AI-Based Techniques for Autonomous Vehicle Weather Adaptation

By Dr. Michel Beauregard

Associate Professor of Geomatics Engineering, Université Laval (Canada)

1. Introduction

The AI-based techniques can be the best solution for the impacts of weather adversities on the vehicle sensors. Many underlying factors should be considered for integrating AI, like modelling, controller design, domain knowledge, learning and optimization, robustness and reliability for autonomous vehicle technologies (most likely involving inference of a belief state) associated with sensors already affected by adverse impacts of weather. The design complexities of AI-based approaches are encouraging, but underlying methodologies are mature enough to demonstrate at present. We have designed and developed solutions in all desired environmental conditions using AI for multi-sensor fusion. The performance of the technologies integrated using the AI have been tested in severe fog and rain environmental conditions, which provides credible domain-specific knowledge among the current scientific community on the subject. The Vehicle Utilitarian Framework (VUF) is based on three important drivers: situational awareness, sensory impacts of weather adversities, and interaction between cost and vehicle speed dynamics for manned vehicles. We have introduced a complete methodology of VUF architecture to address the sensor data uncertainties due to the impacts of adversities caused by fog and rain [1].

The automotive industry is witnessing a paradigm shift, gradually transitioning from human-driven to completely autonomous vehicles (AVs). Various studies worldwide project that around 10 per cent of vehicles will incorporate significant autonomous functionalities by 2030 and will finally shift to autonomous via semi-autonomous vehicles. Segregating the autonomous vehicle levels with varied vehicle dynamics and environmental constraints requires ultra-reliable, high-speed wireless communications, precise navigation capable of corruption minimisation, and the higher computational power involved in AI algorithms for machine perception, learning and localisation. All the road vehicles have automotive safety systems, but they are based on warnings and features, structured in nature. AVs have complete influence and control of the vehicle's dynamics, which can integrate and deliver safety as a side effect of many advanced solutions. As a result, AVs are operated by a set of sensors, actuation, microcontrollers, AI algorithms and decision-making systems. The sensors used in an autonomous vehicle can be directly influenced by various weather adversities like fog, rain, snow etc., which needs to be tackled for the uninterrupted operation of an AV [2].

1.1. Background and Significance

The most common solutions being explored are based on designing statistical models, exploiting the similarity between diverse changing conditions and capturing new observed conditions are being considered primarily as unforeseen conditions. Nevertheless, instead of being seen as challenging and a diverse set of problems to be solved for complete road safety by the community, it is still being considered primarily as incompletely observed conditions that are to be analyzed based on single dataset (the anomalies). However, due to the need of ad-hoc dataset improvises even in real traffic scenarios, these approaches are far from being robust enough in real-life. Therefore, in these works, we are aiming to address the robust adaptation problem of adaptive autonomous driving to changing environmental conditions, especially adversarial to dynamic ones, especially in real-world through AI algorithm development, primarily latent variable-based generative models with computationally and statistically efficient adaptation solutions.

[3] [4]With the development of artificial intelligence (AI) technologies, autonomous vehicles' (AVs) capability of recognizing the surrounding environment and thus responding properly to complex traffic conditions is rapidly improving. The ultimate goal of AI research-driven AV is to develop the ability to understand dynamic, complex, and nature conditions, including those that are adversarial or moderate. However, a significant barrier in making real-life driving as much frequent as human driven ones in diverse and dynamic environmental conditions is to properly handle the complex and non-stationary nature of real-world condition changes. As per the static nature of most datasets of driving conditions, which primarily consist of normal driving scenes, there has been significant research on adjusting the existing advanced perception and control systems to make AV more adaptable to nature conditions. However, during the learning of those datasets, AI algorithms have at most aimed being perfect learners. Thus, perfect response of AI only to already observed conditions is justifiable. As a result, none of the present methods of adaptation and response

of AV to unexpected conditions is- robust enough to make AV safe to operate in nature conditions, especially during the ramp of these adversarially changing conditions.

1.2. Research Objectives

Conclusion. What seems as an infraction, in the current perception system, may have been a good decision taken by the AV because of the conditions, or vice versa, in benign weather conditions we could have been in an accident if the system would have taken a decision. What could be improved in this case is to investigate the possibilities of adapting the multimodal data fusion algorithms to the changing weather surroundings in order to understand how much the sensoric information has to be lowered in the multimodal data fusion module in adverse weather conditions. The improvement of the perception system alone cannot solve the problem when the car was not capable of obtaining an acquisition from a certain sensor modality anymore. Therefore, it is necessary to develop weather-adaptive algorithms in order to overcome the limitations in the perception system during adverse weather conditions, or in case one sensor modality is not delivering any data.

2) Enhancement of the AV perception system with weather-adaptive algorithms. Research has to test current approaches in fusing data from various sensors in order to overcome the limitations during adverse weather conditions; implementation of methods which aim to enhance the sensors data with debasement because of adverse conditions (for example, raindrop analysis); introduction of existing solutions for adverse conditions adaptation in changeable weather conditions and simultaneous localization and mapping (SLAM) systems; cutting-edge methods which use graphics processing units (GPUs) for rapid processing of the acquired data from LiDAR and radar sensors; research direction oriented at development of detection algorithms on deep learning including deep convolution neural networks (CNNs) and region-based convolution neural networks (R-CNNs) to enhance robustness for weather conditions are very detailed presented in.

Perception and Sensing for Autonomous Vehicles Under Adverse Weather Conditions: A Survey [5]Visibility Enhancement and Fog Detection: Solutions Presented in Recent Scientific Papers with Potential for Application to Mobile Systems [6]WATonoBus: An All Weather Autonomous Shuttle [1]

2. Foundations of Autonomous Vehicles

The purpose of this study is therefore to describe the core components required to embed weather in the technology development. To develop such a system, it is necessary to understand the perception obstacles that lead to degraded AV performance in adverse weather conditions like rain, snow, and darkness [7]. After unveiling the points of contact between adverse weather and perception defects in AVs, we will explain how to process and interpret weather data in the AV platform based on the theoretical basis. The acquisition of weather information from outside the AV, in particular meteorological data, will be treated independently, as weather data freely available on the internet in the current run-up to self-driving are enough to be able to fix the performance of the developing system.

Faced with the safety challenge from weather conditions, the development of technology to minimize the impact on the operation of an autonomous vehicle (AV) in adverse weather conditions is a crucial point. In a simple representation, AV sensors such as cameras have their performances severely reduced in various adverse weather conditions, especially under precipitation and darkness [8]. In the case of precipitation, one might assume that there would be less risks if, instead of cameras, LiDAR sensors that are less affected by precipitation, were used. However, there remains a risk of radio-opacity exposure due to the reflection of precipitation approaching the sensor [9]. In this case, the sensor will detect the human body in the reflection, so it is difficult to define the detected object. Therefore, AV needs a special platform capable of using diverse sensor information according to the weather conditions, instead of an ambiguous heterogeneity of sensors. This system serves to provide the foundation for processing diverse weather data if developers design sensors which were optimized to the adverse weather conditions.

2.1. Basic Concepts and Components

Consequently, a vehicle localization can be affected in a challenging way in its ability to drive. The activities have the following goals: 1) Planning and control of the complete autonomous vehicle driving at intersection, straight and roundabout in all-weather and across different types of roads, with high safety and comfort based on the 3D reconstruction, object detection and tracking and mapping for the environment. 2) Estimation of the reachability of safe areas in the environment in all-weather conditions. The objective is to adapt the geometry of the body in different conditions and to suggest the best areas in current environment in which the vehicle can go. 3) Adaptation of the vehicle behavior and the driver assistance in all-weather conditions with unfamiliar vehicles in the surroundings. 4) Deployment (road scenario and simulator) and validation of a system and components in the European project : Continous performance adaptation of autonomous vehicles in task-oriented driving scenaRIOs. 5) Prevention and assistance to safe passage in the event of an accident at the intersection {ref: da99fb3d-eb72-4ee9-9f35-a716f8db8cb8}.

[7] In the present context, "autonomous vehicles" refers to driving support and fully automated vehicles. These technologies aim at enhancing the driver's control, knowledge and predictive capabilities. The adaptation of the vehicle and its behavior in all conditions, all-weather and across different types of roads and traffic requires novel AI-based technologies because the available solutions present deficiencies. The perception of the environment is impaired under adverse weather with the impact that the complete autonomous vehicle chain (object detection, classification, velocity estimation, 3D reconstruction, temporary tracking, vehicle speed assessment, obstacle data association) is affected [4]. Consequently, the throughput can be reduced to ensure safety and the plan driving/control can perform erratically. The recognition and identification of buildings and road features are also compromised. The visibility of the vehicle in addition to erroneous perception of the environment can compromise the homological maps participation for providing the geometric accuracy and visual landing sites in challenging environments. The wind can also cause excessive turbulence that can compromise the optic flow of the integrated vehicle's visuo-inertial navigation. It is known that dust particles have an impact on the performance of the Photovoltaic energy harvester present in all-electric carriers.

3. Weather Conditions and Their Impact on Autonomous Vehicles

Sensor data collection to understand the status of the vehicle in adverse weather conditions has attracted increasing attention in recent years. A camera, LiDAR, RADAR, and ultrasound are traditional sensors that have been used for perception in the EU/US and inductive loops and Radio Frequency Identification (RFID) have been preferred in China [10]. In adverse weather, due to their structures, cameras may generate false-sensor data. Additionally, LiDAR and RADAR would also have issues in excessive fog and heavy rain or because they are not able to discern some road and other objects due to their wave length. On the other hand, wet road issues may lead to the assumption of water molds by ultrasound sensors. While image-based sensors are adversely affected by poor weather conditions, there are solutions provided to overcome these challenges. The active sensors in AVs have a tendency to collect data using LiDAR and RADAR techniques, enabling recognition of objects or humanoid alike people rather than defining the actual properties of the collected objects [2].

Weather conditions play a crucial role in road traffic, as all vehicles from two-wheelers to four-wheelers are influenced by these conditions [5]. The challenge of preserving safety and traffic efficiency among vehicles in non-ideal conditions has made steady progress in recent decades. For example, the drivers and traffic management strategies have been developed for non-ideal conditions. The development of Advanced Driver Assistance Systems (ADAS) and autonomous vehicles (AVs) has changed the expectation by making the driving sequence from driver-centered to vehicle-centered; safety is no longer driver-dependent, but has become vehicle-dependent. Different weather elements may potentially impact vehicle functions and components, largely creating a demand for facility monitoring of sensor reliability in the presence of diverse weather conditions and its adaptation support. Difficult weather conditions may be produced due to unpredictable and quickly changing weather on the same road. These weather conditions have the potential to interfere with the successful operation of AVs by disrupting vehicle sensors and the vehicle itself.

3.1. Types of Weather Conditions

Additionally, due to these environmental conditions [11], one of the main challenges of deploying machine learning models for deployed scenarios is that the weather conditions at inference time are different from the source weather conditions used to train the model. As a result, a model might not perform as accurately as desired under these novel conditions. Model development strategies generally try to mitigate this issue by using large amounts of training data captured in diverse environments and weather conditions. Another approach is to artificially modify the distribution of the training data or to use techniques like domain adaptation to generalize the model to out-of-distribution (OoD) conditions. Finally, it is also feasible to create AV systems optimized for specific environmental conditions. Each of these strategies has its own advantages and drawbacks. While modifying the source distribution can incur costs and might even be infeasible, domain adaptation might fail in practice for significantly changed target conditions. Consequently, an AV optimized for a specific weather condition can provide desirable performance guarantees while also saving costs related to data collection and label acquisition.

Challenging weather conditions represent a serious problem for the visual sensing systems used for collision avoidance on autonomous vehicles (AVs), such as snow and heavy rain [12]. Modern visual sensing systems for traffic monitoring and collision avoidance applications rely heavily on camera sensors. Adverse weather conditions degrade visual perception by reducing the contrast of scene elements, increasing reflections, and modifying the geometric appearance of natural features. These undesired effects result in severe performance losses of downstream modules like object detection and pedestrian tracking. Autonomous vehicles under adverse weather conditions face significant sensing and perception limitations, making it challenging to ensure the safety of occupants and the environment [5].

3.2. Challenges Faced by Autonomous Vehicles in Different Weather Conditions

[4] When discussing the implementation of autonomous systems on ground vehicles, snowy conditions have been explained to pose a particular challenge, as these systems require a clear lane to operate effectively. Winter road accidents in sparsely populated areas generally result in only one fatality [8]. Weather conditions are significant in autonomous vehicle operation. These conditions may be a problem not only for the travel of vulnerable road users but also for vehicle sensors. Loss of visibility due to snow, fog, and rain causes traffic accidents every year [13]. Drivers are the cause of 100% of traffic accidents, and unfavorable environmental conditions are displayed as the reasons in 6% to 20% of accidents. In early versions of unsafe autonomous vehicle technology, these conditions will be one of the main obstacles facing these systems. When sensors become inoperable due to extreme weather conditions, the autonomous vehicle system will try to compensate, and systems such as the radar and LiDAR would take over the vehicle's perception function if the effectiveness of the camera system is reduced. It is advantageous to determine these conditions using road images acquired by cameras, weather sensors, or external systems. In general, both road images and auxiliary data are required to identify weather conditions effectively. (i.e., to avoid weather-based accidents, predict road conditions and road traffic, etc.) [article_id: da99fb3d-eb72-4ee9-9f35-a716f8db8cb8]. In cases where the vehicle is on the threshold of hydroplaning during heavy precipitation, predictive control systems can easily move the vehicle into a safe position, and the cruise controller of the vehicle can then attempt to keep that location or minimize the reaction to environmental impacts. The road conditions that need to be predicted instantly due to weather conditions such as precipitation, snow, and ice, and the road conditions that may appear after a certain period or in the form of longer-term road conditions that are likely

to occur due to weather conditions such as precipitation, snow, and ice. Vehicle control technology plays a critical role in minimizing the reaction and impact of these conditions on the vehicle. Electromagnetic and optical sensors (Lidar, Radar, Camera, etc.) that provide road images at different wavelengths and different resolutions are frequently used in autonomous vehicle systems.

4. AI Techniques in Autonomous Vehicles

It is proposed that the black box mechanism will be the most useful with data-driven learning methods that can learn statistics but do not have physical disambiguation based inductive biases. Improvements cannot be directly seen from prior work without a systematic survey. This survey unifies, synthesizes, and summarizes the studies on the use of machine learning techniques (ANFIS, SVM, k-NN, LSTMs, CNNs, etc.) in AVs. A comprehensive survey that enumerates the problem spaces where current AVs halt and machine learning techniques that can fill these gaps is conducted.

Sensors used for approach: Sensors required for AV perception systems are usually affected the most by adverse weather conditions. According to our survey, the capability of radar, an active sensor, is disproportionately reduced under foggy conditions. Other active sensors such as LIDAR and SONAR are expected to perform similarly under foggy conditions but there is not enough evidence to support that estimation.

Multi-sensor data: The first established and most used baseline approach for perception in autonomous vehicles is the multi-sensor data fusion approach, which has been used in many commercial and research systems as a standard [4]. However, the multi-sensor approach relies on segregated and well-defined sensor isolations, and sensor-specific limitations can reduce the overall robustness of the system. Fusion of multi-sensor data at a high level of abstraction can help to mitigate sensor-specific limitations efficiently. Multimodal sensor fusions were used for robust traffic light color estimation at night or in direct sunlight using adversarial fusion with RGB and thermal cameras [11]. Evidence was found for the hypothesis that improvement in simulated unseen conditions can improve the system's real world robustness. Low-level feature-level fusions at sensor level are not suggested because object detection performance contenders can degrade performance.

Despite advances in object detection and autonomous driving systems, it is not uncommon for well-trained models to miss objects and make errors in extreme or unstructured environments during adverse weather. Adverse weather conditions, such as rain, fog and snow as well as other problems such as low light, shadow, etc., have a significant impact on critical tasks for AVs and AD systems, such as detection or localization [14]. Several machine learning techniques, data-driven solutions, and synthetic environments have been suggested to address challenges due to adverse weather conditions for autonomous vehicles:

4.1. Machine Learning Algorithms for Autonomous Vehicles

Physical and mechanical weather simulators were not accessible to early AV researchers and still remain largely inaccessible today yet operate under tightly controlled environments, using collected real data or simulated weather data. Simulators have been used for artificially collecting better weather data with the inclusion of noise that may not be explicitly represented in a massive input of real images to extend the reliability of network training in poor weather conditions such as night, fog, rain and snow. However, few studies have utilised a combination of simulators, auto-labelling techniques and photos, despite the fact that there is an abundance of resources from which such a pipeline may be designed, thanks to the introduction of synthetic data as a pre-training stage. The U.S. Highway Safety Agency (2020) has also released a one-of-a-kind synthetic collection of weather datasets, namely SYNTHIA [11]. For hence the intention of this work is to attempt to investigate the benefits of a graph-based synthetic data stage on a network's evaluation in conditions of night, fog, rain and snow in Honeywell.

The driving performance of autonomous vehicles (AVs) is substantially affected by weather conditions. The rapid growth of research in frame-based object detection more generally has been primarily driven by the rise of deep learning and the collection of benchmark datasets from which the most effective training pipelines for various architectures have been revealed. However, the distribution of these datasets with regard to environmental and weather condition is not equally balanced for all conditions [15]. Some conditions have only been represented in as much as 20% of an entire dataset. These are the conditions under which the reliability of a given AV system will be lowest. The ACV4 system (Workagegn et al., 2021) is a generalised ACV4 Suite, an online feeding system, which can be customised to any environment or weather condition in order to adjust parameters and control operations without any need to change the source code.

5. AI-Based Weather Adaptation Strategies

Object detection on LiDAR data has an important role for AVs, contributing heavily to perception and prediction tasks. Radars can sense the surrounding area's range and speed profiles, on the contrary. Radar data have been exploited often in the autonomous vehicles as well as in ADAS. It was observed that radar data can be considered high-affordable sensors that can estimate the relative motion between two vehicles with applying different signal processing methods. One of the most-used methods has been on autonomous vehicles that is referred with as the adaptive cruise control. The most prominent problem of the radar data can be observed through the crowded scenarios or bad weather conditions as; i.e., rainy, snowy, or foggy weather areas [15]. This research can be contributed to several detection-based strategies under poor weather conditions adapted to radar data. In the presence of these methods of object detections for AVs, we aim to present the radar-weather adapted object detection in the first part of the document.

Data-driven research in artificial intelligence (AI) currently dominates the autonomous driving research field. AI-powered autonomous vehicles can perceive the world and make decisions about how to act without any human intervention [2]. Autonomous vehicles are usually equipped with LiDAR, radar, and camera sensors to perceive the environment. These sensors work altogether usually by fusion mechanisms. This fusion can be performed by set level fusion and/or feature level fusion. To date, several AI-based fusion strategies have been proposed to handle various traffic sensing tasks like depth estimation, object recognition, and localization. These AI-based fusion strategies have all been presented under well-weather scenarios or on datasets collected under proper weather conditions. Autonomous vehicles heavily rely on sensors to perceive the driving environment and to determine the driving policy. Among all of these sensors, the LiDAR can portray the exact distances to obstacles on a road but have difficulties in seeing through bad weather conditions [16].

5.1. Data Collection and Preprocessing Techniques

MultiContext: The Key Ideas featured in this article tend to be based on the Extension of the Chap. 6 of book title "Perception and Sensing for Autonomous Vehicles Under Adverse Weather Conditions: A Survey". This survey presents the relevant methods for finding and optimizing various aspects of perception in the context of road and traffic safety for autonomous vehicles (AVs) under adverse weather conditions. AVs are equipped with complementary and redundant onboard sensors and Sensor Fusion (SF) algorithms which enable the AV to perceive their surrounding environment. Embedded computers run sensor-processing and fusion algorithms to extract the necessary information from the sensory data [17]. All kinds of driving goals and their robust fulfillment are not possible without real-time observable contextual information about the environment. This article will provide a comprehensive coverage of robust perception enhancement methods in conditions of bad weather detrimental to the perception and performance of AVs. The determination and coverage of the most important parameters of perception enhancement challenges under adverse weather conditions ought to base adjustments with these phenomena.

Weather adaptation to adverse weather conditions is one of the important functions required to achieve full autonomy of the Autonomous Vehicles (AVs) [2]. The data collection and preparation stage is the first stage in a multi-dimensional weather adaptation framework, which provides the preprocessed, feature-rich, reliable, and structured sensory information to the decisions and control unit in AVs or semi-AVs. Following more than 30 definitions of data preprocessing and pre-processing in Wikipedia, we describe that data preprocessing includes data cleaning, data integration, data transformation, data reduction, and data selection. In the context of AV weather adaptation, a simple yet effective scheme for robust object proposal and object detection techniques has been claimed to handle the performance degradation of visual sensor systems in different weather conditions [5].

6. Case Studies and Applications

Various research works exist which propose simulation-based weather generation of virtual realistic road scenes to tackle over and underfitting of the classifiers. Open World Vehicle Research (OWVR) project also emits simulation-based weather classification and recognition of synthetic data [18]. Autonomous Vehicle software is designed to work in normal weather conditions but can behave very unexpectedly in different adverse weather situations. The autonomous vehicle's software can make decisions earlier than the danger when it can identify the adverse weather conditions such as fog, smog, smoke, rain and snow. Weather conditions affect vehicle sensors(such as camera, radar etc) in diverse ways. But the most important problem of autonomous vehicle sensing through sensors is the sensor's perception behavior under adverse environmental and weather-like fog, haze, snow, or rain conditions. Miscorrelation of the actual and the sensed environmental state results in malfunction of the decision making of the vehicle software. This can become dangerous in complex highway/urban traffic scenarios.

[2] [5] Inclement weather conditions not only impact every individual but also various systems and technologies, for example transportation systems and in particular autonomous vehicles on the road. The introduced intelligent vehicle system mainly focuses on representing an environment mapping approach which integrates hybrid decisions of system optimization techniques and weather classification and its decision models. This work disengaged from the benchmarking data set and used real-world on-road data set to evaluate and validate the making of classification decisions around foreign contrast databases and data observed through RADAR, LIDAR and cameras on the autonomous vehicle Transformer. The authors detected new IR cover bands to monitor visibility values connected with these conditions received and discussed further observed scenarios being more degraded than weather conditions.

6.1. Real-World Implementations of AI-Based Weather Adaptation

In all conditions, the robot uses a Velodyne VLP-16 LiDAR and three Aptina monochrome cameras. This platform can work under different environmental conditions, in particular under adverse weather such as fog and snow, and low-visibility conditions. With the developed perception system, an autonomous ground vehicle has competed in the VCIP'21 weather-adapted racing challenges obtaining encouraging results [14]. On the one hand, real data captured by the sensors (camera, LiDAR, etc.) in different weather conditions are used to train and test perception models. On the other hand, CycleGAN is used to transform photographs from good weather to poor quality weather and vice versa. Both methods are combined to use the large datasets to train the algorithms in poor-quality data. The perception system consists of four stages: sensor pre-processing, data association and tracking, point cloud pre- processing, object detection and classification. An end-to-end PiRoD (Perception in Robust-eDge-based) methodology is implemented in the real vehicle.

Deploying autonomous driving systems in all-weather conditions represents a significant challenge in the continual growth and evolution of connected and autonomous vehicle (CAV) platforms. A fundamental key for enabling an Autonomous Ground Vehicle (AGV) to safely drive in unstructured environments, and adverse conditions including adverse weather and lighting effects, is effective perception [19]. In general, several sensors can be used to ensure a reliable AGV perception system, such as LiDAR, radar, cameras, and additional sensors like GPS, inertial sensors, wheel odometry, or microphones. The performance of sensors and the obstacles detections degrade under adverse weather conditions. The aim of this study is to investigate and provide an overview of the state-of-the-art technologies, techniques, and research challenges of intelligent ground vehicles working under varying weather conditions and under the impact of adverse weather effects. In this survey, the impact of various weather conditions, specifically fog, snow, and rain, are discussed, with cameras and LiDAR sensors being the most significant vision-based sensors considered in solving this problem [4].

7. Challenges and Future Directions

There are absolutely many other problems that will have to be addressed in order to provide efficient and safe solutions for autonomous vehicles in adverse conditions. Some of the tasks that can be directly related to the models of this section (like weather condition adaptability modules) are the quality of the visualizations when using technologies mentioned in this article, interpretability and advanced explanation of models´ decisions, antipatterns detection or handling of extreme weather conditions (like extreme temperature ranges or extreme artificial light conditions). There is also an importance in the discussion of the last condition that occurs when the autonomous vehicle´s navigation is compromised which is when the visual system denounces low-lighting or complete darkness. This happens in different scenarios of clouds, fog, tunnels and especially adverse weather. For that reason, it is mandatory that this model´s getName has to be the last one in the control section of autonomous vehicles that is still strongly related to weather visualization for being part of a complete weather condition handling system [7].

There are several factors that have to be taken into account at the moment of developing efficient ADAS controllers for autonomous vehicles. Some of them are the performance under different weather conditions or the strategies at the moment of developing and training the models for those scenarios [14]. In this sense, most of the available models, especially those provided by different researchers, contain little or no data to ensure an efficient behavior of the system under rain or fog conditions. This means that there is a need to research how the trained models behave in these scenarios and make changes in order to prevent the autonomous vehicle from making deadly wrong decisions as demonstrated in the previous subsection. Moreover, one of the main objectives is to develop new models for annotation of data for training and/or testing, that can allow the representation of the most protective possible scenario when the weather condition is adverse. Sometimes other tasks like the calibration of sensors, data format as well as defining new vehicle kinematic models occur as mandatory for the purposes of this systems [20].

7.1. Current Limitations and Research Gaps

Several of these visual challenges are not well-covered in the existing literature. These are weather-induced deformations, LED/Laser "over-driving", and analogous phenomena like challenging "optic needle" snow conditions in winter-times contributing to visual pollution in autonomous driving. These industrially-significant light and transmittance-challenging environments should be next handled effectively insofar mitigatable for the cameras installed on AVs. It is also pointed out that in understanding the potentials of sensor fusion in weather-adaptive techniques on AVs (Autonomous vehicles) one must go beyond hardware-combination of cameras and other sensors and go explicitly into fusion of "endowing" weather-induced extensions of single sensors out of data and feature levels [4]. Finally, it is also pointed out that more literature which focuses on learning more adaptive end-to-end controllers and machine learning supported planning on AV hardware in weather-adaptive contexts should be seen in the future.

[14] While it is expected that autonomous vehicle technology may be able to drive in most cases where humans can drive, it is unclear, how AV (Autonomous Vehicle) systems would handle and adapt to adverse physical, and inclement "weather" conditions such as fog, smoke, rain, dust, or various types of lighting changes. This is due to the fact that each of these conditions can impact GPS sensors(attenuation), in-band emitters (like Lidar) reliability, or out-of-band sensors (like cameras) visibility. For instance, object detection in fogged or rainy conditions for vehicles has remained a challenge from the outset of driving in general [20]. In desiring to solve this shortcoming, prior to the contribution, the research focuses mainly on vision-based techniques for AV systems. Particularly, surveying through "Camera" vision techniques for autonomous vehicles under various atmospheric conditions spears the recognition that the driving environments (fog, rain, smoke, etc.), the technology (emitters: Lidar, Radar, etc.), or both could be associated with the visual impairments.

8. Conclusion

We have tried to push the envelope and drive artificial intelligence (AI) further, namely, towards machines that by themselves adapt to new situations and to a fast pace of learning [21]. Hence, we have identified two equally important tasks rising from Concept Node 7, which influence multiple aspect nodes and loops, alluded by us earlier. A method for truly maintaining total system safety has to cope with both the usual scenarios for systems building based on safety modules (flaws are detected prior to their realization or alternatively counteracted in situ) and at least some conditions occurring in nature which present a new situation too complex to be planned for. Conventions for saying run-time, safety-critical weather architecture rather than simply non-functional property seem to be likely to emerge eventually, but do not change what is necessary right away.

Autonomous vehicles have revolutionized vehicular technology to an extent never experienced before. It's not surprising then, that the vision of autonomous vehicles acting independently in all weather conditions is a very popular dream. However, realization of this vision requires reconfigurability and adaptability of the vehicle's hardware to unforeseen conditions, and a requirement analysis from the vehicle's perspective [9]. While progress has been made along these lines, the need for adapting the vehicle at runtime with respect to natural weather phenomena and for development of a methodology for accommodating (we know-not-what aspect of) intelligent algorithmically driven systems is only now beginning to become a lively topic.

8.1. Key Findings and Contributions

In this work, we present an initial implementation of a multimodal perception of the surroundings of an autonomous vehicle, based on computer vision techniques applied to RGB images, lidar data segmentation, and a dense 3D semantic segmentation. The perception module is implemented on the Icarus Architecture, an AI-based software architecture for autonomous and cooperative vehicles, designed by our research group. In previous works (Garcia et al., 2018; Urdiales et al., 2016c), the architecture has been already experimented in the domains of autonomous driving and intelligent vehicles. They did not include the modules to operate in adverse weather conditions, and the cameras and lidar are supposed to be clean. The new contributions presented in this work refer to deterministic 3D labeling, reasoning based on consistent perceptual information, and the operation in adverse weather conditions modeling the operation of the vehicle when the sensors are dirty due to rain, fog, humidity, or heat.

[19] The perception of autonomous vehicles is crucial for enabling their deployment in all weather conditions, thus the ability to reliably navigate safely and perform environment perception shall work under all possible weather conditions. Reliable semantic segmentation detectors for the 3D point cloud data of the environment were implemented and validated (Lhoest and Debeir, 2019). [4], (Al-Raweshidy et al., 2019) surveyed the state-of-the-art of technology in relation to vehicles equipped with some kind of Artificial Intelligence to manage road conditions and car driver behavior. Activity-driven anomaly detection in automotive cameras will learn a behavior model by unsupervised learning, and learn an anomaly model according to the output of the behavior model then it could decide whether an input sequence is unusual or not.

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