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Analysis of LiDAR and Camera Data in Real-World Weather Conditions for Autonomous Vehicle Operations

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Abstract

Autonomous vehicle technology has the potential to improve the safety, efficiency, and cost of our current transportation system by removing human error. With sensors available today, it is possible for the development of these vehicles, however, there are still issues with autonomous vehicle operations in adverse weather conditions (e.g. snow-covered roads, heavy rain, fog, etc.) due to the degradation of sensor data quality and insufficiently robust software algorithms. Since autonomous vehicles rely entirely on sensor data to perceive their surrounding environment, this becomes a significant issue in the performance of the autonomous system. The purpose of this study is to collect sensor data under various weather conditions to understand the effects of weather on sensor data. The sensors used in this study were one camera and one LiDAR. These sensors were connected to an NVIDIA Drive Px2 which operated in a 2019 Kia Niro. Two custom scenarios (static and dynamic objects) were chosen to collect sensor data operating in four real-world weather conditions: fair, cloudy, rainy, and light snow. An algorithm developed herein was used to provide a method of quantifying the data for comparison against the other weather conditions. The results from these performance algorithms show that sensor data quality degrades by an average of 13.88% for static objects and 16.16% for dynamic objects while operating in these conditions, with operations in rain proving to have the most significant effect on sensor data degradation. From this study, it is hypothesized that advancements in data processing algorithms can improve the usability of this degraded data. In future work, we seek to explore fault-tolerant sensor fusion algorithms that can overcome the effects of adverse weather.

Introduction

Autonomous Vehicles (AVs) are capable of drastically changing the way people get to and from their destinations on a global scale. These major changes will result in benefits to multiple demographics of society. One example is by providing a means of transportation for people with disabilities allowing them to be more independent in society, increasing their quality of life [1, 2]. Another impactful application for AVs which will shape the future of transportation are shared autonomous-vehicles (SAVs). Fagnant and Kockelman [3] predict that the number of vehicles on the road could be reduced tenfold by using SAVs. A transition to SAVs would have many beneficial outcomes such as, fewer cars on the road leading to less congestion and lower emissions, lower travel costs as people will share vehicles, and an increase in quality of life and productivity for people [4, 5].

AVs consist of a few major subsystems that work collectively to achieve self-driving: perception, localization, path planning, vehicle control, and system management. Perception allows the vehicle to "see" it's environment using sensors. The most common sensors are LiDAR, camera, radar, and ultrasonic, although there are some studies suggesting the investigation of others like ground-penetrating radar [6] and infrared [7]. This subsystem is essential as it is how AVs gathers information about their environment and it provides the input to the autonomous operations. Localization gives the vehicle a sense of where it is in the world, typically using GPS, but can also be done with LiDAR [8]. Without localization, AVs would have no sense of direction or where they are located, meaning it could never plan a route to follow. Path planning is done using the outputs of the perception and localization systems to determine where the vehicle should go. Vehicle control tells the actuators what to do in order to reach the path planned by controlling the steering, brake, and throttle. Vehicle control is typically done with a PID controller, but other methods (i.e. Linear Quadratic Gaussian (LQG), Model Predictive Control (MPC), etc.) have been investigated. The system management subsystem ensures safe operations by monitoring the functionality of all subsystems. These systems work together to achieve the ability for autonomous operations. A visual of this network can be seen in Figure 1.

Current AV technology lacks the ability to operate under certain inclement weather conditions (e.g. snow-covered roads, heavy rain, fog, etc.) with the same performance as operations in fair weather [10, 11]. The reason for the decrease in AV performance under these conditions is the degradation

FIGURE 1 Overview of the systems involved in AV operations, indicating the system of interest for this study. Image received from [9].

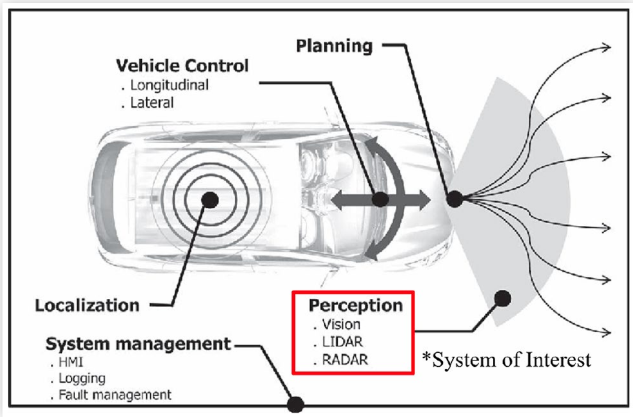


FIGURE 2 Examples of inclement weather conditions for top left) snow-covered roads, (top right) fair, (bottom left) heavy rain, and (bottom right) heavy fog.

of sensor data [12] via the perception system. As AVs rely entirely on the perception system to provide accurate data to the path planning and control systems, it is essential for the perception system to function effectively in these cases. Without understanding how weather affects this data, it would be nearly impossible to develop algorithms to process this data correctly for proper path planning and vehicle control [13].

The system of interest for this study is the perception system. This is considered the most important system since all other systems rely on the quality of the incoming sensor data to achieve precise and safe autonomous driving. Just as humans rely on their senses to traverse, AVs need to receive accurate information from their surroundings to do the same. This information received is the data coming from the various sensors. If this data gets affected by different operating conditions (e.g. weather), then the vehicle has a difficult time seeing its environment, leading to potential failures.

Similar work has been previously done in multiple other studies in which weather affects on the perception system were studied. Zang et al. setup three scenarios in a simulation and analyzed received signal power and detection range for LiDAR, radar, and camera [14]. Rasshofer et al. conducted analyses of weather affects on LiDAR sensors via simulation [15]. Leudet et al. trained Deep Neural Networks (DNNs) using a simulation for operating in different weather scenarios [16]. These studies perform in-depth analyses on affects of weather on AV sensors, however these studies used either simulation or controlled testing environments to collect their data. It is important to collect data from real-world testing environments if AVs are to be deployed in the real-world. While testing in simulation and controlled environments add to the knowledge and provide methods of improving the systems, they do not suffice for real-world deployment [17]. One of the focuses for this study was to perform the tests during real-world conditions.

Inclement weather conditions within this paper are defined as any real-world environmental condition that potentially cause unintended changes to sensor data. These conditions include heavy rain, snow covered roads, heavy fog, etc. (see Figure 2). However, It is not just these severe weather conditions that take a toll on the sensor data. Operating in conditions like these require more focus on the perception, path planning, and vehicle control systems, but the focus for this study is the perception system. To achieve a well-rounded idea of how the perception system becomes affected in any type of operating condition (severe and/or low-intensity conditions), the focus of this paper is to study the low-intensity weather conditions. These conditions are fair, cloudy, rainy, and light snow. The camera images in Figure 5 show the different conditions in which data was gathered. The tests done in this paper will also be conducted in real-world scenarios without an enclosed, controlled environment. This is done to remove assumptions made about the characteristics of certain weather conditions.

The purpose of this study is to collect sensor data from a LiDAR and a camera in four real-world, low-intensity weather conditions: fair, cloudy, rainy, and light snow. The collected data was analyzed visually by comparing incorrect classifications of the NVIDIA Drivenet classification script and graphically by plotting the average number of LiDAR hit points to understand what the variation in the data was between each condition. These comparisons were then used to predict what techniques can be followed to develop a more robust data processing algorithm when operating in inclement weather conditions. There will be more discussion of these techniques in the conclusion section.

Methodology

The tests in this study were setup to collect uninfluenced, real-world data. There was no controlled environment or simulation for data collection in this study, it was desired to test in conditions which were not subject to a controlled environment or simulation since AVs do not operate in these environments. This allows for the data to be subject to practical, real-world, weather conditions. Additionally, these tests were all conducted under low-intensity conditions, so no severe weather data is included. This was intentional as one goal of this research is to begin the understanding of the affects of weather on the perception system with low-intensity weather conditions before testing in severe conditions.

Test Setup: Hardware

The hardware components used for testing include a power inverter, an NVIDIA Drive Px2 for computation, a 2019 hybrid Kia Niro as the vehicle, a Sekonix NA 1262 camera, a Slamtec RPLIDAR A2 LiDAR, a 4ft tall dummy human (static test object), and a human for dynamic object testing. The inverter was installed onto the 12V battery of the 2019 Kia Niro which was used to power the NVIDIA Drive Px2 (NDPx2) that acted as the processing unit for data collection (see Figure 3 for system setup). The camera use GMSL protocol and was plugged into the NDPx2's GMSL camera ports. The LiDAR was connected through a USB to the ports of the NDPx2. The NDPx2 ran both the LiDAR and camera data collection software while storing the data in an external hard drive. The data was later analysed using a different desktop PC. Figure 3 shows the NDPx2 and inverter system installed in the trunk of the Kia Niro.

Two obstacles were used for testing, one static and one dynamic. The static obstacle was a 4ft tall human dummy, while the dynamic obstacle was a human walking at about 2.5mph from left to right of the sensor setup at the same distance away from the sensor setup as the dummy (5ft, 10ft, and then 15ft). The purpose of having a static and dynamic obstacle is to observe if the weather affects static and dynamic objects differently. Driving operations contain both static and dynamic objects so it is critical to gather data with both objects in the scenario each time [18].

The camera was chosen for its compatibility with the NVIDIA Drive Px2 development environment. The LiDAR was chosen because it is supported in ROS (Robotic Operating System) and it is a low cost LiDAR. The software setup used for these sensors are discussed in more detail in the next section, 'Test Setup: Software'. Important specifications of the camera and LiDAR can be seen in Table 1.

Test Setup: Software

Specific software was used to operate and record the sensor data. The NVIDIA Drive Px2's operating system was flashed

FIGURE 3 Inverter and NVIDIA Drive Px2 installed in the trunk of the Kia Niro.

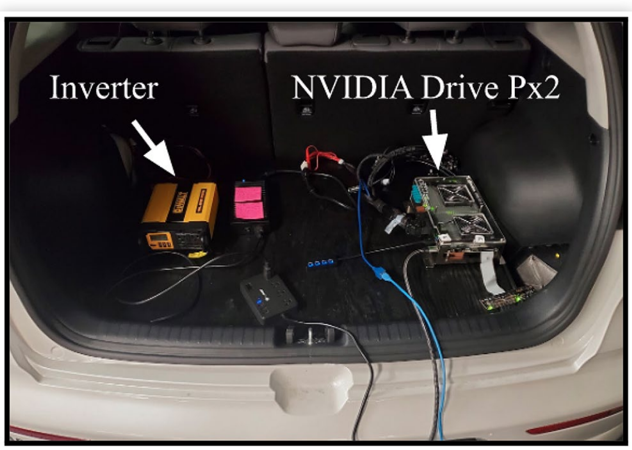


TABLE 1 Sensor specifications.

Sensor	Camera	LiDAR
Name	Sekonix NA 1262	Slamtec RPLIDAR A2
HFOV	120°	360°
Samples per Time	30 fps	360 scan/s
Range	-	18 m

onto the system using the NVIDIA's SDK manager from a host machine. The operating system is Ubuntu 16.04, but comes preloaded with example files from NVIDIA which allow for running various operations with a camera (object detection, free space detection, etc.) [19]. The NVIDIA Drivenet example file which ran object detection and classification algorithms was used for the camera during testing. The file used was the 'sample_drivenet' binary file located in the SDK. This script was written in C++ and classifies objects for driving (e.g. signs, people, cars, traffic lights, etc.) using the live camera data. Running this script instead of just recording video allowed for an observation of whether the classification algorithms become affected by these weather conditions. A comparison of the classification accuracy between the conditions was done and will be shown in the 'Results' section.

The LiDAR was run by using an open source ROS (Robotic Operating System) driver developed by the LiDAR manufacturer, Slamtec, made available via GitHub [20]. This repository was beneficial as it provided a necessary driver to run the LiDAR which provided more time to be spent on the research instead of developing a LiDAR driver. Using ROS provided additional benefit as ROS's data collection functionality was utilized to collect the LiDAR data which could later be rerun for analysis. The ROS function used for data collection and data replay is called 'rosbag'. To collect data on all topics (ROS's message sending terminology) being published while running the LiDAR driver was 'rosbag record -a'. This stored all the topics into a file that was rerun on the desktop PC for data analysis.

Test Procedure

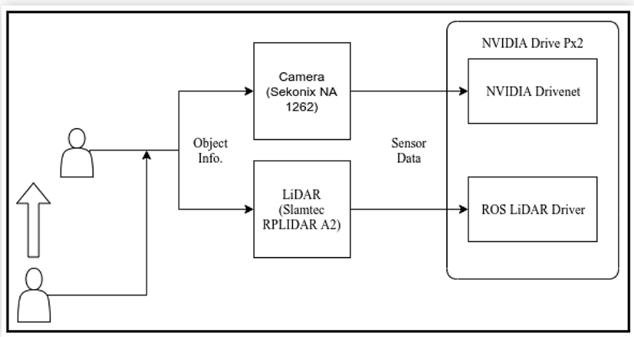
The tests were conducted in Kalamazoo, Michigan in October 2019. Testing was conducted in fair, cloudy, rainy, and light snow weather conditions. The same testing procedure was followed for each condition. The sensors were placed on a cart at a height of 3ft. This height placement was important as it needed to be lower than the 4ft tall dummy so the object was in the same plane as the LiDAR. The Kia Niro was parked in the WMU MCO lab with the backend facing the garage door so testing could be done outdoors. This allowed for access to outdoor weather while keeping the sensors dry. Done for each weather condition, these steps were followed for data collection:

1. Place the human dummy 5ft away from the sensor setup.
2. Run the LiDAR and camera scripts and wait 30 seconds.
3. Introduce dynamic obstacle, crossing the scene from left to right.

4. Stop the scripts. Repeat for obstacles placed at 10ft and 15ft.

A layout of the testing process is shown below. Two objects are setup in the test environment, which one is a human dummy (static object) and the other is a person walking across the sensors field of view from left to right (dynamic object). The object data is captured by the camera and LiDAR. The sensors send the sensor data to the NVIDIA Drive Px2. The NVIDIA Drive Px2 was running the NVIDIA Drivenet to overlay object detection and classification on the camera data while also running the ROS LiDAR Driver to run the LiDAR while also collecting the data using 'rosbag'.

FIGURE 4 Overview of the testing procedure showing flow of data.



Results

The LiDAR and camera data visualizations can be seen in Figure 5. Rviz was used for the LiDAR visualization after the data was collected. Rviz is a data visualization tool within ROS that gives the user the ability to look at either real-time data or data gathered in the past by replaying the bagged data which was collected using 'rosbag'. Rviz works by plotting the LiDAR data points in which the two variables are angle and distance. The camera images have the NVIDIA Drivenet classification output overlay on-top of the images.

LiDAR Analysis

Quantification of the LiDAR data was needed to compare the data collected in different weather conditions. This was done by calculating the average number of hit points received from the static and dynamic objects. A hit point is when the LiDAR receives a return of a transmitted signal. These are visualized as the red dots seen in the LiDAR visualizations in Figure 5 which are plotted at the hit point value (distance) with the angle of the LiDAR's rotation in which the hit point occurred. The number of hit points was calculated by running the LiDAR 'rosbag' data for each test and adding up the total number of hits on the static object in each single revolution of the LiDAR. For the static object, only the range of angles in which the object was placed in the view were observed (-10° to 10°). The use of the average of hit points from each object was done in order to quantify LiDAR data so a proper comparison of operating in fair, cloudy, rainy, and light snow weather

FIGURE 5 Visualizations of the LiDAR (left) and Camera (right) data for (a) fair, (b) cloudy, (c) rainy, and (d) light snow weather conditions

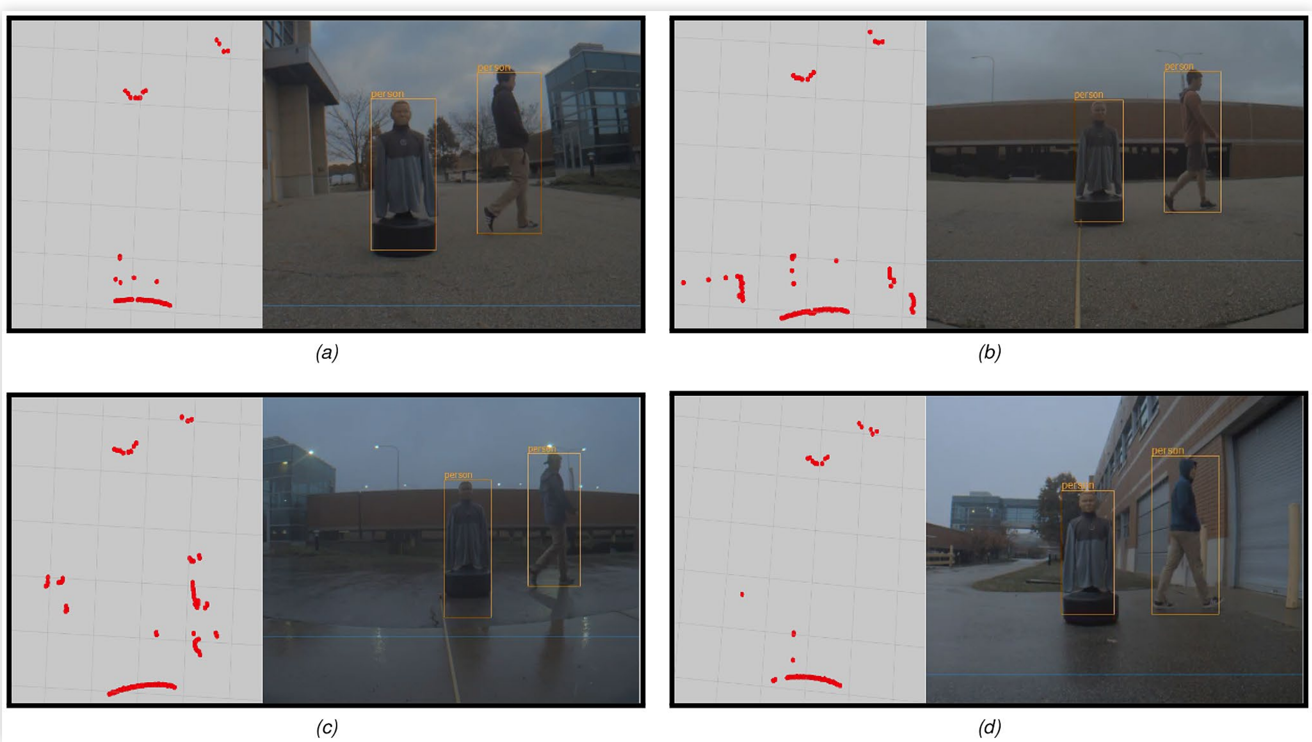


FIGURE 6 Average hit points of the static object.

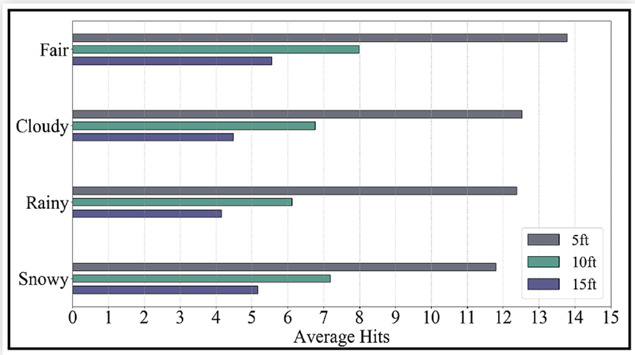
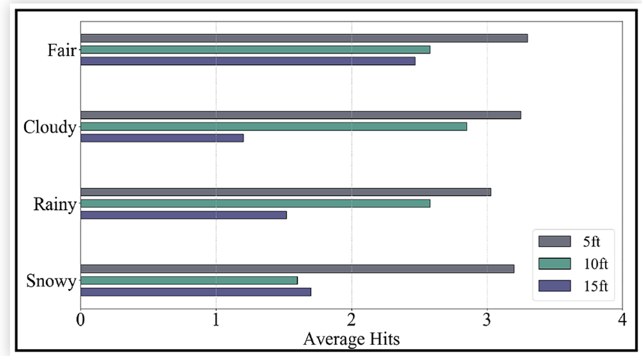


FIGURE 7 Average hit points of the dynamic object.



conditions can be done. The average was calculated using equation (1).

$$\%\ reduction = \left(r_f - r_i\right) / r_f * 100 \quad (1)$$

Equation (1) was used to calculate the percent of average hit reduction for the three inclement weather conditions, where r_f is the average number of hits between each testing distance for the fair weather condition, $r_f = \sum_{n=1}^{3} h_n$. h_n is the average number of hits for each testing distance, n (5ft, 10ft, 15ft). The total average for each inclement weather condition r_i, was calculated the same way.

The fair weather condition was used as a baseline to compare the effects of weather on the other three conditions. The percentages of average hit count reduction on the static object were calculated to be 12.93%, 17.1%, and 11.6% for the cloudy, rainy, and light snow conditions, respectively. The values received are interesting as it was expected for snow to have the highest average hit deviation from the fair weather conditions, however, the LiDAR actually was able to receive more hits in the light snow condition than any of the inclement weather conditions. This may be caused because the snowy environment in which the tests were conducted were in very light snow, not causing much of a deviation from the fair condition.

The percentages of average hit count reduction on the dynamic object were calculated to be 12.59%, 14.39%, and 21.8% for the cloudy, rainy, and snowy conditions, respectively. In this case, the light snow condition had the most effect on the hit returns of the dynamic object. From Figure 7 it is clear that the light snow condition was effected most once the distance of the objects was more than 5ft. The 10ft average hit returns of the snow condition was about 1 hit less than the cloudy and rainy condition, this is the main test that led to the major increase in hit reduction for the snowy condition.

Camera Analysis

The camera data was analyzed by comparing the accuracy of the NVIDIA Drivenet classification algorithms between weather conditions. The accuracy in the videos from each condition was found by counting the number of inaccurate classifications through each test. These inaccurate classifications included things like classifying a light pole as a human, a human face as a traffic light, a wall as a car, etc. A few examples of inaccurate classifications can be seen in Figure 8. Having inaccurate classifications like these while operating an AV can be a major flaw as it can lead to unintended vehicle reactions. Since the path planning system relies on the perception system to provide accurate information about the environment to give the control system proper commands for safe control outputs. It is necessary to minimize classification errors for safe self-driving in these weather conditions so the vehicle does not take unsafe actions.

After reviewing the data from all four conditions, the total number of inaccurate classifications was found. These values can be seen in Table 2. It was found that fair weather had the least amount of inaccurate classifications while light snow conditions had the most. Even though fair weather had the least number of incorrect classifications, it still had more than expected for these tests, it is assumed that is from the testing environment not being a driving environment, so the DNNs (Deep Neural Networks) trained were not familiar with this environment, making some incorrect classifications.

FIGURE 8 Examples of inaccurate classifications of the NVIDIA Drivenet.

TABLE 2 Inaccurate classifications for each condition.

Condition	No. of Inaccurate Classifications
Fair	6
Cloudy	7
Rainy	8
Light Snow	9

Once the camera was introduced to more inclement weather conditions, the ability of the classification algorithm to be as accurate as the fair condition was lower. The top right image in Figure 8 actually shows a snowflake being classified as a road sign, indicating that the elements of weather play a role in. Adding more noise to the image (in this case, snowflakes) gives more room for error in the classification algorithm. Since it is unknown how the DNN model was trained for the NVIDIA Drivenet, it cannot be known how improvements can be made to this system directly, but it can be assumed that training the DNNs in more adverse weather conditions, it should have less error.

Conclusion & Discussion

This study shows that data becomes affected while operating in inclement weather conditions. While these weather conditions are not severe, there is sensor data degradation of 13.88% for the static object and 16.16% for the dynamic object, averaging to a total decrease of 15.07% in the average hit count for LiDAR data. Additionally, an overall increase of inaccurate classifications of camera data running the NVIDIA Drivenet classification tool were observed.

Methods to improve the usage of the LiDAR data would be to implement more robust data processing techniques or more robust sensor fusion algorithms. Since the LiDAR returns were still received for each condition, the data is not completely degraded. Further data processing techniques can be used to increase the data quality such as filtering static objects and dynamic objects into separate categories, using DNNs for object classification of LiDAR data, object tracking, etc. By applying these techniques in fault-tolerant sensor fusion algorithms, proper object detection and classification will be achieved to provide accurate information about the vehicle environment to provide the path planning system high quality data.

For the camera classification improvements, it is needed to either develop a different classification tool which will be more robust in different operating conditions, or conduct additional training of the classification tool to lower the incorrect classifications in these different weather conditions. A new tool can be developed based on NVIDIA Drivenet's trained models, or investigation of different Convolution Neural Network architectures can be done to choose the best type of DNN architecture for AV applications which would involve development.

For future work, there will be additional data collection done in more severe weather conditions utilizing higher performing LiDARs, additional cameras for a 360° FOV around the vehicle, and inclusion of radar sensors. It is desired to use a vehicle with this sensor suite to drive in city and highway settings for diverse drive-cycle data collection. One of the main goals of this series of researches is to collect data in real-world scenarios, hence, various drive-cycles and variations of weather conditions. Additionally, more research is to be done on different sensor fusion algorithms to detect objects using this data in adverse weather.

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Definitions/Abbreviations

AV - Autonomous Vehicle

DNN - Deep Neural Network

LiDAR - Light Detection and Ranging

HFOV - Horizontal Field of View

FOV - Field of View

FPS - Frames Per Second

SAV - Shared Autonomous Vehicle

NDPx2 - NVIDIA Drive Px2

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