Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

Bonn-Aachen
International Center for
Information Technology

R&D Project Proposal

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

Kevin Patel

Supervised by

Prof. Dr.-Ing. Sebastian Houben
M.Sc. Santosh Thoduka

February 2023

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 multi-modal 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 multi-modal 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.
  - Multi-modal
    - 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 used sensor in autonomous driving systems. Although millimetre wave radar has been widely used in mass-produced cars for active safety functions such as automatic emergency braking (AEB) and forward collision warning (FCW), it is overlooked in autonomous driving from the perception task point-of-view. Radar seems to be more resilient in weather conditions. According to Ijaz et al. [22] and Ismail [23], in rainy conditions, radar exhibits lower attenuation than LiDAR. Radar at 77 GHz demonstrates approximately 3.5 times lower attenuation (10 dB/km) compared to LiDAR at 905 nm (35 dB/km), highlighting its better robustness. Experiments [24] [25] [26] [27] [17] [24] reveal attenuation and backscattering under dust, fog, snow, and light rain are negligible for radar, while the performance of radar degrades under heavy rainfall. However, one of the major drawbacks of radar is its low resolution. Radar point cloud is much sparser than LiDAR, which makes it difficult to use in perception tasks.

- 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. Until a few years ago, the single image de-hazing algorithm based on physical priors was still the focus [36] [37]. However, deducing these physical priors requires professional knowledge and it is not always available when applied to different scenes. With the advance of deep learning theory, more and more researchers introduced this data-driven method into the field. Chen et al. [38] found that de-hazing models trained on synthetic images do not generalize well to real-world hazy images. Zhang et al. [39] used temporal redundancy from neighborhood hazy frames to perform video de-hazing and collected a dataset of real-world hazy and corresponding haze-free videos. Existing deep de-hazing models are not suitable for ultra-high-definition images due to their high computational complexity. Although the field has approached maturity, the main-stream methods still use synthesis data to train models. Because collecting pairs of hazy and haze-free ground- truth images need to capture both images with identical scene radiance, which is almost impossible in real road scenes. Still, there are some professional haze/fog generators that imitates the real conditions of haze scenes [40] [41].

- C-R Fusion: [42]
  - Model inspired by C-L fusion
  - Shows the importance of radar in object detection

- K-radar: [43]

  - 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 [44]
- There is no general guideline for network architecture design, and the below questions are still open[45]:
  - "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 [45]

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 multi-modal 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[43], DENSE[15], aiMotive[46]

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.

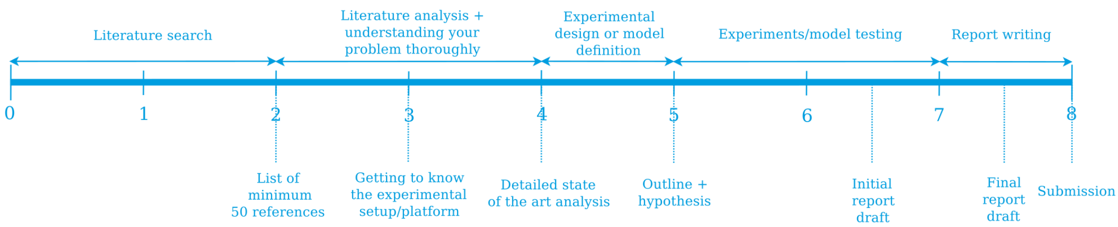

Figure 1: My figure caption

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 multi-modal 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.

References

[1] Ekim Yurtsever, Jacob Lambert, Alexander Carballo, and Kazuya Takeda. A survey of autonomous driving: Common practices and emerging technologies. *IEEE access*, 8:58443–58469, 2020.

[2] Alexander Carballo, Ekim Yurtsever, and Kazuya Takeda. Libre: The multiple 3d lidar dataset. *2020 IEEE Intelligent Vehicles Symposium (IV)*, pages 1094–1101, 2020.

[3] University of Michigan. Getting traction: Tips for traveling in winter weather, 2020.

[4] Federal-Highway-Administration. How Do Weather Events Impact Roads? - FHWA Road Weather Management.

[5] NOAA US Department of Commerce. Getting traction: Tips for traveling in winter weather, Nov 2016.

[6] Matthew L Brumbelow. Light where it matters: Iihs headlight ratings are correlated with nighttime crash rates. *Journal of safety research*, 83:379–387, 2022.

[7] Graham Cookson. Weather-Related Road Deaths in Europe £15bn+ Per Year — INRIX, 2 2022.

[8] MarketsandMarkets. Sensor fusion market by technology - 2022 — marketsandmarkets.

[9] Straits Research. Wearable sensors market, 2021.

[10] Mordor intelligence. Precision farming market analysis, industry report, trends, size, and share.

[11] Fortune business insights. Aerospace and defense materials market size, share, and report, 2027.

[12] Holger Caesar, Varun Bankiti, Alex H Lang, Sourabh Vora, Venice Erin Liong, Qiang Xu, Anush Krishnan, Yu Pan, Giancarlo Baldan, and Oscar Beijbom. nuscenes: A multimodal dataset for autonomous driving. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 11621–11631, 2020.

[13] Pei Sun, Henrik Kretzschmar, Xerxes Dotiwalla, Aurelien Chouard, Vijaysai Patnaik, Paul Tsui, James Guo, Yin Zhou, Yuning Chai, Benjamin Caine, et al. Scalability in perception for autonomous driving: Waymo open dataset. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 2446–2454, 2020.

[14] Julius Ziegler, Philipp Bender, Markus Schreiber, Henning Lategahn, Tobias Strauss, Christoph Stiller, Thao Dang, Uwe Franke, Nils Appenrodt, Christoph G Keller, et al. Making bertha drive—an autonomous journey on a historic route. *IEEE Intelligent transportation systems magazine*, 6(2):8–20, 2014.

[15] Mario Bijelic, Tobias Gruber, Fahim Mannan, Florian Kraus, Werner Ritter, Klaus Dietmayer, and Felix Heide. Seeing through fog without seeing fog: Deep multimodal sensor fusion in unseen adverse weather, 2020.

[16] Raffi Mardirosian. Lidar vs. camera: driving in the rain. [Last accessed 10 April 2023], 2023.

[17] Shizhe Zang, Ming Ding, David Smith, Paul Tyler, Thierry Rakotoarivelo, and Mohamed Ali Kaafar. The impact of adverse weather conditions on autonomous vehicles: how rain, snow, fog, and hail affect the performance of a self-driving car. *IEEE vehicular technology magazine*, 14(2):103–111, 2019.

[18] Alexander Carballo, Jacob Lambert, Abraham Monrroy, David Wong, Patiphon Narksri, Yuki Kitsukawa, Eijiro Takeuchi, Shinpei Kato, and Kazuya Takeda. LIBRE: The multiple 3d lidar dataset. *arXiv preprint arXiv:2003.06129*, 2020. (accepted for presentation at IV2020).

[19] Thomas Fersch, Alexander Buhmann, Alexander Koelpin, and Robert Weigel. The influence of rain on small aperture lidar sensors. In *2016 German Microwave Conference (GeMiC)*, pages 84–87. IEEE, 2016.

[20] Sinan Hasirlioglu, Igor Doric, Christian Lauerer, and Thomas Brandmeier. Modeling and simulation of rain for the test of automotive sensor systems. In *2016 IEEE Intelligent Vehicles Symposium (IV)*, pages 286–291. IEEE, 2016.

[21] Yuxiao Zhang, Alexander Carballo, Hanting Yang, and Kazuya Takeda. Autonomous Driving in Adverse Weather Conditions: A Survey, December 2021.

[22] Muhammad Ijaz, Zabih Ghassemlooy, Hoa Le Minh, Sujan Rajbhandari, and J Perez. Analysis of fog and smoke attenuation in a free space optical communication link under controlled laboratory conditions. In *2012 International Workshop on Optical Wireless Communications (IWOW)*, pages 1–3. IEEE, 2012.

[23] Ismail Gultepe. Measurements of light rain, drizzle and heavy fog. In *Precipitation: advances in measurement, estimation and prediction*, pages 59–82. Springer, 2008.

[24] Martin Adams, Martin David Adams, and Ebi Jose. *Robotic navigation and mapping with radar*. Artech House, 2012.

[25] Graham Brooker, Ross Hennessey, Craig Lobsey, Mark Bishop, and Eleonora Widzyk-Capehart. Seeing through dust and water vapor: Millimeter wave radar sensors for mining applications. *Journal of Field Robotics*, 24(7):527–557, 2007.

[26] Ruoyang Xu, Wei Dong, Akash Sharma, and Michael Kaess. Learned depth estimation of 3d imaging radar for indoor mapping. In *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 13260–13267. IEEE, 2022.

[27] Rossiza Gourova, Oleg Krasnov, and Alexander Yarovoy. Analysis of rain clutter detections in commercial 77 ghz automotive radar. In *2017 European Radar Conference (EURAD)*, pages 25–28. IEEE, 2017.

[28] Bin Yang, Runsheng Guo, Ming Liang, Sergio Casas, and Raquel Urtasun. Radarnet: Exploiting radar for robust perception of dynamic objects. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XVIII 16*, pages 496–512. Springer, 2020.

[29] Ze Liu, Yingfeng Cai, Hai Wang, Long Chen, Hongbo Gao, Yunyi Jia, and Yicheng Li. Robust target recognition and tracking of self-driving cars with radar and camera information fusion under severe weather conditions. *IEEE Transactions on Intelligent Transportation Systems*, 23(7):6640–6653, 2021.

[30] Flir. fused aeb with thermal can save lives.

[31] Research testing on adas autonomous vehicle technologies.

[32] Peter Radecki, Mark Campbell, and Kevin Matzen. All weather perception: Joint data association, tracking, and classification for autonomous ground vehicles. *arXiv preprint arXiv:1605.02196*, 2016.

[33] Kun Qian, Shilin Zhu, Xinyu Zhang, and Li Erran Li. Robust multimodal vehicle detection in foggy weather using complementary lidar and radar signals. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 444–453, 2021.

[34] Dan Barnes, Matthew Gadd, Paul Murcutt, Paul Newman, and Ingmar Posner. The oxford radar robotcar dataset: A radar extension to the oxford robotcar dataset. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 6433–6438. IEEE, 2020.

[35] Nathir A Rawashdeh, Jeremy P Bos, and Nader J Abu-Alrub. Drivable path detection using cnn sensor fusion for autonomous driving in the snow. In *Autonomous Systems: Sensors, Processing, and Security for Vehicles and Infrastructure 2021*, volume 11748, pages 36–45. SPIE, 2021.

[36] Robby T Tan. Visibility in bad weather from a single image. In *2008 IEEE conference on computer vision and pattern recognition*, pages 1–8. IEEE, 2008.

[37] Jean-Philippe Tarel and Nicolas Hautiere. Fast visibility restoration from a single color or gray level image. In *2009 IEEE 12th international conference on computer vision*, pages 2201–2208. IEEE, 2009.

[38] Zeyuan Chen, Yangchao Wang, Yang Yang, and Dong Liu. Psd: Principled synthetic-to-real dehazing guided by physical priors. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 7180–7189, 2021.

[39] Xinyi Zhang, Hang Dong, Jinshan Pan, Chao Zhu, Ying Tai, Chengjie Wang, Jilin Li, Feiyue Huang, and Fei Wang. Learning to restore hazy video: A new real-world dataset and a new method. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9239–9248, 2021.

[40] Valentina Mușat, Ivan Fursa, Paul Newman, Fabio Cuzzolin, and Andrew Bradley. Multi-weather city: Adverse weather stacking for autonomous driving. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2906–2915, 2021.

[41] Radu Timofte, Shuhang Gu, Jiqing Wu, and Luc Van Gool. Ntire 2018 challenge on single image super-resolution: Methods and results. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 852–863, 2018.

[42] Felix Nobis, Maximilian Geisslinger, Markus Weber, Johannes Betz, and Markus Lienkamp. A Deep Learning-based Radar and Camera Sensor Fusion Architecture for Object Detection, May 2020.

[43] Dong-Hee Paek, Seung-Hyun Kong, and Kevin Tirta Wijaya. K-Radar: 4D Radar Object Detection for Autonomous Driving in Various Weather Conditions, June 2022.

[44] Di Feng, Christian Haase-Schütz, Lars Rosenbaum, Heinz Hertlein, Claudius Glaeser, Fabian Timm, Werner Wiesbeck, and Klaus Dietmayer. Deep multi-modal object detection and semantic segmentation for autonomous driving: Datasets, methods, and challenges, 2020.

[45] Yi Zhou, Lulu Liu, Haocheng Zhao, Miguel López-Benítez, Limin Yu, and Yutao Yue. Towards Deep Radar Perception for Autonomous Driving: Datasets, Methods, and Challenges, May 2022.

[46] Tamás Matuszka, Iván Barton, Ádám Butykai, Péter Hajas, Dávid Kiss, Domonkos Kovács, Sándor Kunsági-Máté, Péter Lengyel, Gábor Németh, Levente Pető, Dezső Ribli, Dávid Szeghy, Szabolcs Vajna, and Bálint Varga. aiMotive Dataset: A Multimodal Dataset for Robust Autonomous Driving with Long-Range Perception, November 2022.

[47] Author Name. Book title. *Lecture Notes in Autonomous System*, 1001:900–921, 2003.

[48] Cristian Tangemann. Sensor fusion, 2022. Accessed on 29.09.2022.

[49] Markus Willems. A dsp for implementing high-performance sensor fusion on an embedded budget, Nov 2021.

[50] robert laganière. Sensor fusion for autonomous vehicles: Strategies, methods, and tradeoffs, 2022. Accessed on 18.12.2022.

[51] Dan Leibholz. Real-time sensor fusion challenge, 2022. Accessed on 29.09.2022.

[52] Ann Steffora Mutschler. Sensor fusion challenges, 2022. Accessed on 29.09.2022.

[53] Gregory-Koshmak et al. Challenges and issues in multisensor fusion approach, 2022. Accessed on 29.09.2022.

[54] Michael Ulrich, Claudius Gläser, and Fabian Timm. Deepreflecs: Deep learning for automotive object classification with radar reflections. In *2021 IEEE Radar Conference (RadarConf21)*, pages 1–6. IEEE, 2021.

[55] Florian Drews, Di Feng, Florian Faion, Lars Rosenbaum, Michael Ulrich, and Claudius Gläser. Deepfusion: A robust and modular 3d object detector for lidars, cameras and radars. In *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 560–567. IEEE, 2022.

[56] Yrvann Emzivat, Javier Ibanez-Guzman, Hervé Illy, Philippe Martinet, and Olivier H Roux. A formal approach for the design of a dependable perception system for autonomous vehicles. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pages 2452–2459. IEEE, 2018.