Towards Fully Autonomous Vehicles: A Review of Current Approaches for Dealing with Adverse Weather Conditions

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Abstract

Autonomous vehicles (AVs) can, and have, driven millions of kilometres on live roads. Academia produces countless studies with respect to autonomous vehicle navigation and competitors across the world are testing AV fleets and pushing the limits of what they can accomplish. What is promised is a safer and more accessible transportation network in the future. Nevertheless, a major constraint to AV deployment is their ability to operate in adverse weather conditions. AV navigation and object detection relies on inputs from state-of-the-art sensors, including GPS, LIDAR, camera, and radar. Unfortunately, extreme weather conditions can induce drastic variations in the data gathered or the ability for trained models to correctly assess environment status. In this work, we identify two critical challenges with respect to AV operation in harsh weather, being dataset bias and real-time perception, and summarize recent works making progress in these domains. We conclude with recommendations for future research directions and promising methodologies.

1 Introduction

Interest in the widespread adoption of autonomous vehicles (AVs) has surged in the past few years, as more and more experts recognize their potential to improve road safety, reduce congestion, and promote independence and mobility for those unable to drive. The SAE Levels of Driving Automation, the prevailing framework for defining levels of autonomy, describes Level 5 vehicles as having full autonomy, meaning they are capable of handling any and all driving conditions and situations. This is the ultimate goal for many companies, including Uber, Tesla, Toyota, and more. However, a large barrier to achieving this level of autonomy is the challenge of ensuring that AVs are able to operate under adverse weather conditions, including rain, snow, and fog. This is of particular concern for countries like Canada, where road conditions for half the year are sub-optimal. In this review, the major challenges associated with adverse weather driving will be summarized, and the prevailing approaches for tackling these problems will be examined.

We identify two major hurdles that must be overcome in order to develop Level 5 AVs capable of handling adverse weather conditions. The first is the real-time perception of the vehicle's surroundings - autonomous vehicles rely on a constant stream of sensor data to be able to accurately perceive their surroundings, and certain weather conditions like rain, snow and fog can heavily impede the AV's perception capabilities. The second hurdle is the development of algorithms that are adequately equipped to handle such weather conditions. In particular, this means training AV models on datasets that encompass the full range of driving conditions the vehicle might encounter.

This work contributes to the existing body of knowledge by describing two key factors regarding AV navigation in adverse weather conditions. These factors were identified through our literature review and we highlight their importance in the adoption of autonomous vehicles. Moreover, we summarize and consolidate current works attempting to address these challenges and conclude with recommendations for directions of future work that show potential for major progress.

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1.1 Real-Time Perception

Factors such as precipitation, intense light, debris, and fog can significantly reduce visibility, posing safety risks for both human and autonomous driving agents. The varying operating requirements of AV systems further compound these risks due to drastic temperature changes inherent in volatile climates. In their comprehensive review, Zhang et al. (2023) delve into these concerns, which we summarize here to set the stage for the research discussed in this literature review. Notably, LiDAR sensor performance suffers in heavy precipitation or environments with homogeneous particle distributions like dust and sand, while temperature fluctuations can lead to nanosecond-level delays in measurements. Although radar is weather-resilient, criticisms arise regarding its object detection resolution, motivating ongoing advancements in radar technology. Cameras, susceptible to failure in harsh climates with intense light or reflections, face the risk of generating false positives. Ultrasonic sensors, with limited range yet robust reliability in adverse conditions, emerge as promising options for perception and sensing in close proximity to the vehicle. Global navigation systems remain relatively unaffected by weather but prove unreliable in tunnels and other subterranean environments.

1.2 Dataset Bias

In addition to the perception challenges described above, it is important to recognize that there are issues within the autonomous driving agents themselves. Many autonomous driving tasks, such as lane detection or pedestrian avoidance, rely on supervised learning techniques, which means these algorithms are highly reflective of the datasets on which they are trained. However, most autonomous driving datasets cover only optimal driving conditions, which can lead to vehicles that are under-equipped to deal with snowy and rainy driving conditions. Some progress has been made on this front; most notably, the Canadian Adverse Driving Conditions (CADC) Dataset from Pitropov et al. (2021), which was released in 2020, and is the first and only dataset of its kind to include snowy driving conditions. In general, however, collecting representative adverse weather driving data remains a challenge.

The remainder of this paper is structured as follows. In section 2, we review various papers considering the adverse weather autonomous driving problem, and organize them according to whether they address the perception problem or the dataset bias problem. We then conclude with a discussion in section 3 summarizing promising future research directions.

2 Review

We first turn our attention to the issue of dataset bias, as described in section 1.2. The papers reviewed in this section make various attempts to augment existing data or simulate environments demonstrating adverse weather phenomena. We then highlight several works aimed at improving real-time perception for AVs across various sensors such as LiDAR, camera and radar.

2.1 Addressing Dataset Bias

2.1.1 Data Augmentation

The collection of image-based autonomous driving data under adverse weather condition is critical for training models that are capable of dealing with such conditions, but it is costly and hazardous. Praveen et al. (2017) overlay 2D images with rain/fog effects, with the aim of generating large amounts of adverse weather data that can be used to train autonomous driving models. They implement a rain model, rain on windshield model, and fog model separately, each with variable parameters such as rain drop radius, brightness, and speed of falling rain among others. They then validate these models by using the synthetic data to train various de-fogging and de-raining models.

Autonomous vehicles heavily rely on vision-based sensors like RGB cameras. The effectiveness of these sensors for tasks such as object detection and segmentation can be significantly compromised in harsh weather conditions. Consequently, training perceptron models with real data that includes harsh weather scenarios becomes a logical choice. In their work, Mușat et al. (2021) introduces an architecture designed to generate datasets using a generative adversarial network (GAN). Commencing with the original unpaired dataset, each image is augmented to simulate seven different harsh conditions. The architecture employs CycleGAN to extract synthetic harsh condition filters from the unpaired dataset captured under real conditions. The outcome is an augmented dataset featuring generated harsh weather scenarios, incorporating both real and synthetic conditions. This dataset serves as valuable training data for perceptron models, guiding AVs in determining appropriate actions or trajectories under challenging weather conditions.

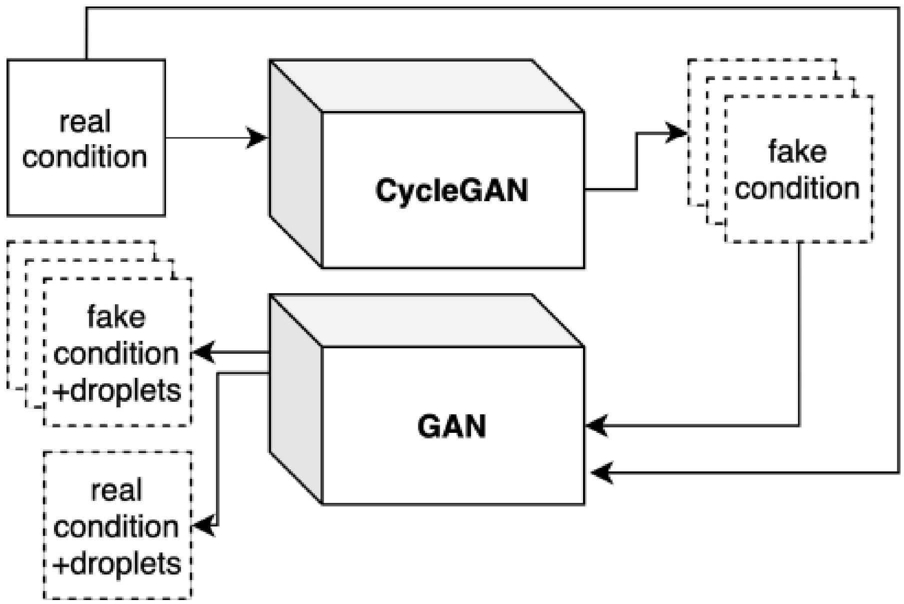

Figure 1: Algorithm architecture to train CycleGan and generate synthetic weather conditions (Mușat et al., 2021).

As previously discussed, model robustness and accuracy of predictions are jeopardized by harsh weather conditions. Generative AI emerges as a potential solution to address these challenges. Specifically, WEDGE (Marathe et al., 2023), a 2D detection system, leverages the generative model DALL-E to augment the dataset by creating new data samples. Real-world scenarios encompass a multitude of factors, including diverse weather conditions, varying intensities, and adherence to road rules. WEDGE is designed to encompass out-of-distribution scenarios, expanding the model's capability. However, it is crucial to acknowledge the potential pitfalls of incorporating extensive variability. The API might generate scenarios that deviate from realistic conditions, posing a challenge in maintaining fidelity to real-world constraints. Balancing variability in generative models is essential to ensure that generated scenarios align with the plausible conditions encountered in the real world.

2.1.2 Simulation

Diverse and challenging harsh weather conditions pose a significant hurdle in establishing a robust dataset for autonomous vehicles. Simulation emerges as a practical and cost-effective solution for testing AVs. AutonoVi-Sim (Best et al., 2018), comprised of high-level modules, facilitates the development and testing of autonomous vehicles under various conditions, including traffic rules and diverse weather scenarios. Each module within the simulator introduces a new variable for testing the vehicle's performance. By combining multiple modules, such as those simulating weather effects and driving rules, complex scenarios can be generated to thoroughly assess the capabilities of autonomous cars. This approach not only enables the creation of intricate testing scenarios but also aids in narrowing down the search space when troubleshooting faults. By systematically examining the impact of variables such as rules, vehicle behavior, and road conditions, it becomes more manageable to identify the root cause of issues within the system.

Another critical concern for autonomous vehicles is the detection of edges and road boundaries when covered in snow. Liu et al. (2022) conduct such a simulation study, leveraging the Unity3D graphics engine, to investigate and address this challenge. Simulation of Urban MObility (SUMO) and Robot Operating System (ROS) controlled vehicles are introduced into these environments and their behaviours are compared. A human operator first navigates the simulated vehicle and behavioural cloning allows for the ROS system to replicate the human vehicle control based on in-engine images. The experiment shows that under certain speeds the ROS system can correctly navigate a snow-covered road surface. The addition of tracks in the snow further improve the ability for AV navigation, though further research is suggested to increase the complexity and applicability of the simulation.

Figure 2: Visualization of simulation within Unity3D graphics engine (Liu et al., 2022).

2.2 Addressing Real-Time Perception

2.2.1 Camera

Historically, real-time object detection methods based on convolutional neural networks (CNN) have faced speed constraints, often resorting to shallow networks as a result. Subsequently, R-CNN methods emerged, employing a two-stage process where bounding boxes are generated by a regional proposal network (RPN), followed by training a CNN for classification. Despite their accuracy, these methods still pose a computational burden unsuitable for real-time applications. Ghosh (2021) introduce the You Only Look Once (YOLO) method, a recent advancement in real-time object detection, in the context of vehicle identification in images under adverse weather conditions. YOLO stands out by simultaneously generating bounding boxes and class probabilities, and accuracy is assessed through the intersection over union (IOU) between generated bounding boxes and ground truth. The authors demonstrate YOLO's superior performance in terms of both accuracy and speed when compared to conventional R-CNN methods, leveraging publicly available datasets like CDNet 2014 and LISA 2010.

In their work, Rjoub et al. (2021) enhance the You Only Look Once (YOLO) CNN framework for object detection in autonomous vehicles (AVs) operating in challenging weather conditions. Their modified approach incorporates Federated Learning (FL), enabling each connected AV to function as an independent model in an ensemble training paradigm. Initially, a global model is trained on a base dataset, and this model is then shared with all AVs in the network. Subsequently, each AV independently trains its own model by randomly selecting a subset of the remaining training data. At predefined intervals, the global model undergoes updates through an averaging process across all individual AV model parameters. The study applies this methodology to the Canadian Adverse Driving Conditions Dataset (CADC) and showcases enhancements in prediction accuracy, scalability, and computational efficiency.

Many works in this domain typically assume that training and test data share the same distribution and that models are trained accordingly. However, it is recognized that a model trained under clear weather conditions may not perform optimally in adverse weather, such as fog. J. Li et al. (2023) challenges the aforementioned assumption by introducing an adversarial gradient reversal layer to address domain shifts for both image and object-level classifiers. To achieve this, the approach incorporates both convolutional neural networks (CNN) and Region Proposal Networks (RPN). The CNN and RPN are employed to extract image-level features and generate object proposals, respectively. Subsequently, object-level extraction is carried out through a pooling layer, and a detection head is utilized to produce the final result. This comprehensive methodology aims to enhance the model's adaptability to diverse environmental conditions, acknowledging the limitations of assuming identical distributions in training and testing data.

In the work by Abbasi et al. (2023), the authors develop a fog evaluator algorithm to identify images that are taken under foggy conditions, as well as a modified version of the standard YOLO model, called IA-YOLOLv3, designed specifically for foggy images. They suggest passing all images through the fog evaluator first, to classify them as either "foggy" or "not foggy", before then applying either standard YOLOv3, or their modified image-adaptive IA-YOLOLv3. The fog evaluator uses a model called Haziness Degree Evaluator, which looks at saturation, brightness and sharpness to deduce whether a photo is hazy. Foggy images are then passed through their IA-YOLOLv3 model, which learns a CNN-based parameter predictor (CNN-PP) that is able to estimate hyper-parameters of filters that can be used for pre-processing, to de-fog the images. They argue that differentiating between foggy and not-foggy images is critical, as passing non-foggy images through de-fogging models can result in the loss of important image details. Their results find that the accuracy on foggy images goes from 63% with regular YOLO to 73% with IA-YOLOLv3.

2.2.2 LiDAR

Snowy conditions have been shown to adversely affect LiDAR sensors, resulting in inaccurate sensor data and potential safety issues for autonomous vehicles. The article by Do The and Yoo (2022) introduces a model, dubbed MissVoxelNet, to enhance the accuracy of 3D object detection models in snowy weather conditions, addressing the challenges faced by LiDAR sensors. The overall architecture involves VoxelNet and Voxel Feature Encoding (VFE) to project the point cloud into a lower dimensional representation. A Deep Mixture of Factor Analyzers (DMFA) network and a Miss-Convolution layer is then used to recover missing points in the point cloud caused by harsh weather. Finally, a strategy similar to single shot detection is used for object identification and three 1×1 convolution layers are employed for classification. The study utilizes a newly generated synthetic dataset, Snow-KITTI, based on the LISA simulator and KITTI point cloud data, to evaluate the model's performance under varying snow intensities. The results demonstrate that MissVoxelNet outperforms existing models, such as Pointpillar, SECOND, and PV-RCNN, particularly in snowy conditions, showcasing its efficacy in recovering 3D features. The article highlights the potential of the proposed model to improve the safety and reliability of autonomous vehicles in adverse weather.

Kurup and Bos (2021) propose an alternative approach to filtering snow from LiDAR point cloud data using a density-based clustering approach which they call Dynamic Statistical Outlier Removal (DSOR). This approach introduces a consistent measure of distance between neighbouring points observed both close and far from the sensor, which has been an issue in previous methods. The mean and standard deviation of distances between neighbouring points is used to calculate a dynamic threshold to identify outliers in a neighbourhood which can be then be filtered from the point cloud. The authors show that their method eliminates more snow corruption correctly, yet also removes more non-snow points compared with other methods.

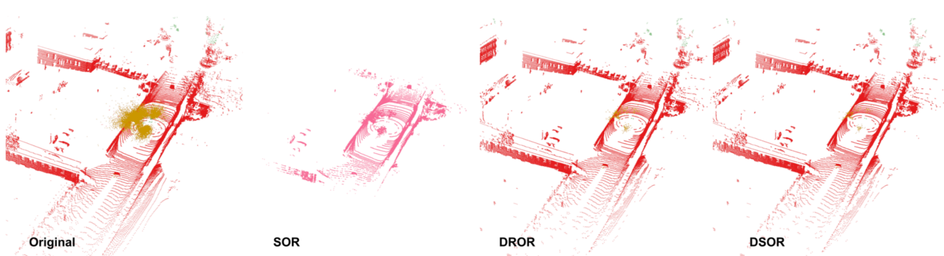

Figure 3: Comparing filters: DSOR outperforms SOR and DROR in removing snow clutter, preserving environmental features in LiDAR perception (Kurup & Bos, 2021).

2.2.3 Radar

In autonomous driving, automotive radar sensors play a vital role in detecting objects under challenging conditions at a low cost. Radar's ability to penetrate obstacles like smoke or fog makes it versatile for object detection in diverse weather conditions. However, limitations arise in detecting items with low angular resolutions across various azimuths and elevations. Recent advancements have achieved an azimuth resolution of 1 degree, yet challenges persist, especially at greater distances. While previous studies proposed solutions involving deep learning or Bayesian-based models, the work by P. Li et al. (2022) takes a unique perceptron-only approach. It centers on the intuition that consecutive frames likely share similar attributes, such as object characteristics, size, and length. The proposed method introduces a temporal relational layer and incorporates an inductive bias to mitigate the blurriness associated with low angular resolution. This specialized layer is designed for temporal feature extraction between consecutive frames, leveraging shared attributes and appearance based on intuition. The approach aims to enhance object detection performance in autonomous driving scenarios.

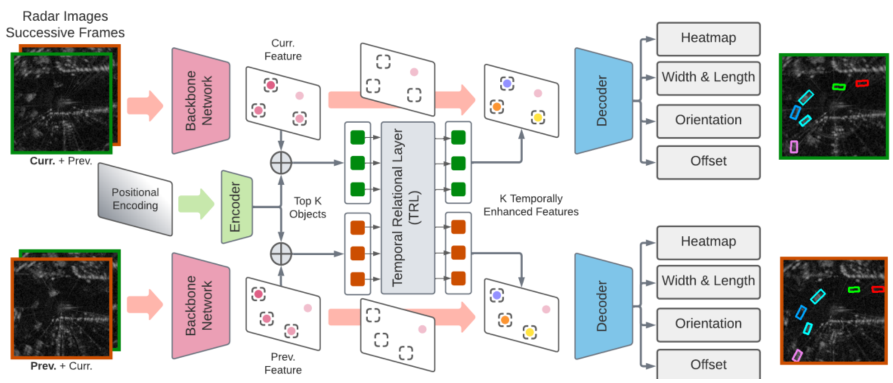

Figure 4: Algorithm architecture for feature extraction from radar (P. Li et al., 2022).

3 Discussion

This comprehensive literature review on autonomous vehicles (AVs) operating in adverse weather conditions reveals two primary challenges: real-time perception and dataset bias. To address real-time perception challenges, advancements in sensor technologies, such as LiDAR, camera, and radar, have been explored. Future research in this area should focus on the integration of multiple sensors for improved performance and the development of robust algorithms to enhance object detection. Many of the works highlighted only considered a singular sensor as input which can be significantly enhanced by fusing together several sensors and their data (Zhang et al., 2023).

With respect to tackling dataset bias, innovative strategies such as data augmentation and simulation have been proposed to generate diverse and representative datasets for training AV models. The importance of addressing the scarcity of real adverse weather driving data cannot be understated, emphasizing the need for artificial or synthetic datasets to bridge this gap. Future research directions should involve creative feature engineering to introduce variability into simulations, consideration of noise within sensor modules, and exploration of transfer learning approaches between simulated and real-world conditions.

In conclusion, promising future research directions include further exploration of multi-sensor fusion, development of algorithms resilient to extreme weather conditions, and the incorporation of more diverse and realistic scenarios in simulated environments. Additionally, efforts should be directed towards building larger and more representative datasets that encompass the complexities of adverse weather conditions to continue fostering advancements in AV navigation and safety.

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