AI-Based Techniques for Autonomous Vehicle Collision Detection and Mitigation

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1. Introduction to Autonomous Vehicles

The possibility of using advanced infrastructures, for monitoring, protecting, and providing autonomous vehicles with useful warnings, also in the presence of potentially harmful events on a single carriageway road, has recently led to a massive increase of interest in these technologies. The advanced solutions for steering actuator management and intelligent driver assistance, together with the extreme potential of communication systems (especially V2I, but also V2V), guarantee safe obstacle avoidance when the onboard devices are no longer sufficient to decide on the correct action [1].

One of the most crucial functionalities of autonomous vehicle control systems is their ability to avoid collisions with other vehicles and pedestrians [2]. In general, collision avoidance systems have a wide range of solutions to control the vehicle in critical situations, such as the warning of onboard systems, physical intervention on the brake or on the steering wheel, as well as complete management of the vehicle during autonomous driving. The most advanced systems can manage these solutions by identifying the best one for the specific situation, also involving additional data coming from the external world on the basis of calculations performed on received information. The perception of the environment is performed by using radar, cameras, lidar, and, when available, Taillight-based speed assist and control (TSAC) cameras. The latter technology enables vehicle-to-vehicle (V2V) communications, as well as vehicle-to-infrastructure (V2I) communications.

1.1. Definition and Overview

However, it is reported that the impact of human error still remains the spoiler in about 90% of car crashes. The main factors contributing to vehicular traffic accidents include delayed reaction, cutting in among vehicles, distorted pedestrians moving, poor visibility, absence of tracking and lack of suitable devices for split-second analysis. In the reviewing application, during the operation of the autonomous vehicle, some essential issues related to sensors not concentrated primarily on collision prevention, monitoring the driver's condition, sensing perils and maintaining the vehicle. This directs to make the vehicles which are digitally competent to come up with reliable results and help in reducing the probability of crashes. Also, the versatile role of AI techniques in recognizing road collision, another survey takes AI into picture, whose counterpart is also combined in the survey with better understanding for certain calm environment in the study social background. The literature also provides a survey for AI used for pedestrian tracking for collision prevention of autonomous vehicles. Also in any case involving the report on surveying AI and their role when A claims AI employed systems for controlling accidents of autonomous vehicles must need be scrutinized. This is vulnerable in recognizing the diversity of signals for omnidirectional motion settings worldwide [3].

The rise of intelligent vehicles has drawn much attention from researchers, governments, and automobile industries. It covers the development of advanced driver assistance systems (ADAS), connected autonomous vehicles and electric vehicles [4]. Intelligent vehicles are designed to rely on perception of their surrounding environments, which is a crucial factor to ensure the performance and safety of their application. Research on collision avoidance has become a hot driver research topic for many years. According to the 2021 report in Statista, the sales of new energy vehicles have soared to around 3.5 million. A robust intelligent control system plays a key role in preventing collisions on highways and urban streets. Systems of vehicle collision detection generously employ a set of sensors or radar systems to identify the required safety distance [1].

1.2. Evolution and Current State

Various algorithms and techniques have been devised to better assess whether a problem lies with the onboard sensors or communication links. These problems may often be resolved by integrating onboard sensor data with information from connected vehicles. Many self-repair techniques have been proposed should faults occur. Recent research is now moving its focus towards various types of collisions that may hamper the performances of vehicles on the roads today [1]. For example, rear-end collisions are becoming particularly dangerous due to onboard driverless vehicles following the leading vehicle too closely. The result, potentially, is a chain reaction that may behave very differently to human drivers slowing down once a lead vehicle decelerates. Developments are being made to address these types of problems. Another common form of collision today is that of turning vehicles. Right-of-way authorities have not been granted to automatically turn at most junctions. At present, efforts in this area are diverging into two main pathways. The less effective and cheapest way first aims at determining whether the AV has right of way by communicating with all near-waiting vehicles and/or a traffic management system. The more effective and currently most researched approach is establishing inter-vehicle through on-road processing and cooperation irrespective of whether the downhill vehicles are connected. This research aims at enabling an AV turning competitor to automatically opt out of deadlocks even if the hilltop vehicle in the intersection has failed to stop at its red light.

The development of affordable, reliable, and safe Autonomous Vehicles (AVs) is gaining momentum. The technology for autonomous operation has improved significantly since autonomous vehicle navigation and autonomous cruise control became widely available in the early 2000s. Since then, manufacturers have included progressively sophisticated features and functions that minimize driver intervention while enhancing safety and reducing total system variables. The prognosis for the future of autonomous transport is that driverless vehicles will become increasingly common as the collision risk trends down. This evolution is occurring at a rapid pace, with advancements reported almost on a daily basis that attest to the immense research and development efforts taking place today in the move towards full AV deployment [4].

2. Importance of Collision Detection and Mitigation in Autonomous Vehicles

To mitigate against these detected collisions, AI-based methods have been utilized primarily due to their adaptability, prediction capabilities, and generalization power applications and methods, such as the use of deep learning algorithms, have been considered during the literature review to find out their efficacy [5] concerning mitigating vehicle collisions. Unlike AI-based methods that rarely require a significant redesign to allow for retraining due to some minor but significant changes in the traffic environment, rule-based methods have a limited ability to manage vehicle control strategies like lane change, braking system, and steering system. Furthermore, the integration of advanced sensors and GPS, along with the propagation of trillions of vulnerable road users and autonomous vehicles equipped with sensor technology, internet of things (IoT), cloud computing, and Vehicular Ad-hoc Networks (VANETs), have available various innovative data sources which enable and enhance the potential effectiveness of ADAS technologies. The success of autonomous driving does not only rely on technological advances but also on advancements towards safety, comfortability, reliability, social, and ethical issues. Guided by traffic management intelligence, probable accidents and critical traffic conflicts can be mitigated to reduce the relevant temporal "safety control" on camouflaging the feature-rich maps that contain personally identifiable information.

Autonomy, be it partial or full, is at the crux of any advanced driver-assistance systems (ADAS) [6]. Achieving ADAS, in essence, relies on the development of techniques and methods to detect and prevent potential vehicle collisions in the shortest possible time [7]. To ensure self-driving vehicles' safe navigation and minimize potential traffic accidents, a response to the detection of abrupt changes should be implemented as quickly as possible. Collision detection and collision risk assessment of such dangerous events are some of the critical components of autonomous vehicle navigation, decision-making, and control that form the core interest of this paper. These objectives can be achieved by adopting different perception and navigation systems and fusing them to facilitate multi-modal collision detection. Object detection, tracking, vehicle pose estimation, pedestrian detection, cyclic-headlight detection, and collision risk assessment. Numerous risk assessment models such as time-to-collision (TTC) and probabilistic approaches are widely discussed in ADAS technology that surveys the associated literature. Over the years, vision-based sensors have experienced significant technological advances and have gained some importance in different ADAS techniques and algorithms all due to their capability of generating lots of relevant data sets.

2.1. Safety Implications

Recent research primarily focuses on detection technologies for incident prediction, such as cameras, radars, and ultrasonic sensors. AI-based models for detecting collisions in different environments are frequently discussed in the literature. AV safety will hinge on accurate technologies for predicting risk and rapid responsive decision-making technologies for avoiding incidents. In the literature, these topics are surveyed in individualized, fragmented reports, but they are crucial to understanding human vehicle operation standards. With that is mind, this paper synthesizes relevant studies to arrive at a comprehensive integrated outlook along with thorough discussion on the safety and stability components. AV operation parameters pertaining to the vehicle navigation, autonomous driving modes, and autonomous vehicle interaction with the environment are steadfastly defined and emphasized. Specifically, AV performance assessments and gauging the levels of the nested keywords operation safety, navigation safety, scene/external safety, and interaction safety serve as their corresponding key contributions. It will be shown that vehicle operation, scenario safety, and vehicle safety are three important themes.

Traffic accidents are a primary concern worldwide, causing numerous fatalities and injuries. The proper implementation of technology allows us to surpass human limitations, thus enabling improvements in improving safety and security in road traffic. The introduction of autonomous vehicles, intelligent transportation systems, and fully automated cities, all of which are based on scenario real-time control, will enable improvements in traffic safety beyond detecting events associated with it in real time. Autonomous vehicle (AV) technologies aim to reduce accidents and injuries occurring on public roads by enabling vehicles to be self-reliant, independent of their environment and of human interaction. An important step toward achieving this goal is the detection and mitigation of traffic conflicts and collisions2 [8]. Moreover, the ability to evaluate the safety of Autonomous Vehicles (AVs) is critical in order to determine whether they can guarantee the designated safety. This study employs a Conflict Object Completion Module and a Supervised Classification Module to predict the risk of an impending collision.

2.2. Legal and Ethical Considerations

When designing an autonomous vehicle, it is important to consider the factors of legal and ethical correctness as there are various choices and it is difficult to define the optimal set of choices. They may adversely affect road safety. It is seen that different behaviors will be socially expected in different countries due to different cultures. The legal and ethical problems that will be experienced if the vehicle could be aware of the reluctance of people to be near it due to the considerations of social distance due to the COVID-19 pandemic or other contagious diseases. Therefore, it appears to be necessary to develop methods to integrate ethical and moral values into autonomous vehicles for each individual depending on the location and regional values and to add a preferences module to the autonomous vehicle software and hardware.

[9] [7] Legal and ethical considerations in the design of intelligent transport systems stem from the fact that automatic decisions made by AI controlled systems will inevitably be associated with legal and social issues. Many collisions can occur due to AV design deficiencies which are directly related to ethics and morals. Integration of ethical and moral background speech in AV software design is a necessary condition for achieving acceptance of the general public. According to an alternative point of view, while enacting a regulation; it is necessary to assume that these cars can cause accidents due to their faults which is an approach that is not favorable.

3. Fundamentals of Artificial Intelligence in Collision Detection

The coupling of artificial intelligence with car game simulations, onboard cameras, and onboard sensors increases driver vigilance especially on difficult and highly automative roads. When an autonomous vehicle has identified a collision threat, the system must automatically switch to fully autonomous mode including steering, braking, and throttle so that the collision can be avoided. This article presents also some types of models used for the automatic detection of emergency vehicles only. These are models that have been based on machine learning techniques such as the Multilayer perceptron (MLP) model and the Discriminant model. The embedded system of the SHERPAL will be equipped with the sensor and camera model presented in this article and also will be equipped with a launchable helmet designed for collision avoidance.

Safety systems based on the human driver alone cannot reduce the accident rate and especially not to the zero accident concept. Autonomous and connected vehicles are the new trends for various purposes such as emergency driving, and Intelligent Transport Systems (ITS) [10]. In this article, we present the fundamentals of artificial intelligence in collision detection. In particular, we discuss a thorough review of the domain of collision threat detection in the automotive context and the methodologies that have been developed for collision detection [3]. We have reviewed different well-known collision detection methodologies that use machine learning. Different methodologies of collision detection based on customized car games and on-board cameras and sensors are discussed. In addition, we present different models that have been developed for the automatic detection of traffic on semi-autonomous vehicles that are often used in humanitarian missions such as ambulances and fire trucks [11].

3.1. Machine Learning Basics

To address this issue, recent publications exhibit that deep learning approaches have shown substantial improvement in performance, especially for visual inputs. Convolutional neural networks (CNN) have been applied to vehicle collision detection, localization, and trajectory forecasting effectively, in particular, in real-time scenarios [12]. However, a few limitations with deep learning methods encompass the following. They necessitate ample data and computing resources in order to establish adequate models. This could be the primary limitation, especially for acquiring sufficiently diverse, faultless, non-exaggerated, and practical data. Moreover, deep learning methods for numerous tasks still need an excessive amount of computational time notwithstanding the strong computation power.Accordingly, given their capability in mitigating the drawbacks related to traditional machine learning algorithms, ensemble learning methods might further bolster deep learning, giving rise to what are often called hybrid models or dual models.

Machines are aimed at mimicking the human brain. And the tree representations are a model for classifiers to emulate brain functionalities by processing the input and continually updating their knowledge [6]. In fact, given their remarkable properties with respect to generalization, there is no better specific classifiers. A decision tree is an extremely easy to comprehend and helps to gauge the attributes in their relative strength of predictability. Maintenance and implementation are relatively low effort, so decision trees are used by policy makers in healthcare, marketing, and finance. Yet decision trees are also vulnerable. Their key flaws embody vulnerability to overfitting, lack of path optimality, and instability. One way, therefore, to reduce decision tree vulnerability is to superimpose a layer of learning capability. A default choice might be to use the selection of attributes for an attribute algorithm to aid overcome the constraints or drawbacks. [13] However, the performance of the decision tree model will be considerably improved with the use of ensemble learning systems, like the bagging, boosting, random forests, and Adaboost, which mix the predictions of various weak classifiers to generate one reliable classifier. Prior literature explores numerous machine learning methods including decision trees, random forests, logistic regression, support vector machines, etc., for autonomous vehicle collision detection and mitigation. However, these methods are incapable to effectively manage the non-linearity and inclusion of irrelevant attributes with extra computational time increasing.

3.2. Deep Learning and Neural Networks

Similarly, traffic conflicts and accidents are critical events that must be detected and defined accurately using sensors and computerized techniques so that warnings can be issued for imminent crashes. As machine learning is transforming the design process of many signal processing systems, it is a viable candidate for the early detection of such accidents. Though advanced driver assistance systems are equipped with various sensors and networking devices to detect potential accidents, computerized models have been found to be quite efficient and reliable prediction systems. In ever increasing complexities of human activity recognition systems, deep learning may unsurmount problems and hence calls for the need of cleverly designed deep ANNs, such as CNN and RNN. The superior performance in real-time application, e.g., lane and sign recognition makes them suitable for application in activity recognition field as well. With growing deployment of vehicles and augmentation in vehicle density, safety remains a serious concern. Therefore, this survey focuses on AI based methods for online accident detection pre-anticipated behavioral pattern generation for the alert system at driving scenarios.

[14] [15]With their ability to learn representations of data through multiple layers of increasing levels of abstraction, Deep Learning (DL) models are particularly suitable for information-intensive tasks such as object recognition and classification of drivers' activities. Driven by major advancements in the field, DL algorithms are now known to outperform other AI approaches on various image-based transportation applications, such as traffic sign recognition, pedestrian detection, traffic light detection, and lane marking detection. Even though recent DL-inspired architectures have solved a number of transportation problems, such as collision detection and driver behavior prediction, their planned applications are still premature. It is apparent that early detection of adversarial road events (such as collision detection) and continual monitoring of driver behavior and the environment is critical for the success of autonomous vehicles. Various DL-incorporating techniques perform human activity recognition in the context of intelligent surveillance by identifying or recognizing a set of activities, such as walking, running, picking or dropping a bag, throwing an object and kicking, etc. It is important to note that achieving such attributes is not a simple task. Owing

to the exponentially large possibility of such human activities, harvesting a very large data set that properly captures all sort of activities becomes very challenging. Therefore, human activity recognition is a challenging field and with the passage of time, many researchers have shifted their focus to develop new and efficient ways for human activity recognition.

4. Sensors and Data Acquisition for Collision Detection

The collision monitoring system, also denoted as collision prediction or collision avoidance system, is composed of a collision detection layer, a velocity planning layer, a path planning layer, and an actuation layer. The Actuation Layer is the lowest layer in the hierarchical framework and is responsible for runtime and safetyrelated tasks. The low-level controllers are the combination of the stabilization of the system, torque feedback, and actuate the steering and force actuators. The primary aim of the low-level controller is to maintain the stability of the vehicle and smooth different controllers. Indexed of the ultrasonic sensors for frontal investigations indicate that the physical ultrasonic sensors are easily damaged, malfunctioning, or deactivated by the interferences of a few circumstances, such as fog, darkness, and so on. Of course, it is necessary to achieve augmented safety in accidents.

[5] Many methods have been proposed in the context of collision detection for underwater vehicles. These approaches use a variety of sensors like GPS, LIDAR, cameras, ultrasonic sensors, tables, and others. A solution for collision detection and avoidance using omnidirectional vision based on a combination of the proposed worst-case-integrated-time-to-collision method and the framework of potential collisions based on the computation of the critical voronoi boundary curve is described. An experimental setup is used for validation. This system calculates the omnidirectional visual perceptions of moving obstacles from an underwater vehicle and based on these data, the proposed methods for collision detection and avoidance provide an area method that suggests the danger zone for the moving obstacle, precisely determining the motion of anticipated collisions.[16] Various sensors are essential for safety in different kinds of driving, including cameras, radars, LiDAR, etc. Sensors provide environmental information, vehicle position and transient state information, and the object detection function, which can perceive the environment, providing a basis for safety-controlling decision-making and reducing the chance of accidents. Object detection at the base of the vision sensor, the ultrasonic sensor, the millimeter wave radar, and the laser sensor is crucial and related to a great deal of application in the engine self-driving, the robot, etc. In

the field of collision detection, results have been oriented in a variety of sensors like camera sensors, vibrational sensors, etc. The camera sensor, due to its high resolution, high frame rate, cheapness and high popularity, has made it the most appropriate sensor for use. Changes in ambient light and weather conditions like fog, rain, and snow have a direct influence on the accuracy of goal detection in relation to the vision sensor.

4.1. Types of Sensors

In order to improve perception and increase safety, future vehicles will need to fuse and leverage data from multiple sensors and cameras. This will improve perception, increasing safety in all-weather long-distance vision and collaborative perception. A camera has a simple structure and low cost, while the radar sensor offers a good range and works well in rain. Furthermore, sensor fusion offers potential for progression in end-to-end collision detection technology in the event that a sensor feeds incorrect input judging an object as not being close or not being an obstacle determined through vision. Radar sensors, in particular, react too late to static obstacles but, with the aid of a camera, the perception of static objects is dispersed with a large enough distance to react in a timely manner. The primary drawback of lidar as a sensor perception technology is a pedestal in price and poor performance in snow and rain. This is where the advantage of camera technology lies in detecting snow and rain. Even when these issues are considered futile, the weakness of camera technology remains in long-distance and precise detection. Eventually, in terms of various traffic conditions such as speed and obstacle shape, multiple sensors, including cameras, lidars, and radars are necessary. For example, radar offers a very wide range and good performance even in the rain but is not always useful in providing a precise obstacle or an exact distance.

Lidar, also known as LASER imaging, detection, and ranging, works on the principle of light detection and ranging. Lidar uses a sensor to measure distance to a target by illuminating the target with laser light and measuring the reflected light. Lidar has been widely used in autonomous vehicle collision detection and mitigation. The perceived surrounding environment and its trajectory profiles are the most important qualities to help prevent crashes using deep learning [17]. Among the awareness sensors on autonomous vehicles, lidar is essential for detecting obstacles in the blind spot. In this context, it isn't uncommon for self-driving cars to incorporate one or more lidars on the top of the vehicle to form a complex LiDAR system to generate a 360-degree vision, where an obstruction in any direction can be detected by another sensor in any other direction. These lidar sensors are highly beneficial but a bit costly and fragile at the same time. Radar, and ultrasonic sensors, and cameras are other essential sensors [18].

4.2. Data Processing and Fusion Techniques

As another school of strategies, late-fusion-based approaches process the output from various modality (i.e., vision or LIDAR) independently and then combine the final outputs, typically using a fusion subnetwork on the top. These late fusion approaches perform different tasks on the modalities independently and then combine the outputs. Then the fused output for the prediction and is known as the late fusion point cloud LiDAR, receives the image as input and then processed with a 2D object detection network. By leveraging these early fusion methods, the recent designs such as PointRCNN, PV-RCNN, Fused-MLP, and such models have demonstrated improved performance on detecting 3D objects by combining the 3D point cloud data with the images [19].

Robotic systems and, specifically, autonomous vehicles require robust and reliable methods for initiating collision avoidance or mitigation strategies. Sensory information is crucial to the detection and classification of various objects in the surrounding environment. For typical robotic systems relying heavily on the sensory feedback, including portable robots, unmanned surface and undersea vehicles, and unmanned aerial vehicles, various sensors are integrated to provide environmental awareness. However, similar to system paralysis, the incoherent sensory ambiguity forming issues in a multi-sensor can be complemented with sensory fusion techniques to enhance robustness and make reliable decisions robust. In recent years, AI-based techniques, especially perception models based on cutting-edge deep learning techniques (CNNs, such as Faster R-CNN or YOLO[Redmon, 2018]), have developed significantly [20].

5. AI-Based Techniques for Collision Detection

In conclusion, the conventional methods of machine-based learning are not comprehensive in the driving scenario and have not obtained a satisfactory performance. Using a neural network will reduce computation time and data processing time to a certain extent. However, a lack of robustness is still a problem. Cham and Hall propose a novel solution for deep learning safety in autonomous vehicles by observing the sensor status and providing a tailored augment sample production strategy. The safety improvement for AV largely depends on training data, so deep learning applications might pay attention to cost attributes derived from (DES) [7]. The methodology is less computationally expensive and produces a smaller model size than conventional deep neural learning (DNN) models. This will allow for the installation of a complex deep learning framework in on-board autonomous driving platforms with low power and storage capacities. The proposed model will not reach a new state-of-the-art-performance score. However with such a lightweight model, and high efficiency in computing speed, it can be largely implemented in various vehicles around the world.

An AI system detects and triggers the operation of the Automated Emergency Steering System (AES) for collision avoidance strategy during lane change in an intelligent vehicle. It involves the risk prediction indicated by vehicle collision path predictions and emergency avoidance path planning. The vehicle trajectory tracking, lane tracking, and vehicle lateral stability control of the autonomous vehicle are effectively improved by applying a collision detection and mitigation set of strategies based on machine learning [21]. In a further study, the deep neural network is trained by using large-scale traffic accident data to estimate the risk of rear-end collision. The collision risk level of multi-target collision risk for non-leading vehicles is also estimated by the proposed RBPF-based algorithm [4]. To evaluate the proposed method under a variety of traffic scenarios, a series of rear-end collision and multi-target chain-collision scenarios are made in a driving simulator adopting different driving speeds and minimal headway distance of emergency initial reaction.

5.1. Image Recognition and Object Detection

Object detection has been one of the main challenges for autonomy since the initial designs of these systems. In the last few years, various architectures optimized for object detection algorithms have been proposed. As a result of these developed architectures, real-time objectives are being approached and computational requirements are decreasing. In literature, various object detection. algorithms and/or strategies have been proposed to name a few of them: YOLO (You Only Look Once), (SSD) Single Shot Multibox Detector, R-CNN (Regions with CNN), Fast R-CNN , Faster R-CNN, Mask R-CNN, Retina Net [22]. Each method has its own limitations and advantages; this depends on the aim of that system such as real-time processing, memory usage, accuracy and reliability of detected objects and collision free decisions. Though published studies claim the near optimum performance and maximum reliability in their designed architectures, real-world applications are different from theoretical analysis of algorithms.

The safety of the passengers in a vehicle has been the main concern of the automotive industry since its inception. According to official datafrom the National Highway Traffic Safety Administration (NHTSA) and the Insurance Institute for Highway Safety (IIHS), 36,560 people died in traffic crashes in the US in 2018, among which 9,778 were due to car crashes [23]. This rate has been increasing over the years and new strategies for reducing or maybe stopping the trend should be developed. Despite efforts made by vehicle manufacturers, car crashes continue to be frequent and some of the main reasons are category related to human errors or sensing issues. However, autonomous vehicles (AVs) can eliminate the error caused by human intervention and facilitate transportation by defining optimal paths [13].

5.2. LiDAR and Radar Processing

The digital spatial model of LiDAR generates timely and accurate data regarding the surrounding objects. However, this technology is not without its demerits. Expensive equipment with high power consumption and temperature influences have negative effects on the detection of objects. Yet, to some extent, it's still hard to achieve highly accurate object detection in the scenarios; in which multiple types of objects are distributed densely in the LiDAR line of sight [5]. There are two radar systems used for the collision avoidance; one is the LIDAR system, Technical Specification RSCS9630, and the other one is the short to medium range radar system, Technical Specification RSCS9633. The radar systems emit the pulsed electromagnetic signal (signal type is either frequency modulate continuous wave (FMCW) or direct sequence spread spectrum (DSSS)) and received reflected signals from the surrounding targets like ground, obstacles, and the first and the last point of the main track with a great deal of accuracy [24]. This method generates the spatial and velocity information of the detected targets within the field of view and also reports the measurements of other targets that are still on the track. The range information of the detected targets is taken both after the offset correction and before the offset correction for the liDAR system. The LiDAR processing constitutes one of the most relevant parts of the vehicle perception system and gets plenty of interest in the scientific community. The reason is due mainly to the fact that strategies for this kind of data processing are important for the definition of the route to be followed by driverless cars [25]. For this reason, it is expected that this module can continue to remain an integral part of the perception module and therefore be used to obtain an accurate representation of the scenario. These avoid collision systems are usually based on the threshold process of the predicted trajectory and need rapid and reliable algorithm. The result of the algorithms must be as fast as the required cycle of the autonomous vehicle, where cycle times are around 20 ms. At the same time, this avoid-collision system needs to be reliable (high detection rates with very few falsely detected, obstacles). To achieve these two needs, a great deal of the work currently focuses on the development of high performance data analysis methods, and many of the methods aim to provide real-time performance in a variety of environments, or adaptations of the methods to the acquisition of multiview data for different scenarios.

6. Case Studies and Applications

The absence of adverse environmental support specifications in the sensor characteristics is an added complication. Making robust autonomous vehicles that are conscious of the accidents and transfer collided decisions into a stop state will contribute significantly to safe and effective driving in real-world conditions [26]. As systems integrated with different sensors can have individual weaknesses, multiple system integration is thought to enhance robustness. Constructing a deceleration controller and conforming to environmental limitations such as flipped sensors, low-visibility conditions, and subtle brightness changes are among the methods considered. Consequently, the danger levels of the detected conditions wear varying risky situations. For example, some fatal conditions such as vehicle flip are automatically recognized as a critical dangerous condition and classified as max risk conditions [27].

The development of self-driving cars has been an active field of research for more than a decade. The properties of autonomous vehicles, like sensing capability and action choices, are deeply related to the perception units and engineering choices for decision making frameworks. The practical nature of this field enables a wide array of real-world applications to occur. Unfortunately, some phenomena such as sun glare can interfere with different kinds of sensors, resulting in malfunctions. For instance, in heavy rain, sonar sensors may regard the raindrops as an obstacle. Some others such as the low quality of data fusion and flipping when using heavy fog can lead to more adverse conditions.

6.1. Industry Examples

Visual perception has also been applied to the detection of collision risks and collision behaviors of ships, mobile robots and other moving objects [5]. An increased focus on machine learning algorithms is improving the robustness and accuracy of AI techniques. These techniques promise robust, weather-independent, and real-time qualities for collision information detection and evaluation. They also ensure essential determinations on the quality, appearance, location, and priority of surrounding vehicles, in view with their driving trajectories. Only when autonomous vehicles correctly predict the driving behaviors, intended trajectory, and collision risks of surrounding vehicles shall they better monitor potential traffic conflicts and take advantage of proactive means to alleviate potential crashes at different safety levels.

To develop autonomous vehicles capable of predicting and avoiding potential traffic conflicts, it is essential to determine and monitor the driving behaviors of surrounding vehicles. Traditional sensor systems such as laser radar, CCD cameras, lane-keeping assistants, vision sensors, intervehicle communication, and driver assistance have been implemented in the automotive industry for early warning systems, e.g., collision-avoidance applications, embedded in intelligent transport systems (ITS) [24]. However, these sensors and systems have limitations such as the inability to work in poor weather conditions, the need to follow exact driving trajectories, the sensitivity to the driving quality of the driver, and the requirements to enable the communication between vehicles. To address these challenges, as well as to advance further development of autonomous driving, artificial intelligence (AI)-based techniques are leading the endeavor by fusing signals collected from various sensors embedded in modern vehicles to characterize the surrounding traffic scenes and detect the status of person-driven or autonomous vehicles through real-time monitoring of traffic information [7].

6.2. Research Initiatives

Research has presented earlier the effectiveness of a new situation-aware algorithm based on the Markov decision processes (MDPs) that was able to react quickly to unexpected manoeuvres and to identify the intentions of other vehicles at an intersection. The algorithm is compatible with the onboard sensors of a fully equipped car, suggesting other potential benefits and applications such as being efficient in traffic lights or in coasting warning systems, especially in greedy traffic with validated results in field tests. Another research focuses on correlating the corner positions in the frontal laser radar picture with the GPS dwell time to perform a reliable, low-latency measurement of the local approach direction [28]. Ultimately, this measurement could be integrated into a collision warning system or into a target recognition algorithm. A 3D LIDAR-based solution was proposed to extract geometrical measures that exploit the vehicle's front camera to retain stochastic data. Up to 12–38 ms of advance warning time was obtained for forward and rear vehicles in freeway scenarios [24].

Preserving road safety is significant to avoid human injuries and properties damage. Thus, we have provided broad knowledge about the enhancement of safety for road users by considering several aspects, such as main potential applications of collision imminent detection and mitigation technology, related work, challenges, and future trends. The utilization of the intelligence-based safety system significantly increases safety for road users, reduces accidents, and heavily minimizes accident-related damage and casualties [10].

7. Challenges and Future Directions

However, due to unanticipated system behaviors and environmental variations, there is a significant risk of collisions when autonomous vehicles are widely used. Managing this risk is non-trivial, particularly when considering the large-scale deployment of autonomous vehicles in complex environments. To discriminate accident hotspots and alert potential threat scenarios, the knowledge gap around issues of traffic-specific cooperativity and autonomous vehicle driving strategy in high- traffic scenarios is suggested [29]. Note that this review identified "Limitation of data used for scenario generation" and the "Failure to handle small objects" to be open problems in autonomous systems development. Recent research in ideal driving strategy is focusing on further developing cooperative perception and modelling of traffic flow using data fusion, artificial intelligence, and saturation-enhanced traffic flow theories. Open problems related to AVDS are mainly focused on cooperative driving. For autonomous car driving, scenarios in high-density, deep learning models, favorable driving behaviors and evolutions in social and cognitive sciences are some of the recent research directions. Novel research is needed to solve the problem of limited data used for scenario generation of accidents; it is further necessary to propose mechanisms that can effectively handle small objects being on the path of an autonomous vehicle, and scenarios in both high and low-density traffic. Future research directions related to self-driving vehicles are mainly related to saturated traffic theory and cooperative deep learning models are the topics to be addressed by researchers [4].

Recent advances in computational intelligence, deep learning, and other artificial intelligence (AI) technologies have shaped autonomous vehicles into agile, powerful and sustainable solutions with great promise for future automotive transportation systems. The impact of these vehicles on road safety, scene risk assessment and optimal collision mitigation strategies can be highlighted from highly them. Autonomous vehicles and vehicle-to-vehicle communication are the underpinning technologies for smart and efficient transportation systems incorporating advanced driver assistance systems (ADAS). It is necessary to develop intelligent transportation system schemes to minimize traffic congestion and gas emissions, which has attracted much research attention on intelligent decision-making techniques for deploying autonomous vehicles in a coordinated manner and with safety being the key priority [8].

7.1. Interpretable AI for Safety-Critical Systems

Decomposable output based AI architectures have incentivized the researchers to focus on end-to-end neural networks to alleviate cascading adversarial disruptions. Additionally, the performance of the modular-based approach heavily relies on existing perception and knowledge-based approaches. Dealing with adversarial disruptions in AI models is another piece of evidence about the sensitivity of their decision boundaries against slight domain shift. Adversarial robustness has attracted many researchers working in security and safety, yet only a few cases are available for accident-rate-related modulation. This is the reason we are witnessing a move toward adversarial robustness in various types of fusion networks such as outputs of perception systems of AVs as inputs of the decision-making block. The contribution of the content of what each article calls "Adversary" is not limited to critical implications. It also participates in a variety of fields such as domain adaptation and domain generalization which are capable of improving the generalization capabilities of these deep learning models.

According to Emunovic et al., the safety of Collision Avoidance Systems (CAS) is a critical issue and the main concern for reducing crash severity. In fact, the course of a collision may be dominated by CAS and thus the success of both occupied and unoccupied vehicles may partly rely upon their sophisticated algorithms. Foolproof perception and critical risk prediction are the most challenging and vital aspects. Though they had significant performance in dealing with closed-set categories, the available object perception methods (LIDAR, RADAR, vision-based methods) often face difficulties in real-world applications such as handling the occlusion case (harbor between vehicles), inferring the position of an unseen object, and run-time complexity [a compact comparative study on these three is available in]. It is important to know not only the location, but also the instantaneous status of all objects, and even the interactions between them. In the CAS case, this means the logic prediction of the time-to-collision (TTC), and consequently an early and trustful warning.

7.2. Regulatory Frameworks and Standards

The presented draft includes several interferences with the AV, environment and its objects. In the general rules, the proposed provisions encompass the integration of technical functionalities in the vehicle, as a prerequirement for operation on road; also, deployment of AVs as PyTAs or in emergency situations is not admissible. In the technical rules, recommended and required functionalities are described to enable an autonomous operation. In the licensing system context like the request for AD-ready Fahrerlaubnis. Limitations for the operation from the AVSmit besonderem Zweck to the need of human control for EdAD, are described In conjunction with the international descriptive safety maturity levels, a loaded responsibility scheme for the AxS4 is described by characteristics and planned legal adaption. This includes also required data sources for HAD maps and further pre-conditions to operate.

[4]The disruptive nature of autonomous vehicles makes it necessary to have a structured regulatory framework and to manage potential challenges. The German draft of a new law on autonomous driving introduced basic rules to allow the use of self-driving vehicles equipped with AI. Several key technology-related aspects of autonomous vehicles (AVs) are addressed, e.g. testing, driving license and the importance of ethical rules. Furthermore, the current, national, and international regulatory drafting process is discussed.

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