Herkansing

Improving the reliability of AI object detection models in autonomous vehicles under adverse environmental conditions

Project 7/8

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30-6-2024

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Abstract
Autonomous vehicles (AVs) promise safer and more efficient transportation but face challenges in adverse weather conditions, which affect their sensing abilities. This research aims to enhance the robustness of AI models in AVs under such conditions, focusing on sensor fusion and data augmentation techniques. The primary stakeholders of this research are the RDW, which hosts the Self Driving Challenge, and future student teams participating in this competition. The methodology involves a literature review of different sensor fusion and data augmentation strategies. Sensor fusion integrates data from multiple sensors to improve perception, while data augmentation creates more diverse training datasets for better performance in different weather types. The study found that multi-sensor data fusion and training models with real-world all-weather images significantly improve detection performance in adverse weather conditions. However, challenges like processing speed and hardware costs remain. Recommendations include implementing both sensor fusion and data augmentation to develop more reliable AI models for AVs. Also, balancing model complexity and real-time processing needs is recommended to ensure the best performance.

Introduction
The core system behind autonomous vehicles (AVs) is perception and sensing of the environment. AVs are able to sense their surroundings and navigate safely with little to no human help. These vehicles could benefit society in many ways, like improving the transportation systems. Inevitably, these vehicles have some issues, the perception and sensing ability in adverse weather conditions decline rapidly, making AVs a potential danger on the roads.

According to the World Health Organization, approximately 1.19 million people die each year as a result of road traffic crashes, and 20 and 50 million people suffer non-fatal injuries [1]. Two thirds of these fatalities occur among people of ages between 18 and 59 years [1]. One of the many reasons for dangers on the road is adverse weather conditions. On average, global precipitation on land occurs 8% of the time [2]. It’s a fact that the risk of traffic accidents in rainy conditions is 70% higher than normal [3]. Improving the reliability of AI object detection models in AVs under adverse environmental conditions is essential for ensuring safe autonomous transportation.

This research is particularly significant for stakeholders such as the RDW, which hosts the Self Driving Challenge. They could potentially benefit a lot from the results of this research, and of course the Self Driving Challenge itself. Future student teams participating in this competition could also greatly benefit from the results of this research since it provides a good starting point when developing AI models for AVs.

My team and I take part in the Self Driving Challenge, a competition that involves developing a self-driving vehicle. During the training and testing of AI models for our AV in the self-driving challenge, we encountered significant issues with object detection under different lighting conditions. This experience led us to speculate that adverse weather conditions could similarly impact the performance of AI models. Recognizing the importance of this issue, we started searching for methods to improve the robustness of AI object detection models in autonomous vehicles under such conditions.

This research explores the current limitations and challenges faced by autonomous vehicles, specifically focusing on the impact of adverse weather conditions on the perception and sensing abilities of the vehicles. The goal is to review existing techniques and algorithms that enhance the robustness of AI models in AVs, with a focus on sensor fusion and data augmentation. This study aims to contribute to the development of safer autonomous driving systems by answering the following question: How can the robustness of AI object detection models in autonomous vehicles be improved to ensure reliable performance under adverse environmental conditions? The related sub questions are: What are the limitations and challenges associated with current approaches to improve the robustness? What are the specific adverse environmental conditions commonly encountered by autonomous vehicles, and how do they affect the performance of AI object detection models? What are the existing techniques and algorithms for improving the robustness of AI object detection models in adverse environmental conditions? How can data augmentation strategies be effectively utilized to improve the reliability of object detection models in adverse environmental conditions? How can sensor fusion methods contribute to the robustness of AI object detection models in adverse environmental conditions? What are the trade-offs between speed, accuracy and robustness in the development of AI object detection models?

Methodology

This research employs a mixed-method approach to investigate methods for enhancing the robustness of AI object detection models in AVs under adverse environmental conditions. The research is structured to answer specific research questions concerning the effectiveness of sensor fusion and data augmentation techniques.

The research begins with a literature review to establish a foundational understanding of current limitations and challenges faced by autonomous vehicles in adverse weather conditions. This section involves gathering relevant literature from academic journals and conference papers. The focus is on identifying common adverse environmental conditions that impact AI object detection models in AVs and understanding the specific problems these conditions cause.

The literature review will focus on recent studies and advancements in sensor fusion and data augmentation techniques relevant to AVs. Databases such as IEEE Xplore, Google Scholar, and ScienceDirect will be used to gather peer-reviewed articles and papers. These sources were chosen, because they provide reliable and accurate information.

1. Current limitations and challenges in autonomous vehicles

Autonomous vehicles have fascinated a lot of people, promising effortless and safe transportation in the future. However, despite significant progress, AI-driven vehicles still encounter various restrictions and obstacles that hinder their widespread adoption. Certain limitations can be addressed with improved technology, but others are simply unavoidable. [4]

1.1 Common adverse environmental conditions

AVs encounter a range of different environmental conditions that can have significant negative impact on their performance. The most common adverse conditions include poor lighting (nighttime driving, tunnels, and shadows), bad weather (rain, fog, snow, and ice), and physical obstacles (debris, and pedestrians) [5]. Situations like these form unique challenges for the algorithms used in AVs.

1.2 Impact on AI object detection models

AI object detection models used in AVs are particularly sensitive to these conditions. Poor lighting leads to reduced visibility, which causes the object detection models to miss or misclassify objects. For example, shadows and dark environments could obscure objects or distort their appearance, making it difficult for models to perform optimally. Inclement weather conditions, such as rain and fog, can introduce noise in sensor data, which reduces the accuracy of object detection algorithms. Snow and ice can obstruct lane markings, road signs, and lots of other objects, leading to challenges in the navigation on the AVs. Physical obstructions and dynamic environments make the detection process more difficult by introducing unexpected variables that must be interpreted by object detection models [6]. These factors call for the development and implementation of robust and adaptive AI models capable of maintaining high performance regardless of the environmental challenges.

2. Techniques and algorithms for enhancing robustness

The key component of autonomous vehicles are sensors. AVs rely on various types of sensor technologies to perceive the environment and make logical decisions based on the gathered information, much like humans do. Under ideal conditions, these sensors provide enough information for autonomous transportation. However, there are several challenges in real-world application. One of such is adverse weather conditions. The significant impact of adverse weather on autonomous driving has spurred the development of various solutions. The widespread adoption of machine learning and the rapid advancement of powerful sensors have led to the integration of multiple sensors to reduce weather effects.

AI models in AVs analyze data from various sensors to perceive and understand the vehicle's surroundings. By combining the strengths of multiple sensors through sensor fusion, AI models can significantly improve their performance in adverse weather conditions.

2.1 Multi-sensor data fusion

While sensor technology has made impressive advancements, AVs face a major challenge when relying on just one type of sensor in adverse weather conditions. Every sensor has their own strengths and weaknesses. Cameras, for example, perform well in well-lit environments but struggle in fog, rain, and low-light situations. LiDAR, on the other hand, can create detailed 3D maps but can be disrupted by heavy snowfall. Similarly, radar may have difficulty distinguishing objects in heavy rain due to reflections. Without additional sensors to compensate for these limitations, a single bad weather event can make the entire object detection system unreliable, potentially rendering the AV dangerous to its surroundings. Moreover, completely disregarding additional sensors is not a safe option. Without any sensors beyond cameras, AVs would be practically blind, making safe operation impossible. Thus, one must consider integrating different types of sensors to assist the AI object detection model in AVs to perceive the surroundings and make suitable decisions. [5]

It is evident that a single sensor alone cannot ensure safe navigation through adverse weather conditions. However, the combination of multiple sensors could improve the perception capabilities as demonstrated by the improved point cloud resulting from LiDAR and camera fusion in Figure 1.

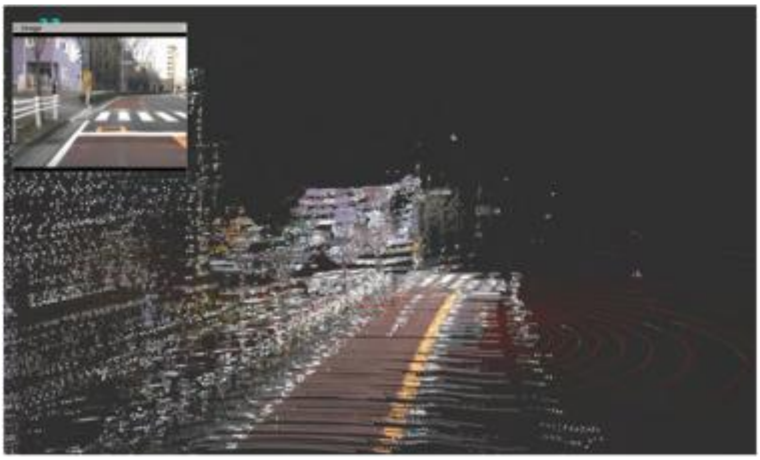

Figure 1. Fusion of 3D point cloud data and camera imagery. [5]

The redundancy of sensors ensures that AVs maintain situational awareness, even when one sensor performs unfavourable. AI models trained with fused sensor data can achieve higher accuracy in object detection [5]. For example, integrating visual data from cameras with depth information from LiDAR helps the model to better differentiate objects and understand the environment, even in poor weather conditions [5].

LiDAR and radar data can be combined to produce detailed and accurate maps of the environment. AI models can then use these maps to navigate more effectively, avoiding obstacles and maintaining a safe path even when visual information from cameras is obscured by rain or snow [5].
AI models can also be designed to adapt dynamically based on sensor input. For instance, during heavy rain, the model can rely more on radar and LiDAR data and less on camera data, ensuring that the AV's decision-making process remains reliable [6].

2.2 Data augmentation strategies

Another method for improving the performance of AI models in adverse weather is data augmentation. A study conducted by Gupta et al. used the Berkeley Deep Drive BDD100K dataset for training object detection models. Various weather augmentation methods were used on the images. These models were then divided in five image sets based on their augmentations. Lastly, the DAWN and Udacity datasets were used to test the trained models. [6]
The study found that training models with real-world all-weather images resulted in the best overall detection performance across all weather conditions [6]. Moreover, it was found that models trained on clear weather images achieved the highest accuracy of positive predictions [6].
These results suggest that incorporating real-world weather diversity into the training dataset is crucial for robust object detection in diverse weather conditions. However, the study also found limitations with applying denoising methods to test images before object detection. Often, these methods resulted in a decline in overall detection performance compared to using the original images containing noise [6]. While some denoising algorithms might improve specific metrics like precision in certain weather scenarios, the overall impact on detection performance was negative [6].

3. Trade-offs in AI model development

Developing robust and reliable AI models for AVs is a fascinating, yet complex challenge. Many factors impact the robustness of AI models, of which some are unavoidable. When developing AI models for automotive uses, certain trade-offs have to be made.

3.1 Accuracy and generalizability of models

Training AI models for AVs can be a challenging task. It often requires finding the right balance between accuracy and generalizability. While it's important to have highly accurate models trained on large datasets which contain ideal weather conditions, these models may struggle when faced with real-world scenarios, where fog, rain, snow etc are common occurrences. Similarly, focusing on training models with datasets that contain solely bad weather data can improve performance in those conditions, but might lead to reduced performance in good weather. So a trade-off in accuracy and generalizability of AI models is inevitable.

3.2 Complexity and speed of models

Complex AI models have the potential to achieve better accuracy. However, it's important to note that these models also demand more computational resources to function properly. When it comes to AVs, making decisions in real-time is extremely important. While a simpler model trained on a simpler dataset may allow for faster processing, it could potentially sacrifice accuracy, especially in challenging weather conditions where detecting objects with more detail is crucial.

3.3 Sensor fusion and increased costs

Sensor fusion enhances the perception system of autonomous vehicles as discussed before. However, implementing sensor fusion can be costly due to the additional hardware needed. Although, relying on fewer sensors reduces the cost of the vehicle, it also reduces the reliability of the AV. In this case, finding a balance between relying on fewer sensors and integrating sensor fusion is a key trade-off with major impact on the reliability of AVs.

Results

This research aimed to enhance the robustness of AI object detection models in autonomous vehicles (AVs) under adverse environmental conditions, focusing on sensor fusion and data augmentation techniques. The findings from the literature review provide several key insights into the impact of adverse conditions on object detection, the effectiveness of multi-sensor data fusion, and the role of data augmentation.

First, the research highlighted that adverse weather conditions such as rain, fog, snow, and poor lighting significantly impair the performance of AI object detection models. These conditions introduce noise and reduce visibility, leading to a higher chance of missed or misclassified objects.

Multi-sensor data fusion proved to be an effective method to improve the robustness of AI models in adverse conditions. The integration of data from different sensors, each with its strengths and weaknesses, provides a more complete and reliable perception of the environment.
Also, dynamic adaptation of AI models to prioritize certain sensors based on current weather conditions ensures consistent performance. For instance, during heavy rain, models can put more emphasis on radar and LiDAR data and less on camera data.

Data augmentation also proved valuable for improving AI model performance in diverse weather conditions. Expanding training datasets to include a variety of weather scenarios made the models more resilient. Models trained with real-world all-weather images performed best across various conditions. Data augmentation using weather-specific modifications, such as adding rain or fog effects to training images, enhanced model robustness. However, applying denoising methods to test images before object detection often led to reduced performance.

Additionally, the research looked at some trade-offs which are to be considered in AI model development for AVs. It was found that balancing accuracy and generalizability is crucial. Models trained on large datasets with ideal weather conditions may struggle in real-world scenarios with adverse weather, and models trained on datasets containing solely adverse weather data may perform poorly in good weather conditions. Complexity and speed of AI models also pose a challenge. More complex models achieve better accuracy but require more computational resources which could affect real-time processing speeds. Lastly, the additional costs of hardware must be considered when deciding whether to implement sensor fusion.

Conclusion

Autonomous vehicles (AVs) promise us enhanced transportation safety and efficiency. However, their effectiveness is greatly challenged by adverse weather conditions, which easily affect their ability to perceive and sense the surrounding environment. This research aimed to answer the question: How can the robustness of AI object detection models in AVs be improved to ensure reliable performance under adverse environmental conditions?

The findings prove that relying on a single sensor type is insufficient for safe operation of AVs under various conditions. Each type of sensor has its own strengths and weaknesses. For example, cameras struggle in low-light environments, while LiDAR can be disrupted by snowfall, and radar can have issues in rainy weather. Combining data from multiple sensors through sensor fusion is crucial to improve the robustness of AI object detection models. This way the situational awareness of AVs can be ensured in all types of weather conditions.

Additionally, data augmentation strategies could be used to improve the robustness of AI models in adverse weather conditions. Strategies like implementing weather diversity in training datasets seems like a promising approach in enhancing model performance in various weather conditions. However, applying denoising methods to test images before object detection could lead to reduced performance, suggesting that some noise might help models to be more robust. Nonetheless, some challenges remain and seem inevitable, since they're caused by other factors. For example, trade-offs between model complexity and real-time processing capabilities are caused by hardware cost and processing speeds.

To answer the question of this research, the robustness of AI object detection models in AVs can be significantly improved through sensor fusion and data augmentation strategies. However, addressing trade-offs and technological limitations remains crucial for the development of safer and more reliable autonomous driving systems.

Based on the research and issues we encountered during training and testing of AI models for the Self Driving Challenge, we believe that sensor fusion and data augmentation should be utilized to improve our models. Sensor fusion must be utilized to prevent the issues caused by changes in lighting as mentioned before. In addition, data augmentation should also be implemented to develop a more general AI model that can operate reliably in different environmental settings, for instance on different tracks at different times of the day with dynamic weather. Furthermore, the model cannot be too complex since the AV needs real-time object detection capabilities. Lastly, we should strive to get the most out of the camera and LiDAR fusion, as these are the only sensors we have access to due to our limited budget.

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