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Master's Thesis

Object detection in adverse weather conditions using tightly-coupled data-driven multimodal sensor fusion

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I, the undersigned below, declare that this work has not previously been submitted to this or any other university and that it is, unless otherwise stated, entirely my own work.

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Abstract

TODO: add abstract

Acknowledgements

TODO: add acknowledgements

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Introduction

In the realm of autonomous driving, the ability to detect objects in challenging weather conditions remains a critical area of research. Consider a scenario where a self-driving vehicle navigates a winding mountain road at night amidst fog and rain. The limitations of the vehicle's visual cameras become evident as they struggle to detect objects due to reduced visibility, highlighting the crucial need for advanced object detection methods in adverse weather conditions. This is particularly significant in emergency situations, like when a deer suddenly appears on the road, necessitating quick and accurate object detection to prevent accidents [3] [4] [5].

As depicted in Figure 1.1, the performance of various sensors in automated systems under different conditions has been extensively analyzed. Cameras, for instance, excel in recognizing colors and signs but falter in dark or distant object measurement. Conversely, thermal sensors maintain efficiency in poor weather but lack color detection and texture information. Radar sensors are adept at speed measurement and are less hindered by visual obstructions, though they produce sparse and noisy data. LiDAR sensors, meanwhile, provide excellent object shape and size mapping but underperform in poor weather conditions [6].

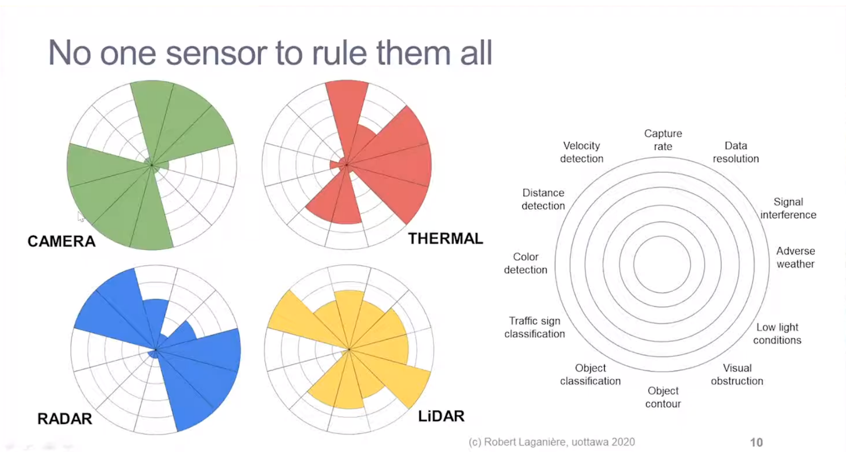


Figure 1.1: Sensors modality characteristics [6]

To overcome these limitations, this project proposes the development of a tightly-coupled multimodal sensor fusion system, as exemplified in Figure 1.2. By integrating cameras, radar, and LiDAR sensors, this approach harnesses the unique strengths of each to create a comprehensive and reliable object detection framework. The fusion of these complementary sensors, coupled with advanced machine learning algorithms, aims to significantly enhance the range, accuracy, and reliability of detection in adverse weather conditions. Effectively synthesizing diverse data sources enables the creation of a robust and responsive system that overcomes the weaknesses of any individual sensor type.

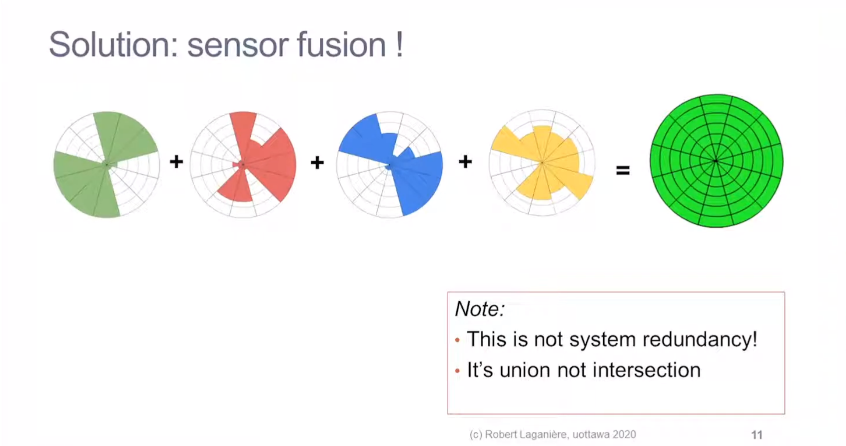


Figure 1.2: Sensors modality characteristics [6]

However, the integration of different sensor types presents its own set of challenges, such as varying resolutions, sampling rates, and the need for sophisticated calibration and alignment techniques. These hurdles necessitate the development of efficient and scalable algorithms and hardware architectures capable of processing large volumes of sensor data with minimal latency.

Despite these challenges, the anticipated outcomes of this project are transformative, with potential applications extending beyond autonomous vehicles to drones, surveillance, and security systems. By enhancing situational awareness through optimized sensor fusion, the project aims to foster safer and more efficient operations across various sectors. The primary objective is to ensure safe and efficient autonomous driving in adverse weather conditions, prioritizing the safety of passengers, other drivers, and pedestrians. This will be achieved through a sensor fusion system designed for minimal latency, enabling the processing of data from multiple sensors in near real-time.

The project will also delve into specific aspects of object detection, such as identifying various entities like cars, trucks, pedestrians, and cyclists, and will focus on detection in adverse weather conditions like fog, snow, and rain, which pose significant challenges to visibility. The 'tightly-coupled' approach refers to the intricate integration of different data modalities, combining features at various levels for optimal results. The 'data-driven' aspect emphasizes leveraging existing datasets to enhance performance, while 'multimodal' pertains to the utilization of diverse sensor types. Finally, 'sensor fusion' is central to the project, entailing the amalgamation of data from different sensors to improve environmental perception and object detection capabilities.

1.1 Motivation

The motivation for the research topic is deeply rooted in the understanding that weather phenomena significantly impact traffic and transportation safety. Adverse weather conditions, such as rain, snow, sleet, and fog, are major contributors to the high number of vehicle crashes and fatalities worldwide. This problem is particularly acute in regions with severe weather variations.

In the United States, over 30,000 vehicle crashes occur annually on snowy or icy roads, resulting in over 5,000 fatalities and 418,000 injuries, as reported by the Federal Highway Administration [7] and the US Department of Commerce [8]. The Insurance Institute for Highway Safety (IIHS) underscores this issue, noting that the likelihood of fatal crashes increases by 21% during snowy weather conditions, primarily due to reduced visibility, compared to clear roads. It has been proven that the risk of accident in rain conditions is 70% higher than normal [9]. A 2018 report by the National Highway Traffic Safety Administration (NHTSA) further underscores that adverse weather conditions were involved in 4,000 fatal crashes [10].

In Europe, adverse weather conditions are responsible for 25% of all road accidents. Frost, ice, snow, and rain significantly reduce drivers' perceptible range from hundreds of meters to just a few meters, leading to over 12,000 fatalities annually on European roads due to weather-related accidents, as indicated by the European Commission and the European Transport Safety Council (ETSC) [11]. This drastic reduction in visibility poses a major challenge for effective obstacle or object detection, a critical component of road safety in adverse conditions.

In the context of current advancements in autonomous vehicles (AVs), a persistent challenge remains their operation in inclement weather conditions such as heavy rain or snow, which raises safety concerns. Extensive research and trials have been conducted under adverse weather conditions, yet the Mcity shuttle, for instance, ceases operation when continuous use of windshield wipers is necessitated in rain or snow [12]. Tesla's autopilot system exhibits a limited capability to navigate through mild rain or snow, provided road markings are visible, but encounters difficulties in more severe conditions like heavy storms or obscured lane lines [13]. Similarly, General Motors' Super Cruise, another prominent Level 2 autonomous driving system, explicitly restricts the use of its self-driving function in hazardous conditions, including rain, sleet, fog, ice, or snow [14]. These limitations indicate that, despite advancements, autonomous vehicles are not yet reliable enough to operate independently of human drivers in all weather conditions. Consequently, overcoming these environmental constraints is imperative for the advancement of autonomous driving systems (ADS) into a new era of complete autonomy.

The relevance of this research extends beyond road safety, impacting sectors such as autonomous vehicles, healthcare, precision agriculture, environmental monitoring, aerospace, defense, and industrial automation. For instance, the market for sensor fusion in autonomous vehicles, vital for enhancing object detection capabilities under adverse weather conditions, was valued at USD 594.4 million in 2019. It is projected to grow to USD 1563.5 million by 2025, according to MarketInsider [15]. This growth reflects the increasing reliance on advanced sensor technologies, such as radar and vision sensors, for autonomous emergency braking (AEB) systems and other ADAS applications.

Similarly, In the healthcare sector, the market for wearable sensors, which typically integrate multiple sensors for comprehensive health data, is expected to reach over $1.5 billion by 2030 [16]. The precision agriculture and environmental monitoring markets are anticipated to reach $10.5 billion by 2026 [17], while the aerospace and defense sector is projected to reach $23.83 billion by 2027 [18]. Each of these sectors can benefit significantly from advancements in sensor fusion technology, enhancing efficiency and reducing production costs in industrial automation.

The focus of this research on developing and applying data-driven multimodal sensor fusion techniques for object detection in adverse weather conditions is vital not only for improving road safety in autonomous vehicles but also holds the potential to revolutionize various technology-driven sectors. By addressing the challenges of object detection in complex and unpredictable weather conditions, this research aims to contribute significantly to the fields of autonomous vehicles, healthcare, environmental monitoring, and beyond.

1.2 Challenges and Difficulties

The field of multimodal sensor fusion, particularly in the context of adverse weather conditions, presents a series of distinct challenges that are critical to the advancement of reliable object detection systems. These challenges range from the scarcity of specialized datasets to the intricacies of fusion architecture, computational demands, and the search for effective network design and generalization. This section outlines the key challenges in this field.

Scarcity of Adverse Weather-Related Datasets: A fundamental challenge in this field is the lack of datasets that capture adverse weather conditions through multimodal sensors. Most existing datasets are oriented towards clear weather scenarios. For example, popular datasets for multimodal sensor fusion include camera and LiDAR but often lack radar sensors. These include KITTI [19], ApolloScape [20], and Waymo [21]. There are datasets that incorporate radar sensors, such as VoD [22], TJ4DRadSet [23], and PixSet [24], but they do not cover an extensive range of adverse weather conditions. This limitation restricts the development and validation of object detection models in more challenging environmental conditions and hinders the advancement of robust object detection systems capable of performing reliably under diverse weather conditions.

Limitations in Fusion Architecture: The predominant focus in the current landscape of fusion architectures is on middle or feature fusion, with only limited exploration in the area of tightly coupled fusion networks. This trend poses a particular challenge for sensor fusion that involves radar data, which tends to be noisier and sparser compared to the data produced by cameras and LiDAR. The scarcity of research on tightly coupled fusion methods for integrating such diverse data types is a significant obstacle in developing efficient and effective multimodal fusion systems.

Computational Constraints: Another significant barrier is the computational demand required to train large, complex networks. This requirement often exceeds the resources available to many researchers, restricting exploration in this field and slowing the advancement of more sophisticated fusion methods.

General Guidelines for Network Architecture: Currently, there is no standard or widely accepted framework for the design of network architectures in multimodal sensor fusion, leading to several unanswered questions. Key considerations, as highlighted by Feng et al. [25], include:

- ”What to fuse,” such as LiDAR, radar, various camera types (color, thermal, event), or ultrasonic sensors;
- ”How to fuse,” with possibilities including addition or averaging, concatenation;
- ”When to fuse,” which can range from early, mid, late, or a combination of these fusion stages.

This absence of a clear guideline results in uncertainties regarding the optimal choices for integrating different modalities in sensor fusion.

Limited Generalization from Previous Studies: Many existing studies in multimodal sensor fusion have focused on results from their baseline models and custom datasets. This narrow scope limits the generalizability of their findings, as these models may not perform as well under different conditions or with alternative datasets.

Advanced Fusion Methods and Temporal Information: While recent datasets have begun to include baseline models featuring basic fusion methods, there is notable potential for significant performance enhancement. This can be achieved by incorporating advanced transformer-based architectures, known for their superior handling of complex data patterns and scalability. Additionally, employing sophisticated fusion techniques, such as tightly-coupled fusion, which integrates data more closely and efficiently, could further optimize the sensor fusion process. Additionally, the integration of temporal information in sensor fusion is an area that is yet to be extensively explored. Although not a focus of this project, it represents a promising direction for future research.

Addressing these challenges is critical for advancing the field of object detection in adverse weather conditions using multimodal sensor fusion. This research will contribute to this effort by exploring these underdeveloped areas, aiming to find more robust and effective object detection systems.

1.3 Problem Statement

The field of object detection using multiple modalities has become a topic of increasing interest in recent years, reflecting the growing demand for advanced sensing technologies in various applications, especially in autonomous vehicles and robotics. However, the comprehensive analysis and practical application of state-of-the-art multimodal object detection methods under adverse weather conditions remain largely unexplored areas. The crux of this research project is to bridge this gap by providing an in-depth analysis and practical implementation of cutting-edge techniques in multimodal object detection. The project will explore the integration of multiple sensor modalities, including but not limited to cameras, LiDAR, and radar, to enhance detection capabilities in challenging weather scenarios.

A pivotal challenge in this field is exploring an effective fusion strategy that capitalizes on the complementary strengths of different sensors while mitigating their individual limitations. For example, the integration of visual camera data with radar information presents a complex yet crucial research question. This research aims to explore an optimal fusion strategy, a technique that effectively combines the unique strengths of each sensor type, thereby creating a more robust and accurate detection system. The strategic combination of these modalities holds the potential to significantly enhance object detection performance, especially in conditions where traditional single-sensor systems fall short.

To empirically validate the effectiveness of the proposed methods, this project will conduct comprehensive experiments under a variety of adverse weather conditions. The performance of these methods will be rigorously tested and compared using renowned publicly available datasets, such as DENSE [1] and nuScenes [2]. These datasets, known for their suitability in evaluating performance under challenging environmental conditions, will serve as the benchmark for assessing the robustness and reliability of the proposed multimodal object detection techniques.

Additionally, this study will compare the proposed methods to the best existing methods by comparing their outcomes. This comparison will not only highlight the efficacy of the new methods in adverse conditions but will also shed light on the strengths and weaknesses of each approach. Through this evaluation, the project aims to contribute significantly to the body of knowledge in multimodal object detection, providing valuable insights for future research and practical applications in this rapidly evolving field.

2

Related Works

2.1 Adverse Weather Conditions Influence on Sensors

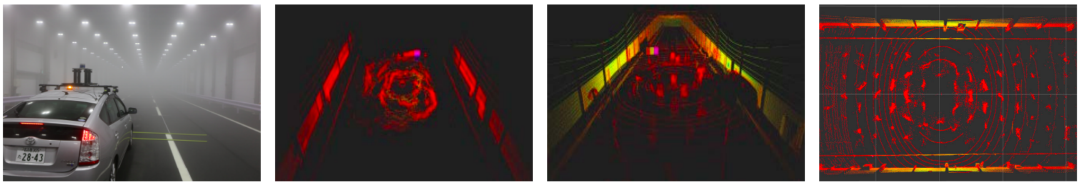
In the evolving landscape of autonomous robotics, particularly in the domains of self-driving vehicles and autonomous drones, object detection stands as a paramount challenge in computer vision. These cutting-edge applications necessitate precise 2D or 3D bounding boxes for objects within complex and often unpredictable real-world environments. These scenarios commonly involve cluttered scenes, varying lighting conditions, and notably, adverse weather conditions. To tackle these multifaceted challenges, state-of-the-art autonomous vehicle systems are increasingly reliant on a suite of redundant sensor modalities. Recent studies, such as those by Caesar et al. [2], Sun et al. [26], and Ziegler et al. [27], highlight this trend. These sensor modalities extend beyond traditional cameras and LiDAR, encompassing radar and emerging technologies like far-infrared (FIR) and near-infrared (NIR) sensors, which are proving instrumental in enabling reliable object detection in adverse conditions [1].

For standard perception systems in autonomous vehicles, the camera remains an indispensable, yet highly vulnerable sensor to adverse weather conditions. Despite its high resolution, a camera's functionality can be severely compromised by a single water drop on the lens or emitter during rain [28], as illustrated in Figure 2.1. In conditions like heavy snow or hail, image intensity can fluctuate, and object edges may become obscured, leading to detection failures [29]. Additionally, cameras are susceptible to strong light interference, either from direct sunlight or artificial sources like urban light pollution, causing significant operational challenges [30].

LiDAR, the second-most common sensor in autonomous driving systems, exhibits a different response to adverse weather. As Fersch et al. [32] suggest, LiDAR sensors with small apertures are relatively unaffected by moderate rainfall. However, intense and uneven precipitation can generate fog clusters, potentially resulting in false obstacle detection by LiDAR systems. Hasirlioglu et al. [33] demonstrated that rainfall rates exceeding 40 mm/hr significantly reduce signal reflection intensity. Dense fog and smoke, along with strong light, can adversely affect LiDAR sensors in challenging conditions [30, 34]. This is exemplified in Figure 2.2, which showcases an instance of LiDAR's performance in fog, where it erroneously creates small false obstacle clouds. Similarly, Figure 2.3 illustrates how LiDAR's ability to measure distances is compromised in foggy environments. This contrasts with radar technology, whose outputs remain largely unaffected under similar conditions. Such discrepancies highlight the limitations of

Figure 2.1: Van occluded by a water droplet on the lens [31]

LiDAR in adverse weather and the need for integrating complementary sensor modalities for enhanced reliability in autonomous driving systems.



(a) Fog chamber (b) Point clouds in fog (c) Point clouds in rain (d) Rain pillars as detected by LiDAR

Figure 2.2: LiDAR performance test (a sample from LIBRE [4] dataset)

Radar, the third critical sensor in autonomous driving systems, is frequently used in mass-produced cars for active safety functions like Automatic Emergency Braking (AEB) and Forward Collision Warning (FCW). Its role in perception tasks for autonomous driving, however, is often undervalued. Unlike cameras operating in the visible light bands (384–769 THz) and LiDARs in the infrared bands (361–331 THz), radar utilizes longer wavelength radio bands (77–81 GHz). This attribute ensures its robust performance in adverse weather conditions [35]. Studies by Ijaz et al. [36] and Ismail [37] indicate radar's lower attenuation in rainy conditions compared to LiDAR. At 77 GHz, radar exhibits approximately 3.5 times less attenuation (10 dB/km) than LiDAR at 905 nm (35 dB/km), showcasing its superior robustness. Various experiments [29, 38–41] have demonstrated that radar's performance is minimally affected by dust, fog, snow, and light rain, although it degrades in heavy rainfall conditions. Figure 2.4 from the DENSE [1] dataset exemplifies this, showing radar's ability to detect vehicles under dense fog conditions, where cameras and LiDAR fail. Nevertheless, radar's low resolution and sparser point clouds compared to LiDAR limit its utility in perception tasks. The emerging 4D radar technology, while promising denser point clouds, lacks public datasets in adverse weather conditions for validation.

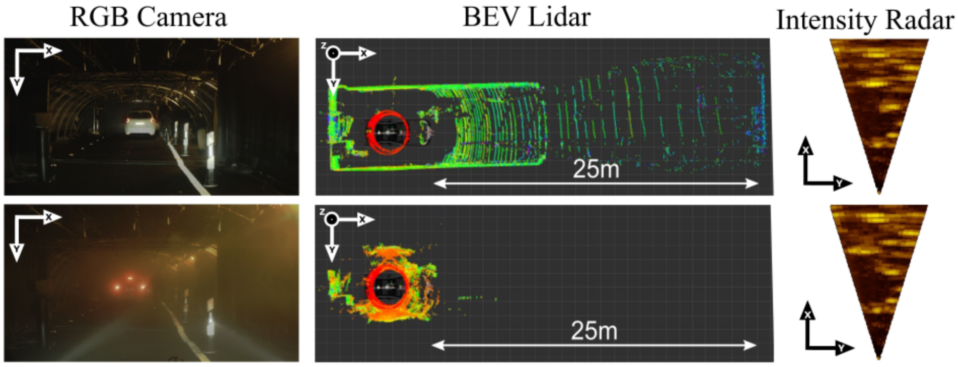


Figure 2.3: 1st row: clear weather condition, 2nd row: with fog. Shows that lidar affects by the fog but radar intensity remains the same [1]

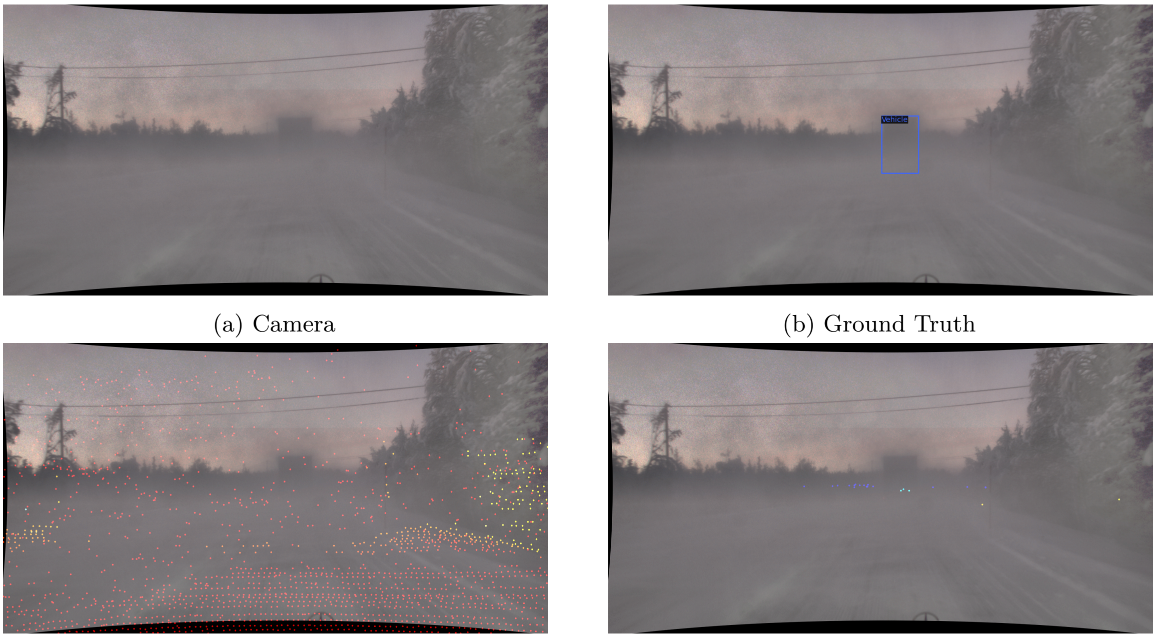
The combination of LiDAR and camera technologies alone has proven insufficient for navigating through adverse weather conditions with adequate safety assurance. However, the integration of these with radar, infrared cameras, gated cameras, stereo cameras, weather stations, and other weather-related sensors presents a new paradigm in autonomous vehicle perception. This multimodal sensor fusion, as evidenced in Figures 1.1 and 1.2, offers a composite strength that individual systems lack. Consequently, research groups worldwide are exploring various permutations and combinations of these sensors to enhance the reliability and safety of autonomous driving systems in challenging weather conditions.

2.2 Multimodal Sensor Fusion

The concept of multimodal sensor fusion has become increasingly pivotal in the field of object detection, particularly under adverse weather conditions. This approach integrates various sensor inputs to enhance perception and object detection capabilities, addressing the limitations inherent to individual sensors. A notable contribution in this field is the work of Radecki et al. [42], who conducted a thorough review of sensor efficacy across diverse weather conditions, including wet environments, varying light conditions, and dusty atmospheres. They developed a sophisticated system capable of object tracking and classification through a real-time, joint probabilistic perception algorithm. This algorithm dynamically selects the most appropriate sensor subsets based on prevailing weather conditions. By intelligently weighting sensors and accurately quantifying parameters specific to each weather scenario, the system not only improves the baseline of perception ability but also enhances its robustness and reliability. This work underscores the importance of real-time strategy adaptation and smart sensor subset selection in maximizing the accuracy and dependability of multimodal perception systems.

However, Radecki et al.'s study [42] has certain limitations, notably its focus on optimal weather conditions and the omission of heavy traffic and urban environments. Additionally, the study does not explore deep learning-based fusion techniques. Future research could address these gaps by employing similar approach for object detection in challenging weather datasets.

In 2019, FLIR System Inc. [43] and VSI Labs [44] tested the first-ever fused Automated Emergency



(a) Camera

(b) Ground Truth

(c) Lidar

(d) Radar

Figure 2.4: Dense fog influence on sensors (a sample from DENSE dataset [1])

Braking (AEB) sensor suite, comprising a thermal long-wave infrared (LWIR) camera, a radar, and a visible camera. The LWIR camera, operating in the 8 µm to 14 µm range at ambient temperature, was part of this groundbreaking sensor suite. The suite's performance was evaluated against standard AEB systems using radar and visible cameras under various conditions, including daytime, nighttime, and transitions from tunnel exits into sun glare. The results revealed that while most AEB systems function effectively during the day, they almost invariably failed under adverse conditions, often colliding with mannequins. In stark contrast, the LWIR sensor suite successfully avoided collisions in these challenging scenarios, highlighting the efficacy of fusing camera and radar data in adverse weather conditions.

However, the use of a thermal camera as part of the sensor fusion raises concerns about the durability of such temperature-sensitive devices in real-world settings, necessitating further validation to ascertain their effectiveness in adverse weather [29].

Another significant development in multimodal sensor fusion is the CameraRadarFusionNet (CRF-Net) proposed by Nobis et al. [45]. Inspired by previous works on camera-LiDAR fusion [46, 47], the CRF-Net was designed to determine the most beneficial stage for sensor data fusion within a neural network architecture for detection tasks. Utilizing the nuScenes [2] dataset and their own TUM dataset, they introduced a novel training strategy, BlackIn, focusing on a specific sensor type. The fusion method employed, element-wise addition, demonstrated superior performance over an image-only network on both datasets, underscoring the significance of incorporating radar data into detection tasks.

Nevertheless, Nobis et al.'s approach [45] exhibited only marginal improvements in detection performance over the baseline image network. The absence of an RGB sensor ablation study in their work left questions about the system's robustness in case of camera failure. According to Safa et al. [48], pre-processing the radar data before fusion could further enhance performance, suggesting an area for potential improvement in future research endeavors.

Building on the concept of multimodal sensor fusion, Yang et al. [49] introduced RadarNet, a novel framework for object detection and velocity estimation. RadarNet is distinctive for its dual strategy of leveraging both radar and LiDAR sensors for perception. It employs an early fusion technique to learn joint representations from these sensors, while its late fusion phase incorporates radar's radial velocity evidence to enhance object velocity estimation. This approach was rigorously evaluated using the nuScenes dataset [2]. However, a limitation of RadarNet, as noted by Yang et al. [49], lies in the radar sensor data from the nuScenes dataset, which is characterized by low resolution, thus restricting its effectiveness in object detection. This issue of low resolution and erroneous elevation estimates, as highlighted in studies like Ulrich et al. [50] and Drews et al. [51], suggests a potential improvement for RadarNet: the integration of a higher-resolution radar, such as the one from the K-Radar dataset. This 4D radar, with a significantly wider elevation angle, could enhance the performance of RadarNet, overcoming the limitations of conventional radars.

In a similar vein, Bijelic et al. [1] from Mercedes-Benz AG conducted an extensive study focusing on enhancing detection performance in adverse weather through deep multimodal sensor fusion. Their experimental setup included a diverse array of sensors on their test vehicle, including stereo RGB cameras, a NIR camera, a 77 GHz radar, dual LiDARs, an FIR camera, a weather station, and a road-friction sensor. They introduced an innovative entropy-steered fusion approach, attenuating regions of low entropy while amplifying those with high entropy during feature extraction. This method, trained using clear weather data, showed impressive adaptability to adverse weather conditions. The fusion network was designed to maintain consistency across different scenarios, with all sensor data projected into the camera coordinate system. Their findings demonstrated that this fused approach significantly outperformed LiDAR or image-only methods, particularly under foggy conditions.

Additionally, Bijelic et al. [1] contributed to the research community by providing the SeeingThroughFog or DENSE dataset. This comprehensive dataset, comprising 10,000 km of driving data recorded in Northern Europe, spans a range of weather and illumination conditions. The dataset includes detailed annotations for various weather frames, including clear weather, dense fog, light fog, and snow/rain, making it a valuable resource for future studies on multimodal sensor fusion in challenging weather scenarios.

However, the study by Bijelic et al. [1] also presents certain challenges. The projection transformation technique used in their approach may lead to the loss of crucial radar spatial information. Moreover, the extensive array of sensors required exceeds typical expectations for autonomous driving systems, posing implementation challenges in real-world scenarios. The large volume of data from multiple sensors could potentially impact the algorithm's response and reaction time. Additionally, the radar's performance was constrained by its limited azimuth and elevation resolution [34]. Future research could focus on enhancing the network architecture, possibly through the integration of higher resolution radars and transformer-based approaches, to further refine the performance of sensor fusion in adverse weather conditions.

Liu et al. [52] presented another innovative approach to target recognition and tracking by fusing radar and camera data. In their methodology, radar is the primary sensor, complemented by camera data as secondary information. This fusion was evaluated under challenging weather conditions, including rain, fog, and low visibility nighttime scenarios. The results demonstrated that radar-based detection was highly accurate in detecting moving targets in wet weather, while the camera excelled in target classification. The combined radar and camera data exhibited a superior performance, surpassing LiDAR-based methods by over 33%, highlighting the effectiveness of this fusion approach in challenging weather scenarios.

The exploration of multimodal sensor fusion for enhanced vehicle detection under adverse weather conditions continues with the work of Qian et al. [53], who developed the Multimodal Vehicle Detection Network (MVDNet). MVDNet uniquely incorporates LiDAR and radar data, utilizing a two-stage attention block within its fusion module. The network first applies self-attention to each modality to extract features, followed by the blending of these features with region-wise features through cross-attention mechanisms. This fusion technique has shown to be particularly effective in foggy conditions. The performance of MVDNet was rigorously tested and validated on the DENSE [1] and Oxford Radar Robotcar [54] datasets, where it demonstrated a notably improved performance compared to LiDAR-only systems in foggy environments.

Despite its robust performance, MVDNet's design by Qian et al. [53] has certain limitations. One significant issue is the misalignment between LiDAR and radar data within the dataset, which could potentially compromise the network's effectiveness. Furthermore, the simple label assignment strategy employed in the loss computation and the region-of-interest (ROI) assisted fusion design might limit the model's overall performance. These aspects suggest potential areas for improvement, possibly through the adoption of more advanced fusion techniques and refined label assignment strategies, as indicated in studies like Yang et al. [55].

Continuing in this vein, Rawashdeh et al. [56] proposed a CNN-based sensor fusion approach aimed at detecting drivable paths. This approach integrates data from cameras, LiDAR, and radar and was evaluated using the DENSE dataset [1]. Their multi-stream encoder-decoder network is designed to counter the asymmetric degradation of the input sensors effectively. The depth and number of blocks allocated to each sensor in the architecture were determined by their respective input data densities, with the camera being the most dense, followed by LiDAR, and radar being the least dense. The fully connected network's outputs are transformed into a 2-D array for input into the decoder. The researchers demonstrated that their model could effectively ignore misleading road lines and edges, thereby accurately delineating the general drivable area.

However, Rawashdeh et al.'s approach [56] also presents certain challenges. The method lacks a comparative analysis with other state-of-the-art methods in the field, leaving its relative effectiveness somewhat uncertain. Additionally, the study does not delve into the real-time processing requirements or the computational costs of the proposed algorithm. These factors are crucial for practical applicability, especially in scenarios requiring rapid decision-making and processing, like autonomous driving in adverse weather conditions. Addressing these gaps could significantly enhance the feasibility and implementation potential of their sensor fusion approach in real-world applications.

2.3 Synthetic Data for Adverse Weather Conditions

The use of synthetic data and advanced image processing techniques has been a subject of considerable research focus. One prominent area is the application of de-hazing techniques to mitigate the impacts of adverse weather on visual data. Historically, physical priors have been employed for this purpose [57, 58]. However, with the advent of data-driven approaches, particularly deep learning, new methodologies have emerged. These deep de-hazing models, while innovative, often suffer from high computational complexity, making them less suitable for ultra-high-definition images. Chen et al. [59] highlighted a significant limitation of these models: their training on synthetic images does not effectively generalize to real-world hazy conditions. Conversely, Zhang et al. [60] leveraged temporal redundancy in video de-hazing, assembling a dataset comprising real-world hazy and haze-free videos. The challenge in this domain lies in obtaining paired hazy and haze-free ground-truth images, which is difficult in natural settings. However, this obstacle can be somewhat mitigated through the use of professional haze/fog generators that simulate real-world conditions [61, 62].

Another emerging trend in this field is the exploration of synthetic data generation for adverse weather conditions using Generative Adversarial Networks (GANs). Researchers such as Sun et al. [63], Zheng et al. [64], and Lee et al. [65] have investigated this approach, utilizing clean weather datasets like KITTI [19] and Cityscapes [66] as a basis. These methods predominantly involve the creation of artificial fog or rain images, supplemented by a limited selection of actual images captured under specific fog or rain conditions. However, the efficacy of these algorithms in diverse adverse weather scenarios remains somewhat ambiguous. A critical concern is whether these synthetic data-driven approaches can perform effectively under various real-world adverse weather conditions. Additionally, the methods for evaluating their real-world applicability and effectiveness in such scenarios are not fully established [67]. This gap in the research indicates a need for further investigation and development to enhance the reliability and applicability of synthetic data generation techniques in the context of adverse weather conditions for object detection.

2.4 The Role of Simulation in Autonomous Driving Research

The advent of autonomous driving technology, especially in challenging weather conditions, has significantly benefited from the utilization of simulation platforms and specialized experimental setups. One such noteworthy tool is the CARLA simulator [68], a widely recognized virtual platform. CARLA is particularly advantageous for researchers as it enables the creation of intricate road environments and the simulation of numerous non-ego entities in scenarios that would otherwise be impractical or prohibitively expensive to replicate in real-life experiments. This capability is crucial, considering that specific weather conditions, particularly those related to extreme climates or certain seasons, are not always readily available for testing. For example, tropical regions cannot easily conduct tests in snow conditions, and the unpredictability and brevity of natural rain showers may impede the collection of comprehensive experimental data. Most importantly, conducting tests in actual adverse weather conditions not only presents logistical challenges but also introduces significant safety risks. In contrast, simulators like CARLA offer a completely safe environment, eliminating the dangers associated with real-world testing [34].

However, the effectiveness of virtual datasets and simulation platforms in accurately representing real-world phenomena remains a topic of debate. The extent to which a simulator can truly mirror real-world conditions is an open question. Developing more realistic simulators is a key challenge in this domain. Additionally, determining the most effective methods for integrating real and virtual data is another critical area of ongoing research [25]. These aspects underline the need for continuous improvement in simulation technologies to ensure that they can effectively support the development and testing of autonomous driving systems, especially in the face of adverse weather conditions. The quest for more realistic simulators and the optimal blend of real and virtual data stand as important open questions, driving the future direction of research in autonomous driving simulations. Due to these reasons, this project will focus on the real-world datasets for adverse weather conditions.

3

Methodology

How you are planning to test/compare/evaluate your research. Criteria used.

3.1 Available Datasets

The majority of deep multimodal perception approaches rely on supervised learning, which necessitates the use of high-quality, large-scale multimodal datasets with labeled ground truth for training deep neural networks. Several multimodal datasets, such as KITTI [19], ApolloScape [20], and Waymo [21], are prevalent in the domain of LiDAR-camera fusion. However, a significant number of these datasets are collected under clear weather conditions or lack a comprehensive array of sensors, including cameras, LiDAR, and Radar. A notable limitation is the scarcity of multimodal datasets that are collected under adverse weather conditions and incorporate at least all three of these essential sensors. Table 3.1 summarizes some of the available multimodal datasets[1] for evaluating the performance of deep multimodal perception techniques in adverse weather conditions. Note that highlighted datasets are used for the project. The dataset are sorted in ascending order with respect to year.

TODO: add histogram of object classes for DENSE and nuScenes datasets

Table 3.1: Multimodal Adverse Weather Conditions Datasets. Sensors†: C-R-L-N-F denote Camera, Radar, LiDAR, Near-infrared, and Far-infrared sensors, respectively. Weather Conditions‡: F-SN-R-O-SL-N denote Fog, Snow, Rain, Overcast, Sleet, and Night conditions, respectively.

Name	**Sensors†**	**Weather Cond.‡**	**Size (GB)**	**Year**	**Citation Cnt.**	**Reference**
DENSE	**CRLNF**	**F, SN, R, N**	**582**	**2020**	**269**	**[1]**
nuScenes	**CRL**	**R, N**	**400**	**2020**	**3459**	**[2]**
The Oxford RobotCar	CRL	R, SN, F	4700	2020	317	[54]
EU Long-term	CRL	SN, R, O, N	NA	2020	72	[69]
RADIATE	CRL	F, SN, R, O, SL, N	NA	2021	132	[70]
K-Radar	CRL	F, R, SN	13000	2022	15	[35]
Boreas	CRL	SN, R, O, N	4400	2022	38	[71]
aiMotive	CRL	R, O, N	85	2023	3	[72]

The datasets for the project are selected based on the following criteria: - Available Sensors, at least it should have camera, radar, and lidar - Adverse weather conditions, - Dataset documentation and

[1]For all the datasets, formal registration form is required to fill to access the dataset

accessibility, - Usage by publicly available methods (so that comparison is possible) - Perception Task, eg. Object Detection - Radar datatype, the data should be available in point cloud format - Time-synchronized and calibrated data

After considering above criteria, the following datasets are selected (also highlighted in the table): - DENSE - nuScenes

3.1.1 DENSE dataset [1]

TODO: paraphrase The Dense dataset [1] focused on evaluating multi-modal fusion algorithms under adverse weather. In addition to LiDAR and a stereo camera, it is also equipped with several all-weather sensors, including one frontal long-range radar, one gated camera working on the NIR band, one FIR camera, and one weather station sensor. The data are captured in various natural weather conditions, including rain, snow, light fog, and heavy fog, as well as in a controlled lab environment in a fog chamber. However, the dataset only provides sparse radar targets with limited FoV and poor resolution. The dataset is recorded in urban city, suburban, highway, and tunnel areas. It coveres several weather conditions like light fog, dense fog, rain, snow, and night. The dataset is used by several multimodal sensor fusion publications for object detection. Table 3.2 higlihts the sensor setup and dataset statistics for each dataset. Geographical coverage of the data collection campaign covering two months and 10,000 km in Germany, Sweden, Denmark, and Finland.

Dataset	**NuScenes [2]**	**DENSE [1]**
Sensor Setup	6	2
RGB Cameras	6	2
RGB Resolution	1600x900	1920x1024
Lidar Sensors	1	2
Lidar Resolution	32	64
Radar Sensor	4	1
Gated Camera	x	1
FIR Camera	x	1
Frame Rate	1 Hz/10 Hz	10 Hz
Dataset Statistics		
Labeled Frames	40K	13.5K
Labels	1.4M	100K
Scene Tags	✓	✓
Night Time	✓	✓
Light Weather	✓	✓
Heavy Weather	x	✓
Fog Chamber	x	x

Table 3.2: Comparison of Dataset Features

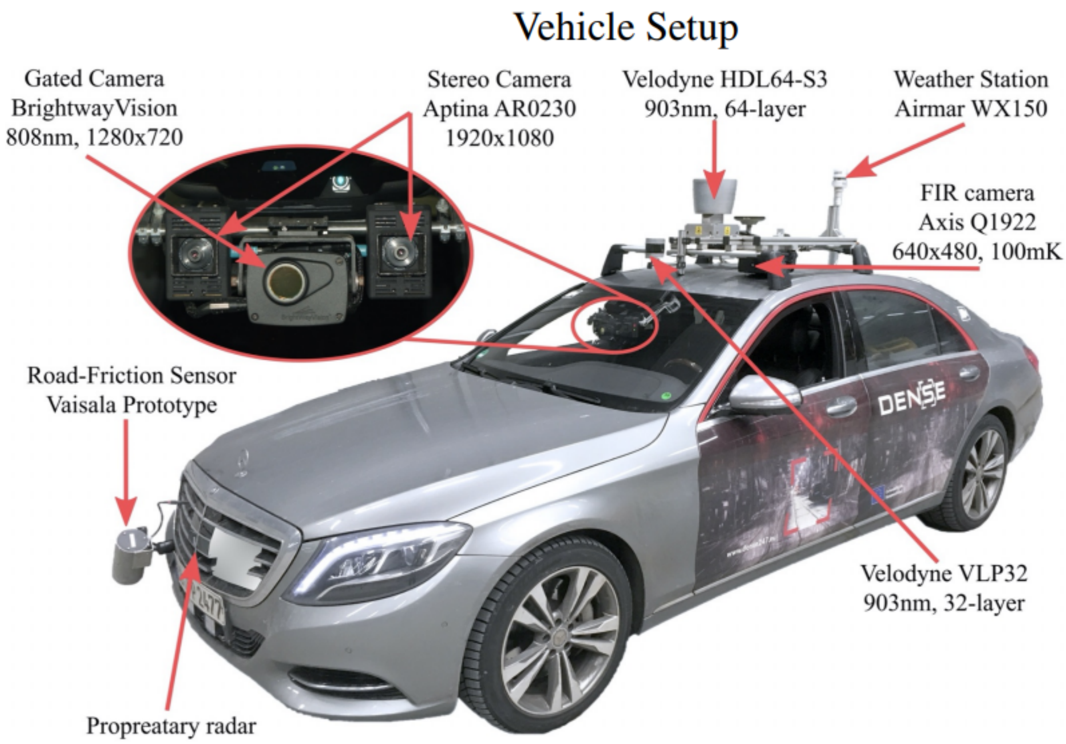


Figure 3.1: Test Vehicle Setup [1]

3.1.2 nuScenes dataset [2]

NuScenes [2] is the most popular dataset for its large-scale and diverse scenarios. The capturing vehicle is equipped with a 32-beam LiDAR, 6 cameras, 5 long-range multi-mode radars, and a GPS/IMU system. It provides 3D annotations of 23 classes of road users in 1000 scenes, with a total of 1.3 million frames. Although, the radar used in nuScenes has a sparse data, but it is good dataset to start with and also well documented. Scenarios: U, S, and H stand for urban (city), suburban, highway Radar datatype: pointtcloud

3.2 Setup

3.3 Experimental Design

3.4 Evaluation Metrics

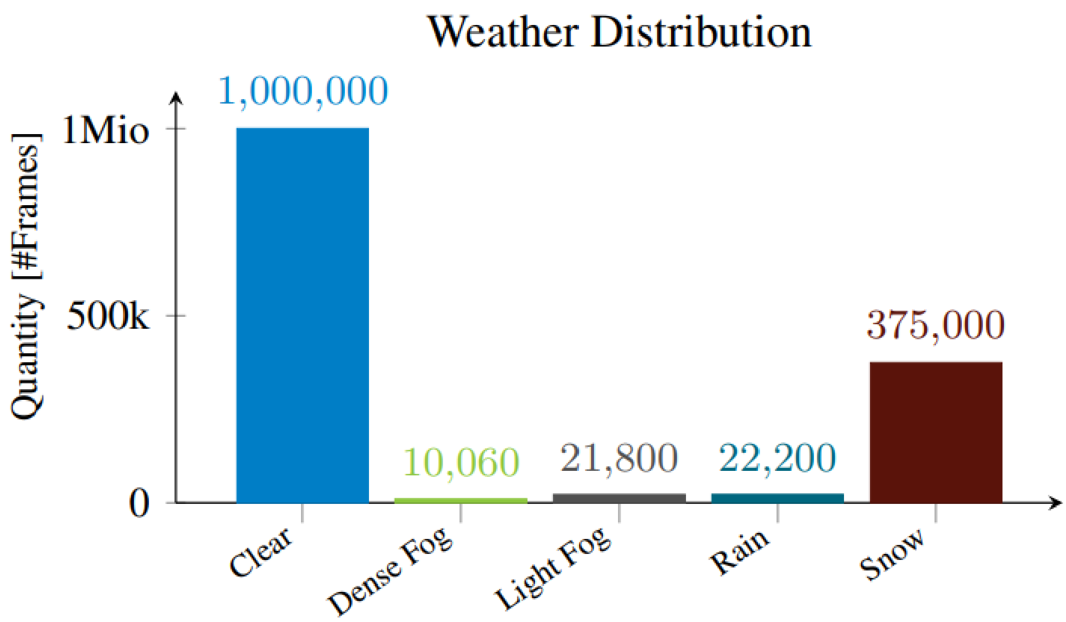


Figure 3.2: Distribution of Weather Conditions [1]

4

Solution

Your main contributions go here

4.1 Proposed algorithm

4.2 Implementation details

5

Evaluation and Results

5.1 Experiment Description

Describe the experiments/evaluation you are performing to analyse your method.

5.2 Experimental Setup

Describe your experimental setup in detail.

5.3 Results

Describe the results of your experiments in detail.

6

Conclusions

6.1 Contributions

6.2 Lessons learned

6.3 Future work

Utilization of 4D Imaging Radar in Adverse Weather: There is a notable lack of research utilizing 4D imaging radar sensors, especially in adverse weather conditions [73]. Given the potential of these sensors in challenging environments, further exploration in this area is essential. The K-Radar dataset [35] is a step in the right direction, but yet to be explored.

A

Design Details

Your first appendix

B

Parameters

Your second chapter appendix

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