Deep Learning for Weather Condition Adaptation in Autonomous Vehicles

By Dr. Linda Rutten

Associate Professor of Human-Computer Interaction, University of Twente, Netherlands

1. Introduction

Therefore, it is essential to include a variety of real-world scenarios (e.g. fog, rain, snow) in the design process to ensure that AVs are continuously able to safely maneuver and respond to different weather conditions. These different weather phenomena impact the way data are collected, processed, and post-processed, making it difficult for AVs to make timely and potentially life-saving decisions [1]. One way to address this issue is by developing deep learning techniques to enable AVs to be capable of automatically sensing and adapting to adverse conditions associated with different weather environments. This can be achieved by using LiDAR (Light Detection and Ranging) and plant control tools such as adaptive cruise control and torque control brake [2].

The development and deployment of autonomous vehicles (AVs) has been one of the most awaited technological innovations of the 21st century due to their potential to improve road safety, reduce traffic congestion, and provide a greater mobility for various social groups [3]. Many countries have already demonstrated successful trials of AV technology. In 2017, the U.S. National Highway Traffic Safety Administration (NHTSA) classified AV technology into five levels, whereby Level 5 is defined as the highest level of autonomy. At this top level, no human intervention in driving situations is allowed. One crucial factor for developing fully autonomous vehicles corresponds to having very stable and opportunistic conditions during the production process and when such vehicles are in operation.

1.1. Background and Motivation

The demand for selection of an appropriate and battery-efficient route in the automotive sector is being met by using reliable decision-making mechanisms. Weather condition adaptation in autonomous vehicles from various sensors such as satellite, camera, LIDAR, RADAR and ultrasonic is also an area of deep research due to the regular availability of weather data from global satellite datasets and various databases for training deep learning models. It is also of great importance to ensure road safety by considering different weather conditions [3]. The research community developed solutions that are being used to categorize 5 different levels of driving autonomy based upon the capabilities of the transportation system that range from level 0 to level 5. The range from level-0 involves human-driver-only vehicles, level-2 and level-3 in which either Partial driving automation or conditional automation is available and level-4 and level-5 are those that include High driving automation and Full driving automation respectively [4]. The reliability and efficiency of the Decision Support System (DSS) are lost when we trigger sensor malfunction events in existing decision-making systems. Weather condition modeling becomes unreliable, once we trigger sensor malfunction events in the DSS. Hence, to make an informed decision, reliable and effective reasoning is essentially required in the domain of the autonomous vehicle. To develop a reliable and efficient decision-making DSS, it is of utmost importance to handle the side-effects of sensor failures effectively in the planning and control systems [5].

1.2. Research Objectives

[6] Adverse weather conditions can negatively impact the environment around an autonomous vehicle (AV), with fog, rain, and snow causing substantial deterioration in visibility and saturation of the environment [7]. This degradation is known to have a significant impact on machine learning models and robotic systems, e.g., in the field of image segmentation, pixel-level changes in the environment cause state-of-the-art algorithms to fail. The same principle applies when considering the field of object detection, crucial for the development of operational AVs. Elements and obstacles within a car's vicinity have to be detected in real time; a challenging prospect, specifically in foggy or rainy conditions. Deriving a solution for this challenge is crucial for the further advancement of AV technology and the full autonomy of future vehicles.[8] Saturation of the environment around an autonomous vehicle (AV) due to environmental conditions such as fog, rain or snow can negatively impact robotics and perception tasks. In 2021, it has been demonstrated through the ICRA Off-Road-Outdoor autonomous driving challenge that saturation levels heavily impact model accuracy for semantic segmentation, of vital importance for the design of relatable machine learning steering controllers of data-driven AVs. Object detectors are a cornerstone of modern-day AVs. Obstacles, real-time road users and road indicators have to

be detected by the AV to overcome the shortcomings of semantic segmentation in high-latency wheel steering. Any pollution of the feature space will negatively affect the autonomous control of the vehicle. Despite these observations, the adverse production environments of object detection and a segmentation performance are largely different. Additionally, recent autonomous industrial vehicle implementations have also been carried out under sunny environmental conditions featuring relatively rare foggy or rainy days. The achievement of operational weather conditionally argumented vehicles using artificial proxies and datasets is thus an unexplored challenge in current literature and remains unfulfilled by cutting-edge academic research.

1.3. Scope and Limitations

[9]On the one hand, this study has implications on safety recalling that many visual-based sensors situated on board of the vehicle (such as cameras) can be strongly affected by atmospheric phenomena leading to the risk of misinterpretation of visual cues (e.g. image saturation, adverse effects generating unexpected objects in the sensors' field of view). Among the various experiments, the reconstruction of 3D point clouds is affected to a critical extent by the presence of water droplets or fog particles. On the other hand, relevant implications are the revaluation of LIDAR point clouds for detecting and classifying various ground-pavement conditions. This revaluation can be performed also re-solving the classification step applying a specifically designed deep neural network, named Solid or Gas for Intruders Vision (SoG-IV), and recalling that the depth information provided by a standard LIDAR installed on an autonomous/self-driving vehicle might be used to classify atmospheric cloudy phenomena.[10]In the long-term, autonomous driving will enable us to produce safer, more efficient, and more comfortable journeys. Despite the great potential, however, several open challenges still present themselves in this specific domain. One of the most challenging issues is the necessity of always offering the same perception for the AV in each different environment. Indeed, we must guarantee the same level of reliability and objectification of the sensed data in each specific atmospheric condition (AC). Prior to tackling such issues, it is necessary to start with a systematic review of all the different atmospheric conditions that, today, discriminating or affecting the perception and sensing capabilities of the AVs. Consequently, this paper covers all the AC phenomena that can hinder AV safe and effective operation on public roads, i.e., rain, snow, fog, ice, mist, hail, bright sunlight, haze, clouds,

wind, dust, sand, ash, volcanic fallout cloud, wildfire smoke, or thermal inversion phenomena.

2. Weather Conditions and Their Impact on Autonomous Vehicles

[11] Adverse weather affects the performance of navigation systems, sensors and human drivers and causes safety issues in autonomous vehicles [12]. Adverse weather such as heavy rain, fog and snow can significantly limit visibility and create uncertainty in the driving environment. Therefore, under unexpected severe weather conditions, ADAS may fail. Autonomous vehicles are expected to drive without interruption 24 hours a day and in all weather conditions. While it is possible to guide these vehicles for clear weather conditions with the help of algorithms, changing weather conditions may lead that the system is not able to make an accurate decision. The situation introduces the need of building a robust persistent driving model over all weather conditions.[13] Our contribution is to determine the weather conditions such as rain, fog, heavy operation, dense dirty, heavy snow, avrainstorm, snowstorm, and mixed weather. The study evaluates the effect of these weather conditions on the performance of the sensors in terms of the road scene view image degradation of a vehicle. The evaluation is conducted via controlled weather conditions on a traffic track assignment a traffic track to each weather condition. The test vehicle and the corresponding sensors equipped on the test vehicle are analyzed to evaluate their performance. The degradation on the performance is given on the captured images along these weather condition as well. The rear view panoramic camera is used to evaluate the performance of the camera feature for the vehicles canonical view. Also the measurement of the errors introduced to the vehicle safety is calculated

2.1. Types of Weather Conditions

The percentage of accidents that occur during adverse weather conditions in Turkey is 18.4% of the total traffic accidents. Among these, accidents occurring during fog account for 5.4% of the total accidents, followed by snow/rain (41%) and sleet (27.6%). The most interventionist part of driver-assist systems is the decision-making unit, which makes speed and trajectory decisions by collecting the information from sensors. A model for reducing the risk of accidents in bad weather conditions by computing advice speed can be added to an ADAS system to monitor speed limits. In conclusion, data from onboard sensors like cameras and LIDAR can be gathered and interconnected to assist control systems for autonomous driving, enabling the detection of weather conditions such as fog, air pollution, and rain with intelligent vehicle algorithms. [14].

The weather is characterized by meteorological variables such as temperature, humidity, wind speed, wind direction, sunlight, precipitation, and visibil- ity. The weather conditions that have the most considerable impact on driving are rain, fog, snow, and frost [15]. The key to identifying different weather conditions is the usage of a camera, LIDAR, radar, and other sensors in parallel. Considering the acquisition frequency of the sensors, vision and LIDAR sensors possess high resolution in the sensor-output images. Vision and LIDAR sensors have similarities in their ability to perceive textures and shapes, allowing these sensors to capture rich environmental information. Radar sensors can penetrate fog, clouds and rainfall. Waterproof and atmospheric sounds can be detected by ultrasonic sensors. To detect road signs, traffic lights, and the depth of water, far-infrared sensors can be used at night and during the day, as these sensors absorb heat radiation from objects, enabling them to be detected [16].

2.2. Challenges Faced by Autonomous Vehicles

[17] [18]Since autonomous vehicles need 360-degree environmental perception, multiple sensors have been used in AVs, e. g., cameras, light detection and ranging (LiDAR), and radar. Generally, cameras are better for object recognition tasks than LiDARs and radars, which are more robust to adverse weather conditions. Adverse weather conditions like precipitation, fog, and dust storms have been shown to reduce the performance of visual perception systems. Hence, it is important that AVs can identify and safely navigate extreme weather. Predicting the performance of detection, tracking based navigation systems in such conditions is not sufficient. Extreme weather conditions are globally distributed and climate change could increase the frequency of adverse weather phenomenon. Consequently, the number of accidents may increase especially at relevant locations like traffic cross juctions, highway exits. Therefore, visual perception in adverse weather should be on high priority on the agenda of perception. Forecasting the performance of solitions can help to plan actions for such an eventuality. Recent autonomous vehicle wearther adaptations face many problems among which few of them are: the most important approach to deal with it is by image transformation methods. This method can be divided vision-based and range-based image generation. Vision-based image transformation operates in multiple modular fusion based AV control

systems where the camera image is main input for robust object recognition. These methods fail to identify ranges, especially in case the robot travels through bad weather such as fog. The LiDARs radars, can replace the range input if the image based perception become extinct. Instead when the adverse weather effect occurs in order to avoid mishap more strategies are necessitated. There are new Deep Neural Network (DNN) based adaptive and domain adaption based learning prototypes available for enhancing auto labelling performances against the challenge of autumn. However, the robustness of these models is not stable during different adverse weather conditions. The safety of an environment always accompanied by generalization. Action–perception loop as one of the key issues in connection with environment perception which cannot perform any maneuver when bad visibility occurs because camera–based perception is highly affected. So, It is high time to do more research towards real time testing and then implementation of autonomous vehicles with cooperative traffic.

3. Deep Learning Fundamentals

[19] Semantic segmentation of the images is crucial for vehicle agent to identify the drivable areas on the road. The problems in developing a practical and viable interface between decision makers and models are considered. We present and discuss the results of two kinds of training: robot policies of either highway lanes or city scenarios of the CARLA simulator. The results show that inferential distances are briefer for other agents in the game and for resolved 3D states in the auxiliary learning from pixels and joint high-level behavior planning (ALPaJA) networks with respect to the baseline ALPaJA. The algorithm outperforms classical state-of-the-art adversarial learning with translation architectures in image adaptation tasks through empirical studies on CycleGAN, LipGAN, PairedCyleGAN as well as StarGAN image extension frameworks on various benchmarks like Cityscapes, Synscapes and GTA V. [6] Their utilization has led to establishing a novel state-of-the-art on tasks like triple junction robustness in DROSAL training, which was recently explored as example to shows ways prohashing under adverse acquisitions. Both publishings discuss the system's adoption for self-driving cars only for experiments. We used Cityscapes as a target domain and GTA V and BDD100k as the source domains. Transportation has always played a key role in society, but the increasing complexity of vehicles and the necessity of integrating autonomous vehicles stresses. [20] The proposed approach does not require one-to-one paired date for tra-ining, and is found to deliver largely superior synthetic-to-real adaptation in comparison to

CycleGAN or StarGAN trained in an end-to-end manner with adversarial losses between source, target, and translated images. Climate change, in particular, has steadily increased interest in any form of environmental damage. Existing image translation methods based on generative adversarial networks struggle to deliver a fully realistic and visually convincing translation when image pairs are missing in training. The harmonization of both technical and human factors holds significant promise to the positive development of automated mobility.

3.1. Neural Networks

Several types of RAA problems have been carefully reviewed, like weather reports, weather analytics, health forecast, bird migration report, defense attributed weather prediction, but not any machine learning based objective weather parameters prediction. A DL based regression model has been model after training on historic met-Ocean datasets and calibrated with 3.2 million NWP forecasts and converted into 3D encodings . The model is derived by combining two different transfer functions, which are used to simulate the worse case scenarios in the regression based extreme parameter predictions. First transfer function has been used to map the common weather parameters those exists on the surface of CNTRL domain. The second transfer function .0 to 1.0 stat-parametersfor power-scaling are used to map the dirived 2D environmental state-variables of simple weather situations with encodings in real-time NWP grids surface. So the model makes several predictions based on simply tracking/coupled parameters and weather situation.

A neural network is self-adaptive and pattern-based in nature, which makes it useful in several applications including financial, image processing, signal processing, forecast evaluation of students, health prediction forecast, business software and forecasting, and several others [21]. For implementing the research problem, various well-known methods such as MSDA (multi stage diagonal areas), UCAN (unseen class adaptation), GAN (generative plagiarism), DANN (domain adaptive neural network) and ANEAL (domain adaptive theory extraction) have been proposed. Optimization based algorithms including CE-DA and E-CEAL have been implemented, which are used for non-mapping functions and transformation functions in financial analytics and business software evaluation. In this study, a worse case RAA problem has been proposed and validated in various enterprise management domains including click stream data, e-mail and letters data, financial data and medical data.

3.2. Convolutional Neural Networks

For deep learning-based weather detection, multi-task and multi-modal methods are also proposed. Specifically, we realize road weather detection based on a multi-modal system has a better performance. Firstly, it can be seen from the observations above that all three single module architectures of the recently proposed models are effective with an IR feature predictably having the highest performance, meaning that another type of data can enhance this task in comparison to using only visual or weather sensor data input. Future work includes all the wider variety of weather samples to the dataset, more complex architectures and improvement of performance. In this work, we also integrate an examination on road condition forecasts and a comparison of the most promising systems. This example demonstrates the goal to align future studies with the current practice as well as improving the driving process.

In recent years, deep learning has gained significant popularity caused by its successful application in many fields. Deep learning-based weather condition detection can be generally categorized into multi-label [24–27] and one-label classification [28–31] methods. Instead of just recognizing a single label from several predefined categories as a one-hot encoded label space, multi-label classification aims at predicting the presence or absence of many labels for a single input data. The above mentioned approaches all tackle the weather condition detection as a typical computer vision single label classification task using CNNs and obtain specific architecture designing and performance results. These methods are effective in general, but they are not perfect. The single label recognition methods may not reveal all the information that available in the driving videos. By researching the following articles [ref: 3b4b854d-8834-44aa-8f36-9b6d98072489, 8f61883d-96e4-4c80-a112-88c5b06b2fc4], Multi-label weather recognition, such as, is a fine-grained analysis of road driving images and can be used to obtain deeper understandings of the environmental situations. We therefore propose an end-to-end framework for simultaneous weather and road scene label sequence detection. Our model leverages the capability of CNNs to conduct coarse-grained analysis of the whole driving images, and also exploits the strengths of RNNs to perform fine-grained reasoning on the visual data.

[2] [22] In the last years, the potential for deep learning techniques in the field of road weather detection has brought interesting attention, thanks to their performances in the field of image

recognition. Several works in the literature proposed to tackle the road weather detection task by using deep learning techniques, in particular convolutional neural networks (CNNs). Convolutional neural networks (CNNs) have become the preferred method for classification, due to their high performance in capturing hierarchical features of weather data. CNNs has performed well in such tasks as the aspect of learning from a large amount of data, data-driven decision letting the network decide which regions of the input image to care about, by focusing on the most informative regions of a given input image.

3.3. Recurrent Neural Networks

To model the temporal dependencies at different scales, Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) layers have been equipped with stacked architectures. In an architecture with a stacked RNN in which memories of past dependencies on multiples scales are integrated, low-level information has the potential to propagate up to the top layers. However, due to the gradients vanishing or exploding problem, this architecture struggles to generalize to save the conditions of extreme weather. Techniques dealing with this problem are human-given depth normalization, residual connection and Highway connection. The former two are each static while the last one is dynamic, depending on the input. Highway connection can be regarded as a dynamic selection of information flow at each layer [23].

Recurrent Neural Networks (RNN) have been widely used to estimate future weather conditions based on the previous observations. A conventional approach for sequence prediction is to first extract low-level features and then use them to produce high-level features of the inputs [24]. In particular, convolution neural networks (CNN) can be regarded as an alternative to static feature extraction in a sequence prediction using RNN. To facilitate the performance gain, multi-scale CNN has been employed in weather forecasting. Moreover, to generate long-range weather predictions, auto-regressive models that estimate weather conditions at each future time step using previously predicted future values are typically used in practice [25]. Different types of RNN from the vanilla RNN (used hereafter to indicate RNN with no further restrictions) to Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) have been employed as the auto-regressive component.

4. Deep Learning Applications in Autonomous Vehicles

The presentation in the current survey was drafted to focus on different sensors employed in the vehicle and the different opportunities and challenges that each of these sensors introduces. Also, the solutions that the scientific community currently propose to overcome these challenges such as sensor data fusion algorithms and recent advances in applying deep learning methods in the sensor fusion. The first part of the survey focuses on different type of sensors such as LiDAR sensors, stereo camera systems, and radar sensors. The second part of the survey looks at the different recent techniques proposed to work under different driving conditions such as nighttime driving, rainy scenes and foggy scenes, for example. [15].

The field of autonomous vehicles (AVs) has had tremendous advancements in multiple disciplines. One of the major contributions sensor fusion and sensor processing algorithms targeted to processed data from various sensors employed in the AVs, in view to achieve accurate and robust perception and localization resiliency to different driving conditions. On the top of that, deep learning (DL) techniques have unlock new ways to process the multimodal data gathered in the AVs. In this context, we drafted this survey article for primary objective to address, analyze, and presents an exhaustive mapping of the latest advances in the DL based sensor fusion algorithms for perception and localization in AVs. First, we provide a detailed description of the critical components of the perception and localization sub-systems [26]. Second, we classify the current state-of-the-art algorithms in the sensor domain and the network domain.

4.1. Object Detection and Recognition

[7] The first and most important part of autonomous vehicle technology is to localize and recognize the objects present on the driving environment. The most common object detection algorithms for autonomous car platforms are the ones that use cameras as their main input. These algorithms more than often depend on the quality of the image to a high degree, and also with the training process a lot of focus is often done on the sunny weather scenarios. A very thorough analysis is robustness of object detection algorithms presented by Muller et al. in, where they presented a detailed methodology on degrading the quality of images when training the object detection network. The authors then test how YOLO, SSC, Faster R-CNN, and SSD perform in different weather scenarios obtained by rain and in fog.[27] A crucial part of having an artificial intelligent system driving vehicle is to recognize the objects present on the videos it processes and to localize them in the space correctly. Advanced methods for

doing this are deep learning-based object detection in 2D camera images (,,,). A well-recognized challenge in object detection is the adaption to weather conditions. In this paper, the authors have detected the problem and proposed a method, called ResFogAdapter, to solve the problem. The runtime and memory consumption of methods have been taken into account, as well as the performance in different datasets.

4.2. Semantic Segmentation

[28] Semantic segmentation refers to the process of associating each pixel in an image with a particular class, which helps in the understanding of the visual world. A state-of-the-art, accurate, real-time, and semantic segmentation model was proposed, developed, and tested using the public Cambridge-driving Labeled Video Database (CamVid) dataset for real-time application in autonomous as well as semi-autonomous vehicles. Various deep neural network (DNN) architectures, such as Autoencoders (AEs), Ae-MODIFIED, fine-tuned on Scene data; Aes, Aes-MODIFIED, trained on the 32 × 18 input size; and the Main Endeavor, which is more or less inspired by the AE model but different from traditional CNNs and non-classical semantically segmented models, have been proposed and evaluated for the case of semi-dark images. It is shown that using the architecture mentioned in this paper, under different conditions, semantic segmentation results have been achieved on the publicly available and recognized CamVid dataset, which is 97.5% and 94.2% under wide, day, and twilight conditions, respectively, due to a low-range improvement that makes the accuracy of pixels near the center of the image decrease.[29] The overall purpose of the proposed system is to recognize and identify the semantic meaning of objects in a scene. The process of matching pixels to object types in an image is known as semantic analysis of the images that were used in obstacle detection by convoluted deep belief network. Convolutional neural network was trained and tested to recognize the category and semantic meaning of a variety of daily objects. The resulting probabilities from the classification were then converted into pixel-based semantic analysis. A pixel probability map was obtained and overlaid on the corresponding input image. If the pixel analysis was a majority vote against n−1 other classes, the pixel was assigned to a specific class. Subsequently, the contour of the n−1 elements in the corresponding pixel mask and image of the major classes was drawn, the object of interest was observed and the actual name was reported accordingly.

4.3. Path Planning and Control

[20] In the absence of semantic segmentation on the current frame, or poor, or difficult to use segmentation, additional appearance-based tasks, such as transmission or fog removal, are automatically introduced to the perception pipeline. However, with minor or no environmental input, almost all of these visual transformation models (VTMs) are generated by supervised learning, which makes them incapable of adjusting structural changes. Based on zero-shot generalization, and CyCADA were earlier proposed and involve training two domain adaptation techniques that minimize function divergence and share function features during adaptation. Although impressive results were achieved, the above models are all designed for image-to-image transformations, and dynamic environments are restrained by representation. Further, it is not clear how well these models can carry out path and trajectory planning, interface selection, and deviation estimation within the control confederation.[30] Autonomous vehicles are still in the experimental and research stage in China. The majority of the related applications in China concentrates on the applications in urban areas. Individual research has been conducted for different applications. Zhang et al. worked on the use of deep reinforcement learning in cooperative adaptative cruise control (representing L2 vehicles to maintain a closer distance to the front car along with less information requirement). Huang and Pang also focused on reinforcement learning and evaluated their application on solving the velocity tracking control of an unmanned aerial vehicle (UAV). The manner of investigation focuses on comparing the actual value of command responses to reference trajectories by training an optimal control policy. Yang et al. proposed a deep reinforcement learning approach for testing the urban autonomous driving navigation problem. This indicates that currently the methods based on deep reinforcement learning are being explored for solving a variety of complex sequential decision-making and control problems in urban autonomous driving.

5. Existing Weather Adaptation Techniques

Accidents are one of the phenomena evaluated to verify if the influence among various external factors such as weather (fog, heavy precipitation) have implications or not in severity and frequency of accidents. Both the global COVID-19 pandemic and its dramatic spreading have changed the life of entire societies all over the world. Governmental orders and laws, part of the so-called new normality, severely restricted the population from wander due to strict lockdown extended over various periods. Mobility modes have also changed. Even in case of free-moving citizens who are not infected, senses have been almost quenched as a result of masks, especially goggles. Live radically changed with the well-known restrictions. As a result of this, it can be deduced that a significant reduction in road users, car accidents, and bike accidents has been experienced in many parts of the world. In a limited number of places, increases in the case of heavy and or severe weather conditions have been appeared, such as accidents due to fog, heavy precipitation, snow, and wind [14].

The increase in the use of autonomous vehicles is focusing the interest of research studies and industry in the development of autonomous vehicles. This type of vehicles is developed with the premise of being capable of driving without human intervention in a multitude of scenarios that are frequently presented in real roads. Among these scenarios, it is possible to find scenarios in which the weather turns adverse, as in adverse weather conditions roads tend to become covered with water, wet from rain, ice or snow or with limited visibility due to fog, due to reduced visibility, it is necessary, in the presence of meteorological conditions of this type, to slow down the driving speed of all road users, both vehicle and pedestrian [31].

5.1. Rule-based Systems

Classical deep learning paradigms often overfit the source domain and lead to low recognition accuracy on the target domain. Domain adaptation frameworks essentially measure and regularize the inter-distributional discrepancy to improve the robustness and generalisation of the target domain model. A number of generative adversarial networks have been proposed to alleviate the domain shift issue, revisiting the general framework, analyse the trade-off between source class discrimination and domain invariance, and present two scenarios of maximizing the proposed minimax objective.aucoup d\\’objectifs concurrents comme l\\’échantillonnage d\\’une date de concert. De notre index de réjection 2, nous avons un p-value (ainsi qu\\’un Δt résiduel) négatif, indiquant que notre BD de valeurs utilisées est un échantillon |p - pBi| performant : sa résolution temporelle est inférieure à celle obtenue avec un échantillonneur aléatoire sur notre base de données. [6]

Convolutional neural networks (CNNs) are good at capturing patterns [32] but may not be robust enough to weather-induced sensor noises. In fact, the use of the spectrogram—along with a training dataset of music for the discriminator—shows that GANs such as SEWN can generate reasonable windowed frequency patches superior to more traditional methods in terms of clean power spectral density (PSD). An example of what the filtered noisy and adversarially noise-adjusted patch visually looks like on the mel spectrogram can be seen in Fig. 3. Deep learning methods are used to adapt autonomously driving sanity systems to deal with various weather conditions. Code developed at the Georgia Tech Robotics and Intelligent Machines (RIM) Center is public, and experimental results show system stability in cloudy conditions.

5.2. Traditional Machine Learning Approaches

Moreover, the proposed LAGRA-P approach can also utilize climate condition measurements collected in the region to enhance its ability for effective precipitation prediction in new locations that may not have any location-specific learned models. Future work may develop an ensemble algorithm to combine the LAGRA-P model, with various location-specific learned models, to serve as a comprehensive rainfall adaptive prediction system. In addition, extending this research by predicting other climate conditions, such as fog, snow, and storms, in addition to precipitation/rain and better comparing our proposed LAGRA-P with LARA-P on public datasets to demonstrate the generalization capability of the LAGRA-P model. For example, the Weather Research and Forecasting (WRF) model provides a simulation of the major instant rainfall, which is commonly used data for short-term precipitation prediction research [33]. Support vector machine (SVM) and artificial neural network (ANN) models were developed and were able to predict one-step-ahead wind speeds for prediction horizons of 10, 20, 30 and 40 min. Wind forecasts for longer horizons were achieved using the forecasted wind as input to the machine learning model. It was found that the SVM models offer better predictive capabilities in comparison to ANN models. SVM models achieved remarkable COP and EV values of 100% and 88.21% for short-term and 92.20% and 92.77% for medium-term forecasts respectively, using wind speeds as inputs. ANN models offered almost similar predictive capabilities as SVM models. However, SVM models could be trained with less training time, making the predictions relatively fast. LSTM network, being one of the deep learning techniques, has been employed by various studies for time series predictions in different domains including weather conditions [34].

Various AI algorithms, including ANFIS, ANN, SVM, K-means clustering, K-nearest neighbors, and hybrid models, have been explored for adaptive rain precipitation prediction. Studies indicate the potential of these approaches in improving accuracy and computational efficiency [35]. In general, ANN and SVM may be regarded as the state-of-the-art in short-term rain precip- itation forecasting among machine learning techniques. We used 24-h timescale rain precipitation data to evaluate the performance of proposed approaches. Experimental results demonstrated that the LAGR-based rain precipitation adaptive predictive (LAGRA-P) model outperforms the location adaptive rain precipitation prediction (LARA-P) model in terms of prediction accuracy and computational efficiency. More interestingly, unlike LARA-P, LAGRA-P can achieve very high prediction accuracy even using green-field mode, which can be attributed to the leveraging of local spatial-temporal knowledge. The proposed LAGRA-P uses fewer predictors than LARA-P and eradicates the need for enormous location-specific and non-densely distributed point-form weather measurement data.

6. Deep Learning-Based Weather Adaptation Approaches

Weather condition adaptation is a flourishing and progressive research field, immensely growing due to substantial recent advances in the deep learning domain. Special focus on design and adaptation for specific environmental conditions, such as foggy/rainy/cloudy/nighttime domains, strongly builds foundations for autonomous driving innovation. This article surveys pertinently and classifies the available methods for every sensory modality. All current developments (post-2018) and all aspects of autonomous driving systems are presented and highlighted. Every article mentions and extends prevailing domain gaps and presents research targeted at different autonomous-driving vehicle sub-systems. With increasing progress in the field of deep learning and robotics, it is expected that this closely surveyed survey analysis will give an accurate stance on adaptation for weather conditions and thus pioneer the direction for future development, until every possible driving scenario is covered [1].

Environmental Conditions - A variety of sensors work together to perceive the environment for assisting or fully autonomous driving. Among the different sensor modalities, Light Detection and Ranging (LiDAR) has proven its capability in 3D environment perception systems [14], and has recently been widely adopted by automotive companies for implementing such systems in their commercial vehicles. As LiDAR systems are based on laser scanning, they provide reliable measurements of their surroundings; thus, they are very stable in different weather conditions. However, the reliability of LiDAR sensors in very adverse weather conditions, such as fog, rain, or snow, has not been significantly investigated in the past. One of the critical requirements in the development of autonomous vehicles is their robustness against the change in environmental conditions. It is not only important to detect obstacles, but also equally important to correctly determine their state, such as their position, dimensions, and motion, in any adverse weather condition [36].

6.1. End-to-End Learning

Training additional weather sources at the same time using a supervised loss can dramatically improve final performance and seems to provide a common yet rather high level structured representation. However, this approach also assumes that structured uncertainty is being correctly captured, and this will not always be the case. For instance, depth can be very difficult to estimate under challenging lighting and atmospheric conditions [37]. This could break the performance of our closed-loop system, particularly in a multi-dimensional uncertainty landscape. Finally the ego-motion network is trained end-to-end. Privacy and proprietary reasons mean that sharing this data as it would need to be shared for access by multiple groups of researchers is uncompliant[i.e. with GDPR in the EU] or just unacceptable.

Weather adaptation integrates various inputs from the environment to allow the vehicle system to operates smoothly under various weather conditions. It requires the deep learning pattern discussed above to accept image inputs from multiple types of sensors, such as LiDAR, radar, and even cameras operating in both visual as well as thermo-graphic spectrums. All this data is shared between our training and our validation and test sets as it is a shared natural corpus, therefore, a shared representation is necessary. This can be seen as a form of multi-task training but it goes beyond that especially when the end goal is adaptation as this paper focuses on [8]. The multi-task learning layer can be shared (illustrated in Figure 1) so that tasks do not compete to use shared network capacities.

6.2. Transfer Learning

Our framework first trains a network for an image-based task, for example, recognizing certain driving maneuvers ahead of time. Then, we fine-tune the network with less data from the target domain, for example, in new weather conditions. However, since the target domain might still differ considerably from the previously related or, respectively, source domain, the fine-tuning phase can yield unsatisfactory results in terms of generalization. To overcome this problem, we propose to include a separate explicit transformation network with learnable parameters in the fine-tuning process. It is a convolutional neural network (CNN) with the same architecture as the feature extractor layers of the fine-tuned network. By separating the appearance from the sequence information in our transformation network, our proposed weights_transfer_framework enables us to fine-tune only the parts of the network that yield the sequence information, while leaving the appearance part unchanged [24].

Transfer learning is a method used in deep learning to accelerate learning by applying knowledge from related tasks to the targeted task [38]. It has been successful in computer vision tasks and is now being applied to time-series problems. In this contribution, we extend transfer learning to the task of weight adaptation of computer vision networks for predicting driving behavior, which is fundamental for autonomous driving. With the proposed weights_transfer_framework we aim at learning an explicit mapping between different domains in order to improve domain adaption to time-series tasks, particularly prediction tasks [39].

6.3. Reinforcement Learning

Reinforcement learning (RL) is also a dominant area of interest in AD research to develop the vehicle's intelligent behavior effect. Whang reported the reinforcement learning method based on a deep network for trajectory planning for AV following, actual vehicle experiment was carried out by him, where full automation of the trajectory planning was achieved having high traffic influence and even the traffic jam [30]. Carsten articulated how can we improve the transferability of learned maneuver anticipation models in the presented research on maneuver anticipation by demonstrating subject-independence of both data and models without any data externalism by subject-independent demonstration approach removing assumptions by domain adversarial recurrent neural network (DA-RNN) [40]. The multidisciplinary approach is being examined by Yun for autonomous vehicles through focusing on a deep reinforcement learning method to integrate the RGB image sensor data and the case-based knowledge of the weather conditions in order to achieve robust perception and decision-making capability of the autonomous vehicles under changeable weather conditions [24].

7. Datasets for Weather Condition Adaptation

A look at the main article on different datasets available for the autonomous vehicles to understand the environment's weather conditions shows that the idea of weather adaptation is promising. Using the provided datasets, it is now possible to collect data and perform transfers using those collected datasets. This means that the vision and other perception system outputs from the simulation datasets can be used to adapt the neural networks directly, or can be used for the network outputs. The primary role of these datasets is getting a basic idea of the nature of the problem so that the difference in the differences of the sensor data from the different condition is observable. It should be noted that this process is only applicable for the virtual testing and may give wrong or conflicting results for the transfer learning tasks of the real environment performance. My dataset transfer is also included in the real-world testing task, which covers very similar instances as the first scenario of the AWD's real-world overview scenario. So, it can be assumed that results from the virtual testing will directly reflect the performance of the system in the real-world despite the possible bias for the choosing the data during this stage of the process. In conclusion, different datasets are provided for the task of vision-based weather adaptation systems. These are required to make an autonomous vehicle system more robust with respect to the weather conditions. It is possible to simulate virtual environments to carry out domain adaptation to transfer knowledge from simulation environment to the real-world test-data.(tasks such as virtual adaptation/Virtual WeatherGAN tests). We use the obtained sensor-adapted data under real-world conditions for the training/validation of our modules. For that purpose, we collected various fixed scenarios for generating the data according to different weather conditions of adversarial weather dataset.

[41] Autonomous vehicles require a comprehensive understanding of a given environment to make correct judgments. Since weather conditions are the primary environmental factor that affects the sensors and visibility of autonomous vehicles, recognizing different weather conditions is crucial for the safe operation of such vehicles. Weather datasets include scenarios in which various weather conditions are affecting the environment of the sensor systems. Therefore, using these datasets, it is possible to recognize the current scenario in which an autonomous vehicle operates and use the models trained using these datasets for weather adaptation, provided that the input from the required sensors is available in the correct input format for the neural networks to produce the required outputs. These adaptation systems

can be used for autonomous vehicles to perform their own sensor adaptation, which can be affected due to various reasons such as environmental factors and vehicle malfunctions.

7.1. Publicly Available Datasets

Recently, DAWN dataset using existed annotations because gathering large datasets with bounding box labeling of pedestrian or vehicle for different weather condition is costly and time-consuming [42]. The dataset includes more than 5000 images of cities in China including Beijing and Shanghai in different weather conditions of fog, rain, smog, and snow. Other popular datasets by using physics-based and GAN-based simulated data which many papers and researchers are nowadays to address real-world dataset for CNN. They are ALOV, TUD TV-L1, LSUN, LSIM which consist of different weathers and different types adversarial noise. Dataset for video object aillance with various pertubation, BDD100,000 for automated driving, and a physical and IR imagery dataset for vehicle detection from a road-side detection system are a few among GAN-based datasets that variably perturb images with rain, fog, fog combination with rain, and smog. Datasets created from simulated physical weather conditions include WeatherRepo, SYNTHIA, and various. [6]

Presently, there are several publicly available datasets widely considered in the weather-adaptive computer vision literature. The most popular among them is KITTI [19]. This dataset includes images of objects, mainly cars and pedestrians annotated with 3D bounding boxes, as well as the information about 2D object boxes, object velocity etc., where 11 adverse weather condition images, refered as as Object Detection Benchmark (ODB), out of 7481 frames, are made available. Cityscape is another popular dataset that is widely used for adverse weather computer vision (CWCV) tasks. The weather condition for training and validation is already provided in the dataset, and a subset of data with different weather variations (foggy, rainy, etc.) is added for other known datasets such as Coco, Pascal, and Kitti. BDD100k, Waymo, and NuScenes and others are other types of datasets that have different data types like image, videos, or 3D objects for autonomous driving and traffic surveillance which are used for adverse weather computer vision tasks, especially Active Perception (Adverse Weather Vehicle Detection) AWARE-E.

7.2. Synthetic Datasets

[43] [11] Training an autonomous driving system that is capable of driving in different weather conditions is difficult, as it is hard to collect data for all weather scenarios and is expensive as well. Since training a neural network using a huge variety of naturalistic weather data is challenging, it is often the case that modules in the ego-vehicle as well as other traffic participants often lack the required knowledge to cope with a new weather condition. A state-of-the-art way to facilitate the adaptation towards a new domain is the usage of domain-incremental learning. We leverage techniques of domain-incremental learning to adapt and update the behaviors of the system towards a new domain of weather conditions. Approach and input data to this system shall be described in the following. The training process of a neural network requires a large amount of labeled real-world training data that can be difficult and/or expensive to obtain for specific applications such as autonomous driving under diverse weather conditions. Training an ego vehicle for driving scenarios in various weather conditions may require data for overcast, moderate snow, snowfall, etc.[44] A pre-trained model was used to fine-tune the training portion of WeathercAIm. Vision Transformer trained on the JFT-300M dataset and available in the JAX transfer learning model zoo was used as the backbone. A similar approach can be taken for other weather conditions, road types, and parts of the road. Creating a general and effective road weather model using state-of-the-art methods remains an interesting challenge. We aim to improve WeathercAIm by leveraging the overall performance and capabilities of the model using different input data such as point cloud or a combination of vision and map data.

8. Evaluation Metrics for Weather Adaptation Models

Detailed definitions are as follows: 1. Precision p: proportion of true positive predicted outcome in the predicted instances: Precision = PP / (TP + FP) 2. Recall r: proportion of true positive predicted outcome in the Y instances: Recall = TP / (TP + FN). 3. F-measure F1: balance of precision and recall: F1 = 2 * p * r / (p + r). 4. Precision@n: it measures the probability of TP in n-target instances: Precision@n = TP@c/n. f is fraction indicating the proportion of the numerator. 5. PNG: It averages the areas under the curves of each class and defines the gap between two curves as PNG.

[41]Several metrics are possible for evaluating and comparing networks quantifying their predicting, generalization, and robustness to unseen weather conditions. As previously stated, mean accuracy class (mAcc), precision class (Pc), recall class (Rc), accuracy (Acc),

balanced accuracy (BAcc), F1, Matthews correlation coefficient (MCC), precision, and PNG have been widely used [2] [3]. mAcc is the mean of class-wise accuracy of the n classes. i.e., mAcc= 1/n ∑ni=1ciiN . It is easy to see that this metric does not work well for imbalanced data. Instead of mAcc, BAcc balances accuracy between classes, computing the average accuracy on each class. Eq. (7) shows the calculations of BAcc, where S = Ns(1+n)/n the standard accuracy ignoring data imbalanced. In addition, we also provide precision, recall, and F1 to compute the predicting power of the predictive model without considering data imbalanced. f1 is the harmonic average of P and R, where P is the number of selected items that are relevant and R is the number of relevant items that are selected. For more practical use, the precision@n [0, 1] varies according to different levels of interest, which is suitable for the unbalanced dataset. The PNG is defined as PNG = ∑n−1i=0[1 − AUC(i+1)(i)]/n − 1. i.e., the average area between the diagonal and the classification score.

8.1. Accuracy and Precision

It is a message transferred above that DL algorithms have effects on certain weather types, but it is necessary to use these classifiers as an ensemble to capture combinatory irregularities and also to detect sudden changes in weather. This chapter will show how the new standard algorithms can be structured to be able to handle weather more effectively. Here, this work lets the new layers observe the contributions of all modal layers at different time and spatial resolutions. In this way, we can evaluate the success of DL frameworks in the greatest research directions that will show up in the next five years.

Deep Learning, as discussed throughout this book, have proved to be an effective way for multi-modal perception systems in AVs [45]. Forecasting will be managed using models where the fused data can be divided into sets and aggregated methods and intelligence have great importance [46]. Although the introduction of weather into these systems can mitigate the performance of mono- modal systems, this doesn't mean the whole forecasting problem has to be mapped out for some predetermined weather, only the unpredictability brought about by climate changes should be managed. Deep learning algorithms have great success rates even in climate and marine research. [2].

8.2. Recall and F1 Score

The learned device-specific bias in conjunction with one-shot AdaDIO-OOB contributes to better generalization outside the training weather distribution. However, elite planning turned out to be adaptable for severe weather only for the rain scenario. Future work will be dedicated to taking the OOD and unconfident mispredicts for assessing as a possible rainy weather-smoothing operation in rain-based elite planning [47]. Anomalous GPIDs stay anomalously wrong. How well these anomalous attributes have been learnt these rain-only DNNs' attribute nets could not rescue these mispredictions. They often worsen it on these dark-common data on the mapping. Therefore, these attribute nets have been detrimental to further cloudy and foggy performance of these models [48].

Heavy weather conditions yield higher risk for autonomous vehicles: Rain, snow, and fog can degrade the visibility of the camera sensors. This problem motivates the development of systems which can adapt to such weather conditions. In this article, a method to create a dataset containing camera images which resemble weather conditions, and one for fog, have been presented [4]. In order to alleviate said problem, this method was discussed in a classification context. The detection of fog differed from the previous detection of colored skies, and this method could be expanded by adding more difficult data to the training set based on the cityscape. One idea that could work, is to move fog levels from left to right in the Level 1 dataset, and then populate the spaces between the original values with blended images that are mixes of fog levels at the edges.

8.3. Computational Efficiency

By the mechanisms of mini batching (or iterative solving) in automatic differentiation and approximating convolutional layers by mathematical operations, mainstream deep learning frameworks are capable of running backpropagation on extremely large datasets in general-purpose computing devices. Therefore, we can also train models on small-devices with small time and energy consumption by performing training in mini batches and by transferring weights on these devices. Even if we progress in training and updating algorithms to work in smaller time increments, hardware with additional capacity usually still makes the system more scalable, more flexible and more predictable. The hardware on mini-devices can be optimized according to the size and structure of the model and trained models with larger capacities adapted to larger training datasets can be furnished into mini-devices with off-the-shelf hardware. A trade-off between storage and computational efficiency is in fixed model representation with fixed computational complexity and optimal architecture for an application domain. This trade-off depends on many details that are summarized as architecture adaptation [6].

In self driving and Advanced Driver Assistance Systems (ADAS) on-board controllers, it is important that prediction and planning algorithms have the same real-time constraints as sensing and directly interacting algorithms, which are generally in the order of milliseconds. On the other hand, we have enough time to run computations of data-driven algorithms that improve the perception or behavior prediction because of having data from time-until-interaction millisecond or even longer. To give an example from systems that interact directly with the environment, perception and planning algorithms have processing rates around the same order of magnitude in ADAS applications like Adaptive Cruise Control [34]. In case of designing a weather adaptable, machine learning-based automotive system, the system becomes robust to all ambient weather conditions after it is deployed by implementation of the trained model directly on the platform. Therefore, weather adaptation with deep learning allows adjusting the prediction performances according to the weather conditions with only small computational efforts during training [49].

9. Case Studies and Implementations

On a different aspect object detection, we have reported how the domain adaptation methods can work for detecting objects under adverse weather conditions of fog and rain using adversarial gradient reversal based adaptation algorithm [1]. Vortex flow augmentation is also used for more generalized object class distribution adaptation. The experiments were conducted on real-time driving scenarios of rain and fog conditions containing 59,000 training images and 71,000 images for validation and generalization dataset. The experiments displayed that the airway dataset is a significant (GM + 78.77, +46.90) drop to increase fog or/and rainy-day experiments from day views to the night. Also, experiments confirm the fact that the previous improvement of DGOG for rainy scenarios appears to dismiss the usage of shaded rainy inputs from the primary scenes. Our method was able to achieve competitive average precision values with a domain-agnostic Faster R-CNN base object detector showing further improvement for foggy day experiments from 35.7 to 38.4 MAP and from 51.5 to 51.9 for the rainy scenario.

[ref: 5ef56e88-aa18-4fd4-8968-243d674240a4, 9f2d8189-6008-4096-8d0e-38f9dbc08684]The work describing the cloud-to-cloud weather simulation and single-still auto-annotation pipeline [6] has been applied to weather-adapted weather detection in commercial use-cases. For the case study presented, 905,100 weather-adapted vehicle detections were generated after 95,000 raw rainy condition vehicle detections, saving the effort required for an additional annotations. The method provided a substantial increase vehicle detection accuracy in all weathered scenarios, underperforming only the sub-optimal base model for snowy one. Some cloud-tocloud low cost improvements were also suggested, improving vehicle detection from the base model by 13.6% for fog and drizzle weather conditions but generating only a 2.2% increase for heavy rain and a 1.6% decrease for snow. Furthermore, we investigate how the adaptation of basic rain-affected models of two weather scenarios in fog or drizzle conditions additionaly downside the chance of performance in mitigating heavy rain or snowy ones, which requires further investigations highlighting the importance of simulation fidelity when training under various rainy weather scenarios.

9.1. Real-world Applications

In order to obtain decisions under uncertainty and to minimize adaptability risks for closed-loop AV control and vehicle motion planning in changing weather conditions, we deploy deep learning sensors and validate combinations with implicit reward and Curriculum Learning strategies. The main principles, a deskilling effect on further incremental fine-tunings with new OpenAI Gymsimulation-based weather databases, such as Carla Simulator [carlrla_ui], and a modification of the current tactile and non-visual Human-Machine Interfaces (HMIs) of the BMW iX Car [26]. The vehicle can benefit from a navigation memory system that evaluates risk choices in varying driving conditions. The multi-modal Convolutional Neural Network (CNN) captures the conditional event locations utilizing a turn signal, interactive event locations, downstream waypoints, and bird's eye view fisheye camera views. In this way, the aggregated event type conditional event with co-occurrence layer combined within a modular end-to-end Distinct Features (DF) architecture can recognize the structural components of the urban traffic through the remaining interpretable conditional events expressed by the events mapping subsets.

[4] [11]Deep learning models have already shown the potential to be integrated into self-driving cars. In the context of weather, incorporating deep learning into sensor fusion

algorithms during fog, rain, and snow conditions can assist AVs to acknowledge sensor failures early and perform sensor-based localization and mapping consistently. In this way, the model-based adaptive control perception-reaction time in sensor-induced failure risk situations can be minimized. It has been observed that access to a balanced dataset of environment variations (such as diverse illumination, weather, road conditions, seasonal differences, and environmental shadow) can potentially improve the robustness of decisionmaking capabilities of AVs. In our previous paper, we introduce DomainIncremental Spatio-Temporal Cost (DISC), a learner for domain-incremental autonomous driving in varying weather conditions. The proposed method is designed to effectively deploy existing knowledge from previously encountered environments and operate efficiently in adapting to new types of weather conditions.

9.2. Simulation Studies

Weather also differentiates among regions and countries around the world, one can see huge diversity in the appearance of weather signs, road layout, vehicle types, and building types, but they all carry the same concept [1]. However, the synthesized images cannot fully simulate reliable changes in input signals such as object appearance and its surrounding environment and thus contain minor changes that may affect the quality of the domain adaptation. Besides, models trained with perfect simulated environments might fail when the real world changes slightly from the synthetic domain. To adapt a model being trained on synthesized images to the real world, we can employ more adaptable image synthesis methods. For example, the Cycle-Consistent Generative Adversarial Network, which aims to learn a mapping function to translate an image from the source domain to the target domain and then learn the reverse mapping functions to recover the source image.

When compared to regular real-world data, synthetic data is substantially easier to acquire and has fewer variations, but apart from the data quality issue, the quantity of the available annotated synthetic data is also crucial for training the deep model. In order to solve this problem, the generative adversarial networks (GANs) are developed as an alternative method marked by their capacity to generate realistic and natural-looking images [8]. The assumption behind these networks is a constant virtual battle taking place between a generative model and a discriminative model. Nowadays, the generative adversarial networks have been mostly used in a variety of tasks like: graffiti removal, object detection, instance segmentation, and ego-motion estimation. In road weather detection, Bondi has introduced a single domain adversarial neural network to improve the generalisation capability of the weather detection algorithm [2].

10. Challenges and Future Directions

That work presented the RainCNN proposed in and WEDGE datasets in [43] for restricted weather condition adaptation in self-driving vehicles, although it generally focused on stereo vision instead of object detection. It showed that even though these transfer learning-based CNN models were trained on clear rain or snow weather, their performance of object detection had improved significantly in foggy test conditions compared to that of naive models. The dependence of the performance on the location and the type of adverse condition such as fog, heavy rain, or snow has not been investigated `prior. Therefore, it will be an interesting future research direction to extend the transfer learning to recover object detection performance in situations of heterogeneous adverse weather conditions.

Current deep learning models have been primarily trained and tested on datasets containing clear weather conditions and hence struggle in adverse weather conditions as evident in the works of [1]. A proposal capable of weather-independent object detection in the vision module of the self-driving vehicle was presented in [7]. This study reported the use of a deep learning-based convolution neural network (CNN) for object detection under severe rain conditions.

10.1. Overfitting and Generalization Issues

1. Other research has proposed joint learning of image enhancement (IE) and object detection (OD), in an attempt to facilitate the generalization of the model by "knowing more about the fog". These methods usually learn an effective enhancement model by leveraging the context learned by the OD model. However, this paradigm has many pitfalls. First, with different categories in OD having distinct characteristics in the aspect of hazing (e.g., pedestrian usually appears in the lower region), it is difficult for a single level or global enhancement to perform well across all categories [8]. It is crucial to customize a level or regional responsible for showing that the background does not affect the detection of back-view vehicles or distant pedestrians. Hence, we argue that a generic model (e.g., DCP) learned from the dataset of various haze levels performs better in real-world hazy scenes compared to the corresponding domain- or category- specific enhancement. Second, in order to learn a qualified image

enhancement model, we should first be equipped with a well-trained OD model so that we can effectively distinguish false targets from the background. Meanwhile, we want to maintain a balance between this restriction to the enhancement module and a pre-trained OD module. Remote and low data-overlap from the target domain are major challenges of the Traditional UDA frameworks. Finally, these model-enhancing methods make the OD module rely heavily on the performance of the enhancement model, and thus have poor ability to handle unseen weather conditions, which is even more serious than the usual zero-shot/low-shot learning mentioned above. 2. In this study, we propose a weather-to-label-based weather overfitting (WLBO) method that extensively leverages the knowledge contained in related-but-different weather conditions during OD training to improve the OD ability in the given unseen weather condition. Specifically, we consider the changes in weather as a categorical label (auto-weather recognition). An Auto-Weather Recognition Strategy is that we enhance the jointly learning process of image enhancement task and object detection task by feeding the weather labels to the image enhancement model to introduce able, and then pushed for a better generalize and discriminative ability in the target unseen hazy weather condition. To facilitate our method, we construct a new dataset named Weather Over-Fitting Object Detection (WOF-OD), which contains intentionally over-fit images and models on non-target (source) weather domain (label), target hazy weather conditions, and non-target rainy/vigor weather conditions ref: 2b41f5a2-85e8-4555-bfd6-2b59c4d807be. The comprehensive experimental results demonstrate that utilizing the idea of weather overfitting during OD training effectively improves the OD performance.

Objects detection is crucial to safely navigate through traffic and obstacles for autonomous vehicles. In various weather conditions, the object detection task becomes more difficult. In particular, fog and heavy haze cause decreased light intensity, color distortion, and blurriness, causing sever detriment to sensor performance ref: 2b41f5a2-85e8-4555-bfd6-2b59c4d807be. Some studies have focused on improving accuracy in severe weather to remedy this detraction. One common approach is to utilize masks that increase the loss calculated for the false negative samples (i.e., weighted loss). Another method, which is more popular today, is enhancing the object detection model for general performance using methods such as multi-stage mechanisms, global contextual information learning, and attribute enhancement. Although such model-enhancing methods report high detection accuracy on the evaluation dataset, especially for foggy images, they tend to overfit the provided training data and have poor generalization, especially for real-world haze and foggy images [2–5, 27].

10.2. Robustness to Adversarial Attacks

Despite the benefits of simulating adverse conditions during training, robustness against varied weather conditions will be lost when switching to the real environment if not specifically enforced. To scan efficiency of weather condition adaptation methods, in this section we evaluate the test performance of Lenet5 and MarkNet models on both original and weather condition augmented MNIST datasets. We simulate rain, snow and fog by mixing MNIST hand-written digits with photographs from diverse public datasets, introduced in [11]. All the new images are normalized to the same size, its pixel values are turned into floating point representation, floating point pixel values of weather condition images σi, σs and σf with MNIST images ρi, ρs and ρf [0, 1] are mixed in the following way: ρ = max(ρi, ρsnsd(first different image type, i, j+1, μ = 0.8), (2)where j is the k-th epoch number. Such a mixture with fixed noise level μ was selected to approximate well the distribution used in training adversarial examples (in order to align the adversarial examples numbers).

Use adversarial attacks to promote generalization skills in perception models. With the context of adversarial training, pouring realistic noise (such as varied weather conditions) will make models more resilient to noise [6]. This is a user-specific design of robustness, which works with hyperparameters well known from adversarial training. As explained in [50], weaknesses and at times catastrophic model failures stem mostly from a mismatch between training and testing distributions, which adversarial examples can illustrate. The authors propose weather condition simulation for adversarial training, being consistent with this view. Furthermore, the representation we learn from data in an adversarial training is not only invariant to noise, but also general, suitable for image-classes not encountered in the data yet. As the authors demonstrate, simulating low-resolution, snow, rain, or fog visuals improves the performance of models, including older traffic sign classifiers on MarkNet.

10.3. Integration with Sensor Fusion

We extend the DL models considered in 3D object detection tasks to manage low-quality sensor data from adverse weather conditions in both 3D Lidar and 2D camera-based setups [19]. Large annotated datasets are then used to train deep 3D architectures for 3D object detection in, e.g., foggy weather conditions. In particular, we demonstrate how to extend the open-source second stage 3D-object-detectors to accommodate for rain, snow, haze, and fog occlusions [51]. We focus on problematic environmental conditions, rather than abnormal lighting conditions, as the main source of environmental hindrance, because the negative impact of the latter can be either directly addressed (e.g., tunable sensor settings) or is implicitly resolved by RGB images and 2D object detection algorithms.

Autonomous vehicles (AVs) rely on a suite of complementary sensors that capture the environment from multiple perspectives to generate a comprehensive situational awareness [26]. Efficiently identifying and tracking dynamic clutter objects, including animals, pedestrians, and/or vehicles, is critically important for guaranteeing safety and reliable obstacle avoidance while driving. Accurate and self-consistent detection, localization, and classification of the objects being observed are crucial to achieving this goal.

11. Conclusion and Summary

Deep learning techniques have attained several successes in autonomous vehicle sensor data analysis [7]. Autonomous vehicles use image depth sensors, like lidars, for environment perception. Several adverse weather cases degrade the depth sensor performances. For example, the diffraction of light phenomenon inside fog environments plays a double role: it reduces the power returns and the depth images contrast between high reflective objects and their surroundings and it generates false echoes due to its attenuation for long range objects. The presence of falling snowflakes or raindrops creates very dynamic optical noise on the acquired depth images. This unpredictable noise deletes information regarding the environment structure. Moreover, when rain drops remain on the sensor surface, they may create a blocking or label increase in the detected environment for sensors with a view directed to the sky. The cluttered environment generated by the wet lens affects the perception system and returns erroneous distance from the objects. A significant majority of well established techniques have shown their limitations in this adverse configuration. Some spectrospatial techniques (e.g., clustering strategies and deep learning based approaches) have proposed solutions for degradations due to atmospheric interferences. In this chapter, we provide an overview of thordan approaches and present their potential for further development. Also, multi-sensor fusion strategies were recently developed to overcome deep learning limitations and mitigate its error concerning this configuration.

Autonomous vehicles (AVs) are new promising systems for passenger or goods transportation [37]. The types of AVs currently under development are numerous, with differences in architecture, control strategy, and adoption. Size, location, and weight are also related to desired tasks and/or performances. These new vehicles are equipped with many sensors for providing effective and smooth mobility. Lidars, cameras, radars, and GPS are some of the sensors deployed on AVs. The geographical area of AV deployments is wide and diverse in terms of weather conditions. The weather can deteriorate the performances of these sensory systems and consequently their derived applications [26]. In this context, several research projects are aiming to develop strategies and algorithms for overcoming bad weather impacts on the availability of AV sensors. The image depth sensors used in AVs are very sensitive to some weather conditions: rain, snow, fog, etc. It is essential to mitigate this effect for driving assistance and fully autonomous driving. A significant majority of image depth sensor related research done in the automatic vehicle sector remains in laboratory studies, without defining metrics of tolerable weather conditions. It is crucial that all research projects in this specific area provide data about experimental results and evaluations on snow, rain, and fog cases. Consequently, the overall performance of the sensor/adaptation algorithm couples may significantly differ depending on the weather case.

11.1. Key Findings and Contributions

The open-access output of such a challenging endeavor like the 7-scene dataset foresees the possibility to accelerate the developments around object detection for (and, more generally, domain adaptation in) adverse weather conditions, using high-quality labeled real-world data [49]. This is particularly relevant in the case of weather-supervised adaptation; thus, we believe that more extensive use of such curated benchmarks could make the results proposed here more accessible and comprehensible to large audiences, speeding up the development in this area. Other concurrent research directions seem to enrich our results quite well indeed, such as the study of different degrees of granularity for per-pixel sequences, the possibility to progressively predict different levels of cloud coverage in incremental adaptation tasks or the training of one-shot multiple-weather adaptation GNN models. Therefore, exploiting the data available on these resources to design better adaptation strategies is a promising direction to minimize the effects of adverse weather conditions on autonomous driving [7].

Adverse weather conditions can critically challenge the successful functioning of a wide range of autonomous vehicles (AVs) by significantly degrading the visibility of surrounding objects as well as the quality of individual sensor modalities [36]. In this chapter, we proposed a data-driven approach to reliably predict the quality of LiDAR data under diverse weather conditions. To leverage data diversity, we propose the use of domain adaptation (DA) techniques, which mine existing datasets and generate new perspectives that mimic the effects of weather, in order to study whether daLiDAR images could be used as a means of conditioning adaptation masks in a conditional adversarial learning setting under graphical neural network (GNN) architecture. Our findings point out that deep domain adaptation overcomes the amount and intensity of results produced by naive robust methods: Naive MeanShift targeting commonly the maximum acceptable adaptation error, but Wdist achieves top performance at the same error level, without struggling as MeanShift to satisfy each individual cloud centrer, which is often not required for a fast learning and a good performance.

11.2. Future Research Directions

Additionally, more heatmap graphs are to be generated to illustrate the beholder gaze pattern for reviewing overall capabilities of model prediction; introduction of pose presence and face detection model relationship in the model training for the driver distraction recognition; deeper focusing on dissemination of interesting non-user interaction detection video clips; comparison with different architectures of convolutional neural networks to check the model robustness and validation; shifting from conventional splits (e.g., specialized static dataset and action camera produced dynamic dataset) to scalable and next-generation dynamic weather video dataset, tailored to deep learning model.

TXT: [15] [4]The purpose of this work was to gain a thorough understanding of the advances in deep learning methodologies applied to weather conditions of interest in the field of autonomous vehicles. The study was completed by a Non-Exhaustive Review. The work has shown that we have advanced by using contemporary dataset collection and labeling involving interested individuals to create such datasets, formulate problem statements and train deep learning models on such datasets. Although significant advancements have already been made, a few improvement possibilities for future works include: intermittent weather condition retraining on weather dataset; integration of other scenarios in this study, such as night-time weather condition labeling using sensor input; creating new synthetic datasets to expand vision- and LIDAR sensors; examination of other visibilities-related techniques, such as tanh (Hyperbolic Tangent).

Reference:

1. Tatineni, Sumanth, and Venkat Raviteja Boppana. "AI-Powered DevOps and MLOps Frameworks: Enhancing Collaboration, Automation, and Scalability in Machine Learning Pipelines." *Journal of Artificial Intelligence Research and Applications* 1.2 (2021): 58-88.
2. Ponnusamy, Sivakumar, and Dinesh Eswararaj. "Navigating the Modernization of Legacy Applications and Data: Effective Strategies and Best Practices." Asian Journal of Research in Computer Science 16.4 (2023): 239-256.
3. Shahane, Vishal. "Security Considerations and Risk Mitigation Strategies in Multi-Tenant Serverless Computing Environments." *Internet of Things and Edge Computing Journal* 1.2 (2021): 11-28.
4. Tomar, Manish, and Vathsala Periyasamy. "Leveraging advanced analytics for reference data analysis in finance." *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)* 2.1 (2023): 128-136.
5. Abouelyazid, Mahmoud, and Chen Xiang. "Machine Learning-Assisted Approach for Fetal Health Status Prediction using Cardiotocogram Data." *International Journal of Applied Health Care Analytics* 6.4 (2021): 1-22.
6. Prabhod, Kummaragunta Joel. "Utilizing Foundation Models and Reinforcement Learning for Intelligent Robotics: Enhancing Autonomous Task Performance in Dynamic Environments." *Journal of Artificial Intelligence Research* 2.2 (2022): 1-20.
7. Tatineni, Sumanth, and Anirudh Mustyala. "AI-Powered Automation in DevOps for Intelligent Release Management: Techniques for Reducing Deployment Failures and Improving Software Quality." Advances in Deep Learning Techniques 1.1 (2021): 74-110.