Deep Learning for Autonomous Vehicle Environmental Adaptation and Resilience

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1. Introduction to Autonomous Vehicles and Environmental Adaptation

In real-world scenarios, the AV performance is significantly degraded in harsh weather conditions, e.g., heavy rain, snow, fog, or interference with the sun's rays. Environmental adaptation can address the requirements to facilitate the switching of their focal perceptual tasks, and resilience can support in maintaining an acceptable level of performance under such consideration. These will be very critical for fully autonomous vehicles, where the absence of a human driver requires these systems to manage a much broader range of driving situations, including those in which they face extremely inclement or other unexpected conditions. The resilience capabilities should likely be operating in the background through normal vehicle operations, possibly only with warnings or alerts sent to the system designers for further system evaluation and potentially improved operational results. These are fundamentally deeply affecting perception, mapping, planning, and control. Thus, the primary focus of this survey is to capture all these state-of-the-art techniques applied to sensing and perceiving the surroundings of AVs as well as control technologies used to adapt to and thus overcome adverse environmental conditions.

Recent years have seen a significant evolution in the automotive industry. In particular, the introduction and integration of autonomous vehicles (AVs) is of great interest [1]. AVs present a solution to critical human issues such as traffic congestion, pollution, and road traffic accidents. They can potentially facilitate sustainable trends by reducing energy consumption and improving traffic flow. A significant portion of motor vehicle crashes (around 94%) are due to human errors, the number of which could be decreased by AVs. On the contrary, AV systems can support humans by utilizing accurate sensory data despite unavoidable sensory data transmission delays due to the information processing time. The supplementary sensor fusion technologies further facilitate the detection and the recognition of road users from the sensor inputs, including cameras, LiDARs, and radars. Computer vision-based systems also facilitate traffic flow by analyzing and processing camera-captured images. Therefore, it can be inferred that a considerable amount of human responsibilities can be minimized by delegating the role of system control to AVs via environmental adaptation and resilience.

1.1. Overview of Autonomous Vehicle Technology

[2] The introduction and popularization of deep learning have revolutionized several domains, leading to great success in diverse application areas, including contemporary advances in autonomous vehicle technology, which plays a vital role in people's daily life. The combined interaction of environmental adaptation and resilience is crucial for the safe and reliable operation of fully autonomous vehicles. Adapting to adverse weather conditions not only requires intelligence and perceptive capability but also results in a transformation of the system's nature, configuration, performance, and dynamics. These transformations, in turn, are punctuated by a change in the vehicle's physical interaction with the environment. This review provides a comprehensive coverage of the state-of-the-art technologies recently developed for fully autonomous vehicle technology, in particular emphasizing the latest advances in perception and sensor technologies and the self-driving control mechanism.[3] The uncrewed ground vehicle (UGV) has become increasingly popular in recent years because of the development of the advanced driver assistance-based system and autonomous vehicle technology. Along with safety, route optimization, and efficient delivery, the operation environment for the global positioning system and the performance of on-vehicle systems and components are severely affected by environmental factors such as haze, rain, snow, and fog. With the development of the automatic decision-making algorithm, it is significant to provide the UGVs with the ability to identify the current environment situation. The work proposed in this paper provides a detailed review of deep learning research carried out in the field of autonomous vehicles pending different weather conditions. The recent progress in pseudo-light and depth camouflage attack detection, anti-sea-fog aerial target detection, visual weather adaptation, and fog-to-fog synthesis is supplied in this section.

1.2. Challenges in Environmental Adaptation

One of the biggest environmental factors is the weather, as its variations can alter both the physical dynamics of the vehicle and the environmental perception by sensors. These can further limit vehicle control and introduce uncertainties in the vehicle state estimation. With deep learning, a vehicle's resiliency can be developed by effectively identifying the state of the environment, exploiting the maximum limits of the physical dynamics, and utilizing alternative sensors [4]. In particularly, as a machine-intelligence approach, environmental adaptation has enabled autonomous vehicles to change their configurations and algorithms based on diverse environmental conditions. The aim is to minimize the adverse effects induced by variations in the environment and enable the autonomy systems to maintain best performance. Therefore, the vehicle is being continuously optimized based on its context-awareness, resulting in a higher level of safety and operational efficiency, a reduced energy consumption, productive use of the free empty slots across the modules and an improved user experience. Drawing from the work of Peddisetty and Reddy (2024), which underscores the importance of AI in improving IS project outcomes, this study evaluates the effectiveness of AI-based change management techniques.

[5] Robustness has always been a significant challenge for autonomous vehicles operating in unconstrained environments. Unlike conventional vehicles, autonomous cars rely solely on sensor data to ascertain the current environmental state and make decisions without human intervention. However, different environmental conditions can significantly affect sensors and introduce uncertainties in the measurements. A clear understanding of the current environment is crucial, as it is the foundation for all the built-in controls and algorithms that keep the vehicle within the safety framework [6]. An autonomous vehicle must be adaptable to a wide range of environmental conditions and be able to manage potential challenges that they bring.

2. Deep Learning Fundamentals

In (Schroeper et al., 2018; Chiu et al., 2019) they stressed an incremental learning deep learning approach for self-driving car. To ensure a good road handling performance in this heterogenous road condition, the incrementally trained control network for the lateral vehicle dynamics is implemented in a fast control loop of the self-driving car. The method is demonstrated with a neural network-based lane-keeping system combined with different lane departure prevention and correction strategies. Our method is capable of adapting to and improve on diverse scenarios within a single system. To provide a universal solution despite the multitude of different environmental conditions such as changing road infrastructure and weather conditions, generic lane detection, lane-keeping, lane-change detection, and maneuver planning algorithms are trained on multiple paradigms representing lane scenarios. Thorough experimental validation with a lateral driving automation prototype reveals a strong lane-keeping performance at various road conditions and strong potentials to outperform state- of-the-art lane keepers. [7]Therefore, in order to achieve robustness, increasing system complexity and training on various non-stationary road scenarios is a necessity that was addressed in the article.

Weakly Supervised Reinforcement Learning for Autonomous Highway Driving via Virtual Safety Cages [8]. In (Lange et al., 2020), the authors first discuss various decision planning, vehicle dynamics, and control systems for full autonomy applications. The recent trends for self-driving decision-making are shifting from traditional rule-based, optimization-based techniques to machine learning-based methods for more robust and adaptive behavior. For autonomous control, learning-based approaches offer a more reliable prediction of complex vehicle dynamics under different circumstances. Furthermore, (Challita et al., 2019), the authors targeted developing a robust driving system for lane-keeping in varied weather and illumination conditions. In (Sanberg et al., 2020) in order to address various adversarial attacks and huge safety concerns around current generative, discriminant and hybrid learning methods, deep model sanity-check validation procedures have been proposed. The recent works partially detect and adapt to some unfamiliar situations, but none of them can deal with all these conditions in a reasonable real-time manner. Hence, development of required techniques are crucial and continue to be a topic of interest in autonomous industry.

2.1. Neural Networks and Deep Learning Architectures

The main difference with unsupervised pretraining is that buildings lighter generative models using deep graph-based structures as chosen by unsupervised learning, often indirectly improving subsequent classification performance. A pair of closely aligned papers build up classifiers by directly optimizing the grouping step, viewing this as the core inference problem and ordering the learning process accordingly. Crucially, this release the classifier from clever input pipelining, such as contrast normalization, which still receives hardcore emphasis in much of the neural network literature, causing quite some controversy. Therefore, we will assume a general architecture of feed-forward layered hierarchically generative network, typically denoted under the general terms, "restricted boltzmann machine" or "deep belief network", which incidentally also provides blazing fast inference properties when stabilized into a "fully connected" inference network.

A key strength of deep learning and neural networks in general is their ability to automatically find the "best" features for a given task. This is a property shared by many similar techniques such as kernel methods, and recent work has shown that shallow features computed from pretrained autoencoders can work nearly as well as deep features in vision tasks. Moreover, for this deep learning conference, out of many types of trainable model structures, we focus on models that can learn hierarchical representations. There are various types of possible architectures. Recent results show that supervised pretraining for feature extraction is not always necessary and that good results can be achieved from a random initialized deep architecture combined with a simple fine-tuning scheme using back-propagation. Fully supervised pretraining followed by supervised back-propagation fine-tuning is still popular, with excellent results reported.

[6] [9] Deep learning and neural networks are powerful tools for autonomous vehicle perception, localization and control due to their strong adaptability and feature extraction capabilities. Many researchers focus on how to apply deep learning methods to different autonomous driving systems. There are significant differences in the suitability of various DNN methods for use in the environment adaptation and resilience in autonomous driving, for example, deep reinforcement learning, deep belief networks, and deep Q-learning.

2.2. Training and Optimization Techniques

[10] [11] One of the key techniques for an efficient DRL-based model using large amounts of sensor data is especially the usage of synthetic data to effectively prio-ritize real-world data. Recently, Zeng et al. are able to combine real-world and synthetic data for autonomous driving in simulation only. In other work from Tan et al., a different approach for video-to-control mapping models for autonomous driving, based on real vehicle data together with a smaller am-ount of real-world data is learned. The presented and developed training techniques concerning data processed, sensor fusion, and system design provide insights into several possible avenues for future research. The purpose of an efficient, fast, and resilient training of DRL models can be achieved by the following concepts. For optimal performance, a system should use as much real-world data from as many different driving scenarios as possible. These real-world datasets are then used to pretrain decision control neural networks

that are further improved with real-world data based on perceptual priors. To do that, the decision control model architecture and mentor sampling are used to incorporate perception-based supervised learning knowledge into the training methodology. Results indicate that models that have been pretrained and trained with a perceptually supervised learning channel and real-world data improve driving performance in many different scenarios. [12]

3. Sensors and Data Collection for Environmental Perception

[13] Self-driving dataset annotation techniques need to evolve in order to capture the latest demands and challenges in the automotive deep learning industry. The problem of accurate vehicle detection requires well-labeled datasets, the optimization of precision and recall values, and the use of monocular camera, stereo cameras, and LiDAR sensors to capture the environment in 3D and provide accurate ground truth data. It can be observed that autonomous vehicle manufacturers often use LiDAR and monocular cameras for 3D reconstruction and stereo depth prediction [2]. Vehicle gantry systems and dual GPS systems are used to collect top-view information. Researchers also use the dynamics car-following model of MMOE and the detection and tracking of the latest convolutional neural network (CNN) object to predict the behavior of vehicles. To collect sensors such as 2D information, including RGB-D cameras, thermal cameras, and virtual-reality (VR) devices, and deep learning algorithms, datasets still have to expand. In recent years, sensor placement has developed an increasing prominence as a significant selection for vehicle perception, from conventional onboard sensors to Vehicle-to-Everything (V2X) communication and drones. The placement of sensors in the system of choice assumes a crucial role in making self-driving systems safe and functional [14]. Whether it is placed on the cameras before the windshield, on the roof of the autonomous vehicle, in the smart intersection as roadside units and LiDAR, or on ground vehicles, etc, V2X sensor technology is important in promoting autonomous vehicle environmental perception, V2X communication, and improving the openness of operating space.

3.1. Types of Sensors Used in Autonomous Vehicles

Radar is a widely used sensor in AV systems used to detect an obstacle in the surrounding space of the ego-vehicle. Advantages of radar include low energy consuming and transmission cost. Lidar sensor is another widely-used distance sensor in AVs that can detect obstacles over long-distances in 3-D space. Compared to radar, Lidar can provide higher resolution of the 3-D mapping. One traditional drawback of Lidar is that it is sensitive to weather conditions like raining and snowing. In recent years, camera (RGB camera) has been widely used to detect obstacles and traffic participants in the driving scene and localize the vehicle in the map. Unlike the laser-based systems, the cameras used in AVs have weaknesses in terms of long-distance localization and performance under circumstances with complex light conditions and data complexities. A solution for these weakness of Lidar and camera is their fusion. Ultrasonic sensors are the simplest sensors to understand. They use the power to detect distance by emitting a sound wave and measuring the time it takes for the sound to bounce back. Hydrophones that work underwater are also an example of ultrasonic sensors. Sonar is what we normally use to locate fish in water, which is also a form of ultrasonic sensor.

[6] Autonomous systems, including autonomous vehicles, rely on sensors to perceive the environment. Sensors can be categorized as active or passive sensors. Active sensors work by sensing or emitting pulses or light, a pulse of light is emitted from a sensor to determine the distance to an object. The sensors receive the light returning, and based on the travel time, the distance to the objects is calculated. There are different types of sensors, each of which have their own set of strengths and weaknesses. The four key sensor types used in autonomous vehicles are radar, Lidar, cameras, and Ultrasonic sensors [15].

3.2. Data Fusion and Preprocessing Techniques

Skilled usage of data fusion, and associated data preprocessing, can help make supplied data more robust and have less spurious effects when later stages of training and deployment occur [16]. We believe it can be utilized to harden deep learning models against misclassification errors in real-world environments, such as a burst of failing sensors. In data fusion parlance, many neuro-symbolic questions must be answered about dealing with confidence, uncertainly, and representational fidelity. Since training requirements for the fully end-to-end approach are not present or weakened, we can build a system with a higher resistance to failures [17]. However, data fusion is non-trivial and it behooves us to leverage complementary understandings of both classical signal processing and symbolic AI to guide our deep learning model.

Machine learning paradigms, especially deep learning, are predominantly used in autonomous driving applications for recognizing the driving environment [18]. However, despite their superior efficiency over classical feature-engineering paradigms, deep learning models are known to be vulnerable to noisy or incomplete inputs. These vulnerabilities have an even more pronounced effect when employing data from multiple, complementary sources, as would be the case in any large machine learning task in an autonomous vehicle.

4. Deep Learning Models for Environmental Adaptation

Various sequence-learning-based deep models for driving have been proposed2. In this work, they compute diverse, action-specific, feature expectations of complex sensor inputs and then pull these latent feature–action relations and resultant policies into OoD testing conditioned on novel, unseen context by modulating randomly generated, strongly correlated, and domain-wise temporal dynamics embedding for every action. Data augmentation–style learning (real action sequences) is thus used at model evaluation time. They utilize humans, who are diverse system learners, for data gathering and create (OoD) virtual humans to ubiquitously degrade the abilities of deep driving models in various learning setup scenarios. After presenting the new perception simulator, they investigate the characteristics of the proposed OoD scenarios numerically. They further present many empirical results for the interoperating, standalone visual policy immobilization learning results within human drivers and deep neural networks under degraded testing conditions. Finally, they study the barred road OoD case in a realistic example simulation with further discussion and validation1.

To craft robust driving policies, two challenges are met: data collection from the real world is limited and manually designed objective functions do not necessarily cover all real-world scenarios. The significantly enhanced availability of training data and the ability of deep learning to automatically learn policies has circumvented these limitations1 [19]. However, driving data—the input of autonomously learning policy models—was collected in a cultural and temporal context that might not align with the realization of learned policy models in the real world. Consequently, it is very likely that policies that have been performed very well in the past might not return as good of a performance when experiencing unseen context. This is the famous problem of out-of-distribution (OoD) data and has received much attention in the research community1. For deep networks that power many modern policy models, it is well known that overall task redundancy in the learned features, which the human visual system also uses, generally tends to make those very robust to OoD data2. The last couple of years have gravitated around the general concepts of adversarial (perturbative data augmentation) and style-mixing (learn interdomain style transformation).3 These methods address visual and labeled domain generalization (DG) during training time and also improve the feature robustness to OoD data. Much less attention has been paid to more involved research problems like action long-term dependency (even in the homogeneous distribution case of a single feature-only sequence). From a structural point of view, the hidden feature–action relations are the design blueprint of a driving policy and therefore are much more representative of the overall latent biological driving mechanism than solely visual processing, even though the latter is embedded in action perception. Our motivation is to create diversely behaving OoD testing driving scenarios from a given input such that the visual driving policies learn to be as resilient as possible1 [20].

4.1. Convolutional Neural Networks for Image Processing

A fully connected feedforward neural network which utilizes a pair of stereo panoramic views from a robot to perform multi-goal robot navigation with the Q-learning (a self-supervised learning scenario) solution has been proposed in . The state of the art in obstacle avoidance focusing on propulsion represented by uncertain unsigned scalar speed has been anticipated and solved via exploiting the interior properties of the inherent labyrinth concurrent automatic mapping and localization/displacement (SLAM) unknown environment. Deep learning, particularly CNN, has been successfully used in object detection, object tracking, image sequence segmentation, and scene classification in an adaptive scenario for the urban/suburban and then rural AV surveys. In the context of navigation, neural networks have been used for surrounding scene image classification since the 1990s. Based on a literature review a general forecast on the growing trends in the area of AV controlled environment is visible.

By 2021 fully self-driving AVs are not yet available to public however we can get access to some source codes related to AVs. The open source software Autoware-1.11 has been recently made public, and the second LGSVL Company and University at Buffalo Autonomous Driving Survey is ongoing. However generating high-precision, high-variety perceptual and positioning ground truth in the two platforms is daunting given it is error-prone and time-consuming work, since human-generated annotation can contain errors. A solution is leveraging the existing LGSVL public Toyoto Car Ground Truth Unity environment to change the environment in the Auto-Ware and Lights and Camera Action! (LCAutoWLCA)-

generated domains. The created LCAutoWLCA was used for visual-domain adaptation experiments, manifesting adaptive environment resilience by the self-driving system during training, validation and test of the AlexNet adapted architecture. The created AlexNet gains a gain in accuracy, precision, recall, and specificity.

Deep learning, particularly Convolutional Neural Networks (CNNs), excels in object detection, tracking, image segmentation, and classication stages [21]. CNNs, like AlexNet, have become a standard solution for classication problems, shown in Figure 3. In a set of D. Marfisi CNN for AV Digital Twins launch area exterior camera images has been classied, the same approach has been used in. These days all AV adopter companies use convolutional neural networks (CNNs) to process images coming from their cameral, for instance, Waymo in their AVs use CNNs to detect in urban scenes traffic lights, people, vehicle, cyclists and ledges in roads.

4.2. Recurrent Neural Networks for Time-Series Data

When it comes to the training process in this forecasting framework for operations, recent observations, including the velocity and acceleration as well as environmental inputs in the datasets (because they potentially result in safety incidents), are considered as input features; however, the aim is forecasting passenger number changes, regardless of the two aspects. Besides, the model depends on vectors of historical data concerning passenger numbers as well as environmental inputs. RNN-based models are based on their unique architecture, which is capable of maintaining sequences' distinctive information, and hence, actually scrutinizes historical context and reflects the passenger system's analogous stakes when predicting in the proposed approach. When RNNs are proposed as data-driven models, and the structure links experiences to operators, they are efficient at forecasting the particular future, such is the LSTM. Yet, the simpleRNN tracks the input sequences, while it is hard to address some complex tasks. When it comes to addressing these problems, other time-series data researchers have modified the simpleRNN cell to address the situations predicted in this research. Long Short-Term Memory (LSTM) units, developed by Hochreiter and Schmidhuber, have maintained information over longer time sequences and are deducted from RNNs. In the meantime, the Volunteer Time Scores have been ushered in as cars' real-time delays affecting results. Two distinct groups gather the volunteering statistics of the passenger numbers and time scores every moment on the same line. Manager A in Group A distributes the passenger numbers' voluntary time scores on the considered line. And, manager B in Group B announces solving the voluntary time scores, i.e., car running time and mobility delay from time scores; the recommended actions include reducing the chance of getting engulfed in the accidents by emergency rule.

Recurrent neural networks are significant in processing sequential data like time series, as they can handle variable length sequence. They use memory units such as LSTMs to retain or discard information from previous steps, enabling them to handle longer-term dependencies [22]. RNNs have been widely applied to various domains like language modelling, machine translation, speech recognition, software defect prediction, and network traffic prediction. In machine translation, for example, LSTM RNN has been widely used for its advantages to predict and generate sequences of words. When it comes to time series prediction, especially in electric utilities, RNN becomes more significant as the model can be used to predict future consumption/ generation values based on historical records. You can refer to [23] or [24] for extra details.

5. Simulations and Testing Environments

Both simulation and real-world testing have their own pros and cons, therefore, any successful development of autonomous technology needs an optimum mix of both worlds before the technology before the technology is transferred to the consumer market. Deep neural networks are used in various stages of autonomous vehicle development, most noteworthy for perception systems. Perceptual systems' models are assessed by comparing simulated results with real world ones, so this evaluation technique is limiting, because most of the problematic test scenarios cannot be found in virtual environments. However, small modifications and domain-shifts (in terms of weather, road conditions, sensor performance) can change simulated and real output drastically. Therefore, a robust and reliable autonomous driving model should be the aim of future studies. [11]

Driving simulation studios range from pseudo realistic game style setups intended for entertainment, such as [25] and Test Track at Walt Disney World sponsored by Chevrolet for years (July, 2012) through mid fidelity desktop simulators for driver training in truck, car, and soldier driving (Cooperrider, 2015; Ficklin, 2013) to the high-end building full cabins stitcher together with moving components, visual, audio mock-up, and 3D surround environments, near realistic multiaxis motion, force feedback steering wheels, and programming capability to develop full traffic scenarios, weather conditions, predictive and real time artificial intelligence agents (April, 2020) is required for autonomous vehicle training, verification, validation, and evolution. They can be used widely in different fields of human–women vehicle interaction studies (Yang et al., 2020), vehicle development (Schmuker, 2019), virtual and augmented realities, design and manufacturing processes, medical conditions, reeducation, safety education, and so on.

5.1. Simulators for Autonomous Vehicle Testing

Thanks to the emergence of machine learning and deep learning methods, new algorithms such as graph-based GridNet [26], Gated Fusion Network [11] and RainDenseNets have been proposed and developed to process the sensor data and detect hazards more effectively. Opportunities for creating intelligent automobile systems have also taken off due to the improvement of Semantic Segmentation Neural Network models. Moreover, the expansion of multi-channel LiDAR systems has further reinforced advances in environment perception capabilities, increasing the field of review and extraction for intelligent driver systems models. Furthermore, more complicated and difficult negotiations, including crossing maneuvers and fully integrated car-following maneuvers, can also be performed by DNN -based environmental learning systems accurately.

Driving simulators are a valuable tool to study driver behavior, train new drivers in a total-risk-free environment, and enable unique possibilities for testing elements of Human Machine Interfaces (HMIs). The quality of testing of Advanced Driver Assistance Systems (ADAS) and Autonomous Vehicles (AVs) is heavily dependent on the paraphernalia quality, "testable cases" generated, and the cost-effectiveness of the testing process. Often, real-world vehicle testing is considered as a bottleneck and the most expensive stage in ADAS & AV development [27].

5.2. Real-World Testing Considerations

This paper is organized as follows: Section 2 presents a review of testing of the safety of autonomous vehicles and drivers' expectations. Section 3 discusses autonomous vehicle liability and its determination. Factors affecting the determination of responsibility are also analyzed. We provide conclusive remarks about the research results and prospects in Section 4.

[ref: e2948dd7-79d1-49a5-89e6-c6a6840e7f0c] Understanding whether reinforcement learning models trained in simulation can generalize to real-world data is crucial for training effective control algorithms for autonomous vehicles. To explore this, randomly selected configurations are evaluated and it is observed that the perception modules can generalize relatively well from seeds with high performance. Moreover, it is shown that controllers for a wide range of tasks can be trained solely on synthetic randomized data and still satisfying perform transfer welly in environments drastically different from the ones used for training. Nevertheless, we acknowledge that our findings are contingent upon the choice of simulator and the priors imposed by them. Formalizing the problem of transferring control policies trained in a diverse set of environments from a single simulator requires quantifying the robustness of the policies to numerous sensing imperfections and changes in the dynamics of the vehicle.[28] To reduce the level of disputes and establish the standards, this paper studies the impact of deep learning algorithms on the testing and verification of autonomous vehicle algorithms, accident liability determination, and its influence on public mental health. The level of liability determination influences the psychological expectation of consumers for autonomous. In general, the level of fault determination has nothing to do with the psychological expectations of consumers. Public psychology is more likely to be favorable to autonomous vehicles when they replace drivers. Autonomous vehicles are more vulnerable to accident lawsuits. Even if the current society has changed and accepted autonomous vehicles, there might be also public psychology that shows more favor toward such vehicles. Therefore, it is suggested that it is better to adopt the strategy of positive fault determination in combination with the premium discount and so on in phase.

[29] Real-world tests enable the collection of in-the-wild data and allow to evaluate performance across authorization scenarios, which is indispensable for measuring the true capabilities of algorithms. When considering real-world data setting-beagle evaluations indicate that data plays a crucial role in obtaining credit schemes that generalize well in practice. To investigate the optimal deployment of reinforcement learning agents in the real world, it is crucial to estimate the capability of models to generalize to novel city environments in the real world. Consequently, a metric is introduced which captures the ability of agents trained on synthetic data from a virtual environment to generalize to streets in the real world.

6. Adaptive Control Systems for Resilience

It has now extended to at-environment driving across the year, encompassing driving under severe climate states. The public driving process undertake by today's AVs needs unprecedentedly high definitions of scene interpretation and control of mobility attributes [30]. Consequently, this demands insurmountable computational resources and creates significant challenges in terms of digital files storage and communication requirements for today and the post-2025 periods. DNNs not only have the capabilities to achieve self-optimization with minimal human involvement, but also have high adaptability to novel scenarios. This is immensely advantageous for AVs because it reduces AV's overhead and overcomes their inertia, which is a feature rooted in its hardware, software, and laws that govern AV safety and reliability. Environmental analysis remains an integral AV function. It detects and comprehends infrastructure, pedestrians, vehicles, traffic signs, and regulations that may gloat road and defines IMoDs. It equally offers insight that may be useful in enhancing an AV's flight and managing operations across the surfaces of foreign bodies. For instance, a shared use wireless communication system installed on the Moon and Mars would facilitate the cleaning, ex-checking, packing, sorting, recycling, and digitization to establish a full curb-to-curb road monitoring and operational schema that integrates geo-spatial, communication, infrastructure and digital road factors to inform all AVs in the environment simultaneously.

The main challenges for deploying autonomous vehicles (AVs) reside in the design of systems capable of operating in a safe and stable manner under a wide range of physical and environmental scenarios, as well as under geopolitical and regulatory environments and during any emergent and exceptional situations [1]. The proportion of airborne and terrestrial AVs rose significantly between 2015 and 2019 and will continue to grow during the current decade. AVs provide significant economic benefits by removing labor, enhancing road infrastructure, reducing travel time, reducing accidents, reducing production and service costs, reducing the need for parking facilities, reducing traffic congestion, and exposing users to perils for fewer periods of time. The approval of AVs had primarily raised simple on-road driving with no other road users.

6.1. Model Predictive Control

In the Authors' experimental results, it has been shown an increase of about 8.6% of the number of SΞXs that the user has accepted for DGs with respect to the same system without the self-adaptation and reasoning additional modules. 389, in the comparison with the 78 DGs which could be executed before the personalization strategy proposed in the Especom project. According to the relationship between the social underline present in the users' profile and those trainers done by the app, it is possible to personalise the social composition of the generated DG- X area improving the semantic content of these games and driving the users' interests towards a final desired suggestibility. 6. Conclusions In this paper the approach developed in the Especom project for generating DG systems oriented to the explicit consideration of the peculiarities of the final users has been proposed and a real-world use case has been described in the development of a mobile serious game. A cognitive tailoring approach has been followed and the customization techniques to be added to the generic DG platform have been presented, as well as the DG personalisation process.

[1] [31]In this book chapter we present a Model Predictive Control framework for efficient autonomous vehicle environmental adaptation. The controller uses reinforcement learning and efficient data sharing between different scenarios to improve its driving performance. The learned environment model is used to anticipate future road modality changes, preferred by the host country. This paper has shown that it is possible to design state-of-the-art controller architectures as a pliant referent model and prior belief for the model predictive control loop. The system learns to adapt to their creation spaces, giving them self-diagnosis methods to alert the user when they have been personalized too aggressively.

6.2. Reinforcement Learning for Adaptive Control

The exploitation investigation focused on the determination of the state and action spaces for DDPG, considering the following aspects: the horizontal approach, the random exploration, the vertical approach, and the illustrative study. When it comes to exploitation it is often seen that the design of the reward signal is based mainly in terms of a more comfortable rather than a more energy efficient drone flight. Therefore, the criterion for the selection of the reward signal is that it should be fundamentally different from the ordinary fast drone control. To this aim a comparison of existing reward signal definitions has been drawn and a new definition studied [1]. The new reward function incorporates a parameter, ε, which allows the instructor to control the courage of the generated routes and adjust the ability to abandon a trajectory when exposed to gratified randomness. All the factors that influence the value of the best reward signal in term of traveling effort, flying speed and risk have been incorporated in the experimental comparison to determine the minimized training demands for the visibility, stochasticity and distance exploiting task.

We start by modeling the drone system following a dynamics' formulation. To this design, a non-linear equation was built encompassing the drone dynamics [32]. It is important to highlight that as this problem represents an aerial vehicle control example, and considering the tight constrains imposed by our available space, the full tracking problem formulation is expected to be computationally hard. For this reason a reduced order, aggregated memory state, modeling of the system was chosen for our fundamental analysis in this work. Expansive exploration along the determination of alternative states' parameterisation, alternative models order and types (2D, non-linear models of order 2 including aerodynamic terms, etc) is part of a rich field of follow-up research.

7. Ethical and Safety Considerations in Autonomous Vehicles

Several ethical concerns associated with AVs have been raised, such as the implications on public health (Which Health Care Service Is Needed for Autonomous Vehicles and Intelligent Transport Systems under Artificial Intelligence and Big Data Technologies?), trust and mistrust in automation (Cong et al., 2021), issues of algorithmic opacity and epistemic injustice (Zimmer and Hartzog, 2021) and the potential for maladaptation (El Khamlichi et al., 2021) [33]. Furthermore, there is a growing literature focused on justice and equity (Flakus et al., 2021; Awad et al., 2021). Somewhat recently, an additional concern has been raised regarding the challenging ethical implications of data sharing between AVs (Cong et al., 2021; Cog doing et al, 2020) such as ethical access to sensitive data on patterns of human mobility. In this commentary, we argue that these concerns require immediate research and development attention and ethical reflection. While these concerns are not unique to AVs, the rapidly advancing development of this technology amplifies concerns about relative market disruptions (where incumbents such as taxi drivers, delivery workers, etc., may be displaced by AVs), security (a hostile human could manipulate the sensors of an AV to cause a crash), public safety (encountering a recruel family shooting ebullets into the vehicle), and privacy (a corporation may track the travel patterns of a rival firm) [34] [35].

AV designers (industrial, academic, etc.) have a responsibility to make ethical and human-centered decisions that prioritize human life and welfare above economics and efficiency to the best of their abilities. Commercial and deployed AVs have elicited public and regulatory pushback due to safety fears and hesitation related to the transparency and potential exploitation of collected data. In this paper, we explore these issues while articulating the implications for AV designers.

7.1. Ethical Decision Making in Critical Situations

Any solution will be very complex and a single clear-cut answer perhaps does not exist. In any case, the transport sector has the moral duty to consider and study these situations in order to guide the development of ever-safer and ethically more appropriate systems. In recent years, researchers, philosophers, moralists, programmers, and legislators have been addressing this fundamental problem. Results are to be found in the production of ethical guidelines and in the realization of some proposals that, by taking inspiration from the proposed guidelines, have presented the possibility of addressing the problem of ethical decision making in critical situations, in vehicles that can drive fully autonomously [36].

Artificial intelligence has enabled autonomous vehicles to make decisions in real time. This is both a unique opportunity and a challenge, as such vehicles are required to make ethical decisions in critical situations. This reproduces well-known moral dilemmas, such as the trolley problem, in which decision makers are forced to choose between alternatives with consequences that are ethically ambiguous. Autonomous vehicles, which are increasingly widespread, are likely to face situations of imminent danger in the future, currently known in the literature as ethical decision-making dilemmas. Different types of ethical approaches may be used in order to try to respond to these challenges [37].

7.2. Safety Regulations and Standards

Safety is a multi-faceted and complex concept that is difficult to universally define for autonomous vehicle systems that assess other systems and the operating environment. Moreover, ambiguity and uncertainty in the perception of the environment and in decision making imply that the advent of challenges than in traditional systems and guaranteeing human-like performance may not be a realistic goal for situational assessment or human-level learning modes, both of which are concepts highly relevant to algorithm design [38].

Automated vehicles are generally expected to follow the road regulations and to prioritize safety as the most important requirement. As a result, the decision-making capability of AVs must operate within both legal and ethical boundaries. The excitement and optimism that accompanied the early years of research in this area gradually began to fade as their practical realization approaches. Technical aspects make up the least of the difficulties encountered by the project, the main difficulty is coping with the non-technical aspects of AV deployment, including economic, ethical, and judicial issues. The excitement of spectators can quickly evaporate in the face of vehicle accidents, and issues that were once hailed as scientific discoveries and great improvements in industry technology quickly become weapons of legal accusation, causing excessive anxiety and agitation.

State adapter resilience violates conventional approaches to regulatory compliance, as we seek approval for non-deterministic dosing strategies. Liability in such scenarios is more complex and not necessarily related to traditional driving logic, with experience emerging after prequalification, and in full knowledge of a more complex environment that conventional safety considerations could not entirely address. So, whilst the technology barrier is decidedly less formidable from a safety case perspective, adapting the regulatory landscape to provide a stable dispatch environment for such a system life-cycle presents an unfamiliar challenge [39].

8. Future Trends and Research Directions

Model accuracy and precision in AI learning-based systems have been important criteria to assess their usability and reliability as well as the limits on their safety. Conversely perhaps, the quest to improve learning accuracy and precision has caused the neglect of the performance of AI learning-based systems when affected by large environmental changes [40]. For instance, adverse weather conditions prohibit the use of cameras that are the most accurate perception and obstacle detection sensors for AVs. Vehicle manufacturers provide extensive product specifications in style of radar, camera, and LIDAR radar ranging capabilities in their vehicles and dependability of those perceptual sensors are continually updated to cover challenging AV and ADAS scenarios. However, performance of these systems, that are based on those advanced and sophisticated sensors also decreases when it rains, snows, or generally when the weather is bad. Another system-level property that frequently remains neglected because of the aforementioned classification of the sensor accuracy based metrics, is the combined utility and sensitivity evaluation and balancing. These evaluations account for the contribution level of each sensor towards the cumulative environmental understanding and obstacle detection and evaluating the perceived difficulty of changing the employed sensor values. This is of particular importance in adversarial examples that are caused due to noise or other disturbances in existing sensors which is a growing concern in this area as well.

The widespread use of deep learning techniques for critically important vehicle-controlled and environmental adaptive applications in recent years and their implementation into ADAS, however, opens the door for a new set of challenges related to ensuring the resilience of such systems [1]. Although significant research has been expended on the resilience of ADAS software and controls (including two recent special issues in the IEEE Transactions on Intelligent Transportation Systems), traditional AI approaches, and their weaker learning capabilities, were perhaps less exposed to adversely labeled input material in the form of adversarial examples. Deep learning models are now known to be quite susceptible to statically as well as dynamically constructed adversarial examples caused by malicious disturbances in the system or environmental inputs. Indeed, compared to traditional control- and perception-based AV and ADAS systems, deep learning-based systems suffer from issues related to explaining/interpreting the results obtained as well as a new set of engineering challenges such as tracking performance including non-stationarity, training set matching, robustness against different sensors and sensors degradation, real-time properties including latency, and temporal resolution matching just to name a few. This necessitates new approaches to assess and account for such adversarial examples in deep learning-based AV and ADAS.

8.1. Advancements in Deep Learning for Autonomous Vehicles

Tailoring an RL-based autonomous driving system to a variety of weather conditions and environmental disturbances is a challenging problem. For instance, the dynamics governing a vehicle's motions when it drives on normal dry roads is fundamentally different from when it drives over frosty ice, wet road surfaces, or high wind environments [41]. Conducting a comprehensive evaluation of these weather and environmental conditions is impractical until recently, which might lead to vehicles that can "fail catastrophically in (pace) parts of their trained weather distribution". Adapting highly domain specific simulators, which can accurately capture the detailed necessary dynamics to the full complexity of real-world data, is a tantalizing solution. However, accurately modelling full complex environment dynamics is challenging, leaving this approach with highly domain specific challenges. Virtual-world testing remains as the primary "safety critical" testing environment for current AV development. We conclude this survey by discussing the obstacles and promising future directions for advancing deep learning techniques in the domain of AVs.

Based on the above survey findings, features that can be integrated into emerging autonomous driving systems are discussed. Virtual safety cages are used to convert the imitation learning problem into an easy-to-learn and robust reinforcement learning. They simplify the training process and are interpretable which makes it computationally stable and safe. Each control command predicts a set of possible virtual safety cages which are centered at the front wheel of the vehicle. The agent is then trained to keep the front wheel of the agent vehicle within this safe region [42]. In {PPOtuner}, each imitation model can directly instruct the policy improvement. This makes PPOtuner data efficient to teach the imitation model. Since the PPOtuner directly adjusts the aggregate sum of the feature tensor, so it is model free. It is also less prone to divergence than the PPO-based model. Such advantages make the PPOtuner work well and produce humanlike trajectory as well as a stable policy. The controller control well on the general roads and urban roads. Moreover, the theory of removing the non-optimal region effectively predicted the trajectory of left-turn Yu.

One of the earliest works in neural control for autonomous driving was Pomerleau's ALVINN, which learned to steer a vehicle by observing images from a front-facing camera. NVIDIA's PilotNet adapted techniques like ALVINN to use deep neural networks for lane keeping. Following these innovations, substantial advancements and improvements have been made in deep learning for autonomous vehicles [8]. SPaT Unmasking utilizes sequence to sequence models to predict the phase of the traffic signal from the sequence of unobservable partial sequences of states and phase labels. This not only improves the overall accuracy of the SPaT prediction model, but is also robust to varied states of the surrounding vehicles. The method can be used with two parallel perspective cameras that capture traffic signals beside the stop line, which makes it suitable for infrastructure based signaling systems and as a potential V2I communication channel. This method is especially suitable for edge computing scenarios and the real-time constraints of autonomous driving.

8.2. Integration of AI with V2X Communication Systems

Another important piece of work offers better solutions to the existing transportation infrastructure through a predictive maintenance strategy for vehicles. This is a proactive approach to deal with the malfunctioning of vehicle parts during their designated service intervals. The detection, prevention, and resolution of the vehicle's fault beforehand would show extraordinary improvement in vehicle functionality. An automated vehicle diagnostics platform can efficiently sense the malfunctioning of vehicle components through the captured signals of either driver control (accelerate, brake, steering) or resultants collected through various sensors placed over different vehicle subsystems. Once the malfunction is detected, the vehicle intelligence will generate warning and decision-making scenarios. Decision-making stages involve creating an order of parts, pinpointing the reason behind it, assurance of the part and finally replacing it with a new one. These assignments can be completed in collaboration with a commercial vehicle maintenance and repair workshop made a part of the automated vehicle services platform [6]. With the advancements in electronic power unit engineering inclusive of the embedded software, different research projects in both academia and the industry are focusing on developing new tools, methodologies and strategies to enhance the diagnostic capabilities and prognostic of various electrical components.

Connected and autonomous driving are experiencing major changes and facilitates urban traffic management under connected and automated vehicles' revolution. This survey paper introduces the state-of-the-art of AI research trends in the urban traffic environment including vehicle-to-vehicle and vehicle-to-infrastructure communication. The work elaborates future perspectives and challenges in various interconnected domains like AI, Internet of Vehicles, deep learning, Cloud, Fog, and MEC. Furthermore, the traffic light (TL) phase controller based on the reinforcement learning paradigm is a novel approach when compared with prior art.

Multiple research works are exploring bidirectional communication being employed to extract sensor data to train deep learning networks or collaborate with these artificial intelligence (AI) systems to control the physical environment [43]. For instance, machine learning is leveraged to predict the trajectory of vehicle motion or object detection which is further useful for performing collision risk estimation and navigating traffic [33]. Authors in have proposed reinforcement learning that uses AI for optimizing the parameters of a traffic light controller, maintaining a smooth flow of traffic on a set of connected roads.

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