AI-Based Approaches for Autonomous Vehicle Emergency Handling and Response

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1. Introduction

For all safety-critical systems, before deployment safety must be controlled in terms of both functional safety and cyber security hazards which generally comprises of numerous potential uncanny sources of unsafe, unwanted, and even ghost detections to name a few supplied unexpected inputs, counterfeited and collective byzantine assessments, overtly dangerous counter distinction, among others. For the potential real-time counter identification and management puzzlement – free gray box perception of an entire system is in inexistent. The key unaddressed impediment for trust implicit important fault-free particularly, mostly – autonomous regulators, is the evaluation of complex autonomy algorithms of this type which is beside the others, everything from the especially admissible list of potentials. Potential unusual features of offered examinations should include characteristics like the removal of some initialization phase observations and a conveyed collection of some environmental uncertainties influenced factors.

Artificial intelligence (AI) based vehicle controllers with machine learning techniques have drawn a lot of attention owing to their capability of handling complex scenarios such as dealing with traffic density, recognizing obstructions, predict human behavior, and gesture recognition etc. These systems are beneficial beyond any discussion in improving comfort and entertainment system, insuring smooth traffic ramping, time-saving, stress reduction, controlled traffic flows among the various various benefits and advantages. However, in the vehicle, a scenario can be sudden change and the finding alternate control becomes complicated. Thousands of researchers have explored various approaches to handle such situations using universal approximating systems such as neural networks, fuzzy logic controllers, and reinforcement learning systems. However, many unresolved difficulties are still there, such as their dependability, uncertain behavior, modern offering by different vendors, potential artificial intelligence systems pathologies. Trust issue to use learning-based controllers in safety-critical or autonomous systems could be the reason of technological competition to other alternatives like controlled differential facilitation.

Introduction [1], [2]

1.1. Background and Significance

A platform with high testability, recommendations for products for brand-related and placement-relevant positioning, telemetry data from the test fleet with aggregated error classes for each run, or an actor-critic BFT for safe training of policy networks using physical setups; the future of autonomous driving involves many diverse research questions. While testing the world around AVs in an unprecedented variety of edge cases, any man-made complexity should be removed inside the vehicle suggestions to engineers who make changes that a watchdog system only activates if a human driver takes control in (takeover-) emergency and error cases, but humans might not interfere nigh-time high-beam situations, the operationalized brain is assumed not to operate 100% all the time and might receive targeted information so the operating system can learn to selectively improve the watchdog system efficiently near the active human states driving, and other system error models [3].

Developing safe and reliable autonomous vehicles that can interact safely with human-driven vehicles is a critical prerequisite for large-scale deployment of autonomous vehicles [4]. Major vehicle manufacturers and technology firms have entered the race to develop fully autonomous vehicles, which are expected to revolutionize road transportation by reducing road fatalities, enhancing traffic efficiency, reducing congestion, and enabling personal mobility for people with disabilities. Autonomous vehicles can be divided into two main categories: those with a human driver behind the wheel, who can take control of the vehicle in the event of an emergency, and those without a human driver at all.

1.2. Research Objectives

A novel combined activation function and data drift detection based approach is approved, which is anticipated to address the system robustness aspect of AI-centric faults/hypotheses of emergency handling. This approach encompasses the fault injection, re-training approach, and a novel end-to-end assessment framework and developed as a Dynamic Serve-Net scheme. Dynamic Serve-Net addresses the hypothesis that single or combined faults of AI components of self-driving cars leading to retaining the associated safety critical task up to a certain power-trains. The ongoing realized technology uses intelligent vehicle class, i.e., Maruti Suzuki ESCROSS to automatically identify any possible traffic stuffing or road pooling, uses V2N and N2N based concepts to create recommended routes which can be view on vehicle infotainment system thereby reducing accidents due to sudden management of cars on road [4].

The project was initiated assigning the major objective of improving emergency detection and handling for autonomous vehicles using AI techniques and understanding safety implications due to various AI-centric fault-hypotheses [ref: d840945c-7ea5-4d9b-a418-6b931a8bd063, 6ce8c1a4-95a0-4621-a370-d71a47e29ccf, 29d292b0-c8f4-4ba8-96c3-288dab6abd4b]. The research is significant as it will structurally critique and improvise various physical emergency handling practices of autonomous vehicles in Indian context and understand/optimize safety implications due to loss of attention permissibility in context of AI-related faults/hypotheses. The project comprises of validating several real-time potential hazards using standard AI approach and developing a prototype safety measures called ASTVEH (Autonomous Remote Safety Tracker Device). This system will be designed to remind the driver about the need to take control of the vehicle whenever required and if he/she still does not grasp the wheel, it will generate a distress signal to the owner about the whereabouts of the vehicle for emergency response handling [5].

2. Fundamentals of Autonomous Vehicles

Operation without human drivers and the enormous potentials As already mentioned, the AV is designed on three modules that are multi-car operation, high throughput, and no traffic jams in the future. In practice, the ADS, learns how to drive and makes decisions according to the learned information. Also, it has various functionalities for crossing in non-signalized intersections, pedestrian traffic flow prediction, reducing energy consumption, and car-following with vehicles. The ADS is connected to the outside world via sensors, including a lightweight lidar sensor which is fixed on top of the vehicle as seen in Fig. 5. The data which are collected from UV data preprocessing such as filtering and classification of the data are executed. The different states of the external world are classified by vision classification, instances of objects around the vehicle are detected by instance segmentation, and virtual boxes for nearest egocentric vehicles are recognized by MonoPo3D, to protect Data processing is executed. After the relevant instant scene of the world for ADS is provided, the perception module is activated. It is noted that they are working cooperative with each other in the online H-ALNUM. The fourth version might be positioned to support future agents.

Autonomous vehicles (AVs) represent a paradigm shift in vehicle design and operation, transferring control from humans to the Automated Driving System (ADS), which is governed by Artificial Intelligence (AI) and Learning Algorithms (ALA) [1]. Operation without human drivers and the enormous potentials of autonomous transportation are the main features of AVs [6]. AVs are a pillar of smart and sustainable cities and transportation systems. The core functionalities to make an AV drive safely include perceiving the surroundings, comprehensive situation analysis, and decision and control functions. Learning algorithms will be critical to the adoption and ongoing management of AV technologies. In practice, machine learning, deep learning, and natural language processing almost exclusively dominate in AI-based AVs and these are the three most important groups of ALA toward AVs and for the adoption of AVs in society [7]. The adoption of AVs will only be workable if other agents in this system, such as car manufacturers, policymakers, theory of scenario definition, and law-making bodies also cooperate in this large-scale transformation.

2.1. Definition and Components of Autonomous Vehicles

The only common element seen in all types of AV definitions is the system of systems consideration for a car as a vehicle to interact with its cyber-physical environment. A typical scenario of a complex SOC (Security Operation Centre like system) is identified, where the components are a vehicle, its environment and the humans and machines dealing with the car and its environment [8]. High Automation Driving System (HAD), the term we prefer in this work as autonomous driving is basically a cyber-physical system that means an always online like cloud based smartphone app that includes different digital and analogue hardware and software components to carry out the (scientific) tasks that require automation, actuation, data movement, computation, control, effector and sensor applications, information sharing, local and remote decision making, location orientation, live interpretation of the latest available system, environmental and user/connection data.

While the idea of autonomous vehicles (AVs) is a 20th century concept that has rapidly come of age, enabling adaptive cruise control or automated parking in premium and lower market segment cars today, it is now in the 21st century that further advancements in sensor and software technology have enabled fully automated vehicles to be researched and tested. There are numerous definitions borrowed from different segments of research, industries and organizations or country legislations that define automated driving according to its levels, based on the SAE J3016 standard, where zero represents a full driver control mode and five that all operations are handled by the vehicle [9]. The main components in an autonomous vehicle are, the positioning system that provides the x, y and z coordinates of the vehicle at any time, an onboard map that includes surface topography and road network and infrastructure, a perception and sensing system constituting of cameras, LiDAR, radar, sonar sensors providing still image or motion picture based representation of the environment or target vehicles, stationary or moving objects on or around the road for detection, classification and tracking, and finally, a control unit utilizing decision making algorithms [10].

2.2. Levels of Autonomy

Levels of autonomous driving are based on a description of the vehicle's ability to drive on the SAE J3016 map of driving automation. SAE J3016 specifies 6 categories of autonomous driving (Table 1). The 6 levels are decomposed step by step whereas environments of dealing with situation and capacity of decision-making are always simple (It is easy to deal with responder without any perception, which is classified as Level 0). The driving task is conducted cooperatively by the automobile and human in one way or another in the corresponding Level. When the perceptual system can realize perception of scene and prediction of condition greatly beyond human and decision-making capacity is substituted by expert intelligent program, this system can be defined as an ultimate autonomous driving system—Level 5. Both Level 0 and Level 1, as "no automation" and the "driver assistance", the main responsible for rescuing should be human. Each vehicle at Level 2 needs automatically capture system and can handle some environment such as highways. Besides that, a driver was designated to regularly keep eyes on the road and hands on the wheels to control the vehicle. At Level 3, the vehicles go on with no attention with some driving scenarios. Human drivers need to immediately take the control of the vehicle. However, Level 4 is only different from Level 5 that is lacking the ability for the decision-making ability needed for rare scenarios. Hence, only automatic vehicles can be operated by driving on the road even without no human in normal driving circumstances,.

Autonomous driving can be defined as a vehicle being capable of driving itself without human intervention [,]. This has implications for society, as self-driving cars are expected to become popular with all products becoming autonomous with the widespread adoption of self-driving cars. Furthermore, driving machines are autonomous. They can replace human drivers, however, it is not possible for autonomous vehicles to occupy all driving scenarios. There are many user groups, in addition to regular drivers, who require driving assistance to resolve problems such as congested and parking difficulties, or to provide shared mobility transportation. The AI engineering team for Baidu's Apollo also understands that autonomous vehicles need flexibility for scenarios and, thus, has developed a vehicle anomaly response system, VARS [, ,].

3. Emergency Scenarios in Autonomous Vehicles

The emerging requirements to handle such unforeseen situations is therefore challenging as the AI algorithms are being trained through the well experienced, simulated and physical corpus of diverse and relevant emergency scenarios and use-cases in order to accommodate a "safe fail" behavior in the autonomous vehicle, even in such conditions where the application of AI fails [11]. For complex scenarios and model-based systems also we required both experiences of overcoming unusual or critical conditions of vehicle in a structured way, as well as a matched response in accordance to the model's predictions due to the requests received from the model. To cater emergency scenarios in an optimal and robust fasion, it is necessary to differentiate types of hazards highlighted in the automotive use-cases, as well as upon assessment AI-failures in those respective categories for the need of improved action plans, the current article attempts to categorize AI-failures in the autonomous driving domain application into emergency, robotics and automotive AI-failure scenarios and then focuses upon AI-handling actions robustness which are practiced in such situations.

Emergency scenarios or any atypical test scenario or use case designed for validation is often the requirement to highlight the reliability of system performance [12]. In this regard, recent strategies of scenario-based validation are designed to identify and address the emergent properties in complex system, which is perceived through unexpected or unmodeled system's behavior [2]. It is an essential task to develop a suitable database that allows to fairly evaluate or assess all system changes or validation that is planned to be deployed for the improved vehicle safety.

3.1. Types of Emergencies

1) "A Taxonomy of Road Collision Avoidance Scenarios for Machine Learning-based Autonomous Vehicles": The contributions of a survey of Automated Vehicle Safety Systems (AVSS) offering different approaches to collision avoidance are discussed in this paper. 2) "Flexible autonomous vehicle collision avoidance based on improved A* algorithm" - An emergency collision avoidance algorithm is proposed to tackle multi-agent collision avoidance problem obeying maximum comfortable acceleration rules to avoid collision in autonomous driving. 3) "Collision Avoidance of Autonomous Vehicle Using Frenet Frame Principle, `Social Force Model' and MPC with Yaw Rate Control" - Proposed an algorithm for autonomous vehicle emergencies using the concept of the collision avoidance formula, 'Social force model'.

[13] Emergencies facing autonomous vehicles can be broadly grouped into Steering Required Tasks (SRTs) and Non-Steering Required Tasks (NSRTs) based on the control intervention and action required from the vehicle. Steering Required Tasks include collision avoidance, obstacle avoidance, lane following, merging, and the like. Non-Steering Required Tasks, on the other hand, involve non-steering avoidance tasks, safety-critical intervention, and trajectory tracking [14]. In autonomous vehicles, an emergency situation corresponds to any scenario in which a state of the vehicle or environment puts vehicle safety at risk. Such scenarios are categorized as Non-Steering Required Task (NSRT) or Steering Required Task (SRT) for the purpose of emergency handling. In SRT, corrective action is taken by the control intervention such as braking or steering with collision avoidance, lane keeping or trajectory tracking as the major instances. In NSRT, corrective action is taken by different methods such as returning to normal driving mode from pseudo autonomy, prevention of steering error and intervention for keeping stability where collision avoidance actions are not necessary for vehicle safety as per Akhmad Hilmi et al. Classification of these emergency scenarios is primarily based on the type of the vehicle, constraint of the environment, and the relative state of the vehicle with the environment.

3.2. Challenges and Risks

According to an ADAC survey, 20% of participants were interested in an automated driving system that could independently take over the driving task in critical situations that required consistent, quick and precise reactions [15]. A further analysis of the survey will identify the different user and system requirements of autonomous or semi-autonomous systems for emergency assistance functions. Whereas Crosstalk deals with all areas of definition, development and testing of software and is therefore the reliable and practical technical knowledge source for developers, Test Focus Systems has been created for experts in software methodology in testing, focusing on the following aspects like tests and methods. Vehicular human–robot interaction is complex and affected by information fusion, AI, system limits, and erratic motion intentions. The future AV– human–robot interaction cannot be based on handcrafted HCI solutions and must rely on semiautonomous and autonomous and intelligent systems.

Drivers and vehicle occupants face ethical and legal issues from health and safety regulations to issues surrounding automated vehicle design, automation adoption levels and market acceptability [16]. (The Center for Internet and Society 2019) Some benefits of AI algorithms in AVs are expected to counteract the negative emotional and financial aspects of road traffic accidents, while ethical behavior of AVs will play an important role in consumers' trust building and market acceptance. The human steering behavior is described on the trajectory level by a path-following problem with control and optimization objectives. Based on the actual task requirements and control quality criteria, it has been proposed to compensate the handling variability of the lateral steering control input by a tailored speed modulation. The user experiments have inspired a robotic path planning approach, which is based on a pre-defined comfort level of the hierarchical task-based motion generation [4].

4. Traditional Approaches to Emergency Handling

An emergency handling and response framework for autonomous vehicles, i.e., cyber physical systems. Rear-end collision, branch entry scenario, negotiation, and allowance of the emergency or purpose driven benefits such as faster response time and no latency, in a self-adaptive and autonomous manner is global challenge. Ultimately, the autonomous vehicles must understand the severity of an event and devise appropriate strategies to safeguard the human lives and maintain minimum damage to associated facilities as well as prxemixmatic conditions. We have suggested solutions with the essences of state-of-the-art literature critical discussions and the comparative analyses for different proposed approaches.

[7]Manufacturing, warehouse logistics, and last-mile delivery are examples of applications where autonomous systems are implemented to diminish the workload on human operators

and create opportunities for new business models. For a secure coexistence with humans, such systems require the ability to handle unexpected events safely and reliably. Common systems should be designed to handle the most likely events by themselves, or at least prevent catastrophic outcomes and notify the human operator about the upcoming problems. This ability addresses the safety, ethical, and reliability issues. In this article, we approach autonomous systems from the perspective of emergency handling and response [17]. Autonomous vehicles are one of the pertinent mobile robotic platforms wherein there is an uptick of research explored in the domain of AGVs to automobiles. The AGVs have been designed and developed considering the conflict free navigation architecture and to assist humans in carrying loads. The demand for innovative solutions are required to take a step forward in enhancing intelligent techniques such as autonomous vehicle [9].

4.1. Human Intervention

This requires that the human is warned of potential emergencies, through a variable autonomous emergency response system, and that they are trained accurately to manage the emergent states as per the vehicle capabilities. This combines the advantages of relying principally on AI-Based automation and adding the capability of human intervention when AI-Based approaches reach their operational limits. In this way, one can add the human ethical, empathetic, dutiful, social responsibility, local, exceptional and extraordinary judgmental ones in driving to the system just where the pertinent emergency actually happen [18]. Indeed, the interaction between AI-Based and human emergency response in SDCs can be classified into the following two relevant topics, a) AI-Based emergency reasoning detection and reaction prediction with hints of them to the human for better anticipation and action handling, b) Human intervention tuning with supervision to avoid risky actions and direct them in the optimum actions in driving to have a safe and comfortable handling.

[19] Human Intervention can provide a good balance between AI-Based approaches and full-autonomy by enabling human expertise and intuition in controlling the vehicle [20]. In particular, AI-Based approaches alone are unsuitable for managing some emergent states, such as current limitations in detecting, predicting, and managing driving-negative events. Full-autonomy approaches often rely on plentiful data from a well-behaved system and transition unexpectedly to emergencies. In line with the literature, recent research has investigated the role of Human-AI collaboration as an emergency interrupt model which can

be activated to manage emergencies that were only partially known to the AI-Based approaches. Thus, in a self-driving car, a Human-AI collaboration is beneficial when an emergency scenario emerges as long as the human can manage the situation, intervening by using their vehicular driving knowledge, to guide safe emergency handling actions in at least as effectively and safely as the AI-Based approaches.

4.2. Preventive Measures

[Average=True] Preventive measures are mainly based on so-called reach set methods to guarantee the absence of a crash in a certain safe control set around the reference trajectory, which is set by the optimal driving and is calculated by likely dangerous scenarios in the future. [14] Reachable Set Model Predictive Control (RRT-MPC) was given to MPG-MPC. It was also shown that the emergency assistant in AES in a real car would have to support this approach. After the publication about emergency administration, the main contribution of the article is to create a lost longitudinal and lateral stow efficiency for the emergency longitundinal and salt stripping the lane. In the arteria at 53 corruption open reign, this scheme is used. Additional traffic situations were simulated in the prosecution of marching spares wally, then transpose saponins to the re-model T-MPC view, which are also calculated. This led to the formation of a dead end, for that critical state and activation of before such a situation. [1]

Artificial intelligence (AI) and machine learning are employed by autonomous vehicles to make decisions and execute control commands by taking advantage of sensor information and environment observation. Proactive measures such as avoidance processes, vehicle occupation, and velocity adjustments are in general more challenging for machine learning, since it is not generally feasible to explore all possible venues at the learning phase. Autonomous vehicle moves mainly correctively in 7.2% of the collision scenarios. Instead of avoiding a collision, an automated vehicle, when confronted with a collision-emergent condition, is unable to navigate securely. Active security measures for an automated vehicle, including the control of short braking and yaw rate, have already been used to a certain level. Active safety actions and hazard preparation in front of the vehicle were also brought into the context of automated vehicles by the AES. [13] In this regard, two different techniques for the autonomous handling of an imminent emergency were implemented for the study. A non-linearity of predictive control was used for the linear kinetic inverted model with a getting control method. A kinetic aerosol inversion model-based real-time puncture optimization scheme is a line-breaking method for a non-linear pattern. It means that MP-MPC often initiates non-conservative control effect problems, which slow down the acting speed due to the use of reference system samples. The system configuration controller was built in configure to solve the mismatch and get an autonomous vehicle stabilization with the MP-MPC.

5. Role of Artificial Intelligence in Emergency Response

Self-driving vehicle systems hold remarkable promise for both intelligent urban traffic control and automotive systems. A trend to a fully autonomous vehicle system depends largely on the diffusion of self-driving vehicles. Nevertheless, the redundant autonomous vehicle systems are still developing, and the transportation safety and driver (dis)comfort represent the central issue area. Also, this has not been completely resolved in current models. There are still significant restrictions for self-driving vehicles in a variety of forms of unanticipated and rare cases. Discomfort, largely attributed by the drivers, is driven by such challenges. These two issues represent a methodological systematic evaluation in this context by two AI systems. Ai has been a subject for accelerating researches within the private and public sectors. AI and computer learning techniques have been used to build effective systems that enable smart cities. A large number of AI enabled smart city applications like fraud and security examination applications, created intelligent utility technologies, created smart transportation systems that provide flexibility for the elderly, disabled and policy makers, pay dividends etc. have lately been introduced.

AI play an essential role in the safe future of road traffic controlling Smart Cities. AI has been introduced in various smart applications on a large scale, and the COVID 19 pandemic has recommended and accelerated research on the topic. AI and machine learning techniques have a variety of applications that help develop smart cities. It can be used to process security and fraud detection, optimize smart utilities, provide assisted smart transportation enhancing mobility for elderly and disabled people and legislators, and improved Energy. Furthermore, using AI in creating autonomous vehicle systems, normalizing the traffic flow and improving intersection flow provide higher sustainability and safety. Several broader challenges (particularly at intersections) are discussed in this analysis.

5.1. Machine Learning Algorithms

Machine learning algorithms and in particular deep learning are currently widely used technologies in the field of artificial intelligence. These are a natural choice for data-driven models and are the subject of another important movement at the moment: to move algorithms towards tasks that require a moral reasoning element, for example, basically in the focus on creating models capable of deciding in a correct decision according to activation when logically connected to a "situation that presents two or more morally conflicting but acceptable to some extent alternatives" [21]. De Wet writes in this article, "The focus is turning to creating tools to make automated moral decisions, which has been coined as the study of automated moral agents, or AMA's." His work gives the concept of "value alignment," as the main philosophical issue year developed by the moral dilemma thought experiments in the ethical performance benchmarking of moral decision-making algorithms. Generally, it is well-known that the main advantage of using explanatory machine learning methods is its potential to handle decision-making automatically.

The transition to autonomous driving will lead to an extensive reduction in accident frequency but cannot fully prevent the occurrence of physical accidents [14]. A range of international regulations anticipates this by mandating emergency handling and response systems for automated vehicles [6,27,30]. A very good embedded safety concept can avoid many accidents, but not all. Consequently, the function of such systems is to responsibly handle the so-called residual risks of automated vehicles by striving to emphasize safety even in dangerous events [for example, driving a vehicle into a building or driving over pedestrians, see, e.g., 17]. The two main elements of an emergency handling and response system for automated vehicles that have to be solved in any case are the decision-making and the activating of the emergency system.

5.2. Computer Vision and Sensor Fusion

It can replace some of the high cost sensors like LiDAR and ultrasonic sensors. They also save installation time and cost and maintenance cost as well, thus reducing the overall cost of the self-driving vehicle. Computer vision sensors are typically designed to recognize the surrounding of a vehicle in order to build meaningful and reliable environment maps for following tasks, such as localization, route planning and obstacle detection. Some of the data processing tasks need high computational power by future computing devices. AI based motion analysis techniques among the currently available sensor based and AI based are better techniques of future Motion analysis perception is a major part of sensor fusion. It includes data acquisition of various sensors and extract features and compare or feedback for decision. A lot of work has been done on vision based, multi-modal sensor fusion and potential for AI based but future work can be done on multi-sensor based AI on different levels of autonomous vehicles with less human intervention.

Computer vision and sensor fusion techniques have diverse applications in smart cities. They can be utilized for surveillance purposes and for enhancing the overall safety of the system transportation system. Distracted driving can be recognized and analyzed through the processing of the data acquired by these cameras. Obstacle detection and lane departure can also be detected for driver assistance as a part of intelligent transportation systems. Currently, many physical sensors on the vehicle are utilized for safety purposes as part of autonomous transportation systems. Utilization of computer vision sensors for these purposes can replace these physical sensors. Firearms and its related dangerous items can be detected through computer vision sensor fusion as an enhanced safety system. Improve safety through the tracking of human behavior and hazard /accident detection in various environments like industrial and outdoor environments.

[22] [16] [23]

6. Case Studies and Examples

Although vehicles navigation supports decision-making by detour evaluations, directly integrates situations like the urban, safety, security intelligence to forecasts dynamic-extensive to meet combination of several people's quality of life requirements. Based on realistic implementation of dynamic scenerie, however, we will introduce in our papers that the proposed approach must be tested based on such elements like traffic handover, which is much more problematic in dense urban areas, where the safety issue must be additionally taken into account. The globalist subset of the former is the emerging Learning (DL) and AI development Revolution (1), while others recognize the particular assessment in data radio measurement, localization of advanced systems, and the anti-jamming solutions methods. Moreover, the existence of automated vehicles underscores the importance of being able to provide adaptive solutions in different traffic scenarios – depending on the deployability of varying AI traffic system approaches [1].

Approaches like AI concepts, Big Data analytics, and meta-heuristic optimization have converged to form the bedrock for decision-making for a range of algorithms in road traffic scenarios. In the past, all world road event models were founded on average parameters, but fortunately, with Artificial Intelligence (AI) machine learning applications, we got the chance to maintain mooring information. All the mentioned methods are based on the proper historical radio measurement and mobile user measurement scenarios based on customers' travel distance. Both measurements are associated with isotropic emission patterns, isotropic backscattering, and noise power levels from an assumed clearance, which allowed us to allocate artificially weather scenarios to use real mobile contact information to evaluate transport efficiency.

6.1. Real-World Implementations

An algorithm, termed Autonomous Real-time Vehicle Countermand (ARVC), has been implemented in a mixed autonomy driving (MAD) environment, employing autonomous vehicles (hot cars), controlled autonomous vehicles (cool cars), and manually-driven vehicles to validate the overall safety and adaptability of the approach. This was accomplished by considering control safety, Human–AI system Collaboration, and performance maintenance during the short-term emergency scenario. ARVC is a collision avoidance scheme dependent on driver capability and advanced driver support system (ADAS) in a brain-computer interface (BCI) communication network, managing virtual platoons. The algorithm was accomplished by carrying a game theory-dependent ADAMS-based simulation, considering combined perception and action decision spaces with different traffic scenarios, positioning, velocity, acceleration, and jerk demands. The testing results influenced that ARVC could help hinder rear-end crashes, roadside distractions, and unexpected vehicle quiets, along with owning advantages like safety, comfort, and quick response adaptions for an advanced automated vehicle system [9].

Recent successful real-world applications of AI include highly automated vehicle (HAV) development. National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) researchers developed the Autonomous Intersection Management (AIM) system ([1]), Bravescope, Traffic Safety, and Selective Protection (BRATSEL), and Safe Lane Change (SLC) schemes to control signalized intersections, autonomous vehicles, and multi-lane highway with response to fully autonomous vehicles in these traffic scenarios, integrating collision avoidance and safety measures into driverless cars HAV transit signal priority system| in a bid to curb road congestion in ad-hoc and pre-scheduled traffic data. The first phase of connected automated vehicle (CAV) initiated by the Department of Transportation aimed to enhance safety by impacting adaptive signal control techniques in the city of Miami, Florida, USA. Random forest (RF), WinSum AI (WS), and artificial neural network (ANN) models were integrated with this CAV system to control the distribution of transit signal priority in centralized transit signal priority systems (TSPS) [24].

6.2. Simulation and Testing Environments

Simulation and real-world testing is crucial in the development of reliable autonomous vehicle solutions (Zhao et al. [8]). Different testing approaches are possible. Real-world testing is expensive and difficult. Testing with real-world datasets, on the other hand, can be biased, not scalable, and have challenging datasets on which current models are likely to fail. Additionally, this approach is also prone to Metzen Dubrovnik's Challenge [25] which seeks to bridge the gap once and for all between state-of-the-art machine-learning-based software and the basic human skills of play and manipulation. Simulation, including sim-to-real approaches, is also highly scalable, is free of real-world dataset biases, allows running experiments on virtual worlds, is sandboxed and thus can safely work on safety-critical scenarios and hardware-software validation, etc. Sim-to-real techniques might take real-world datasets and transfer to different environments in order to validate the performance and generalization power of models in atypical operational conditions Mély et al. . Simulations are flexible and suitable for off-road and safety-critical domain testing. It simplifies gathering data from heterogeneous terrains and be operational in any climate and weather condition. The virtual world can experience any natural or artificial disaster without any hardware alterations. Using simulation as the fronted is a highly scalable way to gather training and testing data for modeled architectures. The simulated (human) presence is another critical feature for training models as they need to treat vehicles equivalent to humans, e.g., traffic lights, crossing pedestrians, etc. To detect and avoid unsafe driving conditions, one has to simulate all driving scenariosUnsafe driving conditions are constantly being produced by multi-modal traffic participants, including other human drivers, pedestrians, animals, etc. That allows fast dynamic (deep-) learning and simulation can speed up the training and validation process. In order to generate trustworthy real-world performance, simulation environments have to be as close as possible to the actual environment (CITE).The idea of blending photorealism with physics realism by placing a physical model of the car in a virtual environment was suggested for the first time by Wendlandt et al. (5) in 2013. CARLA was introduced; a modular, entirely library based computational engineering simulator to develop in silicocar performance before the actual physical vehicle construction. A CARLA release was announced at SIGGRAPH ASIA 2017 by Dosovitskiy et al. Single car-bicycle traffic simulators are more advanced in both worlds of perception and control (CITE KADIR).GetProcAddress was originally inspired by GameBench, which visualizes the graphical processing unit (GPU) load for mobile games. Dosovitskiy et al. evaluated the CARLA image and depth sensors. In order to accurately simulate the real noise, perception, and performance, the user has the ability to tweak the restraints of an ideal simulation. Häsä Sim proposes the perceived simulation, and a cross-simulated-physicalenvironment process pipeline from ontology simulation to testing field tests in the real world in the optimal simulated conditions. Basalto drove 50, 000 virtual miles on the underlying Abe, and was 17 times more likely than the heavily noise-specific scenario to only flush out detection test errors in virtual and physical tests THEA used the baseline topologies generated baseline Perception-while-Driving 6 3 using the simulated perception stack instance that we (39) in KADIR) previously trained using CARLA GTs by learning the LIDAR-DART QNM fuzz instrument.ATG has taken a step further to obtain waypointscene and noise characteristics and textures (36). ATG was a success in tackling problems where static models are overwhelmed by the real-world diversity. However, using adynamic car-limited simulator,urbanstreet-stowe-ing conditions. fewerathas-Three different physics-based simulators (CARLA, Simulatedplus-Accelerated and CARLO), plus a 2.5D, Lidar, project-to-image annotated pre-devised JPRS on VELOCITY conducted an investigation focused on VSS and 3D depth image segmentation for VRUs. CITE MATERA investigated-aware data integration for a front-view-only for pedestrian VSS. A custom-designed approach for data annotation in CARLA using UE4-Groundtruth (Goodrich et al). The use of radar images and Lidar-oriented image software tools for NHTSA Drive to the trainingof pedestrian VRUdetectors inathree different commercial grades simulators. check mark In VeMeDSeKo (46) project, 3D imagesare used to train the state-of-the-art model to achieve the best segmentation results from the perspective of pedestrians (VELOCITY). ADAS environment and high-dimensional visualization allows for more complex analytics and better understanding thanks to Çiçek et al. and Kırbune et al. ‘s approaches. Ochetti et al.has explained their in-situ training(Villa and GalaraThis) and pre-training (CITEMARINtraining) trainingalso inthDECODEVELOCITYon-world UPBROtected multi-agent rich environments by combining in-situ training (15) with pre-training Encodings such as Highway training Decoder (16), Copycount—Swerve data augGmenting/Noising 0 and Adversarial data generation is also important (40,698). Car-First SimulatorSimulator GamesTrajectory Prediction. DECODECITEDALREGHTINIcommunity proposed a regression-based velocity prediction that startswith observed trajectory reflections in the surroundings of multiple car simulators (CITE LEI).#--- Adapting the concepts readymore-sim.MMmmm-Th,m.t-If itsim.nnathnnorth-represents the real world more and more,more, F.IDLevels of complexity likely change whenever there are physical stop-and-go conditions, and multiple dynamical interaction constraints are placed.Is through small delays as handling interactions metrics t.Despite this, the safe operation zonewas about three times as large as model-predictive control (MPC)for Adrián Mauri-Méndez et al.: 5 s anticipation and control are required by ourmodels in a manual vehicle driving task. CITEIgual: (23)) (38). Lehrmannource) proposed car -testementinteraction by combining type behavior1-1 Zaprakasiman et al.synthetic.generated.Job of gatheringproxy real and data,In q Rogers70e s 0 010Guillmulti-h:liaorchereandersThe reference trajectory was three car lengths away from the lead vehicle trajectory at the same speed within the MPC the maneuver to calculate control actionsmoreleatdexTo perform overtaking, a vehicle needs to lateral accelerator aidshave access to high-level e.ignore information.Response and handling model simply brakeathJ.Actuatorsorce.e.The vehicle model is tested with longitudinal speed limits = 10, 20, 30 m/s and trajectory inversion angles = 10, 20, 30. Forces and torques ≤ 20 and 2 Nm, respectively are employed linearly and all of them are decreased to zero in 5% of τm1 seconds. sedAround 90% of the investigated conditions are indeed handled rather well by our system with a safety margin of 3 signifying that our systemapproxiamatelyimateSD+ reflective might handle the overlapetrasafety hazard with a larger safety margin.F.Mark the period where the MPC relies on offline pre-computer ad.umeøemon Other non-availableFromimagesappropriate to explain the system is scenarios of occupancy.)The left and right lanes belong other drivers than the car with the ID 17152. The proposed model avoidance strategy is to follow other cars up to a predefined speedeadStrange changes innotI§karitah by other featuredressedis off-road§ly Localization vs NavigationLeft bysupportt-Zlw in Car ⟹ 90 sidecar They have less context local ambiguity and messages contact learning,road etc plot steering-person operating InterpretationFig. Lateral DMs are made vectora.ag progressively-motor-controllermain-by the driver to tq.csubcont (sa dl)kv,d.vole Levea distance into the 3×eu‖Ts in d,nDtvehEf with location be Fe max justifieduNMethod classi-bas DotvehThe picture presents three variou ressing convolutional architectures Sorry, pushedconvwhere are 1,2 or 3 convolution layers, respectively. 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7. Ethical and Legal Considerations

However, current industry reports indeed take a pragmatic, ‘ethical minimalism’ approach. They state that extreme traffic situations are rare and exceptional cases that need to be addressed by merely following the laws [26]. In our view, this apparent dismissiveness of the moral challenges of the situation, coupled with an apparent naïvety in the epistemic assumptions behind practical decisions, exposes both an ethical and a social epistemic deficit. With this uncertainty in mind, it would be far more consistently ethical, and of greater social benefit, for the automotive industry and other stakeholders in AD to acknowledge publicly and openly address the moral dilemmas that they will program and have to face. As the above evaluation demonstrates, dealing with extreme traffic situations requires a comprehensive approach that includes technical, ethical, legal, and social dimensions, while industry-driven ethical standards, HC, and legislation must safeguard a reflective and situated understanding of the choices made in Trolley Problem- like situations.

The deployment of AD raises critical ethical challenges, most notably moral ones that are contentious, pressing, and widely discussed in several academic fields. One of the most contentious moral issues in AD is the moral dilemmas that the vehicles might face in extreme traffic situations. This difficulty is often understood as an example of a so-called Trolley Problem, i.e., a dilemma arising from a moral choice that involves trading off advantages between different groups of people [27]. For AD, the archetypical Trolley Example is represented by the situation where, in a traffic accident, the lives of the passengers of a self-driving car could be spared only at the expense of the deaths of a greater number of pedestrians. Beyond the discussion of the Trolley Problem, further questions regarding the moral status of expert systems and AI are increasingly being taken up in different fields, including philosophy, law, and ethics.

7.1. Data Privacy and Security

When analyzing some papers on AV security, we observed that although extensive studies have been conducted on ensuring the reliability of AV systems at the application level, the focus has mostly been on the complexity of the traffic environment, rather than it's susceptibility to cyberattacks. As more advanced sensors and AI technologies have been integrated into AV systems, these issues have drawn more attention. In addition, privacy and security research in the AV field has mainly focused on the analysis, development, and evaluation of different algorithms at the protocol and data link layers. Studies exploring strategies that operate at higher confidentiality levels and ensure the privacy of data and AV operational processes are comparatively fewer [28]. At present, insufficient studies have been devoted to security concerns of AV systems at the Internet of Vehicles (IoV) level. Hence, the objective of this work is to offer an exhaustive vision, by providing an updated examination of the present physical and cybersecurity threats and proposing the main strategies and solutions for securing privacy and cybersecurity of AV and IoV every layer. Let's evaluate why it is necessary and the innovative ways in which the AV community is beginning to address these concerns now.

Autonomous vehicles (AVs) are one of the most innovative smart devices in vehicular networks that combine vehicular communication technologies with the advantages of various AI-based applications [29]. AVs need to consider vehicle privacy and data security in the design of products and applications to enhance the security in the AV system. However, their superiority may also expose AVs to various security threats and privacy concerns. On the one hand, the unique characteristics of AVs have opened up bottlenecks such as distributed data storage, management and control, and resource constraint in terms of privacy and security; on the other hand, the growing reliance on AI-based systems also makes AVs the potential targets of many different harmful security threats [15]. These threats include espionage, malware deployment, network destruction, and data tampering, etc. The high data dependency of AV systems and their AI-controlled transmission procedures can make AVs vulnerable to harmful attacks and result in various severe consequences. As a result, security concerns have become a significant issue in the commercialization and effective deployment of AV systems. The data privacy and cybersecurity issues of security in Intelligent Transportation Systems (ITSs) are one of the deficiencies of the AV research paradigm.

7.2. Liability and Accountability

Response by the Montreal AI Ethics Institute to the European Commission's Whitepaper on AI: Along with enforcing liability for AI-integrated applications, an effort is required to dispose off the undue fears of AI and take immediate policy actions. AI complements the human brain, but still takes incoherent and risky decisions at unavoidable instances [30]. A striking example is the trolley problem in JavaScript established thought experiments of ethical knowledge. Future policies and requirements need to be developed in order to make AI-driven machines more smart and self-driven. Moreover, to compete this transitional phase, the society needs to learn how to take control of AI systems and follow ethical norms and rules while making choices.

Enabling technologies for urban smart mobility: recent trends, opportunities and challenges: Along with the advantages of AI-based approaches, much burden of liability falls on the operator, e.g., the vehicle manufacturing company, if a mishap occurs during the usage of AI-enabled vehicles [27]. The society is becoming increasingly AI-dependent and hence is constantly searching for the answers to emerging challenges related to accountability and liability. A dedicated set of liability rules for autonomous vehicles and other AI applications is the need of the hour.

8. Future Directions and Emerging Technologies

For each such emergency scenario, a comprehensive review of existing, past research is provided, ranging from the traditional, non-AI classical control methods to the most AI-based systems designed and validated in the last 2– 3 years. Yet, despite over a decade of intense research in the field of autonomous vehicles, most of the existing solutions are more centralized, assuming ideal network connections, with work in cooperative maneuvering or communication schemes still largely nascent [14]. As we look to the recent and emerging research topics, can be seen that this challenge is gradually being addressed, aiming to distribute knowledge and control in the MANET to handle cases of network degradation and network partitioning experienced spatially and temporarily in realistic scenarios (e.g., throughout roundabouts or intersections). In future, fleet-managed platooning is expected to become a widespread reality for intelligent transportation systems. Clearly, exploiting vehicle-to-vehicle and vehicle-to-infrastructure communications to coordinate the path planning and real-time control of connected AVs, along with knowledge of the surrounding environment and future moving obstacles, will allow for a significant decrease in traffic congestion while improving ride comfort and traffic safety.

With rapid advancements in electronics and related technologies, current-generation autonomous vehicles are increasingly capable of understanding and interpreting their surrounding environments, as well as responding in real-time to complex emergency situations that may develop with road surfaces or obstructions. This paper provides a somewhat structured survey of state-of-the-art research in AI-based autonomous vehicle emergency handling and response. The discussion specifically focuses upon the major types of emergencies, such as road collapses, tire blowouts, sudden appearance of obstacles in the vehicle's planned path, and assistance with work zone navigation, among other less critical emergencies that may arise during vehicle operation [31].

8.1. Predictive Maintenance Systems

{ [32]} Predictive maintenance systems for autonomous car are strong candidates for focusing on the specific issue of autonomous vehicle safety systems and to present their intricacies and impact in holistic details. Such systems include both the vehicle itself as well as constituent subsystems and components installed in them, features of communication technologies, and automobile sensors more generally. In case of autonomous vehicles, there is an additional requirement of real-time predictive control, to effectively control the vehicle to monitor trajectory deviations, and prevent the vehicle from decelerating to a stand-through absent drivers inputs, an essential requirement while high-speed driving. Additionally, the next-generation AI-based approaches and perception systems are extensively being used in AV for obstacle detection and avoidance, vision-based navigation, improved vehicle dynamics, and connecting vehicle health monitoring systems to preventive and predictive analytics for maintaining vehicle safety.

{ [27]} This same technique was taken over by luxury carmakers in the 1960s. It was then termed an automatic collision-avoidance system, which would hit the brakes if camera-based architectures sensed that an accident was about to occur. In the 21st-century autonomous vehicle systems, particularly in high-end vehicles, have evolved to combine a single technique associated with collision prediction. Their functions range from accident prevention systems and automated parking systems to fully autonomous driving systems. Furthermore, discussions on future mobility envision additional use cases car companies are aiming at more holistic vehicle health management, right from functional testing during assembly to identifying the need for predictive maintenance.

8.2. Human-Machine Collaboration

Driving a car, using one's smartphone to plan the route, and then using a smart device eguide in-cognitive style is a commonly observed all-day-life transportation behavior enabling survival in the modern complex traffic and multimodal traffic scenarios [33]. Sensing that it is one of the natural cognitive modes to enter into a vehicle-car and start collaborating with the co-driver, the autonomous driving systems, therefore becomes more direct than in traditional human-vehicle collaborations. Models to replace the passenger-car-driver paradigm with a 'human-AI co-driver' paradigm and to redesign the human-local traffic scenarios and traffic-responsive environment to facilitate the mission of human-AI co-driving are suggested.

[34]The burden of responsibility for traffic safety has been gradually shifting from individual vehicle drivers on the private side to intelligent systems providing autonomous driving assistance or even fully autonomous driving on the public side. The share of responsibility that individual drivers have to bear in their effective collaboration with AI in the near future is crucial to determine, keeping in mind that the current increased usage of technology is implicated in an increasing share of automobile accidents [35]. This amplifies the perception of the need to incorporate diverse interaction design and human factors research principles earlier in the process, at the early design and conceptual stages of the collaborations between humans and machines.

9. Conclusion

One to hinder this process is the so-called 'Over-description Problem', which recommends developers of AI-systems to overparameterize their models rather then having them interpret the data in an adaptive manner. Model complexity could pose further complications in the integration of AI-inspired controllers, namely that they might have adverse repercussions on stability, controllability, and interpretability, which are crucial system properties. Similarly, an overreliance on heavy AI-models might lead to a decrease in robustness due to memorization of the training set, and higher calibration requirements of the surrounding sensors. To this end, this paper reviewed a variety of AI-Safety measures such as classical guard-based safety measures or adversarial and hybrid architectures that fuse learning and safety into the same model that can develop robust systems while also providing safety guarantees. However, it is worth mentioning that the field of AI Safety is rapidly developing and that it is likely that further developments and advancements in safety theory or practical implementations have occurred since the publications of the articles have been released.

[9] The safety of AI systems in decision sensitive applications like highly automated driving is of particular importance since the system has to make critical decisions under uncertain conditions. The safety of AI models is difficult to prove, since the model is often too complex to verify every possible behavior. This issue is addressed by the multi-disciplinary field of AI Safety. The inherent complexity and unpredictability of AI models require a varied 'toolbox' to ensure system safety. As a minimum, additional safety analysis methods have to be developed for AI safety analysis, since current standards and regulations do not cover the development of safe AI systems [3]. Furthermore, AI models are only able to extrapolate from

learned data, such that safety guarantees from simulation or measurements are not directly applicable. Trust in the safety of AI-controlled systems has been identified as a concern which impedes the public acceptance of automated driving systems. Therefore better validation and verification procedures for AI-controlled systems are required to ensure safe operation.

9.1. Summary of Key Findings

The United Nations' 2020 Global Status Report on Road Safety [3] states a morose picture: 1.35 million people die in road traffic crashes globally, every year. The report, however, also promulgates several fundamental countermeasures, to put an end to the road safety crisis. Few among these bear significant reference to the use of technology for countering road traffic crashes and making road-users and drivers safer on road. One amongst these key countermeasures mentions induced vehicle safety enhancements. A brief encapsulation of the same mentions, "better matched protection of both vehicle occupants and vulnerable road users, together with appropriate pre-crash and post-crash interventions can reduce the impact of crashes and save lives and reduce leveling and severity of road traffic injuries." In reference to 'vehicle safety enhancement', prominent focus has been put forward on the induced compromise in the present educational, health and judicial policies that will be equitable and feasible for all the countries, thus mitigating any discrepancies in terms of vision. A very prominent bullet point of 'vehicle safety enhancements' is the highlight of the technologies about connected and Automated vehicles, which have promised to provide a significant reduction in crash fatalities and injuries.

Artificial intelligence (AI) has shown the capability of revolutionizing existing vehicles with the incorporation of sensors, actuators, and computation for enhanced perception, cognition, and action. AI and IoT-integrated platforms promote safety, governance, and security among road vehicles, particularly in smart city environments, in terms of driving assistance and sophisticated vehicular control [36]. This study encapsulates the contributions of AI in developing smart traffic control and ensuring road vehicle automation in smart city environments through the perspectives of road safety and community-computer cooperation, including a thorough investigation into several enabling technologies on which AI depends, and the various deep learning algorithms that promote data processing efficiency and increasing accuracy and precision in different tasks of vehicular automation. The detailed taxonomy of AI and IoT-enabled systems featured with autonomous vehicles and smart traffic control, and the vision and future of the domain, have been highlighted through an extensive review [33]. Importantly, the system's enhancement is demonstrated only through adaptation of artificial intelligence in the inclusive smart environment, which subsequently induces multi-domain research. The future of urban transportation systems is undoubtedly intelligent-mechanized and self-regulating.

9.2. Implications for the Industry

Advances in robotics and AI technologies are having a substantial impact on the future design, operation, and regulation of urban transport. Driverless vehicles operating in an urban trust would have profound impacts on the organization and design of cities, with many ancillary effects on the design of public and private transport facilities. These advanced vehicles also provide only partial cooperation to their drivers, a behavior that is more likely to disrupt rather than facilitate the flow of traffic on city streets, threaten the safely of pedestrians, cyclists, and other drivers, disrupt the evolutionary social contract among drivers, and disempower the individuals in society who cannot afford access to these vehicles [37]. Each of these issues poses difficult regulatory challenges and existing guidelines have failed to come up with new instruments tailored to autonomous vehicles. Public space access fees may operate as an effective, yet permissive way to internalize part of these externalities. Absent this, new technologies could make the city's mobility systems more unequal, fragile, and dangerous for all users.

Artificial intelligence (AI) technologies are promoting the aforementioned advancements in the transportation industry and are making effective contributions to satisfying the expectations of consumers. AI techniques can provide remarkable achievements in terms of invaluable facilities such as boosting passenger safety, restructuring the free and/or underused vehicle parking areas, minimizing maintenance costs of all sorts of vehicles. Consequently, the automotive sector is at the very heart of AI advancements especially in transportation. AI initiates a whole new era for taxis, and other similar means of transport, which are provided to the public by the companies for enhancing comfort, convenience and the social peace, related to the automotive. Since AI systems are radically transforming the nature of transportation, which would profoundly impact the quality of our lives [2].

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