Bird eye view for autonomous cars under adverse weather conditions

Abstract

Advanced automotive active-safety systems, in general, and autonomous vehicles, in particular, rely heavily on visual data to classify and localize objects such as pedestrians, traffic signs and lights, and other nearby cars, to assist the corresponding vehicles maneuver safely in their environments. However, the performance of object detection methods could degrade rather significantly under challenging weather scenarios including rainy conditions. Our goal includes surveying and analyzing the performance of BEV methods trained and tested in the paper translating images into maps in which visual data is captured under very often clear and sometimes rainy conditions. Moreover, we survey and evaluate the efficacy and limitations of the model used in the paper.

1 The paper

We have chosen "Translating Images into Maps" as our studied paper. We will try to improve the model cited in the paper under adverse weather conditions.

2 Motivation

In this final milestone, our goal is to to assess whether the model's performance remains consistent and effective when faced with data that is mainly from extreme weather conditions that differ significantly from the conditions under which the model was originally trained and evaluated in. The hypothesis suggests that the model should demonstrate robustness and maintain its effectiveness even in adverse weather scenarios. But first, let us demonstrate why we have chosen this particular hypothesis.

2.1 Introduction

Averagely, global precipitation occurs 11.0% of the time (Trenberth and Zhang, 2018). It has been proven that the risk of car accidents in rainy conditions is 70% higher than otherwise (Andrey and Yagar, 1993). Moreover, 77% of the countries in the world receive snow. The United States national statistics show that each year over 30,000 vehicle crashes occur on snowy or icy roads or during snowfall or sleet (National Oceanic and Atmospheric Administration, 2021). Multiple additional phenomena like fog, haze, sandstorms, and strong light severely decrease visibility and raise driving risks as well (Mehra et al., 2021).

2.2 Nuscenes data set

NuScenes is a large-scale autonomous driving dataset that offers comprehensive sensor data from various cities and diverse driving conditions. It utilizes a full sensor suite, including one LIDAR sensor, five RADAR sensors, six camera sensors, an IMU and a GPS unit.

The LIDAR sensor is used to create a detailed 3D representation of the environment, while RADAR sensors detect object distance, velocity, and angle, which are particularly useful in adverse weather. The camera sensors capture visual information for tasks like object detection and segmentation. The IMU measures vehicle motion, and the GPS provides precise location data for localization and mapping purposes. This dataset facilitates in-depth research and development of autonomous driving systems. Now, let us inspect the impact of the weather conditions on the sensors used for the Nuscenes dataset.

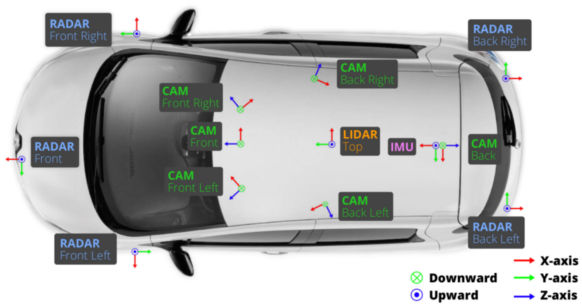

Figure 1: Sensor setup used in the Nuscenes dataset

2.3 Adverse weather influences on sensors of autonomous vehicles

The effect level of each phenomenon on the sensors:
0 - negligible: influences that can almost be ignored.
1 - minor: influences that barely cause detection error.
2 - slight: influences that cause small errors on special occasions.
3 - moderate: influences that cause perception error up to 30% of the time.
4 - serious: influences that cause perception error between 30% and 50% of the time.
5 - severe: noise or blockage that causes false detection or detection failure.

Table 1: Sensor Modalities Comparison

Modality	Light rain	Heavy rain	Dense smoke/Mist	Fog	Haze/Smog
LiDAR	2	3	5	4	1
Radar	0	1	2	0	0
Ground-Penetrating Radar	0	0	0	0	0
Camera	3	4	5	4	3

Cameras are highly susceptible to adverse weather conditions such as rain, fog and snow. The presence of even a single water droplet on the camera's lens can render it ineffective, causing blockages and image distortion. Fog creates homogeneous obstructions, hindering cameras from capturing essential information. Research has demonstrated that relying solely on cameras for perception during rain or fog can significantly increase the failure rate of object detection algorithms.

Similar to rain, snowfall poses challenges for cameras. Snowflakes coming into contact with the lens or optical window can melt and refreeze, resulting in opaque blockages. Heavy

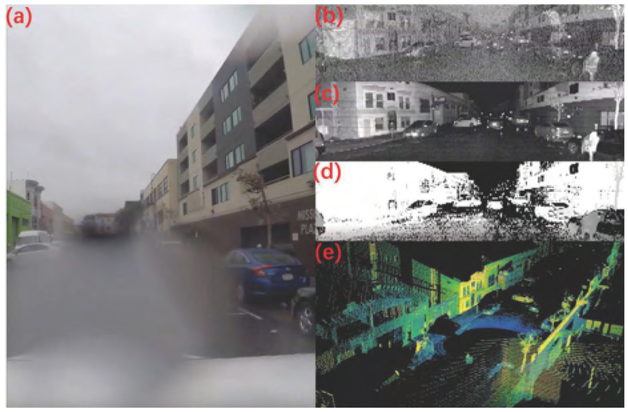

Figure 2: Camera vs. LiDAR in rain condition (Mardirosian, 2021). (a) camera perspective; (b) intensity; (c) reflectivity; (d) noise; (e) 3D point cloud colored by intensity.

snow or hail can cause fluctuations in image intensity and obscure object patterns, leading to difficulties in detection. Additionally, accumulated snow on the ground can obstruct road markings and lane lines, compromising data acquisition and disrupting the perception process.

2.4 Data exploration

The model in the paper was trained on the Nuscenes data set. In this section, we want to explore the potency of extreme weather conditions in this data set. Out of all the adverse weather conditions, we shall mainly focus on 3 main ones : fog , *snow* and *rain*. We can mention that although this dataset might contain some visuals captured in rainy conditions, they do not have weather tagging like other datasets such as BDD100k. The Nuscenes dataset is comprised of high-definition sensor data collected from a diverse set of urban driving scenarios in multiple cities worldwide. It includes complex scenarios with varied weather and lighting conditions. For our purposes, the specific scenarios mentioned above are represented in the Nuscenes dataset and were targeted and tested separately on the model.

We can see that rain data represents 20% of the whole dataset, whereas fog and snow camera pictures are nonexistent in the dataset. This leads us to speculate that a model trained on the Nuscenes dataset will not be able to generalize to cases of rainy conditions, and will definitely perform poorly on fog and snow datasets. It is also worth noting that several images in the data set are wrongly tagged as rainy weather when they actually show clear or cloudy conditions, such as the examples shown in the bottom row of Figure 4.

2.5 Conclusion on the motivation

In summary, our desired contribution to the current state-of-the art BEV transformation models is to add and ensure a certain robustness in situations of bad weather affecting visibility. We demonstrated that the commonly used training data does not emphasize on these scenarios specifically, even though statistically, they are the most prone to incite traffic

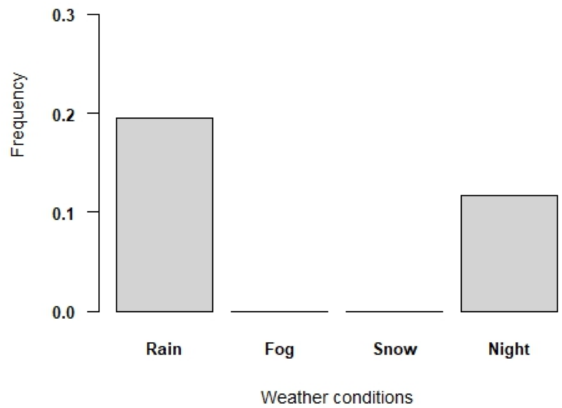

Figure 3: Adverse weather data frequency in Nuscenes

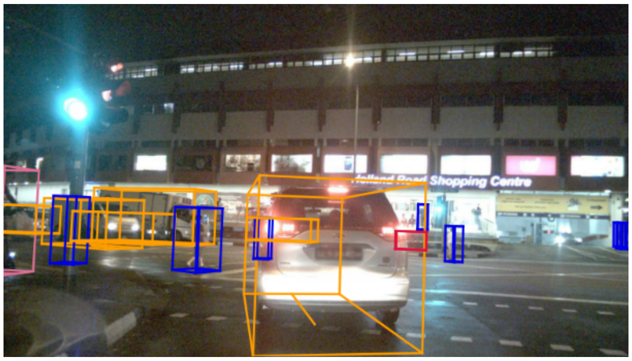

Figure 4: Nuscenes sample with description containing rain as label

accidents, with and without human drivers. One of the different approaches considered for this contribution is virtually adding rain-droplets and rainfall onto the images of the existing dataset and then re-training the existing model. Comparing the previous models accuracy on clean and rainy pictures and the re-trained models accuracy on clean and rainy pictures would serve us as a comprehensive method to evaluate our contribution.

3 Experiments and Evaluation metrics

In a first step, the existing and pre-trained model presented in the paper should be tested on the Nuscenes dataset and the stated accuracies verified and confirmed. The next step would be filtering out the data collected in rainy (and foggy and snowy) conditions, to compare the performance of the model in those situations. Moreover, the entire dataset, or at least a part of the data collected in good weather conditions, augmented with generated droplets on the images would be tested and evaluated on the original model; in the aim to analyze the data augmentation method and it's impact on the performance. Here again, the two evaluations on the original dataset, with and without filtering out good weather conditions, serves as a comparison metric to understand the effectiveness of the data augmentation.

The second step would be to re-train the given model, using the augmented dataset which should heavily represent adverse weather conditions. The resulting model should again be evaluated with the original dataset, with and without filtering out good weather conditions.

The expected and desired final conclusion should show that firstly, in context of good weather, the performance is unaffected. Secondly, the new model should show better performance on images containing bad weather, especially rain droplets.

4 Contribution overview

Effectively, we were not able to complete our desired experiment. We successfully trained the original model on the Nuscenes dataset, confirming the accuracies stated in the paper. This step was necessary for our understanding of the overall functioning of the provided project, but also accomplished the first part of our experiment. Unfortunately, we were lacking all sorts of visualisation classes and did not successfully filter out the specific data needed for the second experiment. However, we suceeded in augmenting the given data to add rain into the pictures, using GANs from the paper "Rain Rendering for Evaluating and Improving Robustness to Bad Weather". The rendered rain was approved visually and we proceeded to render larger amounts of data with that model.

Finally, we could not work out how to feed this new dataset, or even any other differently formatted data, other than the original Nuscenes data, into the given model, neither for training, nor for testing purposes. Therefore, the evaluation of our desired contribution could not be conducted and we have to conclude this project with a desire to continue and validate our hypothesis.

5 Conclusion

This project in the context of the Deep Learning for Autonomous Vehicles class, given by Alexandre Alahi at EPFL, gave us a deeper insight into real world problem statements, experimental approaches aiming for improvements and all sorts of technical difficulties that we had to encounter. In a more general way, we learned to conduct an unconstrained and realistic project and how to understand and reuse previous work. It leaves us hungry and motivated for more and we hope to, one day, be able to contribute and advance research and technology. We want to thank our professor and supervisors for their endless help and guidance and specifically Yuejiang Liu for his patience, support and constant kindness.