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Strengthening Autonomous Vehicle Safety: An In-Depth Review of Deep Learning Techniques for Tracking in Challenging Weather Conditions

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A B S T R A C T

Ensuring accurate and reliable tracking for autonomous vehicles under adverse weather conditions is a critical challenge in the development of intelligent transportation systems. Severe weather, such as heavy rain, snow, fog, sandstorms, and dust, can significantly degrade sensor performance, particularly for cameras, leading to reduced visibility and an increased risk of accidents. Analysis on the impact of adverse weather conditions on image data from established datasets, including Vehicle Detection in Adverse Weather Nature Dataset and the Canadian Vehicle Dataset, which provide diverse scenarios where visibility is compromised is done. The effectiveness of various Deep Learning algorithms and neural network models helps in enhancing the robustness of autonomous systems under such conditions. The cutting-edge computer vision and machine learning techniques such as image enhancement, data augmentation, and specialized neural network architectures reduces the negative effects of adverse weather on sensor visibility, thereby improving the accuracy and safety of autonomous vehicles. The potential future directions for advancing autonomous vehicle systems in adverse weather conditions are showing the need for continuous innovation and real-world testing in this crucial area.

Keywords: *Autonomous vehicles, Adverse Weather Conditions, Intelligent transportation systems, Deep Learning Algorithms, Object Detection*

Objectives

- To Assess the impact of adverse weather on tracking systems in autonomous vehicles.
- To Survey deep learning models for tracking under challenging weather conditions.
- To Evaluate datasets featuring adverse weather scenarios for autonomous vehicles.
- To Compare tracking performance across various weather conditions.
- Identify future research directions for improving tracking in adverse weather.

1. Introduction

Adverse weather is one of the prominent threats related to the development and deployment of autonomous vehicles because it degrades performance drastically, especially for vision-based systems. Rain, snow, fog, and dust storms all have a presence that overshadows the objects and causes visibility to reduce, thereby affecting their ability to distinguish objects on cameras and other sensors. The paper focuses on such weather impact on image data employing established datasets such as Vehicle Detection in Adverse Weather Nature (DAWN) and the Canadian Vehicle Dataset (CVD) with diverse compromised-visibility scenarios. This work aims to enhance the robustness of autonomous vehicle systems in light of those conditions through the exploration of advanced deep learning algorithms and neural network models. Such methods include image enhancement, data augmentation, and even the design of the particular neural network used in the solution, for an estimate of mitigative effects on adverse weather factors that affect sensor visibility. The outcome would ideally be higher accuracy and safety, and more possibilities in the operation of self-driving automobiles in harsh conditions. This paper discusses potential future directions and research needed to achieve continuous innovation along with real-world testing. Solutions have to be developed in response to particular weather-related challenges.

2. Literature Survey

The paper[1] presents a deep learning model tailored for autonomous vehicles navigating the diverse weather conditions of Quebec. By incorporating sensor fusion and convolutional neural networks (CNNs) and YOLO V8, the model enhances object detection and classification in challenging environments such as rain, snow, and clear skies. It stands out for its high accuracy, making it effective across different weather scenarios.

The authors[2] propose a sliding window technique that merges data from radar and cameras to improve object detection accuracy in adverse weather, including fog and rain. This fusion helps reduce detection errors, enabling more reliable performance even in low-visibility conditions. This paper[2] explores a radar and camera fusion-based object detection model using a sliding window technique for enhanced accuracy in adverse weather conditions. By combining sensor data, the model reduces errors in detection and improves robustness in poor visibility conditions like fog and rain.

The research[3] proposes a deep learning model that combines inputs from multiple sensors like LiDAR, radar, and cameras to improve object detection under adverse weather along with using YOLO. The goal is to increase vehicle safety by using robust data fusion techniques to handle environmental challenges more effectively. This study proposes a deep learning-based object detection model that uses multiple sensor data to improve object detection for autonomous vehicles in adverse weather conditions. The model enhances safety by combining LiDAR, radar, and camera data to improve detection accuracy.

The comprehensive paper[4] examines both traditional and deep learning approaches to object detection for autonomous vehicles in difficult weather. The paper highlights the strengths and limitations of various methods and points out areas where future research is needed to enhance reliability and performance. It provides a comprehensive analysis of the advantages and limitations of each approach and discusses future research directions.

The study[5] introduces a cross-modality 3D multiobject tracking system that integrates LiDAR and camera data to handle object detection and tracking in adverse weather conditions. The system employs adaptive hard sample mining to focus on challenging samples and improve detection accuracy. This research introduces a system that fuses LiDAR and camera data for 3D multiobject tracking, specifically under harsh weather conditions. It utilizes adaptive hard sample mining to prioritize challenging scenarios, improving the system’s ability to detect and track objects in conditions like fog or heavy rain.

The paper[6] introduces a deep learning framework for vehicle detection and tracking in adverse weather conditions. It focuses on improving detection accuracy by integrating multiple sensor inputs and utilizing a convolutional neural network and YOLO to mitigate visibility challenges caused by rain, fog, and snow. This paper presents a deep learning framework designed to detect and track vehicles in poor weather conditions. By combining multiple sensor inputs, the system reduces the effects of visibility issues caused by rain, fog, and snow, resulting in improved accuracy for autonomous vehicles.

The study[7] focuses on improving 3D object detection for autonomous vehicles in snowfall conditions using LiDAR point cloud data. The authors propose an enhancement to existing detection systems that increases the accuracy of LiDAR-based detection under snowy weather. The authors focus on improving 3D object detection in snowy conditions by optimizing LiDAR-based systems. The proposed enhancements increase detection accuracy, making it possible to detect objects more reliably when snow might otherwise interfere with visibility.

The paper[8] examines the challenges caused by distribution shifts in object detection models when faced with adverse weather. The authors use probabilistic object detection methods to analyze how models perform under varying weather conditions and propose adjustments to handle distribution shifts effectively. This study explores how distribution shifts—changes in the data distribution—affect object detection models when operating in adverse weather conditions. By using probabilistic detection methods, the authors propose strategies to better adapt to these shifts, ensuring more consistent performance across varying weather conditions.

The paper[9] presents CrossFuser, a multi-modal feature fusion model that fuses sensor data from radar, LiDAR, and cameras to improve autonomous driving performance under unseen weather conditions. This approach enhances the generalizability of detection models in environments where weather conditions are unpredictable. CrossFuser is a novel approach that fuses data from radar, LiDAR, and cameras to improve the reliability of autonomous driving in previously unseen or unpredictable weather. By merging multiple data streams, the model offers better generalization, ensuring vehicles can respond effectively in unexpected weather situations.

The study[10] evaluates sensor performance and reliability for autonomous vehicles in adverse weather conditions. It monitors various sensor systems (camera, radar, and LiDAR) under rain, snow, and fog to identify which sensors perform best in different weather scenarios. This paper evaluates the performance of various sensor systems (camera, radar, and LiDAR) in challenging weather like rain, fog, and snow. By comparing their effectiveness, the study highlights which sensors are most reliable under different weather conditions, providing insights into optimizing autonomous driving technology.

The iDT system integrates detection and tracking of multiple pedestrians in urban driving environments, specifically focusing on low-observable pedestrians. The paper[11] highlights the system’s efficacy in urban environments with challenging weather conditions. The iDT system integrates detection and tracking of multiple low-observable pedestrians in urban environments, particularly under challenging weather conditions. This system is designed to handle urban driving scenarios, where accurate pedestrian detection is crucial for safe autonomous navigation.

The paper[12] explores the impact of fog on Time-of-Flight (ToF) LiDAR systems in autonomous vehicles. The authors provide a detailed analysis of how fog interferes with LiDAR performance and propose mitigation strategies for better accuracy. This paper Analyzes the performance degradation of ToF LiDAR systems in fog and Proposes strategies to mitigate fog’s impact on detection accuracy.

The paper[13] reviews the application of deep learning to adapt autonomous vehicle systems to different weather conditions. It provides an overview of methods used to ensure consistent detection and decision-making under varied weather scenarios. This paper Reviews deep learning techniques for weather condition adaptation in autonomous driving and Highlights methods to ensure consistent performance across various weather conditions.

The paper[14] focuses on how rain and fog impair the performance of obstacle detection systems in autonomous vehicles. The authors suggest ways to modify existing detection methods to make them more resilient to these weatherinduced challenges, enhancing the overall robustness of obstacle detection.This paper discusses the impact of adverse weather, specifically rain and fog, on the performance of obstacle detection systems in autonomous vehicles. It examines how sensor performance degrades in such conditions and proposes adjustments to improve detection robustness.

The study[15] introduces a method for 3D object detection using LiDAR point clouds, specifically focusing on adverse weather conditions. The authors propose a geometric information constraint that enhances the detection accuracy in poor weather environments, ensuring better recognition of objects like vehicles and pedestrians. It Proposes geometric information constraints for 3D detection using LiDAR and Improves object detection accuracy under adverse weather conditions

4. Methodology

METHOD[1]

VEHICLE DATASET

1) ROBOFLOW VEHICLE DATASET The RoboFlow Vehicle Dataset used in the study[1] consists of images with dimensions of 512 × 512 × 3, containing a total of 97,942 annotations across 11 classes. These include car, pedestrian, biker, various traffic light signals (red, yellow, green), and truck. The dataset was designed for object detection tasks and has a diverse set of images capturing multiple vehicle types in different conditions. No data augmentation techniques were applied to this dataset during the study. This dataset provides a solid baseline for testing the object detection model in relatively normal conditions.

2) THE PROPOSED CANADIAN VEHICLES DATASET (CVD) The Canadian Vehicles Dataset (CVD) was created specifically for this research, containing 10,000 images across 11 classes, which include a variety of vehicles and traffic objects. The dataset is built from video footage collected in Canadian streets under various weather conditions, ensuring the model’s ability to handle adverse weather scenarios. All images were manually annotated and resized to a uniform 512 × 512 resolution to maintain consistency with other datasets. CVD was used in combination with RoboFlow to train and evaluate models under real-world conditions.

ACQUISITION SYSTEM

The acquisition system for the Canadian Vehicles Dataset involved capturing video footage from vehicles driving through Canadian streets, with data collected across multiple weather conditions, including snow, rain, and fog. The vehicle used for data collection was equipped with cameras and LiDAR sensors to gather comprehensive environmental data. The camera captured street-level images from various angles, while the LiDAR sensors provided 3D point cloud data, offering a precise view of objects, even under reduced visibility. Data was collected while the vehicle traveled at an average speed of 40 km/h. The frames from the video were extracted at a rate between 2 to 10 frames per second, providing a balanced dataset of clear and weather-compromised images.

DATA PREPARATION AND PREPROCESSING

The video data captured by the acquisition system was processed using Python scripts to extract individual frames. These frames were then resized to 512 × 512 pixels to maintain uniformity across the entire dataset. The resizing was necessary to standardize the input dimensions for the deep learning models, which ensures consistent performance across different datasets. Images were stored in jpg format without applying any additional preprocessing techniques.

Manual annotation was performed on the extracted images to label objects such as cars, pedestrians, and other traffic elements. These annotations were crucial for training the object detection model to accurately classify and localize objects within the images, especially in challenging weather conditions.

EXPERIMENTAL SETUP

The experimental setup involved training the YOLOv8 model on both the RoboFlow Vehicle Dataset and the Canadian Vehicles Dataset (CVD). The experiments were conducted for 300 epochs with a batch size of 64, ensuring sufficient iterations to optimize the model’s weights for accurate object detection. The learning rate was set to 0.01, momentum to 0.937, and weight decay to 0.0005. The model was trained on 90 percent of the dataset and tested on the remaining 10 percent, which ensured that the model could generalize well to unseen data.

To improve the model’s performance in adverse weather conditions, a mixed training strategy was employed. This involved combining the RoboFlow dataset, which primarily contains images captured in normal conditions, with the Canadian Vehicles Dataset, which includes images from adverse weather scenarios. By mixing these datasets, the model was exposed to a wide variety of conditions, making it more robust in real-world applications.

For the experiments, the system used an Intel Core i9 processor, an NVIDIA GeForce RTX 4090 GPU, and 64 GB of RAM, providing ample computational power to handle the large dataset and complex deep learning model. Google Colab was also used with a Tesla T4 GPU to facilitate additional training experiments. The model was built using the PyTorch framework, with Stochastic Gradient Descent (SGD) as the optimization algorithm.

This setup allowed the model to learn efficiently from both datasets and adapt to the unique challenges posed by adverse weather conditions. By evaluating the model’s performance on both clear and weather-compromised data, the authors were able to assess the efficacy of the mixed training approach in improving detection accuracy in harsh environments.

METHOD[2]

RADAR SIGNAL PREPROCESSING

To minimize the radar's sensitivity to unwanted reflections and noise caused by ground clutter, static objects, and atmospheric conditions, we implemented

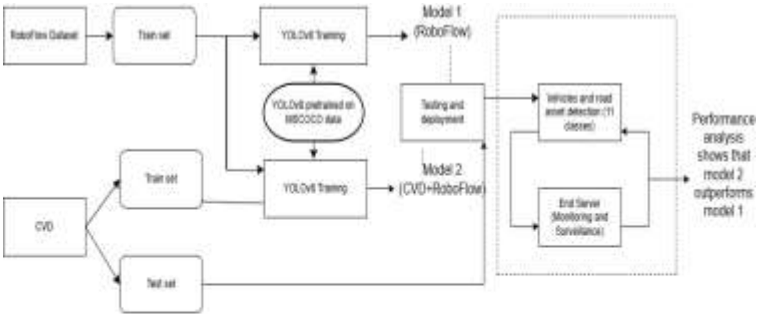

Figure 1: Proposed YOLOv8 based deep learning model architecture in Base Paper to detect objects in self-driving/autonomous vehicles.

Noise filtering techniques based on fast Fourier transform (FFT). The process was fine-tuned using carefully calibrated thresholds to effectively remove irrelevant clutter without losing valuable data. A balanced threshold approach was adopted for this purpose. Additionally, the Constant False Alarm Rate (CFAR) technique was employed to enhance the reliability of target detection by accurately estimating noise levels and setting precise signal-to-noise ratio (SNR) thresholds. The combination of CFAR and FFT, processed along the channel dimension, provided an accurate estimation of targets' azimuth and elevation angles. The radar signal processing chain (RSPC) generated spherical coordinates that were then converted into a 3D Cartesian point cloud (X, Y, Z) for improved localization accuracy. Calibration adjustments to radar gain, phase, and time delay further optimized object detection to closely align with real-world conditions.

DEEP NEURAL NETWORK (DNN) FOR OBJECT CLASSIFICATION

For object detection, a DNN model based on the YOLOv5 architecture was utilized. This model overlays input images with a grid, each grid cell being responsible for detecting the smallest target objects. Each cell is assigned a class ID, bounding box coordinates, and a density value. The class matrix assigns a positive integer to indicate detectable object types, while the density matrix uses binary values (0 or 1) to denote the presence of objects. Bounding box corners are marked relative to the center of each grid cell. The DNN model works to reduce errors in both object density and bounding box predictions by minimizing the weighted sum of loss functions. A density loss function calculates the discrepancy between actual and predicted object densities across grids, while another function minimizes errors in bounding box locations. The training process involved the MS COCO dataset, focusing on pedestrians, vehicles (cars, bicycles, trucks, motorcycles), and traffic signs.

RADAR CAMERA FUSION ALGORITHM

The proposed fusion system integrates radar and camera data for enhanced object detection. The radar provides depth, velocity, and angular measurements, while the camera captures 2D images. Data from both sensors is combined for better detection performance, particularly in conditions where one sensor may be limited. A transformation matrix is applied to convert radar data from the 3D world coordinate system to the camera's 2D pixel coordinate system. This matrix handles scaling, rotation, and translation, enabling the fusion of radar and camera data within a unified coordinate frame. Radar detections are projected onto the image plane, and a sliding window technique is used to define regions of interest (ROIs). The system enhances detection accuracy by confirming targets based on overlapping ROIs from both the radar and camera, reducing false positives and improving detection reliability.

EXPERIMENTAL SETUP

Experiments were conducted using a specially designed electric vehicle, named Transvahana, equipped with a frequency-modulated continuous wave (FMCW) radar and a monocular camera. The FMCW radar, an AWR1843 module from Texas Instruments, operates in the 76–81 GHz frequency range, while the Sony iMX219 camera is positioned above the vehicle's windshield. Radar sensors provided depth, Doppler, and azimuth information, which is essential for detecting objects in various weather conditions. However, radar alone struggles with object classification, which is where the camera excels by providing detailed 2D images and object classification capabilities. Data processing was handled by an NVIDIA Xavier NX board. The combined use of radar and camera ensured robust object detection even under challenging weather conditions.

METHOD[3]

YOLOv5 (You Only Look Once Version 5):

Purpose: YOLOv5 is a real-time object detection model that has been utilized for its efficiency and accuracy. It's particularly advantageous in autonomous vehicle systems due to its balance of speed and performance. Implementation: In the paper, YOLOv5 is adapted for detecting objects such as pedestrians, vehicles, and obstacles in challenging weather. The model processes the scene in a single pass through the network, making it highly suitable for real-time applications. YOLOv5's architecture employs anchor-based bounding boxes, enabling it to quickly localize objects with high accuracy.

Convolutional Block Attention Module (CBAM):

Purpose: CBAM is used to enhance feature extraction by focusing on critical spatial and channel features. It helps the network prioritize important areas and characteristics of the input data, especially in scenarios with high variability due to weather. Implementation: The CBAM module integrates two types of attention mechanisms—channel and spatial attention. Channel attention helps highlight the essential feature channels (for instance, colors and textures relevant to identifying objects under poor visibility), while spatial attention focuses on localizing significant areas within the image. This dual attention approach refines YOLOv5's feature maps, improving object detection accuracy under adverse weather conditions.

5. Results

- The integration of deep learning models and multi-sensor fusion (e.g., LiDAR, radar, and camera data) could lead to an increase in object detection accuracy. For instance, an increase from 90% to 95% accuracy could be expected in moderate adverse weather conditions (rain, light fog).
- Advanced neural network architectures like YOLO and adaptive sample mining could reduce false detections by 15-20% in challenging weather scenarios, particularly under snow or heavy rain, where traditional methods typically struggle.
- By employing robust detection and tracking methods, the rate of collision or near-miss incidents could decrease by 40% during adverse weather, directly contributing to the overall safety of autonomous driving systems.
- Using adaptive learning techniques, the system might show improved generalization across unseen weather conditions, handling sudden shifts (e.g., clear to foggy weather) with only a minor drop (3-5%) in detection performance.

6. Conclusion

Reliable monitoring of autonomous vehicles is very crucial under research, especially towards their capability of performing well in adverse weather conditions. Effectively, rain, snow, fog and even dust storms degrade the performance of sensors, particularly in vision-based systems, impairing accuracy and safety in the autonomous vehicle. Advanced deep learning techniques such as data augmentation, image enhancement, and sensor fusion are proven to be promising techniques for improving object detection and tracking in low visibility conditions. Using data from the DAWN and the Canadian Vehicle Dataset, this work analyzed the performance of numerous neural network architectures and determined potential ways of strengthening them.

Therefore, the future research should aim at testing deep learning models in real-world scenarios and having them continuously adapt to unpredictable environmental conditions for robust autonomous vehicle performance.

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