in autonomous driving requires an accurate and adequate representation of the environment. Previous approaches used traditional methods (e.g., heuristics and numerical optimization), but failed to simulate all possible situations. Deep Learning techniques have recently shown their capability to take decisions in real-time and in complex environments.

Li et al. (2018) used CNNs to imitate human drivers by extracting road scene images to make the right driving decision. Gallardo et al. (2017) present a method to take decisions for AVs through an environment using CNNs especially AlexNet architecture in Krizhevsky et al. (2012). Xie et al. (2019) proposed a lane change approach using LSTM to model the interactions between AVs and surrounding vehicles.

Lane changing maneuvers remain one of the complicated and challenging tasks for AVs. Therefore, it is necessary to develop accurate systems able to make a lane change taking into consideration the movements of surrounding vehicles. Liu et al. (2019b) present a DNN-based method that benefits from the drivers historical experience and V2V information for accurate lane change maneuvers.

Strickland et al. (2018) propose an approach to avoid crashes in emergency situations. To this aim, they used Bayesian Convolutional LSTM to process data and avoid existing collisions. Wang et al. (2020c) use R-CNNs to guide AVs at roundabouts. Their proposal is able to make decisions (e.g., entering or waiting) when AVs arrive at roundabouts.

4.4. Vehicle control

Vehicle control is responsible for correcting errors emanating from motion planning and decision making tasks. The role of the controller in AVs is to stabilize and guide the vehicle along the path. It receives the vehicle states that are estimated by the perception and localization modules. Based on these states, AVs select the suitable control command as shown in Fig. 6.

In this sub-section, we first present the classical AV control strategies that allow to minimise the cost function $\dot{x} = f(x(t), u(t))$ defined over a set of states $x(t)$ and control actions $u(t)$.These traditional controllers can be classified as model-free and model-based.

Model-Free Controllers: This kind of controllers do not use any mathematical model of the system being controlled. They allow to correct the action based on the error between the setpoint and the current state. These controllers are easy to implement because they do not require in-depth knowledge of the system behavior. However, they are difficult to tune, do not guarantee optimal performance, and only work well under limited operating conditions (Samak et al., 2011). An Example of such controllers is the Proportional Integral Derivative (PID), which allows AVs to reach its objective state with as little vibration or jitter as possible. The output of a PID depends on three hyperparameters, one for each term of the controller abbreviation (P-I-D). These hyperparameters are specific to each application (Kiong et al., 1999; Crenganis and Bologa, 2016).

Farag (2020) use PID controller to steer an AV throughout the track calculated by the path planner. The testing results show the performance of PID at different vehicle speeds. Alonso et al. (2013) propose an approach for tuning the parameters of the PID controller based on the minimization of a quadratic function. Their proposal is applied to control AV to follow another vehicle ahead.

Model-Based Controllers: These controllers use mathematical models to control the system being controlled. Kinematic controllers determine the vehicle's motion and ignore internal or external forces acting on the system. They are efficient especially at low speeds when the acceleration is not significant. Satouri et al. (2021) use an example of a kinematic model, such as a bicycle model (Rajamani, 2011), which allows the control of the non-linear vehicle's motion. This model estimates the velocity and steering angle of AV and also the cornering stiffness of the front and rear tires. Their proposal is tested and validated using CarSim simulator; the results show the performance of their model to track the reference path trajectory given by motion planning.

Dynamic controllers take into consideration forces and torques acting on the system to estimate the motion of the vehicle. Model Predictive Control uses linear or non-linear motion models of the system to predict its future states and determine the optimal control action by solving an optimization problem at each time step (Samak et al., 2011).

Funke et al. (2016) combine model predictive and feedback controllers to estimate the steering angle required to arrive at the desired destination while maintaining stability and avoiding collisions.

Li et al. (2017) present an approach that allow to control AV to track the reference path and avoid collisions (e.g., vehicles, cyclists, and pedestrians). Their proposal combines feedforward and feedback controllers (Kapania and Gerdes, 2015) to adjust the steering angle while driving. Ni et al. (2017) use also feedforward and feedback controllers to steer AV along the desired path. Their model estimates the tyre cornering stiffness in order to enhance the robustness of the controller.

Previous controllers require in-depth knowledge of the process and tuning. Moreover, kinematic or dynamic models need to be known before implementing a suitable controller. These controllers are used in specific scenarios and are not adapted to other situations. They need to be re-tuned when the scenario changes. In addition, they do not take into consideration the motion of each road user, such as other vehicles, cyclists, and pedestrians. Therefore, it becomes critical to consider VRUs in general and pedestrians in particular when designing new AVs related approaches. This will help more understanding and thus predicting pedestrians intentions when AVs hit the road.

It is worth noting that these controllers do not deal with complex situations such as dense traffic, intersections, crosswalks, etc. They only focus on controlling AVs to follow the reference path generated by motion planning. For these reasons, AI techniques, especially DL and RL, outperform these traditional techniques by learning from their environment to take accurate control commands (e.g., steering and regulating velocity), as we present in this sub-section and the RL section.

The control system is divided into two categories: (a) longitudinal control: it regulates the vehicle cruise velocity and (b) lateral control: steers the vehicle's wheel for path tracking.

4.4.1. Lateral control

(1) Lateral Control: allows selecting the required steering angle and correcting any errors that may accumulate during driving.

Rausch et al. (2017) propose a method based on CNNs to predict steering angle. They train their proposal with data collected from the camera of AVs. This method has been assessed in scenarios with only a two-lane road without traffic.

Sharma et al. (2018) present an approach to steer AVs in different tracks (e.g., multilane track, and single lane unknown tracks). They use CNNs and TORCS (Wymann et al., 2000) to train and test their proposal with collected data from sensors (i.e., speed, steering angle, throttle, and brake positions). The simulated results show that their model can successfully control the car and complete the entire lap without over the lane markings. However, their method is only simulated in two tracks of the TORCS simulator.

Lee and Ha (2020) combine CNNs and LSTM to estimate the steering angle for AVs. The CNNs is used to extract features from camera images during driving. These features are fed to LSTM to estimate the steering angle.

Maqueda et al. (2018) address the problem of estimating steering angle throughout different day periods (e.g., sun and night days). They utilize CNNs used in He et al. (2016) to train the data coming from event cameras (Lichtsteiner et al., 2008). The simulation results demonstrate that their proposal with using an event camera has performance under different conditions (fast motion, challenging illumination).

Yang et al. (2018b) reported that predicting only the steering angle is not sufficient for vehicle control. Thus, they proposed to include an estimation of the speed control. They used CNNs with 5 convolutional layers and 4 fully connected layers to extract the features from data of Udacity simulator (Public Driving Dataset, 2017). The training dataset, they used includes speed values, steering angles, and video streams from three front view cameras. The extracted features were fed to LSTM to predict both steering angle and speed command.

Chen et al. (2019c) presented Auxiliary Task Network (ATN) method using CNNs in Bojarski et al. (2016) and LSTM to learn to steer a vehicle. They trained their network architecture to predict steering angle based on image inputs of camera. They evaluated their proposal using Udacity simulator and Comma.ai dataset.

Mújica-Vargas et al. (1062) investigate an enhanced chauffeur hybrid method to steer AVs in different situations (e.g., lane changes, traffic lights, traffic signs, and changing from one road to another). Their proposal combined both CNNs and RNNs, where CNNs extracted features of the data collected from Udacity simulator. However, they did not take into account obstacles and other road users.

Kebria et al. (2019) present a CNNs based architecture to reduce training time and predicting steering angle of AVs. They use CNNs to extract important features of recorded images during driving. They conclude that the CNNs architecture with larger filters in their first layers has an outstanding performance.

Yang et al. (2018a) use TORCS (Wymann et al., 2000) and CARLA (Dosovitskiy et al., 2017) simulators for data collection under instead of including different conditions (e.g., day and night). This data are fed to CNNs to estimate steering angle for AVs. However, the authors did not consider other challenging scenarios (e.g., intersection and dense traffic).

4.4.2. Longitudinal control

(2) Longitudinal Control: it is responsible for automated guidance to ensure safety and comfort by regulating the speed of AVs during driving. DL has become a popular method in longitudinal control since it can estimate the right speed based on labeled training data collected in the real world or in simulation environments.

Mohseni et al. (2018) present a Model Predictive Control (MPC) method to regulate the velocity of AVs to avoid obstacles. They train their DNN architecture with data collected from LIDAR sensor (including position, size, and velocity information) for each detected obstacle. The objective of their proposal is to customize the velocity where the obstacle has appeared.

Szilassy et al. (2019) propose a control approach to estimate the velocity of AVs in intersections using DNN. DNN takes positions and initial velocities of AVs as input. However, their proposal does not consider other key parameters (e.g. pedestrian behavior) in intersections.

Al-Sharman et al. (2020) propose a state estimation method based on DNN architecture. They collect data (vehicle states, powertrain states, and brake values) using a real vehicle to imitate a human driver. The data are fed to DNN to predict brake pressure.

4.4.3. Lateral & longitudinal control

(3) Lateral & Longitudinal Control: The previous sections showed that DNN can be trained for longitudinal or lateral control of the vehicle. To improve steering and acceleration mechanisms, longitudinal and lateral controls can be used simultaneously. In the following, we briefly discuss approaches that use both controls.

Chen et al. (2015) proposed a method to estimate control commands (steering, acceleration, and brake). They trained CNNs with 12 h of video data collected by TORCS (2021). Their proposal enables AVs to drive in different scenarios. Devineau et al. (2018) presented a Multi-Layer Perception (MLP) approach to train AVs to drive in challenging situations (including shifting between long straight lines and tight curves) using CNNs. The results showed the effectiveness of their proposal in estimating the steering angle.

Sharma et al. (2019) use TORCS (2021) to collect data (including road images labeled by speed, steering angle, throttle, and brake positions). This data are fed to CNNs for training their to learn predicting vehicle speed and steering angle simultaneously.

Xing et al. (2020) developed an approach to generate lane change in the highway. Though the proposal uses both CNNs and RNNs in the training phase, it has not been tested in critical situations with dense traffic.

In Table 4, we compare existing vehicle control approaches.

4.5. Social behavior of self-driving cars

The automobile industry targets to introduce level five (full automation) AVs in the next few years. Obtaining fully AVs in future transportation systems will depend on how AVs identify the behavior of road users. DL techniques did show promising results in understanding road users' intentions and thus taking timely traffic decisions.

Table 4
Comparison of vehicle control techniques.

Papers	Publication year	Sensor Input	Dataset	Output	Neural Network Architecture	DL Framework	Categories of Control Systems	Hardware	Experiments	Simulator
Chen et al. (2015)	2015	Camera LIDAR	KITTI	steering & acceleration & brake	CNNs	Caffe	Lateral & longitudinal	NVIDIA	Real & Simulation	TORCS
Rausch et al. (2017)	2017	Camera	CARSIM Data	Steering angle	CNNs	Caffe	Lateral	GPU	Simulation	CARSIM
Mohseni et al. (2018)	2018	LIDAR	-	Controlling velocity	FCN	Tensorflow & Keras	Longitudinal	-	-	-
Yang et al. (2018b)	2018	Cameras	Udacity & SAIC	Steering angle & Speed command	CNNs & LSTM	Not Reported	Longitudinal & Lateral	GPUs	Real	-
Yang et al. (2018a)	2018	Camera	Comma.ai & Udacity	steering angle	GAN & CNNs	Tensorflow	Lateral	NVIDIA Titan-X GPU	Simulation & Real	TORCS & Carla
Sharma et al. (2018)	2018	Camera	10 h of driving data	Steering angles	CNNs	TensorFlow	Lateral	NVIDIA CUDA	Simulation	TORCS
Maqueda et al. (2018)	2018	DAVIS camera	DAVIS Driving	Steering angle	CNNs	Not Reported	Lateral	NVIDIA	Real	-
Devineau et al. (2018)	2018	-	9DoF data	Steering angle	CNNs	Not Reported	Longitudinal & Lateral	Not Reported	Simulation	9DoF
Szilassy et al. (2019)	2019	-	-	Acceleration	NN	-	Longitudinal	-	-	-
Kebria et al. (2019)	2019	Three cameras	14412 images	Steering angle	CNNs	Tensorflow	Lateral	Nvidia GTX 1080 Ti	Simulation	Udacity
Chen et al. (2019c)	2019	Camera	Comma.ai	Steering angle	CNNs & LSTM	Not Reported	Lateral	NVIDIA	Simulation & Real	Udacity
Sharma et al. (2019)	2019	Camera	TORCS Data	Steering angle & Vehicle speed	CNNs	Not Reported	Lateral & Longitudinal	NVIDIA Geforce GTX	Simulation & Real	TORCS
Xing et al. (2020)	2020	Three cameras & Velocity BOX	Data collected in real-world highway	Lane change	RNNs& LSTM	MATLAB DL Toolbox	Lateral	Intel Core i7 2.5 GHz CPU	Real	-
Al-Sharman et al. (2020)	2020	CAN bus	Vehicle states & powertrain data	Brake pressure	DNN	Keras	Longitudinal	AMD Radeon? HD 6800 Series GPU	Real	-
Lee and Ha (2020)	2020	Camera	600 GB of raw driving image	Steering angle	CNNs & LSTM	Not Reported	Lateral	GPUs with RTX2080ti & AMD Ryzen 2950x CPU	Simulation	Euro truck
Mújica-Vargas et al. (1062)	2020	Camera	Udacity Data	Steering	CNNs RNNs	Tensorflow & Keras	Lateral	Titan X GPU	Simulation	Udacity

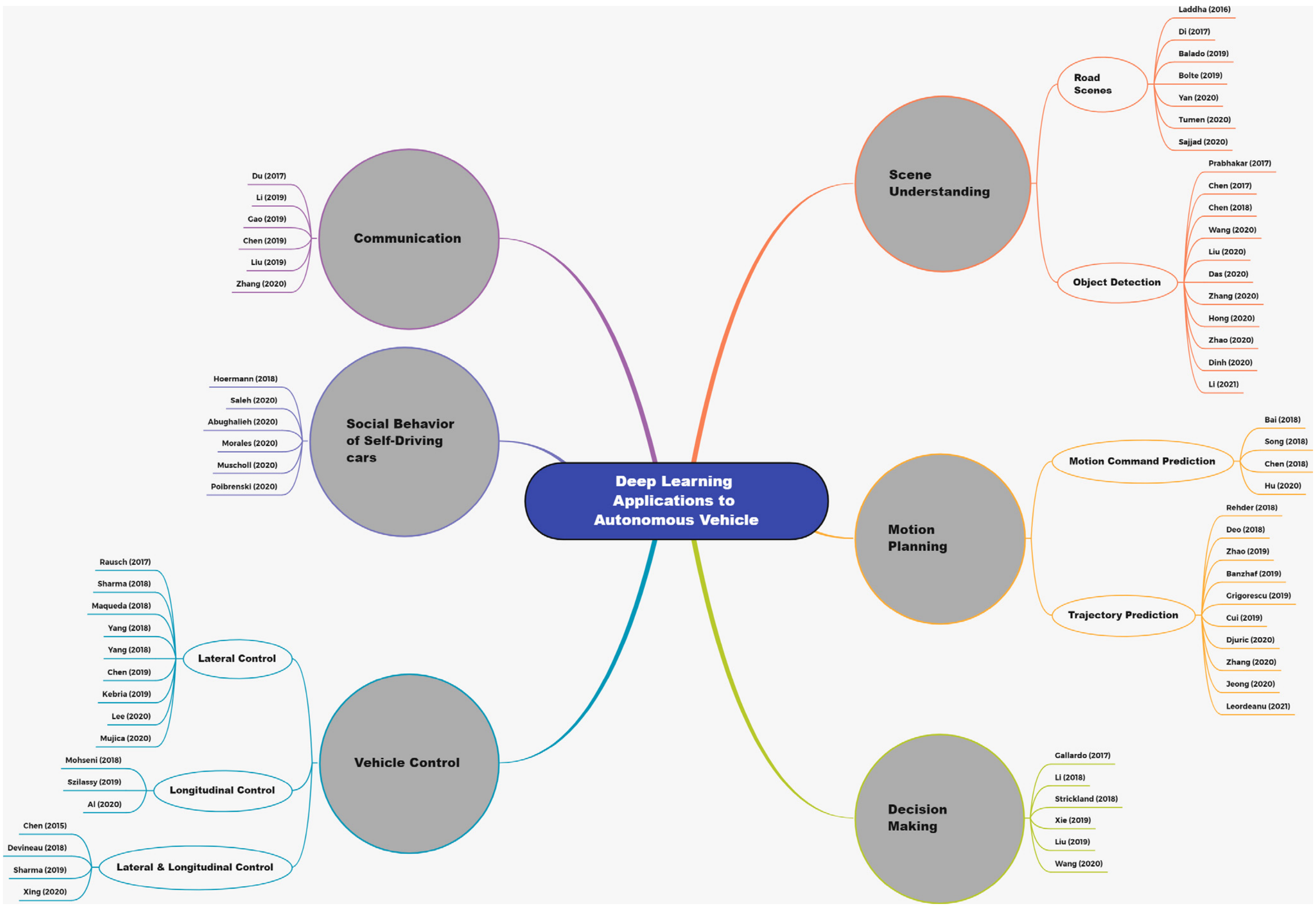

Fig. 7. Applications of Deep Learning techniques in AVs.

Many technologies have been widely used to understand pedestrian behavior on the road, whether by understanding pedestrian movement or analyzing pedestrian behavior and intention. Hoermann et al. (2018) combined a Bayesian filtering technique and CNNs to train data with road users (including pedestrians, bikes, and vehicles). The objective of their proposal is to estimate the intention for each road user.

Saleh et al. (2020) addressed the problem of understanding pedestrian intention in traffic environment. Based only on video from the camera, they detect and track pedestrians in real-time using DenseNets in Huang et al. (2017). The proposed method showed promising results in terms of intention prediction.

Abughalieh and Alawneh (2020) presented an approach to predict pedestrian intention based on CNNs and collected images. Their proposal allows identifying the pedestrian orientation and distance from AVs in crosswalks. However, they do not consider pedestrian poses in real-time.

Morales Alvarez et al. (2020) used the data acquired by sensors, in AVs, to identify pedestrian positions (e.g. poses and location). They used this information to estimate the pedestrian intention to cross based on RNNs. Their results showed that 75% of the test are successful in terms of intention prediction.

Muscholl et al. (2020) used Bayesian networks to understand pedestrian behavior when crossing the street. The results showed that their proposal estimates pedestrian locations better than other existing approaches (Gupta et al., 2018; Huang et al., 2019a; Mohamed et al., 2020).

Poibrenski et al. (2020) used RNNs to estimate all possible locations for each pedestrian on road. The network is trained to predict the pedestrian location based on images collected from the vehicle camera.

Elallid et al. (2022) proposed a model that detects and counts pedestrians in refuge islands using the P-LPN technique. The numbers are updated over time and predict the decisions for AVs using LSTM. The decision depends on the number of pedestrians waiting to cross the road. If their number is large, the AV needs to brake in order to give the chance to pedestrians to cross, otherwise the AV accelerates.

4.6. Communication

Communication technologies have an efficient impact on improving autonomous vehicles' perception and planning capabilities as well as, realizing better vehicle control. In some situations, sensors fail in providing accurate information AVs. In these situations, communication can be used to share information among vehicles.

Channel state information (CSI) is a term used in wireless communications to describe the channel parameters of a communication link. This information represents the cumulative effect of scattering, fading, and power decay with distance and describes how a signal propagates from the transmitter to the receiver.

Du et al. (2017) proposed a LSTM method to solve resource allocation problem in large areas. They collected 24 h of data and they labeled it. Based on historical traffic data their proposal allows to check traffic volume over time.

Li et al. (2019b) propose to improve the reliability of V2I communication by sharing, in real time the data between vehicles and the infrastructure. They used DNN to accelerate the processing of such large amount of data. The test results showed good performances of their method in dense traffic.

Gao et al. (2019) proposed a method to solve the power allocation problem for V2X communication. They used DNN to provide resource allocation solutions in real-time. Chen et al. (2019b) addressed the same problem using CNNs to train data coming from V2I and V2V communication. They concluded that CNNs reduce the network's weights, which accelerates the training process compared to DNN architectures.

Liu et al. (2019a) trained the data (including historical CSI) with LSTM to predict future CSI for managing resources allocation. They normalized the data to accelerate the optimization of the network's weights and find rapidly the optimal solution. The results outperform the method in Xu et al. (2019) in terms of channel prediction.

Zhang et al. (2020d) used DNN to process GPS data, namely timestamp, latitude, and longitude information for each vehicle. This data is fed to DNN to predict CSI.

5. Reinforcement learning based approaches in autonomous vehicles

Despite the promising results of deep learning techniques in AVs, they are still far from being capable of ensuring full autonomy of AVs, especially in decision making, motion planning, and vehicle control. DL based techniques for AVs and DL in general suffer from many drawbacks, chief of which is the need for datasets to learn prediction models and the inability to self-correct in the case of cumulated errors. To overcome these issues, researchers investigated other techniques such as reinforcement learning, which can learn from the environment without the need to collect data. RL enables the model to learn to carry out a task through trial and error.

In this section, we cover existing RL-based methods that aim to solve AVs issues namely (1) decision making, (2) motion planning, (3) vehicle control, and (4) social behavior of self-Driving Cars (See Fig. 9). These are the main fields of RL applications in Autonomous driving.

5.1. Decision making

RL techniques are currently providing better and more precise information to autonomous vehicles by learning from experience and the environment.

You et al. (2018) proposed Markov Decision Process (MDP) to model the interaction between AV and the surrounding vehicles. MDP allows AVs to make suitable decisions when overtaking or tailgating another vehicle, by taking into consideration the road structure. However, more testing in different scenarios is needed to validate their method.

Hoel et al. (2018) presented a method to take decisions (e.g., lane changing, accelerating, and braking) in a highway. They utilized Deep Q Network (DQN) to train their proposal and predict the right decision. However, their approach is not guaranteed to ensure safety in other situations (e.g., roundabouts and intersections).

Unsignaled intersections are considered one of the most challenging scenarios for AVs to make an accurate and timely decision. Isele et al. (2018) proposed a method based on DQN to navigate AVs safely through intersections. The results of their proposal outperform traditional methods (Hafner et al., 2013; Alonso et al., 2011).

Okuyama et al. (2018) combined CNNs and RL to train AVs in a simulated environment with lane markings and static obstacles (e.g human, stopping vehicle). The CNNs take images, captured by the front camera of AVs, to extract the main state features of the road. These features are fed to DQN to predict the action. However, their approach did not take into consideration dynamic obstacles.

Hoel et al. (2019) proposed a tactical decision making approach that combines Monte Carlo Tree Search (MCTS) and RL algorithms to drive AVs in an environment for two highway driving cases (including continuous highway driving and exiting highway). Their proposal is tested in a simulated highway environment, with preliminary results showing the effectiveness of combining RL and MCTS.

Hoel et al. (2020) presented another tactical decision making method for AVs, but in a one-way highway with three lanes. They used RL to estimate actions such as, accelerate, stay in lane, change left, change right, and brake, during driving. The results demonstrated that their approach learns to make effective decisions over the time.

Ye et al. (2019) investigated an RL approach to allow AVs to perform a lane change in a road with a single straight lane (without signal control). The proposed algorithm has been trained using Q-learning in a simulated environment. However, their proposal needs more testing in complex scenarios.

Sun et al. (2020) presented a decision making method for heavy AVs using RL, namely, Deep Deterministic Policy Gradient (DDPG) algorithm. The network receives the information state (including speed and distance from other vehicles) of AVs and then makes a decision. The simulated results showed that their approach learns to take decisions rapidly from an environment.

Duan et al. (2020) proposed a method to train AVs to learn from an environment to take decisions into three maneuvers (including driving lane, right lane change, and left lane change) based on MDP. However, they focused only on highways case without dealing with other situations (e.g. intersection and traffic urban).

Chen et al. (2019a) presented a decision making approach for AVs in a roundabout with dense surrounding vehicles. Their proposal takes information coming from sensors (e.g., velocity and position) for each surrounding object; it predicts the right action using DQN. They simulated their algorithm in the CARLA simulator and showed promising results to solve this roundabout case.

Wolf et al. (2017) used DQN to train AVs in a simulation environment. Using a camera, AVs identify the road and take turn actions (e.g., left, half-Left, straight, half-Right, and right). However, their proposal needs to take into consideration static and dynamic obstacles.

Likmeta et al. (1035) proposed a decision making method in three scenarios (Lane change, crossroads, roundabout). They used RL to train AVs learning to take decisions in these different scenarios. Huang et al. (2019b) trained AVs to take actions (acceleration, deceleration, and steering) using RL by considering state information (e.g., vehicle speed and road distance) to predicts the desired decision.

Hu et al. (2019) presented a decision making approach to navigate AVs in a fusion of two scenarios using RL. Their proposal achieves zero collisions in all tested scenarios. However, this method cannot guarantee safety, especially in real traffic with high mobility.

Wang et al. (2020) presented a method to generate tactical driving in complex highway traffic for AVs. Based on sensors information (e.g., vehicle position and velocity) that feed to DQN to learn to take decisions (accelerate, decelerate, keeping lane, turn right, and turn left) for each vehicle in a highway case. The simulated results demonstrated that their approach improves road safety.

5.2. Motion planning

Nosrati et al. (2018) presented an RL-based hierarchical method to drive AVs in the road with multi-lane using DQN. The objective

Table 5
Comparison of motion planning techniques.

Papers	Publication year	Contribution	Neural Network Architecture	Output	Training algorithm	Evaluated parameters	Planning type	Scenario	Experiments
Paxton et al. (2017)	2017	Linear Temporal Logic	DQN & cDQN	Avoiding collisions Navigate in intersection	Adam optimizer	Constraint Violations & Collisions & Total Failures & Avg Reward & Std Dev Reward	Short term	intersection	Simulation
Zhu et al. (2018)	2018	Human-like autonomous car-following	DQN	Navigating	Minibatch with SGD & Adam & BP	RMSPE	Reactive	urban traffic	Simulation
Nosrati et al. (2018)	2018	Learning for Multi-lane Autonomous Driving using RL	DQN	Avoiding obstacles	Policy optimization method	Average speed & Number of collision per time	Short term	road with multi-lane	Simulation
Fayjie et al. (2018)	2018	Navigation and obstacle avoidance of self-driving	CNNs & DQN	Navigation Obstacle avoidance	Mini-batch	The learning curve	Reactive	urban traffic highways 5 lanes	Simulation
You et al. (2019)	2019	Advanced planning for autonomous vehicles	NN & DQN	lane-shifting speed maintaining accelerating braking	BP with gradient descent	Policy error	Predictive	highway	Simulation
Chen et al. (2020a)	2020	Interpretable End-to-end Urban Autonomous Driving	CNNs & DQN	Avoiding collisions	Mini-Batch	Averages returns	Predictive	intersections roundabouts	Simulation
Cao et al. (2020)	2020	Highway Exiting Planner for Automated Vehicles	DQN	Navigating	MCTS	Highway-exit success rate	Predictive	highway	Simulation
Chen et al. (2020c)	2020	Conditional DQN-Based Motion Planning	CNNs & LSTM & DQN	Steering angle & Accelerator	Adam solver for BP with minibatches	Average deviation & Average time	Long term	intersections	Simulation
Lu et al. (2020)	2020	Hierarchical RL for Autonomous Decision Making and Motion Planning	DQN	Effectuating left-turn	Dual heuristic programming	Average time cost & Completion rate & Avoidance assistance rate & Average time cost	Predictive	intersection without signals	Simulation
Wang et al. (2020a)	2020	Solve hierarchical behavior and motion planning applying RL	CNNs	Avoiding obstacles	Mini-Batch	Success rate & Number of failures	Long term	road multiple lanes	Simulation & Real
Zhang et al. (2020a)	2020	RL-Based Motion Planning for Automatic Parking System	DNN	Steering wheel	BP	Mean sum reward	Short term	parking	Real

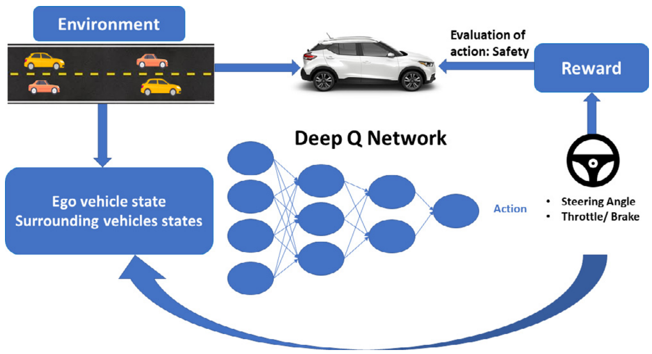

Fig. 8. Vehicle control system using RL.

of their proposal is to avoid obstacles (e.g., other vehicles and or motorbikes) safely. This work still needs to be tested in complex scenarios (e.g., Urban traffic and intersections).

Paxton et al. (2017) investigated Monte Carlo Tree Search (MCTS) approach to generate long-term motion planning tasks using RL. Their approach mainly makes the AVs avoid collisions in intersections. However, their proposal needs more testing in other complex environments.

Zhu et al. (2018) simulated the learning process of AVs in interaction with environment. Based on data from four camera views, results showed that the RL algorithm was able to adapt to different traffic situations.

You et al. (2019) modeled the interaction between AVs and highway traffic, taking into consideration road geometry. Based on Q-learning, AVs learn from their environment to act (e.g., lane-shifting, speed maintaining, accelerating, and braking). The simulated results showed that their method can adapt to other traffic situations with more lanes and vehicles.

Fayjie et al. (2018) proposed a motion planning approach to drive AVs in two scenarios (including urban traffic and highways with 5 lanes). They used CNNs to extract features of data coming from cameras and LIDAR. These features are fed to DQN to estimate the right action (e.g. keep going, left, right, accelerate, and brake). However, their proposal does not take into consideration other road participants.

Chen et al. (2020a) presented an interpretable end-to-end method to generate complex urban scenarios (intersections and roundabouts). RL takes images of both camera and LIDAR as input and avoids collision in dense traffic. The experimental results showed that this approach outperformed other RL approaches (Mnih et al., 2015; Lillicrap et al., 2015; Fujimoto et al., 2018; Haarnoja et al., 2018).

Cao et al. (2020) proposed an RL highway exiting planner approach for AVs. Their proposal allows to estimate the expectation of exiting the highway based on environment observation. The result of their approach showed increases in highway exit success rate by 5% to 50%.

Chen et al. (2020c) used DQN to guide a vehicle throughout the environment. CNNs together with LSTM are used to extract state information from camera images. These features are fed to a DQN to learn motion commands such as, driving straight, turning right, and turning left in intersections. The simulation results showed that the approach learns fast compared to the DDQN method (Wang et al., 2016). However, their proposal does not take into consideration obstacles (e.g., pedestrians, cyclists, and other vehicles).

Even with DL capabilities to learn from the parking data of expert drivers, human knowledge does not guarantee efficient parking. To this end, Zhang et al. (2020a) presented an RL method to train AVs to learn parking strategies using MCTS. Their proposal achieves efficient parking.

Wang et al. (2020a) proposed a motion planning method that detects obstacles in the vehicle's trajectory and avoids them autonomously using RL. They trained their approach in roads with multiple lanes and different traffic densities.

Lu et al. (2020) used MDP to allows AVs to handle complex scenarios (including left turn without traffic signals and multi-lane merging). The objective of their proposal is to train AVs to navigate successfully throughout these two scenarios. Experimental results demonstrated the effectiveness and efficiency of their method.

Table 5 summarizes a comparison of RL-based approaches of motion planning.

5.3. Vehicle control

The objective of RL is to find an optimal control command (e.g., change velocity, brake, or acceleration), by exploring the environment in an iterative manner (Fig. 8). The environment is rewarding the AVs based on their current behavior to correct their errors in the future.

Li et al. (2017) presented a method to control AVs in multi-lane highways. They trained their proposal to take three control commands (decelerate, hard decelerate, and maintain) using RL.

Li et al. (2019a) combined two modules namely perception and control. The perception module takes road images as an input of CNNs to extract state information features. These features are fed to a DQN to learn steering control from the environment. Their proposal is tested in different tracks, with preliminary results showing effective controlling learned by the AVs.

Zhu et al. (2020) presented an RL approach to control the velocity of AVs to rapidly avoid collision using Deep Deterministic Policy Gradient (DDPG) (Lillicrap et al., 2015). The simulated results showed the efficiency of their proposal in terms of safety and comfort.

Amini et al. (2020) used Reinforcement Learning to control AVs when driving in different weather conditions (sun and rain), times of day (day and night), and road types (rural and highway). AVs observe objects (e.g., trees, cars, and pedestrians) and avoid them on the road. The simulation results demonstrated the capability to adapt their approach on real roads.

Guo et al. (2020) presented a lateral control strategy for AVs based on RL in a three-lane highway. The objective of their method is to execute lane change safely. The results showed an improved traffic flow and traffic capacity.

Wu et al. (2020) investigated Differential Variable speed limit (DVSL) method to regulate the velocity of AVs in freeway with five-lanes. DVSL is modeled as an MDP problem and SUMO simulator is used to train AVs to learn through interaction with the environment. The test results demonstrated that their proposal improves safety on the highway.

Chen et al. (2020b) proposed a RL using Monte Carlo Tree Search (MCTS) method for AVs to carry out different maneuvers in order to avoid collisions. They modeled the control process as an MDP problem and used MCTS to generate steering angle. Their proposal showed more stability of control and higher success in avoiding unexpected events.

Zhang et al. (2018) investigated an approach to control the speed of AVs based on DQN and double Q-learning used in Van Hasselt et al., 2016. They trained their proposal with data from a real-world and the results showed an improvement in terms of value accuracy.

Baheri et al. (2020) presented a method to keep lane in urban driving. Their proposal extracts state observation from environment and uses RL to train AVs in CARLA simulator. AVs are simulated in two towns and different weather conditions with successful results for lane-keeping tasks.

Table 6
Comparison of vehicle control techniques.

Papers	Publication year	Contributions	Output	RL Technique	Categories of Control Systems	scenarios	Experiments
Li et al. (2017)	2017	Modeling of driver and vehicle interactions using game theoretic and RL	Decelerate &hard decelerate& maintain	MDP	Longitudinal & Lateral	Multi-lane highways	Simulation
Li et al. (2019a)	2019	Solve the vision-based lateral control employing RL methods	Steering	CNNs & DDPG	Lateral	Different tracks of TORCS	Simulation
Zhu et al. (2020)	2020	Applied RL to real-world driving data for autonomous driving velocity control	velocity control	DDPG	Longitudinal	Six freeway lanes	Simulation
Amini et al. (2020)	2020	Learning end-to-end autonomous vehicle control policies	Steering	CNNs	Lateral	Rural & Highway	Simulation & Real
Guo et al. (2020)	2020	Lane-changing strategy based on RL techniques	Lane change	DQN	Lateral	Three-lane highway	Simulation
Wu et al. (2020)	2020	RL model for differential variable speed limit control	Speed limits	DDPG	Longitudinal & Lateral	Freeway with five-lane	Simulation
Chen et al. (2020b)	2020	Predict driving maneuvers to improve the stability and performance of driving control	Driving maneuvers	CNNs	Lateral	Three tracks of TORCS	Simulation
Zhang et al. (2018)	2018	Control the vehicle speed using RL	Control Speed	DQN	Lateral	Urban traffic	Real
Baheri et al. (2020)	2020	Model-based RL of the complex driving environment methodology	Steering& Acceleration& Brake	RNNs & EN & DN	Longitudinal & Lateral	Urban driving	Simulation
Bouton et al. (2020)	2020	Combination of RL and game theory to learn merging behaviors	Steering & Velocity	DQN	Longitudinal & Lateral	Urban traffic	Simulation
Ye et al. (2020)	2020	Automated lane change strategy using proximal policy optimization-based RL	Lane change & Acceleration	NN	Longitudinal & Lateral	Highways	Real & Simulation
Toromanoff et al. (2020)	2020	Technique coined implicit affordances allowing training of replay memory based RL	Speed & Steering	DQN & Resnet	Lateral	Urban driving	Simulation
Jaritz et al. (2018)	2018	Learning end-to-end driving in rally conditions	Steering & gas & brake & hand brake	CNNs & LSTM	Longitudinal & Lateral	Roads with turns and hills	Simulation
Wang et al. (2018)	2018	Learn an automated lane change behavior	Lane Change	DQN	Lateral	Highway with three lanes in one direction	Simulation
Liang et al. (2018)	2018	Controllable Imitative Reinforcement Learning to achieve higher success	Steering & brake & Acceleration	DDPG	Longitudinal & Lateral	Urban traffic	Simulation

Bouton et al. (2020) addressed maneuvering problem in dense traffic using RL and game theory. Their method is modeled as an MDP problem to allow AVs to keep or change lane in merging scenarios. The results demonstrated that their proposal is able to learn more efficiently compared with existing approaches.

Ye et al. (2020) proposed an automated lane change strategy in highways using Proximal Policy Optimization (PPO) and RL. Using vehicle and surrounding vehicles states, AVs learn to avoid collisions and to effectuate smooth maneuvers. The tests results showed that their proposal learns lane-changing maneuvers effectively and safely.

Toromanoff et al. (2020) presented an RL approach to solve complex situations (including lane-keeping, pedestrians, and vehicles avoidance). They used CARLA simulator to train their model using only a camera to identify urban driving. They used DQN to train AVs to learn from the environment how to handle previous situations. Simulation results showed that their proposal can be generalized for unknown environments.

Similarly, Jaritz et al. (2018) used only a camera to observe the environment to learn estimating the control commands (steering, accelerate, brake) based on RL architecture of (Mnih et al., 2016). They addressed tracks with different roads structure (e.g., turns and hills), graphics (e.g. seasons and location), and physics (e.g., road adherence). However, their proposed approach does not take into consideration collisions.

Wang et al. (2018) investigated lane change control for AVs in highway segment with three lanes in one direction. They used Q-learning to generate lane change taking into consideration the behavior of surrounding vehicles. The experiments showed promising results of their approach in terms of learning the lane change.

Liang et al. (2018) proposed a Controllable Imitative Reinforcement Learning (CIRL) method to steer AVs in mixed scenarios (cars and pedestrians) using DDPG in Lillicrap et al. (2015) and CARLA simulator. Their results outperformed existing RL technique (Dosovitskiy et al., 2017).

A summary of different categories of vehicle control systems is presented in Table 6.

5.4. Social behavior of self-driving cars

Any modeling system must be capable to deal with road user behavior in urban traffic and in real-time. In this regard, RL approaches demonstrated the capability for AVs to understand road user behavior and take the right decisions.

Saleh et al. (2018) presented an intent prediction problem of pedestrians in an urban traffic environment. Based on past trajectories observations of pedestrians, their proposal allows to predict the future pedestrian's behavior using RNNs and RL techniques. The results showed significant improvement in terms of prediction.

Li et al. (2020a) proposed an RL approach to identify pedestrians' behavior and avoid them using MDP. They considered the scenario when the vehicle and the pedestrian are both on a structured two-lane road. The vehicle is driving along the road, while a pedestrian is waiting to cross the road, which may cause an accident. The objective of their approach is to avoid this collision.

Li et al. (2020b) investigated RL method to estimate future pedestrians' positions in complex scenarios. The objective of their

Table 7
Acronyms and their explanation.

Acronyms	Description	Acronyms	Description
AVs	Autonomous Vehicles	**CNNs**	Convolutional Neural Network
RNNs	Recurrent Neural Network	**MSE**	Mean Squared Error
LKN	Learning Kalman Network	**DCTL**	Dense Correspondence-based Transfer Learning
MPC	Model Predictive Control	**LSTM**	Long Short-Term Memory
P-LPN	Pedestrian Location Perception Network	**R-CNNs**	Region Convolution Neural Network
CP-MTL	Cartesian product-based multi-task combination strategy	**AI**	Artificial Intelligence
ML	Machine Learning	**V2X**	Vehicle-to-Everything
V2V	Vehicle-to-Vehicle	**DL**	Deep Learning
RL	Reinforcement Learning	**FCN**	Fully Convolutional Network
WHO	World Health Organization	**SS**	Semantic Segmentation
FG-AI4AD	Focus Group on AI for Autonomous and Assisted Driving	**LIDAR**	Light Detection And Ranging
RADAR	Radio Detection And Ranging	**MFCN**	Motion-aid Feature Calibration Network
DNN	Deep Neural Networks	**NN**	Neural Networks
MV3D	Multi-View 3D networks	**LTL**	Linear Temporal Logic
DDPG	Deep Deterministic Policy Gradient	**MDP**	Markov Decision Process
IRL	Inverse Reinforcement Learning	**NGSIM**	Next Generation Simulation
MCTS	Monte Carlo Tree Search	**RMDN**	Recurrent Mixture Density Network
VANETs	Vehicular Networks	**ACC**	Adaptive Cruise Control
CAVs	Connected and Autonomous Vehicles	**DVSL**	Differential Variable speed limit
3D	Three Dimensional	**deep-MCTS**	deep Monte Carlo Tree Search
ITS	Intelligent Transport Systems	**9DoF**	9 Degrees of Freedom
SAE	Society of Automotive Engineers	**IL**	Imitation Learning
DQN	Deep Q Network	**CIRL**	Controllable Imitative Reinforcement Learning
MLS	Mobile Laser Scanning	**RPN**	Region Proposal Network
InCNet	Inner Cascade Network	**FoFNet**	Fusion of Fusion Network
V2I	Vehicle-to-Infrastructure	**SH-NDS**	Shanghai Naturalistic Driving Study
ATN	Auxiliary Task Network	**GAN**	Generative Adversarial Network
BP	Back Propagation	**RMSPE**	Mean Square Percentage Error
SGD	Stochastic Gradient Descent	**GNSS**	Global Navigation Satellite System
LMRoadNet	LiDAR-based multi-task road perception network	**VRUs**	Vulnerable Road Users
UED	Urban European Dataset	**CSI**	Channel State Information
TORCS	The Open Racing Car Simulator	**CS-LSTM**	Convolutional Social Pooling with Long Short-Term Memory
H-AI	human-artificial intelligence	**PID**	Proportional Integral Derivative

proposal is to train AVs to learn to identify future poses for each pedestrian on the road. Their results outperformed existing works (Van den Berg et al., 2008; Chen et al., 2017b; Everett et al., 2018; Gupta et al., 2018) in terms of prediction accuracy.

Nasernejad et al. (2021) modeled the interaction between pedestrians and AVs in intersections as an MDP problem. Their

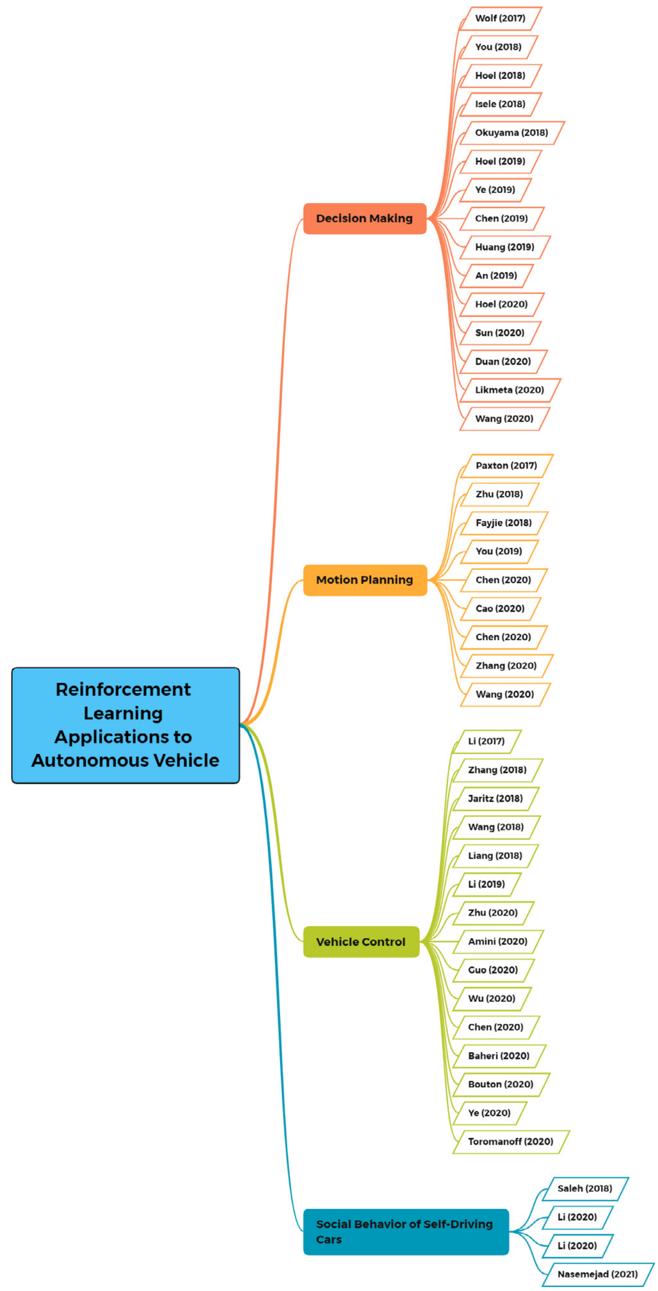

Fig. 9. Application of RL techniques in AVs.

proposal allows AVs to avoid pedestrians based on their behavior in the environment. However, their method is limited only to pedestrian and vehicles interaction while other interactions (e.g., cyclist-vehicle) should be considered.

6. Open research issues and future directions

Despite the significant results of DL and RL-based techniques in autonomous driving solutions, there are many remaining challenges to overcome before full autonomous cars can hit the roads. In this section, we discuss challenges, open research issues, and future directions of DL and RL for AVs.

6.1. Scene understanding

The major challenge for AVs is to have good understanding of the complex real-world. So far, DL methods have shown significant performance to characterize and recognize objects in traffic environments. However our current survey shows that most published papers did not address the problem of AVs in various traffic types, weather conditions, and illumination conditions. Thus, further research should be conducted to evaluate the effects of night-time driving in the snow, and other weather conditions. Also, it is still not guaranteed if training a neural network using known data or other collected datasets would be enough for AVs to understand all possible scenes. That is, are the datasets complete in terms of objects that AVs will encounter?.

The majority of published papers in this field use DL techniques, especially CNNs, to detect and identify objects in the environment. If we want to apply RL techniques to scene understanding and perception, for example, when AVs fail to detect an object, they must correct this error during training. One may argue that how can we find the results?.

Currently, video object detection is a critical challenge for AVs since it is a real-time operation. Further improvement of video object detection is still needed. Das et al., 2020 and Liu et al., 2020 achieve 90 % and 84.6 %, respectively, in terms of accuracy. Then, the accuracy should be improved by using more efficient and effective motion estimation and feature extraction networks.

Real-time perception of the pedestrian location in complex driving scenes is another remaining challenge in AVs related research. Zhao et al. have proposed a solution named P-LPN (Zhao et al., 2020) to categorize pedestrians who are moving in the vehicular lane or standing in the safe sidewalk. However, such approach is still not enough for AVs to understand the motion of pedestrians. Further work on how to integrate pedestrian intention estimation in the model remains of most importance.

One of the drawbacks of DL, for object detection and classification, is the need of huge datasets. Models need to be trained with a large variety of data to eliminate any eventual bias. An AV could react to a situation completely differently, and potentially dangerously, compared to a human reaction. DL methods always use the same optimization algorithms to adjust the weights of neural networks. Thus, they require advanced optimization techniques to obtain acceptable results.

AVs detect pedestrians on the road to identify their intentions. Based on these intentions, AVs take the decision to avoid pedestrians. However, the movements of pedestrians are unpredictable, and sometimes it is difficult to estimate their intentions. How can AVs detect and identify pedestrian behavior in hard situation?

There are many situations that may cause unexpected results. For example, how can AVs deal with snow when it hides traffic lights?

6.2. Motion planning

During driving, how can AVs navigate smoothly and safely in complex urban traffic especially in intersections and during congestion time? Only a few research efforts have been tested in real world. Most of existing works are based on simulations which should be confronted to real-world testing. There is a significant gap between using learning techniques (e.g., DL and RL) in simulation environments and real-world deployments. Also, current works have been evaluated only in specific driving conditions and are yet to be validated in other complex scenarios.

Several proposed methods use SUMO to simulate RL models. However, SUMO is limited to 2D simulations, which makes it not suitable for real world representations. Also, most existing contributions used old versions of simulators such as Udacity and CARLA. Therefore, future approaches should be tested in recent versions that provide new features. For example, the last release of CARLA 0.9.13 allows to include pedestrians (including adults and children) in the simulation with 3D positions. Such new features can help researchers experiment using more complex scenarios.

Most of the proposed approaches evaluate AVs to learn how they navigate safely in scenarios using several simulators (e.g., Udacity, TORCS, and CARLA). However, these approaches need to be tested in real-life scenarios to check whether they maintain their performance in the real world.

6.3. Decision making

In dense traffic it is almost always challenging for AVs to take the right driving decisions because of the high mobility of all road users (other vehicles, bicycles, and pedestrians). DL and RL techniques showed promising results to deal with such situations. However, more complex scenarios (e.g., intersection and crosswalks) are yet to be investigated.

Existing decision making approaches usually use supervised learning techniques to imitate human driving. These methods do not cover all possible driving scenarios. It is extremely difficult to collect all the necessary data for each driving scenario that differs from one country to another.

In addition, researchers have to address two main objectives namely, robustness and flexibility of their proposed approaches, which allow AVs to deal with any situation without prior knowledge.

There are many unexpected events that should be further investigated by researchers. For example, an AV may decide to accelerate because there are no collisions on the road. However, a pedestrian may suddenly cross the road at the same time. This leads us to ask how AVs could avoid this pedestrian. How can DL and RL handle such a situation?.

The studied approaches deploy DL and RL techniques to train AVs to learn from their environment (e.g., highways, traffic, and intersections). However, we note three major unresolved issues, namely:

(i) Most approaches did not take into consideration other road users (e.g., pedestrians and cyclists).
(ii) Almost all used techniques did not deal with different weather and illumination conditions (e.g., snow, and night).
(iii) AVs are trained to learn from simulation environments, but they should be tested in real world to confirm their capabilities.

6.4. Vehicle control

The role of AVs control is to correct any eventual errors generated by the motion planning and decision making tasks. It is still a challenge to build control systems that correct errors in real-time. An open research area is given motion planning of all road users, how Avs should manage speed in order to avoid accidents.

The main challenge for vehicle control systems is to develop methods that deal with different environments. For example, a successful control strategy in urban traffic may not be suitable on a highway with different traffic properties and safety issues.

Several approaches are tested in good weather conditions which are not enough to achieve the safety of AVs. For example, controlling speed or brake on a sunny day is not the same on a snowy day; it is necessary to cover all potential conditions to validate the efficiency of these methods.

The main goal of RL is to maximize the reward. Most proposed methods use large negative rewards to avoid undesired actions. However, arbitrarily choosing these rewards does not deal effectively with an eventual collision on the road. For these reasons, it is necessary to choose rewards using mathematical equations based on the speed and position of surrounding vehicles, ego-vehicle, and other parameters. For example, Knox et al. (2021)

address the problem of rewards design in autonomous driving and present some solutions to help researchers construct rewards.

6.5. Social behavior of self-driving cars

The most difficult task for autonomous driving is to understand other roads users' intentions. For example, pedestrians are the most vulnerable road users, because understanding their behavior is not intuitive and depends on various factors. Therefore, fast prediction of future pedestrians' positions is still a challenge for AVs systems.

DL and RL show their performance to identify objects and avoid them in the environment. But there is still more work to be done to develop efficient methods to estimate pedestrians or other roads participants' intentions in real-time. Especially, in situations that have high mobility (e.g., intersections, roundabouts, and crosswalks).

The majority of researchers limit their studies by protecting only pedestrians and ignore other roads users (e.g., motorcycles, and cyclists), while statistics show that a large number of these road participants die in accidents.

A question that might also be asked is how will/should AVs interact with human-driven? This question should be taken into account because, in the foreseeable future, human-driven cards will continue to be on all roads.

When AVs detect pedestrians, the approaches should not focus only on detecting pedestrians but also understand their motion and intention. If the pedestrian is concentrated when he crosses the road, or not, the proposed methods should identify if the pedestrian is a child, an adult, or an elderly person because each one has their own way of crossing the road.

6.6. Communication

The role of communication is necessary to fill the gap of sensors limitations and more understanding of road participants' movements. However, the main challenge in this field is howto leverage DL and/or RL techniques to process the big data streams coming from V2V and V2I in real-time and then take decisions in a few seconds.

Human-drivers can communicate with pedestrians using signs (e.g., eye contact), which is not possible in the case of AVs. It is important to address this issue in the future to ensure more confidence towards AVs.

Furthermore, V2V communication still does not guarantee reliable AVs will transmission between vehicles. Shared messages may be missed by some AVs. The question therefore is how to build reliable AVs that can drive safely even in the presence of missed shared road information.

AVs can collect road information from other vehicles consequently it increases their training process in the DL process. Then V2V should be fast and robust for sharing these information in order to help other vehicles for sensing the environment.

There still more work to do for developing a collaborative autonomous driving framework based on DL. This can effectively improve learning accuracy and reduce the cost of environment perception and content sharing.

7. Conclusion

Over the past decade, research in autonomous vehicles has gained an increasing attention with the drive for realizing the full autonomy of vehicles. The aim of introducing autonomous vehicles in our roads is to go beyond driver assistance technologies and enable the vehicles to drive themselves without human intervention. Autonomous vehicles can significantly reduce automobility related deaths and injuries and address various long-standing transportation challenges namely, road congestion, travel delay, parking, and safety. Recent advances in Intelligent Transport Systems, computational systems, and Artificial Intelligence have stimulated and paved the way toward the development of autonomous vehicles. This has opened up new opportunities for smart roads, intelligent traffic safety, and travelers comfort.

Few studies have focused on the role of DL and RL techniques to solve the challenges of AVs related to scene understanding, motion planning, decision making, vehicle control, social behavior, and communication.

In this paper, we surveyed the literature on ongoing research works aiming to solve the main AV issues using DL and RL techniques. We presented a taxonomy of the major DL and RL works that have been used so far to bring solutions to the four main issues in autonomous driving.

We shed light on the potential of DL and RL methods in different aspects of autonomous vehicles and highlighted the goals that can be achieved in this field. We also discussed the improvements brought by DL and RL in autonomous driving that allow overcoming the limitations of traditional ML techniques.

Finally, we pointed out major existing research challenges and identified possible future research directions towards developing fully autonomous vehicles. We believe that our survey will serve as a guideline for the future research initiatives in autonomous vehicles.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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