R&D Project Proposal

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

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1   Introduction

1.1   Topic of This R&D Project

- Imagine driving on a winding mountain road at night, with fog and rain obscuring your view, your vehicle's self-driving system struggles to detect objects ahead due to the challenging weather conditions. Suddenly, a deer jumps out in front of your car, causing the system to issue an alert and apply the brakes in time to avoid a collision.

- This scenario highlights the importance of object detection in adverse weather conditions for self-driving cars. Visual cameras, which are commonly used for object detection, may be distorted or obscured by rain, fog, snow, or low light, making it difficult to accurately detect objects on the road [1] [2] [3].

- To address these challenges, this project aims to implement a multimodal sensor fusion system that combines cameras, radar, and LiDAR sensors. By fusing data from multiple sensors and leveraging advanced machine learning algorithms, the goal is to enhance object detection's range, accuracy, and reliability in adverse weather conditions.

- The focus will also be on synchronizing multimodal data, processing dense and sparse resolution sensor data, and using a data-driven approach to optimize object detection performance.

- However, this project also faces several challenges. For example, different sensors may have different resolutions and sampling rates and may require sophisticated calibration and alignment techniques to ensure the accurate fusion of their data. Furthermore, processing large volumes of sensor data with minimal latency requires efficient and scalable algorithms and hardware architectures.

- The proposed system will be trained on a diverse dataset to ensure robustness and adaptability in different weather and lighting conditions. The system's effectiveness will be evaluated by extensive experiments and by comparing existing state-of-the-art methods.

- Despite the challenges, the project has the potential to revolutionize object detection in adverse weather conditions, with applications ranging from self-driving cars to surveillance and security systems. By fusing multiple sensor data sources and optimizing their fusion, situational awareness can be enhanced, enabling safer and more efficient operations in various domains.

- This research aims to facilitate safe and efficient self-driving in adverse weather conditions, prioritizing the safety of passengers, other drivers, and pedestrians on the road. To accomplish this, the proposed approach is to develop a sensor fusion system that operates with minimal latency, enabling data processing from multiple sensors in near real-time.

- Topic naming convention:

  - Object detection

    * Refers to the task of detecting objects within an image or video stream.

    * In this project, the focus is on detecting 2D objects such as cars, trucks, pedestrians, and cyclists.

  - Adverse weather conditions

    * Refers to conditions such as fog, snow, rain, overcast skies, sleet, and dust.

    * These conditions can make object detection more challenging due to reduced visibility or other environmental factors.

  - Tightly-coupled

    * Refers to how different modalities of data are combined and integrated at different levels.

    * Rather than relying solely on early, mid, or late fusion techniques, a combination of features at different levels is employed to achieve optimal fusion results.

  - Data-driven

    * Refers to the use of previously collected data or publicly available datasets to improve object detection performance.

  - Multimodal

    * Refers to the use of different data modalities to improve object detection performance.

    * Examples include sensors such as LiDAR, camera, IMU, GPS, infrared, and radar, with different datatypes such as point clouds, images, and time series data.

  - Sensor fusion

    * Refers to the process of fusing data from different sensors to get a better estimation of an environment and improve object detection performance.

1.2 Relevance of This R&D Project

- The relevance of the research project lies in the fact that weather phenomena have a significant negative influence on traffic and transportation, which can lead to accidents, injuries, and fatalities.

- The statistics show that adverse weather conditions, such as rain, snow, sleet, and fog, contribute to a high number of vehicle crashes and fatalities worldwide.

- For example, in the United States, over 30,000 vehicle crashes occur on snowy or icy roads each year, causing over 5,000 fatalities and 418,000 injuries due to adverse weather-related crashes, according to the Federal Highway Administration (FHA) [4] [5].

- The Insurance Institute for Highway Safety (IIHS) found that in snowy weather, the fatal crash rate is 21% higher than on clear roads, while during sleet and freezing rain, the rate is even higher at 37%. Moreover, poor visibility is a contributing factor in over 7,000 annual crashes in the United States, according to the FHA, and in over 4,000 fatal crashes in 2018, according to the National Highway Traffic Safety Administration (NHTSA) [6].

- In Europe, adverse weather conditions cause 25% of all road accidents, with frost and ice, snow, and rain being the highest contributing factors, according to the European Commission and the European Transport Safety Council (ETSC). Over 12,000 people die on European roads each year in weather-related accidents [7].

- Furthermore, the project's results will benefit various sectors, including autonomous vehicles, healthcare, precision agriculture, environmental monitoring, aerospace and defense, and industrial automation.

- The sensor fusion market for autonomous vehicles is expected to reach $22.2 billion by 2030 at a CAGR of 25.4%, according to Marketsandmarkets [8].

- In the healthcare sector, wearable sensors are estimated to reach over $1.5 billion in revenue by 2030, growing at a CAGR of over 18.3% [9].

- For precision agriculture and environmental monitoring, the market is expected to reach \$10.5 billion by 2026, growing at a CAGR of over 12.6% [10].

- The aerospace and defense sector, including aircraft navigation and control, missile guidance, and military logistics, is expected to reach \$23.83 billion by 2027, at a CAGR of 4.21% [11].

- Even the industrial automation sector benefits from the sensor fusion technology as it can improve the efficiency of the production process and reduce the cost of production.

2 Related Work

2.1 Survey of Related Work

- Object detection is a fundamental computer vision problem in autonomous robots, including self-driving vehicles and autonomous drones. Such applications require 2D or 3D bounding boxes of scene objects in challenging real-world scenarios, including complex cluttered scenes, highly varying illumination, and adverse weather conditions. The most promising autonomous vehicle systems rely on redundant inputs from multiple sensor modalities [12] [13] [14], including camera, LiDAR, radar, and emerging sensors such as far-infrared(FIR) and near-infrared(NIR) [15].

- For a typical perception system, the most common sensor is camera, and it's actually the one element that is absolutely not replaceable in autonomous driving systems. But it's also one of the most vulnerable sensors to adverse weather conditions. A camera in rain, regardless of however high resolution, can be easily incapacitated by a single water drop on the emitter or lens [16]. Heavy snow or hail could fluctuate the image intensity and obscure the edges of the pattern of a certain object in the image or video which leads to detection failure [17]. A particular weather phenomenon, strong light, directly from the sun or artificial light source like light pollution from a skyscraper may also cause severe trouble to cameras [18].

- Second most common sensor available on autonomous driving systems is LiDAR. For the most common weather, rain, when it's not extreme like a normal rainy day, it doesn't affect LiDARs that much according to the research of Fersch et al. [19] on small aperture LiDAR sensors. More serious harm of rain happens when it becomes heavy or unbridled. Rains with a high and non-uniform precipitation rate would most likely form lumps of agglomerate fog and create fake obstacles to the LiDARs. Hasirlioglu et al. [20] proved that the signal reflection intensity drops significantly in a rain rate of more than 40 mm/hr. According to Zhang et al. [21], dense fog or dense smoke cause the same effect as the heavy rain. As mentioned for camera, a strong light also affect LiDAR sensors in extreme conditions [18].

- Radar is the third most crucial sensor in autonomous driving systems and is widely used in mass-produced cars for active safety functions, such as automatic emergency braking (AEB) and forward collision warning (FCW). However, its significance is often overlooked from the perspective of perception tasks in autonomous driving. Radar appears to be more resilient in inclement weather conditions than other sensors commonly used in autonomous driving. As reported by Ijaz et al. [22] and Ismail [23], radar exhibits lower attenuation in rainy conditions than LiDAR. The attenuation of radar at 77 GHz is approximately 3.5 times lower (10 dB/km) than that of LiDAR at 905 nm (35 dB/km), demonstrating better robustness. Multiple experiments [17, 24–27] have revealed that attenuation and backscattering under dust, fog, snow, and light rain are negligible for radar, while its performance degrades under heavy rainfall. However, one of the significant drawbacks of radar is its low resolution, which makes it difficult to use in perception tasks. The radar point cloud is much sparser than LiDAR, limiting its usability. Recently, the next generation of 4D radar has emerged, which can provide denser points compared to conventional radar sensors.

- By now, it's almost well established that the LiDAR or Camera architecture alone is not going to navigate through adverse weather conditions with enough safety assurance. But two forces combining together would be a different story with the additional strength. As a result, groups from all over the world

come up with their own permutation and combination with camera, LiDAR, radar, infrared camera, gated camera, stereo camera, weather stations and other weather-related sensors.

- Yang et al. [28] brought up a modality called RadarNet, which exploits both radar and LiDAR sensors for perception. It uses an early fusion mechanism to learn joint representations from the two sensors, and a late-fusion mechanism to exploit radar's radial velocity evidence and improve the estimated object velocity. They validated their modality in the nuScenes dataset [12].

- Liu et al. [29] raised a robust target recognition and tracking method combining radar and camera information under severe weather conditions, with radar being the main hardware and camera the auxiliary. They tested their scheme in rain and fog including night conditions when visibility was the worst. Results show that radar has a pretty high accuracy in detecting moving targets in wet weather, while the camera is better at categorizing targets and the combination beats LiDAR alone detection by over a third.

- FLIR System Inc. [30] and the VSI Labs [31] tested the world's first fused automated emergency braking (AEB) sensor suite in 2020, equipped with a thermal long-wave infrared (LWIR) camera, a radar and a visible camera. LWIR covers the wavelength ranging from 8 µm to 14 µm and such camera operates under ambient temperature known as the uncooled thermal camera. This sensor suite was tested along with several cars with various AEB features employing radar and visible camera against day-time, nighttime and tunnel exit into sun glare. The comparison showed that although most AEB systems work fine in the daytime, normal AEB almost hit every man nequin under those adverse conditions, while the LWIR sensor suite never knocked down a single one. This work shows the potential of the camera and radar fusion in adverse weather conditions.

- Radecki et al. [32] extensively summarized the performance of each sensor against all kinds of weather including wet conditions, day & night, cloudy, glare, and dust. They formulated a system with the ability of tracking and classification based on the probability of joint data association. Their

vision detection algorithm is realized by using sensor subsets corresponding to various weather conditions with realtime joint probabilistic perception. The essence of such fusion is about real-time strategy shift. Sensor diversity improves the perception ability general lower bound, but the intelligent choice of sensor weighting and accurately quantified parameters based on the particular weather determine the ceiling of the robustness and reliability of such modalities.

- Bijelic et al. [15] from Mercedes-Benz AG conducted a study on improving detection performance in adverse weather conditions using a deep multimodal sensor fusion approach. The authors equipped their test vehicle with various sensors, including stereo RGB cameras, a NIR camera, a 77 GHz radar, two LiDARs, an FIR camera, a weather station, and a road-friction sensor. They proposed an entropy-steered fusion approach where regions with low entropy were attenuated while entropy-rich regions were amplified during feature extraction. The exteroceptive sensor data were concatenated and trained using clear weather data, demonstrating strong adaptation to unseen adverse weather data. The fusion network was designed to generalize across different scenarios, and all the sensor data were projected into the camera coordinate system to ensure consistency. The fused detection performance outperformed LiDAR or image-only approaches under fog conditions.

- Bijelic et al. [15] also provided the SeeingThroughFog dataset for further research on multimodal sensor fusion in adverse weather conditions. This dataset comprises 10,000 km of driving data in Northern Europe, recorded during February and December 2019, under varying weather and illumination conditions. The dataset includes annotations for 5.5 k clear weather frames, 1 k dense fog frames, 1 k light fog frames, and 4 k frames captured in snow/rain.

- Qian et al. [33] introduced a Multimodal Vehicle Detection Network (MVD-Net) featuring LiDAR and radar. It first extracts features and generates proposals from both sensors, and then the multimodal fusion processes region-wise features to improve detection. They created their own training dataset based on the Oxford Radar Robotcar [34] and the evaluation shows much

better performance than LiDAR alone in fog conditions.

- Rawashdeh et al. [35] include cameras, LiDAR and radar in their CNN sensor fusion for drivable path detection, and used DENSE [15] dataset. This multi-stream encoder-decoder almost complements the asymmetrical degradation of sensor inputs at the largest level. The depth and the number of blocks of each sensor in the architecture are decided by their input data density, of which camera has the most, LiDAR the second and radar the last, and the outputs of the fully connected network are reshaped into a 2-D array which will be fed to the decoder. Their model can successfully ignore the lines and edges that appeared on the road which could lead to false interpretation and delineate the general drivable area.

- There are studies out there that use de-hazing techniques to remove the bad effects fro adverse weather. While physical priors were previously used [36] [37], data-driven methods using deep learning have been introduced. However, deep de-hazing models have high computational complexity and are unsuitable for ultra-high-definition images. Chen et al. [38] found that models trained on synthetic images do not generalize well to real-world hazy images, while Zhang et al. [39] used temporal redundancy to perform video de-hazing and collected a dataset of real-world hazy and haze-free videos. Although collecting pairs of hazy and haze-free ground-truth images is challenging, professional haze/fog generators exist to simulate real-world conditions [40] [41].

- The rapid developments of autonomous driving especially in adverse weather conditions benefit a lot from the availability of simulation platforms and experimental facilities like fog chambers or test roads. Virtual platforms like the well-known CARLA [42] simulator, enable researchers to construct custom-designed complex road environments and non-ego participants with infinite scenarios where it would be extremely hard and costly in real field experiments. Moreover, for weather conditions, the appearing of each kind of weather especially season-related or extreme climates related is not on call at all times. For example, it's impossible for tropical areas to have the

opportunity to do snow tests; and natural rain showers might not be long enough to collect experimental data. Most importantly, adverse conditions are usually dangerous for driving and subjects always face safety threats in normal field tests, while absolute zero risks are something that simulators can guarantee [21].

- Few researchers have explored synthetic data generation for adverse weather conditions using GAN-based techniques from clean weather dataset eg. KITTI [43], Cityscapes [44], etc [45] [46] [47].

- Most of the deep multimodal perception methods are based on supervised learning. Therefore, multimodal datasets with labeled ground-truth are required for training such deep neural networks. There are several multimodal datasets available, however, most of these datasets are collected under clear weather conditions. The datasets collected under adverse weather conditions are limited. The following are some of the multimodal datasets for testing the performance of deep multimodal perception methods in adverse weather conditions. Out of all the datasets, only a recently released K-Radar [48] has the 4D radar sensor. Here C-R-L-N-F refers to Camera, Radar, LiDAR, and Near-infrared amd Far-infrared sensors, respectively.

Table 1: List multimodal datasets with adverse weather conditions

Name	Sensors	Link	Year
DENSE	CRLNF	[15]	2020
EU Long-term	CRL	[49]	2020
nuScenes	CRL	[12]	2020
The Oxford RobotCar	CRL	[34]	2020
RADIATE	CRL	[50]	2021
K-Radar	CRL	[48]	2022
aiMotive	CRL	[51]	2022
Boreas	CRL	[52]	2022
WADS	CRLNF	[53]	2023

- C-R Fusion: [54]

    - Model inspired by C-L fusion

- – Shows the importance of radar in object detection

- K-radar: [55]

  - – Released 4D radar dataset

  - – Showed baseline network only, and mAP still 41.1%

  - – But not compared with other multi-modal architectures and does not use advanced NN techniques

2.2 Limitation and Deficits in the State of the Art

- Most existing works fuse RGB images from visual cameras with 3D LiDAR point clouds [56]

- There is no general guideline for network architecture design, and the below questions are still open[57]:

  - – "what to fuse" - LiDAR, radar, color camera, thermal camera, event camera, ultrasonic

  - – "how to fuse" - addition or mean, concatenate, ensemble, mixture of experts

  - – "when to fuse" - early, mid, late, combination of all

- Previous studies lack comparison with alternative models or datasets

- showing only results for their own baseline models and custom datasets

- None of the multi-modal sensor fusion algorithms handle temporal information [15]

- Not much work available utilizing 4D imaging radar sensor [57]

3 Problem Statement

- A thorough analysis and practical implementation of state-of-the-art methods for object detection using multiple modalities including but not limited to camera, LiDAR, and radar

- Determining an appropriate fusion strategy to exploit the complementary characteristics of various sensors

  - How to fuse camera + 4D radar data

- Fusion of spatial and temporal information from multimodal sensors

- If required, use CARLA or other simulators to validate the performance of a model

- Conduct experiments and compare outcomes with various models and adverse weather conditions datasets

  - Datasets: K-radar[55], DENSE[15], aiMotive[58]

4 Project Plan

4.1 Work Packages

Planning is the replacement of randomness by error. (Einstein). Very much like you would never start a longer journey without a detailed travel plan, you should not start a project without a carefully though out work plan. A work package is a logical decomposition of a larger piece of work into smaller parts following a "divide and conquer" strategy. It is very specific to the problem that you are going to address. Refrain from a rather generic decomposition. If your work plan looks similar to those of your school mates, which may address completely different problems then you have not thought carefully enough about how you approach the problem. It is ok to have two generic work packages *Literature Study* and *Project Report*. Discuss your work packages in the ASW seminar.

The bare minimum will include the following packages:

WP1 Literature Study

WP2 ...

WP3 ...

1. ...

WPy Evaluation of approach and comparison with similar approaches

WPz Project Report

4.2   Milestones

Milestones mark the completion of a certain activity or at least a major achievement in an activity. Milestones are also decision points, where you reflect on what you have achieved and what options you have for continuing your work in case you have not achieved what was planned. Above all, milestones have to be measurable. As above, if your milestones are the same as those of your school mates, then you may not have thought carefully enough about how your project shall progress.

M1 Literature review completed and best practice identified

M2 ...

M3 ...

M4 Report submission

4.3   Project Schedule

Include a Gantt chart here. It doesn't have to be detailed, but it should include the milestones you mentioned above. Make sure to include the writing of your report throughout the whole project, not just at the end.
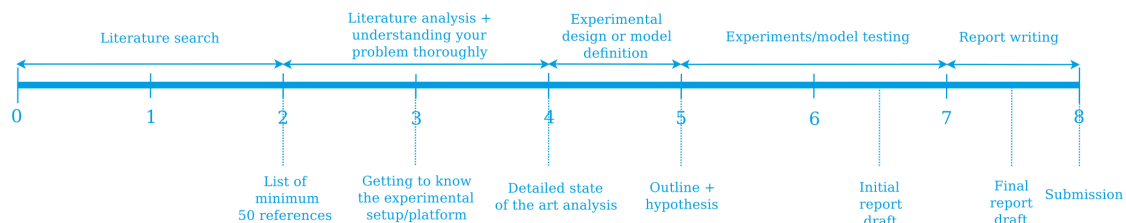

Figure 1: My figure caption

4.4 Deliverables

Minimum Viable

- Comparative analysis of two methods on two datasets

- Detecting single class of objects ex. car, pedestrian, cyclist, truck etc.

Expected

- Compare more advance methods with baseline methods on different datasets

- Detecting multi classes of objects ex. car, pedestrian, cyclist, truck etc.

Desired

- Run experiments on CARLA simulator to validate the performance of a model

    - Note: CARLA simulator doesn't support 4D radar sensor

- Utilizing spatial and temporal information from multimodal sensors

Please note that the final grade will not only depend on the results obtained in your work, but also on how you present the results.

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