INTEGRATING 3D ACOUSTIC SENSORS WITH OPTICAL CAMERA FOR ROBUST SENSING IN ADVERSE WEATHER CONDITIONS

By

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26 February 2025

Declaration of own work

I declare that the work in this MSc dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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26 February 2025

Acknowledgement

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First and foremost, I am deeply thankful to my supervisor, Dr. Amina Hamoud, for her exceptional guidance, insightful feedback, and patience. Her expertise and encouragement have played a crucial role in shaping this research. I am particularly grateful for her continued advice and support during the resit phase, I would not have done this without her mentorship.

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This dissertation represents the culmination of my technical education, the knowledge I have gained throughout this MSc programme and my aspirations for my future career. I am deeply thankful for all the support I have received and am proud to present this academic achievement.

Abstract

In the realm of modern Advanced Driver Assistance Systems (**ADAS**) technology, Light Detection and Ranging (**LiDAR**) and optical cameras have emerged as the predominant sensors within perception systems. Nevertheless, both technologies face significant challenges against diverse weather conditions, where precipitation and atmospheric conditions can compromise their sensing capabilities through scattering and attenuation effects. On the other hand, Sound Navigation and Ranging (**Sonar**) offers distinct advantaged despite its limitations in terms of resolution and detection range, including low power consumption, cost-effectiveness and most importantly its resilience to harsh environmental conditions. Therefore, it is worthwhile to explore the potential of acoustic sensors in this context.

This research project presents an integrated sensor system that combines 3D point clouds from a novel air-coupled 3D ultrasonic perception sensor, developed by Calyo Ltd, a company based in the UWE Enterprise Zone, with data captured by an RGB camera. The goal of this study is to assess the impact of environmental factors, such as rain and fog intensities on sensor performance, and to evaluate the accuracy and reliability of 3D ultrasound technology.

To this end, a series of simulated driving scenarios and a physics model of the acoustic sensor were created in CARLA, a driving simulator platform.The development of object dimensions and distance estimation algorithms will enable the analysis and comparison of sensor data accuracies, signal-to-noise ratios, and attenuation rates in various weather conditions.

Multiple simulated driving scenarios and the physics model of the acoustic sensor were created on the CARLA platform. With the development of object dimensions and distance estimation algorithms, this enables the analysis and comparison of sensor data accuracies, signal-to-noise ratios, and attenuation rates in various weather conditions.

Moreover, this work took into account the attenuation effect of rain and fog particles to model the propagation of acoustic waves. Comparative findings highlighted the robustness and potential of the novel 3D ultrasonic sensor to adopt in adverse weather conditions and to address the limitations of existing technologies. Its resilience to weather-induced noise makes it capable of complementing other sensors in a multi-modal system.

The results of this study offer valuable insights into the adoption and optimization of 3D acoustic sensing

technology in robust perception systems, particularly in the automotive industry. By promoting the use of cost-effective and weather-resilient technologies like sonar, this work contributes to the development of more reliable and robust autonomous vehicle perception systems, advancing the field of ADAS and autonomous driving.

Number of words in the dissertation: 11873 words.

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1 Introduction

1.1 3d ultrasonic sensor

The Calyo Pulse sensor [1] is a **phased array acoustic sensor** that exhibits low **SWaP-C** (size, weight, power, and cost) advantages. It demonstrates resilience to environmental factors such as low light conditions, and is able to propagate through and function normally in challenging conditions such as rain and fog, where electromagnetic-based sensors such as radar and lidar may struggle. Unlike traditional 1D air-coupled range finders and parking sensors which emit single pulse and measure reflections at fixed angles, the Calyo Pulse offers real-time high-resolution 3D imaging with precise spatial awareness. The Calyo sensor provides a cost-effective alternative to LiDAR in terms of near-range 3D perception; and offers enhanced precision for object detection within close proximity in comparison to radar.

The Calyo Pulse sensor leverages time-of-flight (TOF) technology to measure distance and positions of objects. By emitting short bursts of ultrasonic waves, it enables accurate detection of objects positions in the near range with a wider field-of-view (FOV) [2]. It provides excellent scalability and reliability even in challenging environmental conditions, despite scattering and attenuation effects may diminish intensity as the acoustic waves travel through the air.

Figure 1.1: Calyo Pulse 3D acoustic sensor

Interface	USB 2.0 Type-C
Supply voltage	5V DC *via* USB (approximate current draw: **0.15A**)
Power consumption	Less than 1W (**0.7W** average)
Pulse frequency (Tx)	Nominal frequency: **40kHz** ± 1kHz Interchangeable Tx transducers allow frequency customisation for varied user applications
Sensitivity (Rx)	Frequency response range from **100Hz-80kHz**
Scan range*	Detection from **10cm** to **15m**
Range resolution*	Less than **1cm**
Angular resolution*	Approximately **4°** at the centre, widening to **14°** at the edges
Field of view (FoV)*	Horizontal/vertical coverage up to 180°/180° Nominal FoV: **180°/160°**
Scan rate	Up to ~**30Hz** (adjustable) – limited only by acoustic travel time
Ambient operating temperature	$-15°C$ to $+80°C$ ($5°F$ to $176°F$)
What outputs can you achieve?	3-D point cloud data 3-D object location (centroids) 2-D energy-scapes (heat-map slices) Raw Rx signal data (x32) Protective zone (OSSD)
Ingress protection	Splash resistant (front face only)
Construction	Made from anodised aluminium alloy with a matte black finish

Figure 1.2: Technical Specifications of Calyo Pulse Sensor

Device dimensions

Length	Width	Depth	Weight
$59.5mm$	$43mm$	$15.4mm$	$\sim 40g$

Figure 1.3: Sensor Dimensions

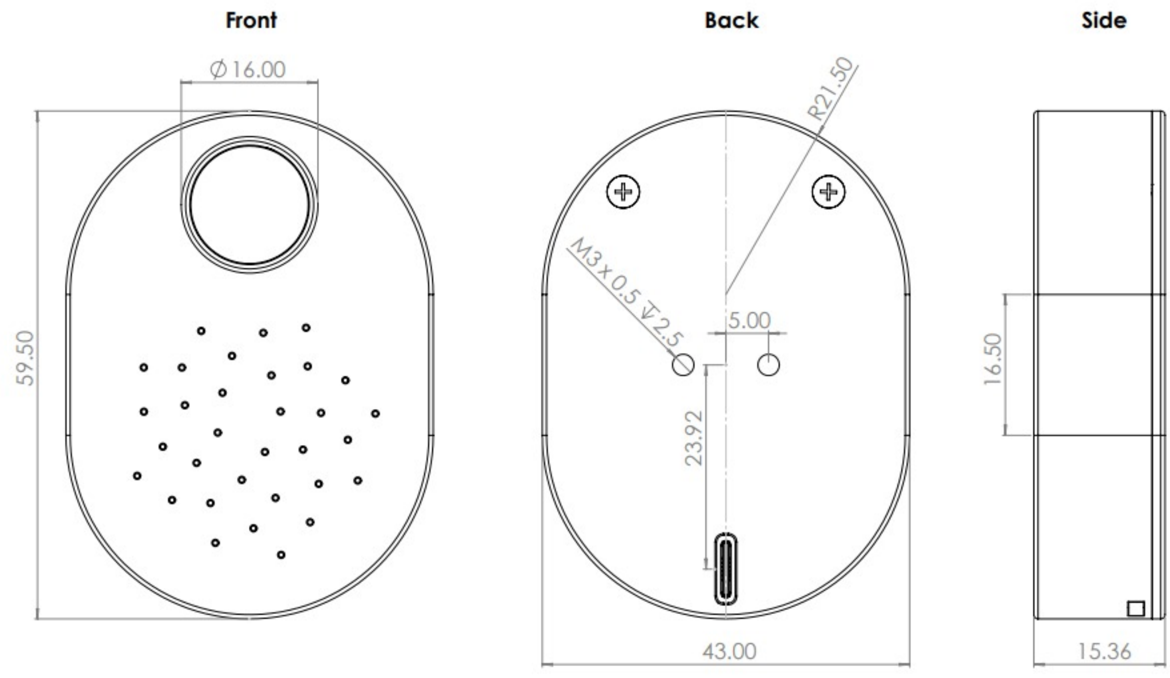


Figure 1.4: CAD Drawings

1.1.1 Measurement Principle

The principle of sonar is as follows:

1. The transducer emits an acoustic pulse.
2. The emitted pulse is reflected by surrounding objects.
3. Reflected echoes are captured by an array of microphones (acoustic receivers) located on the sensor.
4. The time and angle of arrival (AOA) (azimuth & elevation) of the echoes are used to calculate 3D coordinates and distance.
5. The sensor projects these 3D coordinates as point clouds at the end of each measurement cycle.

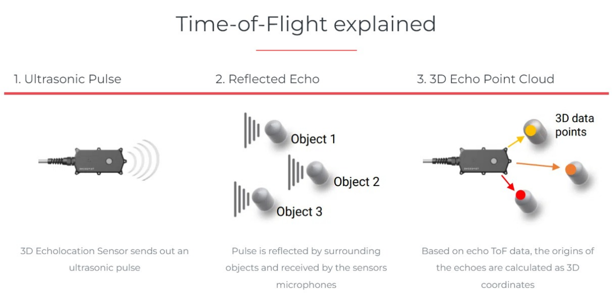


Figure 1.5: Time-of-flight principle of 3D ultrasonic sensor [3]

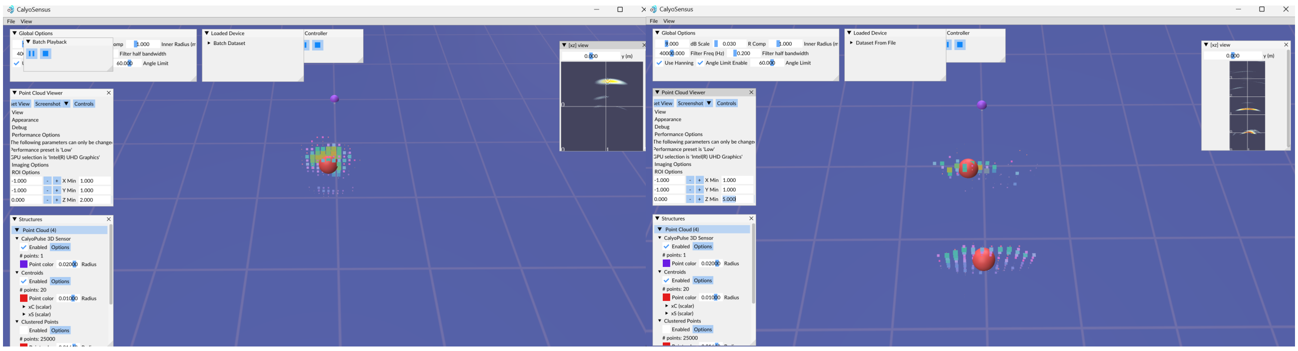
1.1.2 Understanding 3D acoustic sensor behaviour

Experiment were conducted using the Calyo Pulse 3D acoustic sensor in the Bristol Robotics Laboratory (BRL) to gain a deeper understanding of its sensing behaviour and the nature of outputted data. The test scenarios, demonstrated in the images below, explore the sensor's ability to detect multiple objects and track a model car.

(a) Multiple objects detection test

(b) Model car detection test

Figure 1.6: Calyo sensor data collection experiments



(a) Human model detection

(b) Multiple vehicles detection

Figure 1.7: Calyo Sensus sample data collection

Trials have been conducted involving both human model and model cars, as shown in 1.6a. The Calyo sensor demonstrated robust performance in detecting objects from a close range, with successful identification of multiple objects as long as the objects maintain sufficient distance to each other. Noted that the point cloud was only visible clearly after windowing which specifies the Cartesian range of interest. A key observation from the trials was that, compare to LiDAR point cloud data, the output from 3D acoustic sensor was more akin to that of millimeter wave radar. It is difficult to classify and recognize objects solely from acoustic point cloud. Instead, the sensor can reliably detect the presence of objects in its environment.

1.1.3 Simulating Scattering in Rain Conditions

Due to restrictions on outdoor hardware testing, an indoor experiment was devised to simulate the propagation of acoustic waves through water droplets, mimicking rain conditions. A cold coffee drink was placed in front of the sensor to replicate the effect of water droplets on its surface. As shown in Figure 1.8, a scattering effect was observed, causing the point cloud data to become more dispersed. The water droplets introduced additional noise, which affected the accuracy of object detection and clustering.

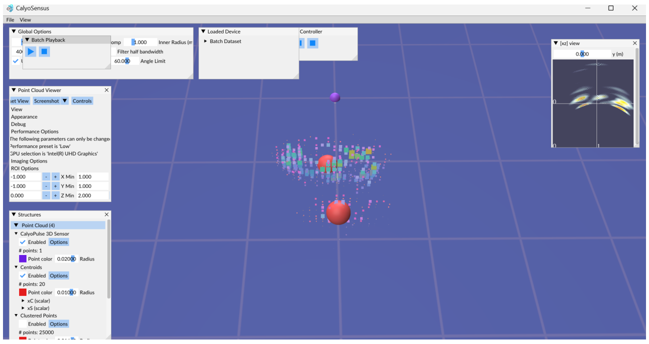


Figure 1.8: Scattering effect happened with the presence of water droplets

This experiment revealed the sensor's sensitivity to small water droplets, resulting in a scattered point cloud. Such findings highlight the need for further investigation into how environmental factors like rain influence the accuracy of the sensor in real-world applications. Additional processing techniques may be necessary to filter noise and improve clustering under these conditions.

1.1.4 Summary

Ultrasound, which is typically used in underwater sonar and medical imaging, has been proven to be highly reliable for 1D distance measurements in everyday applications, such as automotive parking assistance. The Calyo Pulse extends this principle to 3D imaging through beam-forming method, a core technique in both SONAR and RADAR technologies.

Common sensing technologies like cameras and lidar suffer from several limitations. While cameras are useful for visual perception, they require significant computational resources to achieve reliable 3D imaging and often need to be fused with other sensors to function in dynamic environments. Despite their capability to generate high-resolution 3D maps, LiDAR systems are typically bulky, have limited fields of view (FoV), and are expensive, which has hindered their widespread adoption.

In contrast, the Calyo Pulse offers a compact, lightweight, and cost-effective solution with excellent performance in adverse conditions. Its ability to operate unaffected by rain, fog, and poor lighting conditions, along with its real-time 3D imaging capabilities, makes it an ideal candidate for integration into AV systems, providing robust environmental perception and enhancing vehicle safety in challenging environments.

1.2 Motivation

The advent of autonomous driving technology and mobile robots has become an emerging trend in both domestic and industrial contexts, revolutionizing transportation systems by reducing human error and traffic congestion, thereby fostering sustainable mobility. Nevertheless, there are concerns regarding the safety of integrating these autonomous intelligent systems with human and manual-drive vehicles. For instance, [4] reported that self-driving cars could potentially cause collisions with pedestrians at night, even at slow speeds.

Moreover, a survey conducted by Forbes [5] revealed that 93% of respondents in the United States expressed their concerns regarding the safety, privacy, reliability, costs and vehicle lifespan of AV technology. The ongoing occurrences of accidents have culminated in a decline of confidence and a negative perception of the technology among the public. It is challenging to rebuild trust in the technology, as people invariably anticipate absolute perfection.

Adverse weather conditions impose significant challenges to the operation of self-driving cars. Rain, fog, snow and dust can limit visibility, degrade sensing performance and increase the risk of accidents. Even on a sunny day, there have been reports of autonomous vehicles (AV) failing to recognise pedestrians, leading to crashes. To promote AV and mobile robots for everyday use, it is essential to enhance and introduce a more accurate perception system that is also more robust against harsh weather and scenarios.

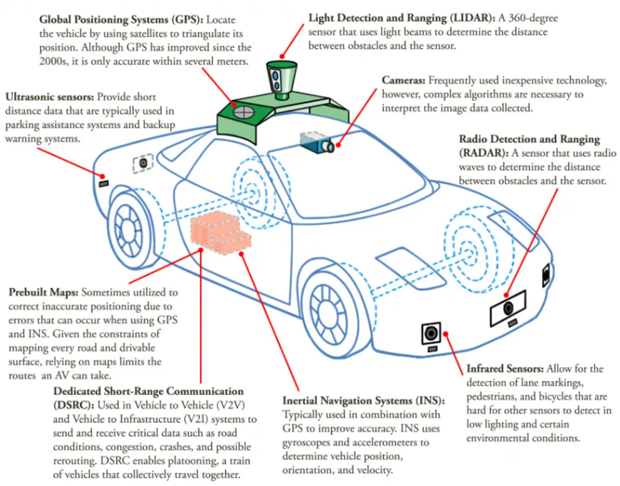


Figure 1.9: Overview of common sensors installed on an AV [6]

In an AV sensing system, lidar, optical camera and radar are commonly included. But, current integration methods offen face limitations due to signal attenuation, diffraction and reduced visibility. The cost of deploying these technologies has also been a significant factor in the slow rate of their mass production and application. As stated by Sonair [7], navigation sensors can contribute more than one-third of the total cost of building a robot. While ultrasonic sensors have traditionally been constrained to one-dimensional (1D) distance calculations for tasks like forward collision warning, 3D acoustic sensors offer the potential for more complex data collection, including azimuth, elevation, and velocity of detected objects. This capability enables the estimation of an object's location and dimensions, making 3D acoustic sensors a promising tool for enhancing AV reliability. The advantages of lower cost, size and power consumption also provide more spaces and freedom to design the robots.

Acoustic waves are notably resistant to environmental interference, including rain, fog and reduced visibility. Their capacity to propagate through such particles could improve AV performance, particularly in scenarios such as lane-changing and low-speed parking.

Apart from adopting artificial intelligence, companies like Waymo are exploring the possibility of acoustic sensor arrays to enhance AV sensing capabilities, with the aim of delivering broader fields of view (FOV), longer detection range and superior navigation in various weather conditions while concurrently reducing costs and computational demands [8].

Despite the limited adoption of ultrasonic sensors in AVs due to their restricted detection range and inadequate object recognition capabilities, their robustness in inclement weather conditions suggests the necessity for further exploration. The potential integration of 3D acoustic sensors into existing perception systems raises the following key research questions:

1. How can the integration of 3D acoustic sensors improve AV safety?
2. How will this technology boost adoption and popularization in the industry?
3. To what extent, can 3D acoustic sensors enhance detection accuracy in real-world scenarios?
4. Can the integration of such sensors restore public trust in AV technology?

Addressing this gap is crucial to advancing the safety and robustness of autonomous systems. Integrating innovative sensing technologies, such as 3D acoustic sensor, offers a unique opportunity to overcome these challenges by leveraging sound wave propagation principles that are less affected by environmental factors. This research aims to explore this potential, motivated by the need for safer and more dependable autonomous vehicles capable of operating in diverse weather conditions. The findings will provide insights into the potential benefits of combining 3D acoustic sensors with camera systems, contributing to a more reliable and robust AV perception system.

1.3 Aims

The aims of this project are:

1. To develop a comprehensive understanding of the physics behind 3D acoustic sensing technology, including its working principle, behaviour, advantages and limitations.

2. To evaluate how environmental factors including rain and fog, affect the sensing performance of 3D acoustic sensors.

3. To compare the sensing performance between 3D acoustic sensor with optical camera, evaluate their individual and combined effectiveness in perception tasks.

4. To explore the feasibility of integrating 3D acoustic sensors to improve perception in low-visibility scenarios, and the potential applications in automotive industry.

1.4 Objectives

The objectives of this project include:

1. Identify limitations of traditional sensors in adverse weather conditions and how 3D ultrasonic technology stand out in such scenarios.

2. Evaluate the affect of varying weather conditions to sensing performance by mimicking physics model of the sensor in simulation and compare captured image and point cloud sensor data with ground truth of object dimensions and locations.

3. Study signal attenuation and intensity degradation of single scattering of water particles in air by mathematical method.

4. Quantify benefits of sensor fusion of integrating 3D ultrasonic sensor and optical camera by measuring key parameters like SNR, attenuation rates, object dimension and distance estimation accuracies for robust perceptions in driving under adverse weather conditions.

2 Key contributions

The key contributions of this research lie in the development and evaluation of a novel 3D ultrasonic sensor model for autonomous vehicle perception in adverse weather conditions.

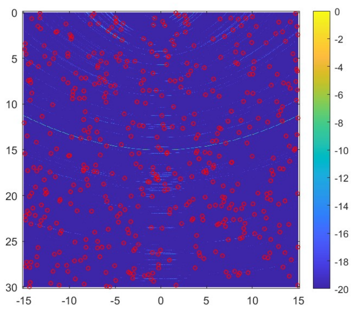
This study introduces a customized sensor in CARLA that inherits characteristics from radar ray-tracing method and time-of-flight (TOF) principle, enabling the generation of a radar-like point cloud with attributes such as intensity and Cartesian coordinates. Urban driving scenarios were simulated in CARLA with the variation of weather parameters. Noise filtering, Gaussian clustering on point cloud and object detection as well as bounding box generation techniques were manipulated to capture valuable data for dimension estimation analysis which facilitates comparison between sensing performance of 3D ultrasonic sensor and optical sensor.

(a) Rain scenario

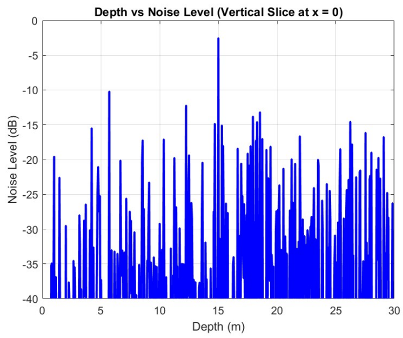
(b) Fog scenario

Figure 2.1: Custom CARLA simulation environments

A signal-to-noise ratio (SNR) over distance analysis was also conducted in MATLAB, drawing upon the theoretical underpinnings of 3D acoustic wave propagation and scattering from one medium to another. This facilitated the simulation and mathematical investigation of the attenuation effect by researchers.



(a) Scattering of acoustic wave at numerous water particles in a medium



(b) Noise level against vertical distance of particles

Figure 2.2: MATLAB SNR vs Distance analysis

Collectively, these contributions serve to enhance the comprehension of 3D ultrasonic sensing in autonomous vehicle applications, with a particular emphasis on scenarios characterised by challenging environmental conditions. They establish a foundational framework for subsequent research endeavours aimed at integrating acoustic sensors with multi-modal perception systems. In summary, this research undertaking systematically examines the impact of rain and fog on ultrasonic sensing, a domain that has received scant attention in the extant literature.

3 Literature Review

3.1 Existing Market Research of 3D ultrasonic sensors

The Toposens ECHO ONE sensor [3] utilizes 3D echolocation technology to deliver robust 3D point cloud data as output in the application of mobile robots to avoid collision and detect stop and warning zones. The product was first launched in 2022 and was widely used in obstacle avoidance and mapping for mobile robots in factories.

Sonair [7] recently introduced Acoustic detection and ranging (ADAR) technology, enabling ultrasonic 3D imaging and omni-directional depth sensing [9]. Their product involves a MEMS transducer that transmits a high frequency ultrasonic signal and then is received and processed. It is target to be deployed in the application of safe autonomous navigation for mobile robots.

(a) Toposens ECHO ONE (b) Sonair sensor

Figure 3.1: 3D ultrasonic sensors in the market

	Toposens ECHO ONE	**Calyo Pulse**	**Sonair**
Detection range	0.2-3m	0.1-15m	0-5m
FOV (Horizonal/Vertical)	55°/55°	180°/ 160°	180°/180°
Accuracy	6cm	0.4cm	1cm
Working frequency	40kHz	30kHz	70-85kHz
Norminal supply voltage (DC)	12V	5V	12-24V
Ambient operating temperature	-10 °C to 50 °C	-15°C to 50°C	N/A
Ingress protection	IP67	IP68	N/A
Outline dimensions	125mm x 56mm x 42mm	59.2mm x 43mm x 15.4mm	N/A
Weight	180g	40g	$\prec$ 100g

Table 3.1: Tech specs of 3D ultrasonic sensors

It is rare to find similar products on the market, demonstrating the novelty of this technology. Instead, 4D millimeter-wave radar is an emerging product that provides the same outputs as 3D ultrasound, including Cartesian positions and relative velocity of reflected signals. It is less computationally intensive than lidar, but has a higher resolution than conventional radar and a longer detection range than acoustic waves. This is believed to be the reason why 3D ultrasonic sensors are rarely seen and used in industry.

3.1.1 Applications

Several studies have demonstrated the applications of 3D ultrasonic sensors in robotics and mapping. For instance, [10] proposed a bio-inspired method using the spatial sampling capabilities of 3D sonar sensors in SLAM. This method extracts motion parameters by comparing 2D horizontal reflectors with 3D frontal hemisphere reflectors. In contrast, [11] introduced a Continuous Time, Frequency Modulated (CTFM) sonar, capable of imaging the full frontal hemisphere, supporting obstacle avoidance, corridor following, and negotiating corners and T-junctions. [12] also applied 3D sonar in mapping by using Median and Savitzky-Golay filters to eliminate noise in acoustic signals, although the use of mechanical-driven 3D ultrasonic sensors with DC motors posed challenges.

In another study, [13] presented an object detection system based on ultrasonic sensors, transforming voxelized 3D point clouds into multi-channel Bird's Eye View (BEV) images. This approach offers insights into potential processing methods for Calyo sensor data, with Mean Average Precision (mAP) at Intersection over Union (IoU) used as an evaluation metric.

It should be noted that most of the research found was on the application of 3D acoustic technology to mapping. It enables fast and accurate mapping of the environment, which then facilitates robot navigation and object detection. However, it hinders one of the major advantages of the technology, which is high resilience in various weather conditions that can induce large noise. These studies showed the feasibility of applying 3D ultrasonics to navigation while the exploration of its potential into sensor fusion and working under bad weather scenarios is very limited. Therefore, this project aims to investigate the potential applications of using 3D acoustics in driving scenarios where drivers may encounter various adverse weather conditions.

3.2 Millimeter wave radar

Millimeter wave is one of the most popular perceptional sensors being used in automotive industry, along with lidar and camera. [14] illustrated the advantages of using 4D millimeter wave radar which offers high accuracy distance and speed detection, low susceptibility to weather conditions and cost effective. However, several researches mentioned the limitations of radar. Compare to conventional 3D radar, it has poor height information and spatial resolution due to antenna layout limitations [15]. The limited bandwidth availability, relatively low detection speed and poor resolution have hindered the development and applications of radar. Also, its sensing performance will easily get affected by atmospheric fluctuation which causes severe attenuation at high frequency [16]. It lacks the capability to discern distinct object types due to above reasons. It provides a gap to study the behaviour of 3D acoustic sensing and how can the technology fill in this shortcoming of radar.

Rain is considered one of the factors to degrade sensor performance at high frequencies, impacting both mmWave radar and ultrasonic systems[17]. This research investigated the rain attenuation effects, modeled using the Marshall-Palmer distribution, and evaluated radar detection range under varying intensities of rain and fog. The paper highlighted a shared foundation on this signal degradation due to environmental factors between radar and ultrasonic sensor. They both rely on wave propagation through the medium (air or water) which affects accuracy, although the latter typically operates at lower frequencies. These findings underline the importance of improving high-resolution time-of-flight (TOF) methods in adverse weather conditions, a challenge faced by both technologies.

The common direction of research methodology regarding the signal attenuation of radar is to apply the principle of target detection, echo simulation and intensity attenuation theory of millimeter wave [18]. Key attributes such as distance to objects, relative velocity and elevation angles are extracted from sensor and calculate the signal-to-noise ratio (SNR) of the reflected echoes under variations of weather to study its influence to intensity degradation [16].

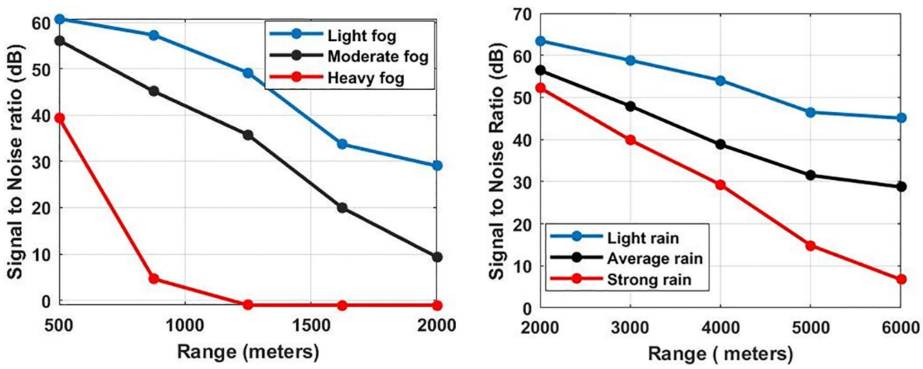


Figure 3.2: Evaluation of SNR under the impact of atmospheric attenuations in rain and fog

Although mmWave radar is considered robust in adverse weather conditions[19], there are lack of researches focusing on developing realistic simulation of radar-based algorithms in robotics. It is challenging to build systematic traffic flow perception system with edge computing devices to acheive high precision for traffic target identification [14]. This projects references the approach of these researches to study the behaviour and weather effect of a particular sensor. By creating a traffic flow perception system simulation, sensing data were extracted to calculate the intensity degradation and SNR of reflected ultrasonic pulses.

3.2.1 Connection between mmWave radar and ultrasonic sensor

Overall, both mmWave radar and ultrasonic sensors share similar measurement principles such as time-of-flight (TOF). Both sensors excel in measuring distance and velocity of detected objects and resilient in low-visibility situations. However, radar faces challenges in terms of spatial and height resolution which 3D ultrasonics may be capable of.

While this review discovered the gap in investigating the potential of fusing 3D ultrasonic sensor with cameras and lidar, and applications apart from navigation, research in radar technology offers valuable insights in studying the signal attenuation effects of 3D ultrasonic sensor under various weather scenarios in simulation environment ultrasonic sensor systems, and the SNR ratio as one of the evaluation metrics.

3.3 Impact of adverse weather conditions

Adverse weather conditions such as rain, fog, snow, and sun glare present significant challenges to the performance of various sensors used in autonomous vehicles. As highlighted by [20], sensors like cameras, LiDAR, millimeter-wave radar (MWR), and GNSS face substantial degradation in perception and recognition capabilities under these conditions.

LiDAR, known for its high angular resolution and accurate range measurements, can operate up to a range of 200 meters. However, it is highly sensitive to environmental changes, particularly in rainy and foggy conditions. In rain, attenuation causes signal degradation, introducing noise and reducing detection range. Similarly, raindrops on the lens of a camera can degrade image quality and reduce recognition accuracy. In foggy conditions, LiDAR's measurement distance decreases further as visibility drops. Fog has the largest impact on LiDAR's detection ability, while moisture on camera lenses can lower image intensity and contrast, blurring the image and reducing detection accuracy. Study suggested that using an infrared camera could mitigate these effects by enhancing visibility in foggy conditions.

mmWave radar, while generally more resilient to adverse weather compared to optical sensors, is not immune to environmental factors. [21] noted that radar's detection range can be reduced by up to 45% under heavy rainfall due to attenuation and backscattering effects. These effects interfere with the radar receiver, diminishing the radar's ability to measure distance and velocity accurately. Nonetheless, radar still excels in velocity measurement and remains less affected by visibility issues compared to cameras and LiDAR.

Ultrasonic sensors, often used in short-range navigation and parking assistance, are similarly affected by adverse weather conditions but have distinct advantages. [22] pointed out, ultrasonic sensors are generally less influenced by low visibility than LiDAR or cameras because sound waves are less affected by fog, rain, or snow. However, the effects of rain, humidity, and temperature on ultrasonic sensors still require further investigation, as environmental conditions can influence their sensing range and accuracy. This is particularly relevant for autonomous driving applications, where precision in detecting the location of objects is crucial. It is more reliable in low visibility environments such as high-glare as the return signal of ultrasonic wave does not get decreased due to low reflectivity.

Dynamic weather, such as changing lighting conditions, can also create sharp intensity fluctuations in camera images, leading to edge blurring and reducing recognition performance [23]. To summarize, most of these studies did not highlight the impact of adverse weather to ultrasonic sensor, as it may not the dominating sensor in autonomous systems. However ultrasonic sensor is indeed more resilient in foggy and rainy conditions compare to lidar, radar, and camera. It is worth comparing the signal degradation between sensors under different weather conditions and explore the potential of sensor fusion with ultrasonics.

TABLE II. SENSORS ROBUSTNESS COMPARISON TABLE

	3D RADAR	*4D RADAR*	*Camera*	*IR Camera*	*GV*	*3-D Camera*	*LIDAR*	*Ultrasonic*
Interference	3	3	5	5	4	5	3	2
Night	5	5	3	5	5	3	5	5
Day time	5	5	5	4	4	5	5	5
Fog	5	5	2	3	4	2	3	5
Rain / Snow	4	4	2	3	4	2	3	5
Temperature	5	5	5	3	4	2	3	5
Tunnels	2	3	5	5	5	5	5	5
Bridges	2	3	5	5	5	5	5	5
Dirt robustness	5	5	2	3	3	2	3	5
Reliability	3	4	4	5	5	5	5	5
Speed dependency	5	5	5	5	5	5	5	1

Figure 3.3: Sensor robustness comparison on adverse weather

3.4 Simulation platform

Since putting hardware into outdoor testing in rain conditions may introduce potential risk to damage the sensor, development on simulation was highly recommended for this project. In fact, simulation platforms have become essential for studying and improving sensor performance in adverse weather conditions, allowing researchers to replicate complex environments and test sensor behavior under controlled, yet realistic conditions.

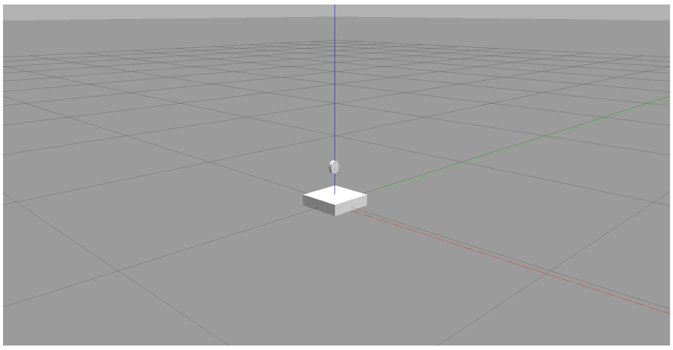
3.4.1 Gazebo

[24] explored the impact of adverse weather conditions on autonomous perception systems by replicating a racing scenario in the Gazebo simulator. Their work introduced a weather augmentation method to evaluate perception system performance in real-time, particularly under rainy and foggy conditions. This included sim-

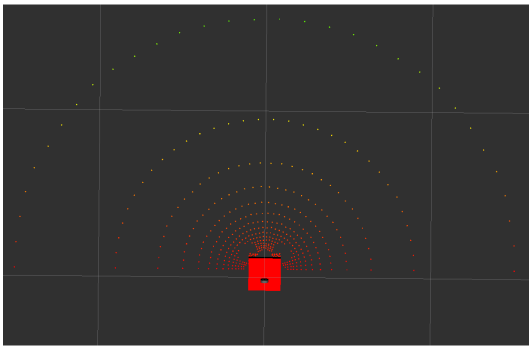
ulating water droplets on the camera lens and varying light conditions. By quantitatively measuring object detection accuracy and latency, they demonstrated how weather conditions can degrade sensor accuracy and increase perception latency, providing essential data for improving sensor fusion strategies and perception algorithms.

The initial approach was to create a 3D CAD drawing of the sensor and include the drawing into Gazebo and visualize the point cloud based on laser scan plugin from ROS2. However, it was then realized that there were no documentation nor references on modifying the laser scan plugin with acoustic wave signal parameters. The resolution of a laser scan point cloud is too high which is able to provide accurate shapes of detected object for recognition.

Moreover, the only way to simulate rain or fog in ROS2 is to use particle emitter function in Gazebo Ignition. In short, it has limited capabilities to simulate realistic weather conditions in ROS2 and Gazebo. Therefore, it was not taken as the final approach in this project.



(a) Gazebo visualization of Calyo sensor



(b) Sensor output on Rviz

Figure 3.4: Calyo sensor modelling based on ROS

Airsim

[25] Microsoft Research created Project Airsim as a simulation platform which focuses on providing high-fidelity simulations and narrow the gap between simulation and reality to aid development of AV. Based on Unreal engine, the platform allows user to reconstruct real world scenes and test with reinforcement learning algorithms. Airsim has ready to use weather API to control weather settings including rain and fog in the simulator.

Despite the well-defined weather settings support, Airsim does not natively support sensor plugins for 3D acoustic sensor and radars. Plus, it lacks documentation and support to customized such sensor into simulation engine. Therefore, this limitation hinders the possibility to adopt Airsim as the simulation platform.

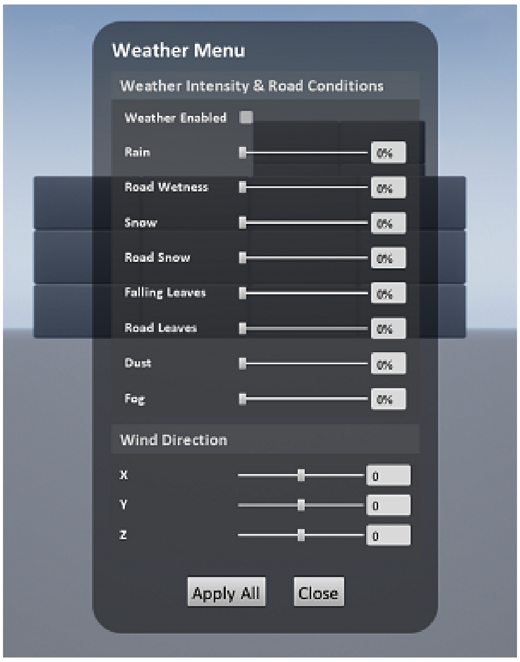


Figure 3.5: Microsoft Airsim weather menu

CARLA

CARLA (Car Learning to Act) [26] is an open-source urban driving simulator also based on Unreal Engine designed for autonomous driving research. The simulator provides a realistic virtual environment that replicates urban settings with high-fidelity graphics, physics, and sensor simulation. It offers a range of pre-built maps based on real-world locations, enabling researchers to simulate complex driving scenarios.

CARLA supports the spawning of multiple vehicles and autonomous driving with ready-to-use and plug and play API. It has sufficient weather parameters including precipitation intensity (rain), fog density and sun altitude angle which can be used to control time of the day and weather conditions in the simulation environment. In terms of sensor plugins, despite CARLA does not natively include 3D ultrasonic sensor, there are supports and documentations regarding the customization of sensor based on ray-tracing method like radar sensor to physically model the behaviour and output of Calyo sensor in the simulation environment.

[27] introduced a novel approach to augment LiDAR data in rainy weather by employing physical modeling methods in simulation. Using the CARLA simulator, they developed a pipeline for LiDAR data collection, with a particular focus on the spray and splash effects generated by the wheels of nearby vehicles. By modeling these effects using a spray emitter method, the study investigated how weather conditions influence LiDAR echo intensity. Their findings highlighted the drop ratio in point cloud density between different datasets, providing a quantitative measure of perception performance degradation due to rain. This approach emphasizes the importance of simulating specific weather interactions, like splash and spray, to better understand sensor limitations.

(a) Radar output (b) CARLA Weather settings

Figure 3.6: Calyo sensor modelling based on ROS

These studies underscore the critical role of simulation platforms such as CARLA, Gazebo, and Airsim in enabling realistic testing of sensors under adverse weather conditions. By simulating environmental interactions like rain and fog, these platforms allow researchers to assess sensor limitations and develop more robust perception models with less computational resources required and eliminate the limitations of reproducing multiple weather and traffic scenario. However, despite the significant advancements made in simulating LiDAR, radar, and camera sensors, there remains a notable gap in the simulation of 3D acoustic sensors and their relevant applications. To date, no research has been found that specifically models the performance of 3D acoustic sensors in simulation environments.

Our project aims to address this gap by creating driving scenarios in simulation with the equipment of 3D ultrasonic sensor and RGB camera, and facilitate sensor data collection analysis in various weather settings. This approach will provide new insights into the behaviour of 3D acoustic sensors, particularly in automotive applications, and contribute to the advancement of sensor fusion strategies for adverse weather conditions.

3.5 Importance of sensor fusion for autonomous systems

Sensor fusion is increasingly becoming a critical approach for improving the robustness and accuracy of perception systems in autonomous vehicles (AVs) and mobile robots, particularly in challenging environmental conditions. Integrating multiple sensor modalities compensates for the weaknesses of individual sensors, providing a more comprehensive and reliable perception of the environment.

[28] highlighted the unique advantages of acoustic sensors in adverse weather, pointing out that they are generally unaffected by rain, snow, or wind noise, making them reliable in challenging conditions. Their study focused on improving object tracking through sound source localization, and fusing the data with LiDAR for

evaluation. By measuring the angular direction accuracy of the acoustic sensor, they demonstrated that sound-based sensing can complement vision-based systems, especially under conditions where optical sensors may struggle. While [29] similarly integrated a low-cost 3D ultrasonic sensor with a 2D laser scanner for mobile robot mapping, using 2D SLAM to create a 3D map. The two studies integrate 3D ultrasonic sensors with lidar as it is less common to install both lidar and radar in a single system because of the expensive cost. Adding ultrasonic sensor provides a cheaper integration to lidar to enhance detection accuracy. Despite the results were promising and accurate, the research primarily focused on mapping and localization. A significant research gap exists in comparing the perception and control precision when fusing acoustic sensors with other modalities, especially in complex outdoor environments under variable weather conditions.

Similarly, [30] and [31] fused sonar and LiDAR sensors in sensor fusion-driven SLAM applications. Both studies were conducted in controlled indoor environments, with limited exploration of how the sensor fusion system performs under adverse weather conditions. Although they demonstrated how fusing acoustic sensors and LiDAR can improve SLAM accuracy, they fell short of comparing sensor sensitivity under different weather scenarios. A comprehensive dataset and more rigorous performance evaluations across various weather conditions are needed to accelerate the adoption of 3D acoustic sensors for applications like mobile robots and autonomous vehicles.

[32]) proposed an information fusion method of radar and camera data under severe weather conditions for target recognition and tracking in autonomous driving. This research highlighted the effectiveness of sensor fusion in reducing detection failures compared to relying on a single sensor. However, Zhou (2022) pointed out that radar-camera fusion faces challenges in terms of accuracy, limiting its adoption in the automotive industry.

There are apparently relevant researches integrating 3D acoustic sensors with lidar and cameras. However, they lack a focus on the improvement from fusing sensors to account for weather conditions. Most existing fusion frameworks do not account for the environmental resilience of 3D acoustic sensors, particularly in automotive applications. Despite there are similar researches integrating radar with camera, as mentioned from the above, millimeter wave radar fails to offer precise height and spatial information, which 3D acoustics is capable of. Our project aims to address this gap by simulating the integration of 3D acoustic sensors with camera, evaluating their sensing performance under adverse weather conditions.

3.6 Justification of chosen methodology and approach.

The approach of this project references to[33] which investigate the rain and fog effects on lidar virtually. It made use of unreal engine's ray-casting module to simulate lidar and consider Mie-Scattering effect on signal echoes and corresponding 3D point cloud by creating virtual rain and fog droplets.

Relevant researches share one common approach to study signal attenuation and signal-to-noise ratio (SNR). A monte carlo method can be used to simulate fog and rain scattering effect to sensor output by creating virtual large particles randomly in the medium, and integrate acoustic scattering theory [34]. Result showed the variation of SNR as a function of the distance between target objects and the sensor and particle size distributions. Relationship between SNR versus distance and precipitation rate can be found by plot and conclude how intensity degrades in different weather scenarios [35].

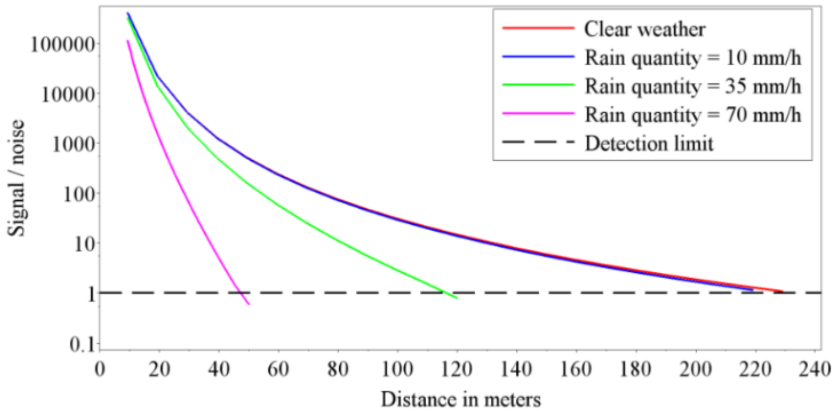


Figure 3.7: Lidar SNR vs Distance of different weather settings

Therefore, in our approach, the SNR degradation versus distance can be calculated by mathematical monte carlo method. The weather effect to object detection will be represented by adding gaussian noise to the received signals and represented by mean square error between sensor data and ground truth from the simulation environment. Such studies offered a baseline and reference on the approach to analyze weather effect on 3D ultrasonic sensor.

3.7 Summary

To summarize, this literature review explored the key principles, market research, applications, and performance of 3D ultrasonic sensors, as well as the similarities they share with millimeter-wave radar in autonomous systems. The review also covered the impacts of adverse weather conditions on sensors, the importance of sensor fusion in enhancing perception in challenging environments, choice of simulation platform and justification to methodology used in this project.

3D ultrasonic sensors are capable of operating smoothly in low-visibility and adverse weather conditions such as rain and fog. Their strong potential in estimating object distances and coordinates presented their potential to be more widely adopted in intelligent vehicle systems. Compared to millimeter wave radar, which has limited capability in height and spatial resolution, 3D ultrasonic may provide an alternative sensing solution. However, limited research has explored the potential of 3D ultrasonic sensors in adverse weather conditions, leaving a gap in knowledge regarding their performance under rain and fog.

The review also examined the strengths and limitations of LiDAR, radar, and cameras in adverse weather. LiDAR offers high angular resolution and precise range measurement, but its performance is significantly impacted by rain and fog due to attenuation, which reduces reflectivity and introduces noise. Cameras, meanwhile, suffer from blurred images caused by moisture and water droplets, leading to decreased recognition accuracy. In fog, both LiDAR and cameras struggle with reduced visibility, and in snow, they may fail entirely due to changes in the road environment and moisture accumulation on lenses.

Millimeter-wave radar stands out for its resilience in adverse weather, as its longer wavelengths allow it to penetrate through rain and fog more effectively than optical sensors. However, even radar experiences limitations, such as a reduction in detection range in heavy rain due to back-scattering and attenuation effects. While radar is excellent for measuring velocity, its precision in object classification and environmental perception is limited compared to other sensors.

3D ultrasonic sensors, though relatively unexplored in the context of adverse weather, have the potential to fill this gap due to their resilience to low-visibility conditions. However, their susceptibility to environmental factors such as rain requires further testing and evaluation. It should be noted that the sensing performance of 3D ultrasonic sensor should still be affected by weather conditions. Through this study, it should enrich knowledge of its sensing behaviour and explore the potential to be an alternative solution to lidar and millimeter wave radar in perception systems.

Few common simulation platforms were studied and CARLA is identified to be the most suitable platform for this research due to its native support for weather conditions settings like rain, fog and sunlight variations. The ability to customize sensor plugins for 3D ultrasonic sensor also make it stand out upon other similar simulation platform such as Airsim.

Sensor fusion studies discussed in this review have demonstrated promising results, especially in SLAM, mapping, and object tracking. However, there remains a significant research gap when it comes to evaluating fusion precision under different weather conditions—especially when incorporating 3D ultrasonic sensors. Sensor fusion methods compensate the limitation and weakness of individual sensor and enhance overall capabilities of perception systems. However, most current research focuses on LiDAR, radar, and camera integration, with limited work exploring how 3D acoustic sensors can enhance perception accuracy, particularly in challenging outdoor environments and under adverse weather conditions. Also, even though researches have already highlighted the limitation of radars in offering real-time, precise height and spatial information, there were lack coverage on taking 3D ultrasonic sensor into consideration as an alternative solution to the problem. Furthermore, the absence of a corresponding dataset evaluating sensor fusion under various weather scenarios represents a key limitation in advancing the use of 3D ultrasonic sensors in mobile robots and autonomous vehicles.

This project contributes to bridging this research gap by developing a simulation-based approach to model the physics of 3D ultrasonic sensors under rain and fog conditions. It quantifies sensor performance degradation using signal-to-noise ratio (SNR), intensity attenuation, and object detection errors while also comparing sensor fusion performance between 3D ultrasonic sensors and cameras. Furthermore, the study evaluates the feasibility of using 3D ultrasonic sensors as a complementary technology to radar and LiDAR in autonomous driving scenarios.

4 Research Methodology

4.1 Approach

This chapter describes the methodologies and technologies used to develop, implement, and evaluate the performance of the Calyo 3D acoustic sensor in the CARLA simulation environment. The study investigates how adverse weather conditions, specifically rain and fog, impact the sensor's perception capabilities. The following sections outline the theoretical background, sensor model implementation, simulation setup, experimental design, and evaluation metrics.

4.1.1 Governing Equations and Parameters

This project is founded upon research conducted on the propagation of compressional acoustic waves in a non-viscous fluid, with a dense and random distribution of scatterers [36]. A sensor model based on the principles of an ultrasonic array was developed, simulating single scattering with the presence of large particles in the air in a two-dimensional space [37].

In the context of this study, we assume that there are N rain droplets distributed randomly in a region, with the locations of the particles known only probabilistically. We consider the particles to be identical spherical scatterers, neglecting any interaction between them and focusing solely on the single scattering scenario. To compute the noise level when an acoustic wave hits each particle, we applied a Monte Carlo technique in MATLAB. We then analysed the SNR ratio degradation on a target particle at different locations.

The problem is commonly treated by utilising the effective-field approach, which models wave propagation through a scattering medium and allows for the consideration of the spatial distribution of scatterers via specific pair-correlation functions.The latter describe the possibility of finding another particle near one fixed particle, on the condition that the underlying particles are not allowed to overlap. In the development stage, the exclusion distance b (i.e. the distance of closest approach between the centres of adjacent spheres) is set to be $b = 2a$, where a is the radius of the particles. This ensures that the spheres do not come into contact with each other.

Firstly, the medium is to be defined. The number of point scatterers N = 500, and the dimension of the medium is 30m x 30m. We assume the radius of rain and fog particles to be 0.2mm and $5\mu m$ respectively [33] [38].

Input Parameters:

- Particle Radius [m] a= $5e^{-}6$ for fog and 0.0002 for rain
- Mass Density $[km/m^3]$ of air ρ_{air} = 1.204
- Mass Density $[km/m^3]$ of water ρ_{water} = 1000
- speed of sound [m/s] in air $c_{air} = 343$
- speed of sound [m/s] in water$c_{water} = 1.5e^3$
- Bulk Modulus which represents compressibility of air and water [Pa] $\beta = c^2\rho$
- Wavenumber [rad/m] $k = \frac{2\pi f}{c}$
- Number of particles per unit area $\sigma = \frac{N}{A}$
- Concentration of particles $\phi = \frac{N}{A}a^2 = \sigma a^2$

Unlike speed of light, the speed of sound and wavelength varies in different mediums. Wavelength equation with references to speed of sound and frequency is given by:

$$\lambda = \frac{c}{f} \tag{4.1}$$

Where: f: Acoustic wave centre frequency = 40kHz

$$\lambda_{air} = \frac{343}{40000} = 0.0086m$$

$$\lambda_{water} = \frac{1482}{40000} = 0.037m$$

Scattering occurs when acoustic waves interact with particles (e.g., raindrops or fog droplets). The two main scattering regimes are Rayleigh scattering and Mie scattering, depending on the particle size relative to the wavelength of the wave.

Rayleigh scattering applies when the diameter and size of the target particle (i.e. water droplets) are much smaller than the wavelength of the incident radar wave [39].

$$\frac{2\pi a}{\lambda_{air}} =\ll 1$$

From the wavelength equation, we can conclude that the wavelength of acoustic waves in air is much smaller than that in water $\lambda_{air} \ll \lambda_{water}$. In such case, we can apply generic situation of effective field method.

Mie scattering dominates when the particle size is comparable to or larger than the wavelength of the acoustic wave. Since the bulk modulus B of water is much larger than that of the air, i.e., $B_w \gg B$ and the size of water droplets is much smaller than the acoustic wavelength in air, the absorption of acoustic waves thus Mie scattering can be neglected in this context.

The raw time-domain signal response is obtained by employing the inverse Fast Fourier Transform (iFFT) of the resulting spectrum. A combination of beamforming algorithms, including the Delay and Sum (DAS) method and the time-reversal MUSIC super-resolution technique, is utilised to compute the scattering field and model output. Subsequently, a vertical slice which focuses on each image point in the x-z plane is taken out to locate the peak amplitude.

$$f_\theta \simeq \frac{1}{i\pi}(T_0 + 2T_1)cos\theta \tag{4.2}$$

$$T_0 \simeq \frac{i\pi}{4}k^2a^2D \quad \text{and} \quad T_1 \simeq \frac{i\pi}{4}k^2a^2M \tag{4.3}$$

where:

$$D = \frac{d_0}{d} - 1 \quad \text{and} \quad M = \frac{m_0 - m}{m_0 + m}$$

Thus, the scattering amplitude of sound waves by small spherical particles propagating through a medium is given by:

$$\psi_s = \psi_i \frac{\pi V}{\lambda^2 r}[\frac{B_w - B}{B_w} - \frac{3(\sigma_w - \sigma)}{\sigma + 2\sigma_w}cos\theta] \tag{4.4}$$

where:

ψ is the amplitude of the incident plane wave

B_w and B are the bulk modulus of water and air

σ_w and σ stands for the mass density of water and air.

To quantify the performance of the algorithm in terms of robustness to noise, a vertical slice of the signal response was taken out with reference to the location of a single target water particle. The peak amplitude can then be recorded. By computing multiple times with random distribution of scatterers and different location of target particle, we analyzed the SNR degradation across distance under rainy and foggy conditions. The signal-to-noise ratio (SNR) is measured in the time domain.

$$SNR = \frac{I_{signal}}{I_{noise}} = 20log_{10}\frac{A_{signalpeak}}{A_{noiseRMS}}$$

Where:

- I_{signal}: Signal Intensity
- P_n: Noise intensity

- $A_{signalpeak}$: Peak amplitude of signal reflected

- $A_{noiseRMS}$: RMS of the noise measured away from the region of signal.

4.1.2 Simulation

In order to evaluate the effect of adverse weather conditions on perception sensors, with a particular focus on the Calyo 3D acoustic sensor, it is necessary to collect sensor output from a designated scenario and compare it with weather variation. The most direct method of doing so would be taking the actual sensor to outdoor test ground with water sprays that can simulate rain and fog. However, given the time and expensive cost required for such a large-scale setup and experimentation, this is not ideal for the purposes of this research.

Additionally, real-world testing lacks the flexibility and diversity to vary testing scenarios. In terms of safety concerns, the manpower required for a live experiment is much larger, which is not realistic for an individual research project. Moreover, the Calyo sensor is claimed to be splash-resistant only, and the potential damage from pressurized water directly spraying onto the sensor is inestimable.Therefore, in this research, the approach adopted is to build scenarios on a simulation platform.

The CARLA simulator was selected as the virtual simulation environment for testing sensor performance in this project. It is an open-source urban driving simulator that provides a realistic framework for testing sensors like radar and cameras in various driving conditions. Its capability to simulate dynamic environments with customizable weather effects (rain, fog), and the possibility and flexibility to implement Calyo sensor into Unreal engine to model its physical behaviour and expose its data via CARLA's Python API, making it ideal for testing how adverse weather affects sensor performance.

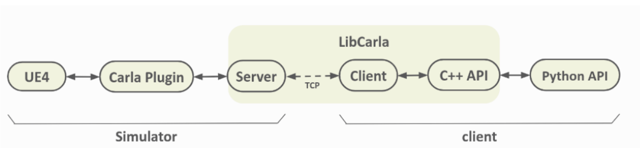


Figure 4.1: Communication Pipeline from Server side sensor to data exposure in CARLA

Pygame is used to visualize sensor data, including 3D point clouds generated by custom sensor modelling the novel 3D ultrasonic perception sensor from Calyo Ltd. The acoustic sensor and camera data are combined to form a real-time representation of the ego vehicle's surroundings, visualizing image captured by the camera and processed point cloud data on the window for debugging purposes.

Custom Sensor

A custom sensor was designed based on the default radar sensor, utilizing ray-tracing principles and integrated into Unreal Engine 4, which powers the server side of the CARLA simulator. This modification enables the simulation of the Calyo sensor. While the sensor's physics are modeled similarly to radar, additional environmental effects, such as scattering and attenuation, have been incorporated to influence point cloud intensity.

The key input and output attributes of the custom sensor include:

Input Attributes:

- range
- points per second
- vertical FOV
- horizontal FOV
- atmosphere attenuation rate

Output metrics:

- Intensity
- Velocity
- Azimuth (Horizontal angle)
- Altitude (Vertical angle)
- Depth (Distance)

Using CARLA's Python API, sensor parameters such as Field-of-View (FOV) and detection range are configured before initializing and deploying the sensor in the simulation. The sensor performs its computations on the server side, generating output data that includes the Azimuth angle, Altitude and distance to the detected object for each point. This information is used to construct a point cloud. A custom Python script processes the data by converting the polar coordinates into Cartesian coordinates, storing the results for further analysis.

$$x = Depth \cdot cos(Azimuth) \cdot cos(Altitude)$$
$$y = Depth \cdot sin(Azimuth) \cdot cos(Altitude)$$
$$z = Depth \cdot sin(Altitude)$$

Weather scenarios

In this experiment, a realistic simulation of various weather conditions is implemented in the CARLA simulation environment. The goal is to study the SNR degradation and performance of Calyo sensor under different environmental scenarios, particularly focusing on the impact of rain and fog. Camera is also added to the simulation as a comparison. Changing the weather parameters in simulation allow setting up the experiment with much less computed resources required and a faster testing. These weather parameters are crucial for studying the signal attenuation of acoustic waves entering from air to water, which affect sensor accuracy and perception in autonomous driving systems.

Precipitation rate, or the rain intensity value ranges from 0 to 100. It enables the simulation of raining conditions from light drizzles to heavy downpours. It changes weather in CARLA environment and is supposed to affect the camera image visualization only as water droplets will blur the camera. In the hypothesis, there are more noises in terms of rainy conditions but the signal attenuation is much less than that of millimeter wave radar, which can be ignored. Therefore, the accuracy of objects dimension estimation by 3D acoustic sensor should be higher than camera in adverse weather conditions. Another parameter wetness intensity is defined to be equal to rain intensity which affects the image captured by RGB camera sensor. In experiments, different levels of rainfall can be replicated by adjusting rain intensity parameter, allowing the evaluation on to what extent weather conditions affect sensor performance.

CARLA's fog density parameter represents fog concentration percentage and simulates real-world fog conditions in the simulation window. The increase of fog density may reduce visibility of the image captured by the camera as objects appear blurry due to light scattering. It may induce difficulties in objects dimension estimation accuracy. Also, fog density increases noise on the 3D point cloud generated by the ultrasonic sensor, lower the intensity values of each point and increase errors in detecting objects by the point cloud.

Fog falloff represents the specific mass of fog. It effectively ranges from 0-5. The higher the fog fall value, the denser and heavier the fog will be, and the fog will reach smaller heights. A value of 1 is approximately as dense as air, and reaches normal-sized buildings. In the simulation, fog falloff is defined between 0.05-0.5, directly proportional to the fog concentration. Fog falloff value affects the fog density which consequently affect the visibility of the camera sensor, thus affecting object dimension estimation accuracy. Overall, these parameters are expected to cause less effect to the output of 3D point cloud generated by the Calyo sensor despite induce more noise and lower signal-to-noise ratio (SNR).

$$fogfalloff = 0.01 \cdot (fogintensity)/2$$

Figure 4.2: Sample simulation environment include camera image and 3D point cloud data

Data processing

Calyo's 3D ultrasonic sensor follows time-of-flight (TOF) principle. The duration t taken for the pulse to be transmitted and received back after hitting an object represents how long the pulse lasts in time. The distance between the sensor and hitted object is a function of time:

$$d = \frac{c_{air} \cdot t}{2} \tag{4.5}$$

Where:

- c_{air}: speed of sound [m/s]
- t: Pulse duration [s]

This distance is represented by default depth attribute of the custom sensor in CARLA simulation environment, mirroring the ray–tracing method of radar plugin. The distance is then be used to calculate the intensity of the receiving point cloud, which can be used for point cloud filtering and clustering in later stages.

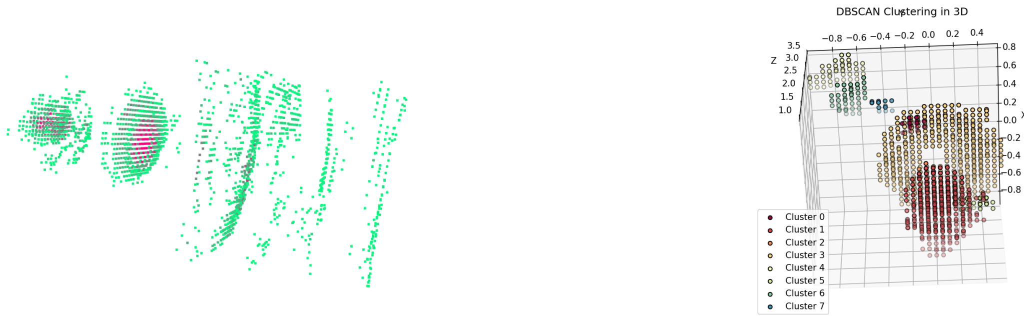
$$I/I_0 = e^{-\alpha \cdot d} \tag{4.6}$$

where α is attenuation coefficient, and d represents distance from the hit point to the sensor.

The attenuation coefficient can be obtained by means of linear regression analysis of the SNR (signal-to-noise ratio) in MATLAB. Following the capture of the point cloud, ground plane filtering is performed in order to leave only points of objects. DBSCAN clustering process follows after filtering to identify objects and esimate their dimensions. Gaussian white noise is then added to the point cloud in order to model the scattering effect caused by water particles. The amount of noise A being added is given by:

$$A = \alpha \cdot R + C$$

where R stands for the rain or fog intensity [%] and C stands for constant obtained from the linear regression method in SNR analysis in MATLAB.



(a) Sample of 3D point cloud visualization

(b) DBSCAN clustering

Figure 4.3: 3D point cloud post-processing

4.2 Experiment Methodology

This experiment examines how a 3D ultrasonic sensor operate under adverse weather conditions by modelling its physical behaviour and collect relevant sensor point cloud for further analysis. The simulation was created in CARLA 0.9.15 in Ubuntu 24.04 using a PC equipped with Nvidia RTX 3080 Ti GPU. Pre-defined driving scenarios were created in the simulator with controlled weather variations, predefined vehicle spawn points and fixed sensor placement. It is a more efficient and less resources demanding method to simulate various weather conditions than a real-world experiment. The sensor data collected was manipulated for filtering and clustering to fulfill the objective of objects detection and corresponding dimensions estimation in Python script.

To ensure a fair and meaningful evaluation, the experiments are designed around several key variables:

Independent Variables	Weather conditions (rain and fog density)
Dependent Variables	Objects Position [x, y, z], Intensity, Velocity, Depth, Azimuth, Altitude
Controlled Variables	Vehicle type, sensors location & configuration, Objects spawn locations, How the vehicle move

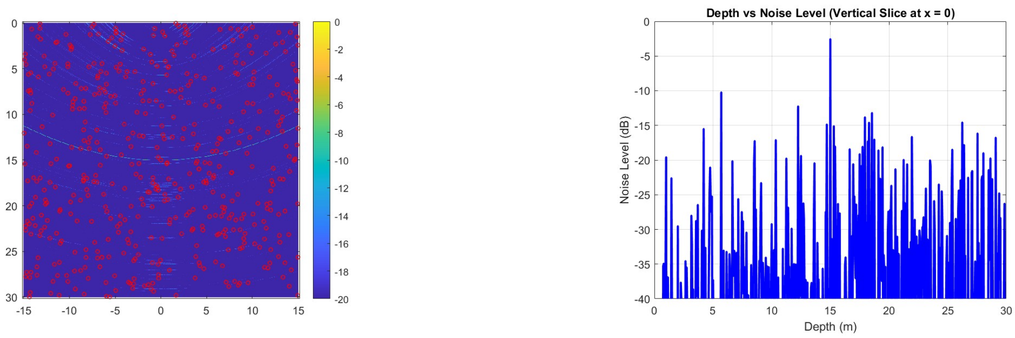
Table 4.1: Experimental Variables

The consistency in ego vehicle spawning, camera and custom sensor configurations, and the simulation scenario such as pre-defining destinations maintain so as to minimize confounding factors and ensuring the variation in weather conditions is the only factor affecting simulation result. Dependent variables include depth, azimuth and altitude similar to the default attributes of radar sensor in CARLA. They are used to compute the Cartesian coordinates of the hit objects. The position coordinates and intensity are saved and processed to form a point cloud which we estimate the object dimensions and compare with the bounding box from camera and ground truth data from the CARLA simulator.

4.2.1 MATLAB

As previously mentioned, an effective field method was utilised to ascertain the SNR of ultrasonic pulses when propagating through water particles in air where scattering occurs.In this study, 10 random tests were conducted for each weather condition (rain and fog), respectively.In each test, the target particle was defined in six different locations (5m, 10m, 15m, 20m, 25m and 30m) away.

In this study, an effective field method was employed to determine the signal-to-noise ratio (SNR) of ultrasonic pulses as they propagated through air containing water particles, where scattering effects played a significant role. A total of 10 random tests were conducted for each weather condition, specifically for rain and fog, to ensure consistency and reliability in the results. Within each test, a single target particle was positioned at six predefined distances from the sensor, namely 5m, 10m, 15m, 20m, 25m, and 30m. The sensor emitted ultrasonic pulses, and their interaction with the target particle was analyzed by extracting signal data along a vertical slice where x=0. This approach allowed for a focused evaluation of signal variations along the propagation axis.



(a) Scattering of acoustic wave at numerous water particles in a medium

(b) Noise level against vertical distance of particles

Figure 4.4: MATLAB SNR vs Distance analysis

Upon interaction with the water particle, the noise amplitude peaked due to scattering effects. To quantify this, the peak amplitude at each defined target location was recorded across all iterations. The MATLAB code was developed to process this collected data, extracting the peak amplitude values and calculating the SNR at each distance. The SNR was computed as the ratio of the signal power to the noise power, where the signal was defined by the received intensity of the ultrasonic pulse, and noise was measured as fluctuations in the background signal. These values were stored and plotted to visualize the trend of SNR decay with increasing distance.

To further analyze the attenuation effects, a linear regression model was applied to determine the relationship between SNR and distance, allowing for the estimation of the attenuation constant. The MATLAB script automated this process by fitting a linear curve to the SNR vs. distance data, providing insight into the rate of signal degradation as the ultrasonic wave traveled through the medium. The resulting plot displayed the SNR on the y-axis and distance on the x-axis, demonstrating a clear trend where SNR values decreased with increasing target distance due to signal attenuation and scattering losses. This plot served as a crucial tool in understanding the impact of environmental conditions on ultrasonic wave propagation and in quantifying the extent of signal degradation over distance.

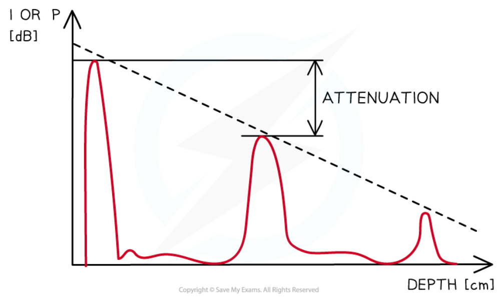


Figure 4.5: Linear regression sample

4.2.2 CARLA Simulation workflow

The workflow for the CARLA simulation begins with the initialization of Pygame and establishing a connection to the CARLA simulator, ensuring that all necessary modules are correctly loaded. Once connected, the simulation environment is configured by setting predefined weather parameters, allowing for the study of sensor performance under different environmental conditions, such as clear weather, rain, and fog. Following the environment setup, the ego vehicle is spawned at a designated location, with both a camera and a customized acoustic sensor attached to it. These sensors play a critical role in capturing environmental data, where the camera provides visual perception and the acoustic sensor generates point cloud data for detecting obstacles.

Once the ego vehicle is fully set up, multiple stationary vehicles are spawned within the environment. When the ego vehicle moves towards the destination across these stationary vehicles, sensors detect and capture these objects and save the image and point cloud. This allows controlled test scenarios where weather condition is the only factor, and simulate the situation when the ego vehicle encounters other objects on road realistically.

The camera and custom acoustic sensors collect data in every simulation tick as the ego vehicle moves through the test scenario. Acoustic sensor data includes the depth, azimuth and altitude towards the hit object, which are then used to compute the position of the objects. This data is crucial for forming the 3D point cloud and estimate the dimension of surrounding objects. Simultaneously, the camera sensor captures real-time images from the ego vehicle's perspective, displaying them using Pygame to provide a visual reference for the simulation.

In addition to the sensor data, ground truth information regarding positions and dimensions of all actors including vehicles are extracted from CARLA world for every simulation tick. This ground truth data was used to evaluate the accuracy of object dimension estimation from the custom ultrasonic sensor point cloud thus to evaluate the weather effect on sensor performance. This ground truth data serves as a benchmark for evaluating the accuracy of the acoustic sensor.

To assess the performance of the acoustic sensor, a comparison process is carried out, where the dimensions of stationary vehicles are computed from ultrasonic sensor point cloud data and ground truth bounding boxes. This step is crucial for validating the reliability and accuracy of the sensor under different weather conditions. Finally, all collected data, including sensor readings, vehicle locations, and environmental parameters, are systematically stored for further analysis, allowing for post-processing, visualization, and evaluation of the sensor's performance across different scenarios.

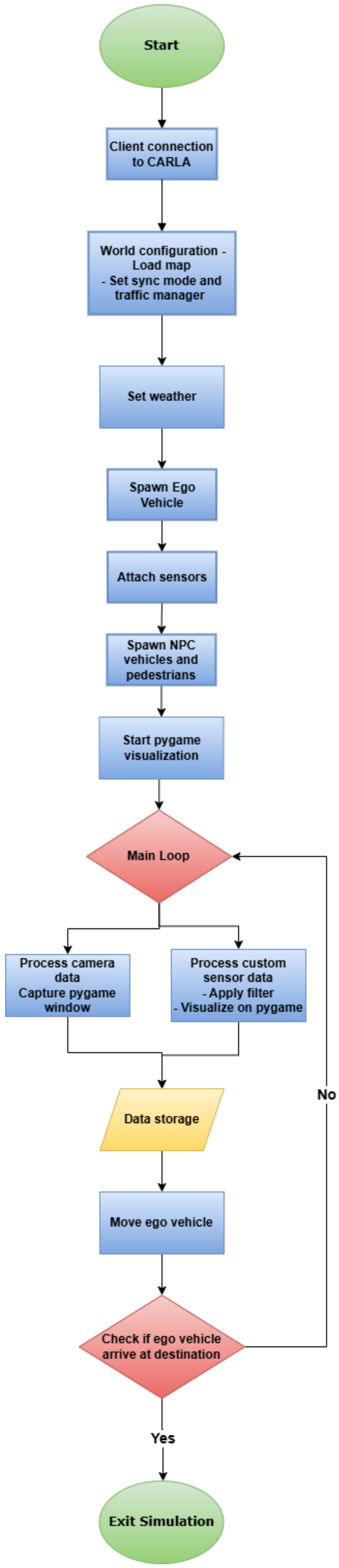


Figure 4.6: Flowchart of custom python script for CARLA Simulation

4.2.3 Scenario Design

There are a total of two scenarios, straight line and junction navigation scenarios, both with multiple stationary vehicles. The difference between two scenarios is to evaluate whether different road scenarios, objects location and angles affect sensing performance of acoustic sensor regarding detectivity and dimension estimation. It is expected that such accuracy from camera sensor will deteriorate across various test scenarios and weather conditions. if the sensing performance of ultrasonic sensor preserves, we can conclude that it is less affected by the change of weather conditions and road scenarios and prove the feasibility of integrating the novel 3D acoustic sensor into perception system in automotive industry to enhance robustness of perception systems and traffic safety.

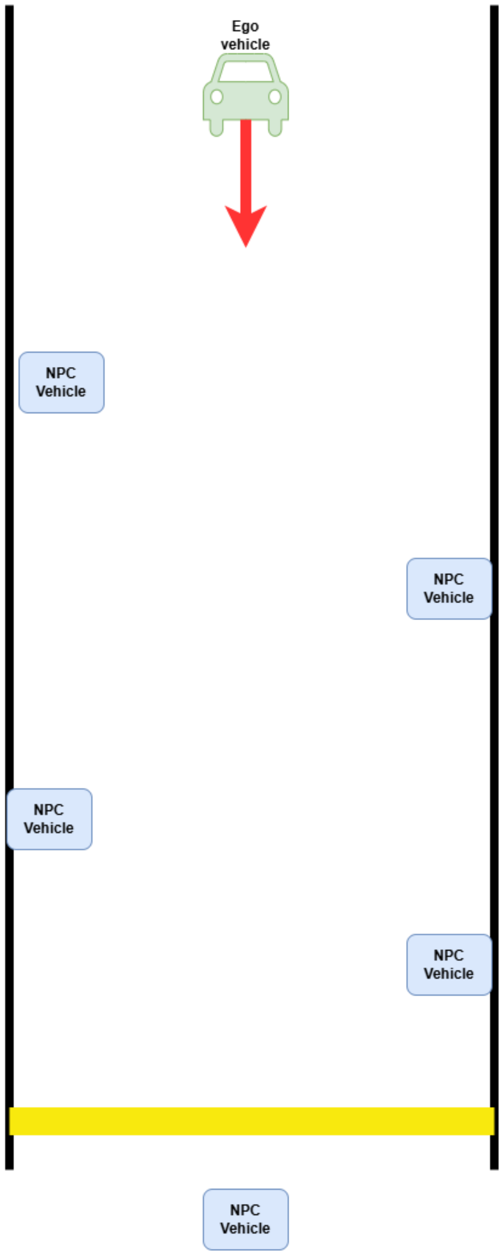


Figure 4.7: Straight line scenario design

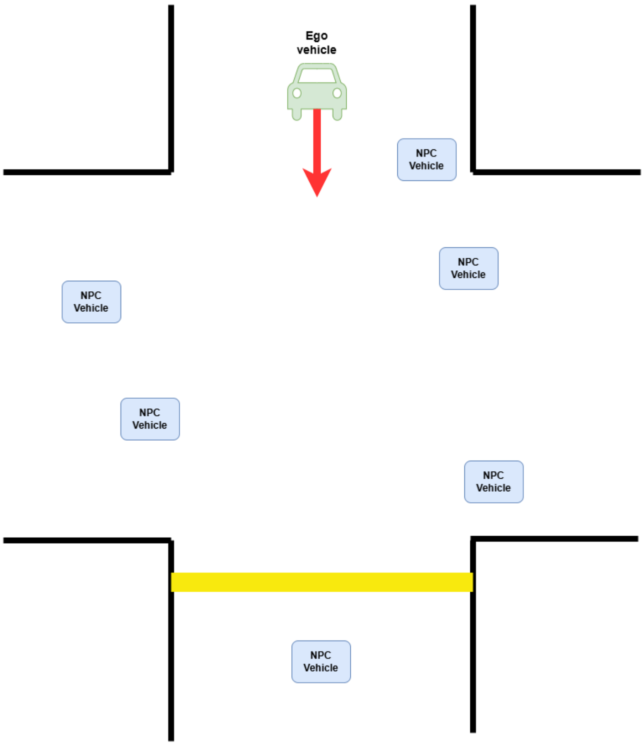


Figure 4.8: Junction scenario design

The most significant variable in this experiment is the alteration of meteorological parameters. The initial condition is defined as clear weather (i.e., no precipitation or fog), as this is hypothesized to provide optimal visibility conditions, resulting in the highest detectivity and, potentially, the greatest accuracy. Subsequently, the precipitation rate is incremented from 10% to 90% in 20% increments to simulate conditions ranging from light to heavy rainfall and fog.

Test Cases	**Scenarios**	**Rain Intensity**	**Fog Intensity**
1	Straight line	0%	0%
2	Junction	0%	0%

Table 4.2: Baseline scenarios

Test Cases	Scenarios	Rain Intensity	Fog Intensity
3	Straight line	10%	0%
4	Straight line	30%	0%
5	Straight line	50%	0%
6	Straight line	70%	0%
7	Straight line	90%	0%
8	Junction	10%	0%
9	Junction	30%	0%
10	Junction	50%	0%
11	Junction	70%	0%
12	Junction	90%	0%

Table 4.3: Rainy Test Scenarios

Test Cases	Scenarios	Rain Intensity	Fog Intensity
13	Straight line	0%	10%
14	Straight line	0%	30%
15	Straight line	0%	50%
16	Straight line	0%	70%
17	Straight line	0%	90%
18	Junction	0%	10%
19	Junction	0%	30%
20	Junction	0%	50%
21	Junction	0%	70%
22	Junction	0%	90%

Table 4.4: Foggy Test Scenarios

4.2.4 Evaluation Metrics

- Root Mean Square Error (RMSE): Used to measure the accuracy of dimension estimations between point cloud and bounding boxes.

- Signal-to-Noise Ratio (SNR): To assess the quality of acoustic sensor signals when the objects location differ.
- Detection Rate: Percentage of vehicles successfully detected under different weather conditions.

The application of point cloud filtering and clustering methods is instrumental in the removal of unwanted points and the facilitation of the identification of objects following the extraction of raw data from the CARLA simulation environment. Subsequently, Gaussian white noise is introduced to the point cloud, with reference to the attenuation coefficient obtained from MATLAB's SNR degradation analysis, in order to simulate the scattering effect induced by rain and fog weather conditions. Following the point cloud post-processing stages, the point cloud is then prepared for the estimation of object dimensions and comparison with CARLA's ground truth information. This process enables the evaluation of the accuracy and robustness of the 3D ultrasonic sensor in adverse weather conditions.

The experiment employs a structured methodology in order to systematically evaluate the performance of the sensor under varying weather conditions. Controlled experiments are used to isolate the effects of rain and fog, while incremental weather variations are employed to reveal their impact on sensor data degradation. Multiple trials and comparisons with ground truth data enhance the reliability and credibility of the results. Well-defined metrics, such as objects dimension estimation accuracy and intensity-based analysis, ensure objective evaluation. This approach guarantees scientifically valid, reproducible results, providing valuable insights into the robustness of the sensor in adverse conditions.

5 Results

5.1 Evaluation and Analysis

5.1.1 Signal-to-Noise Ratio analysis

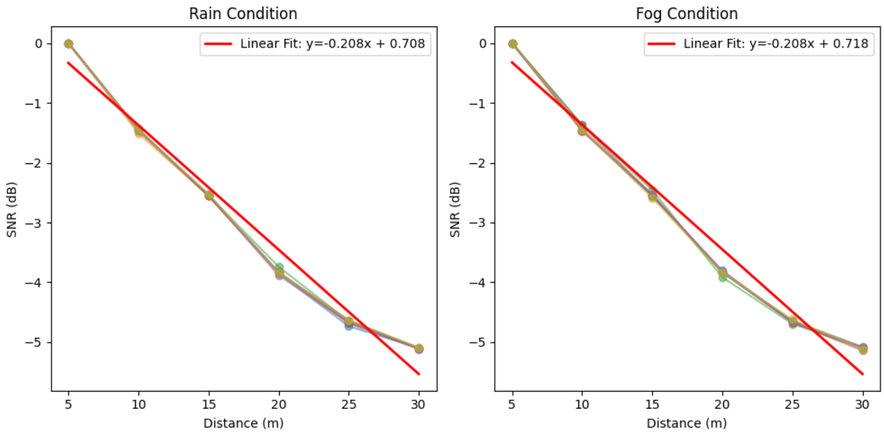


Figure 5.1: SNR vs Distance of Rain and Fog scenarios

A total of six trials, each with a distinct target particle location, were computed in MATLAB and manually located the peak amplitude of the noise level.From the resulting plots, a consistent and relatively linear downward trend in Signal-to-Noise Ratio (SNR) as the distance increases from 5m to 30m is observed. This trend is captured well by the linear fit lines (shown in red) in both rain and fog conditions. The negative slope of the linear equations, approximately -0.208, confirms that SNR degrades at a nearly constant rate over distance, and at the same time implies the SNR degradation is independent of weather conditions in this case, thereby supporting the hypothesis of the resilience of ultrasonic sensors against adverse weather.

By comparing the two linear regression equations:

Rain Condition:

$$y = -0.208x + 0.708$$

Fog Condition:

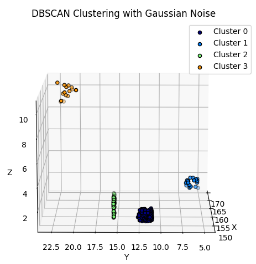
$$y = -0.208x + 0.718$$

The slopes of both lines are almost indistinguishable, indicating that the attenuation rate remains highly comparable in both rain and fog conditions. This finding suggests that the scattering and absorption effects caused by raindrops and fog particles result in analogous levels of signal degradation. The minor discrepancy in the intercept values (0.708 vs. 0.718) indicates slight variations in initial SNR values, yet the overall trend remains consistent.

The findings indicate that the SNR attenuation in both rain and fog conditions exhibits a comparable linear pattern. The near-identical attenuation rates substantiate the conclusion that both weather conditions exert a comparable influence on acoustic wave propagation. This finding is of paramount importance for the evaluation of sensor performance in inclement weather conditions, as it suggests that rain and fog result in analogous levels of signal degradation over distance. The slope value 0.208 was set as the attenuation constant in the physics model of the custom sensor in CARLA simulation to mimic the intensity attenuation of ultrasonic pulses.

5.1.2 Rain Scenario Simulation

A total of 22 simulation scenarios were done with the variation of road settings and rain or fog intensities. The captured images and 3D point clouds by camera and custom 3D ultrasonic sensor were then being processed to estimate the dimension of detected target vehicles in the scene.



(a) Captured point cloud visualization

(b) Vehicle detection on image

Figure 5.2: Example of data analysis

From the plot, the number of points remains relatively constant at low rain intensities with slight increase in heavier rain. Alternatively, the number of points in junction scenario slight increases with proportional to the rain intensities. Note that the quantity of points are generally much denser than that in straight line scenarios. The complexity of scene also contributes to this finding as it induces more noise and lead to a generally denser point cloud even though clustering method has already been implemented.

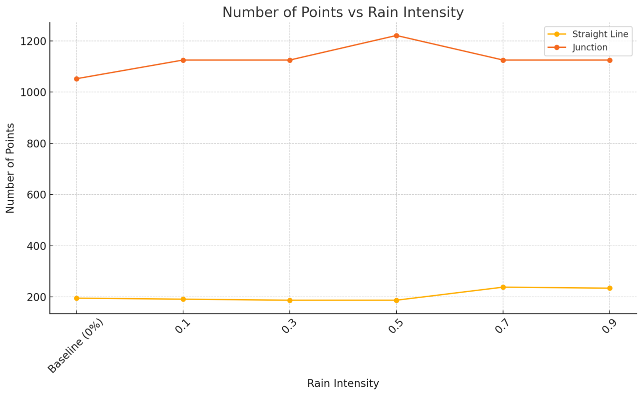


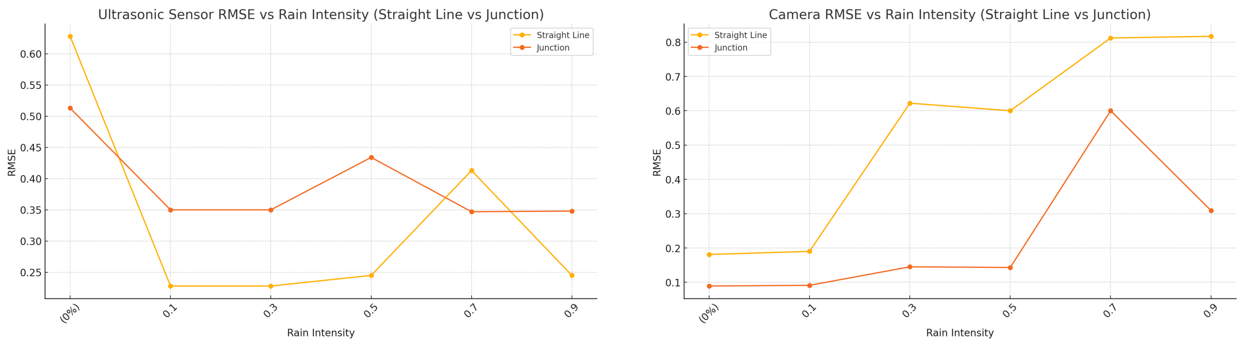
Figure 5.3: Number of points in the point cloud against rain intensity

Root Mean Square Error was computed by comparing the bounding box dimension between captured data to recorded ground truth information. The following plot presents the RMSE for camera and 3D ultrasonic sensor respectively under different rain intensities.

For camera sensor, the RMSE increases as rain intensity increases. The sensor steadily degrades as rain becomes heavier, meaning the sensing performance to estimate object dimensions is severely being affected by rain intensity.

For the 3D ultrasonic sensor, the RMSE starts from a relative high value and then drops significantly which may suggests an improvement under light rain conditions. Although the error still increases as rain intensity increases, the error is generally lower than that of camera sensor. This trend applies to both straight line and junction scenarios.

Therefore, it is evident that the camera sensor is more sensitive to rain interference compared to 3D ultrasonic sensor. Especially in heavy rain, the RMSE of camera reaches 1.0 which mean it completely fails to detect objects on the scene. The results show that the 3D ultrasonic sensor has better weather resilience and sensing performance against environment variations.



(a) RMSE by ultrasonic sensor at different rain intensities

(b) RMSE by camera at different rain intensities

5.1.3 Fog scenario simulation

The simulation was also done for various fog intensities. The following results illustrate the impact of foggy weather on the number of points in the captured point cloud and the RMSE of dimension estimation by camera and ultrasonic sensor in both straight line and junction scenarios.

(a) Captured point cloud visualization (b) Vehicle detection on image

Figure 5.5: Example of data analysis in fog scenario

Similar to the rain scenario, the number of points detected remains relatively stable as fog intensity increases. The total number of points in junction scenario is much higher as the complexity of the scenario increases. This also implies the scattering effect of water particles air to the ultrasonic pulses.

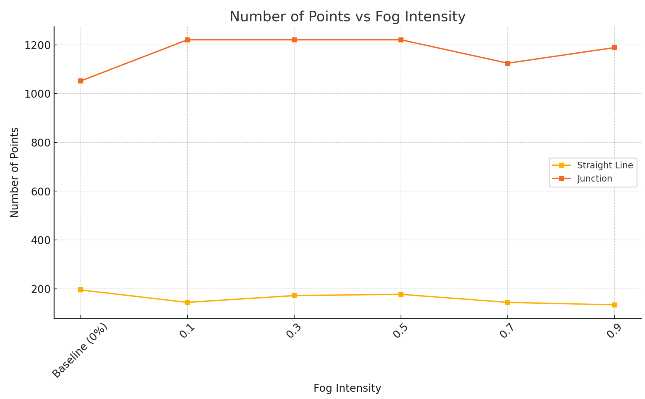
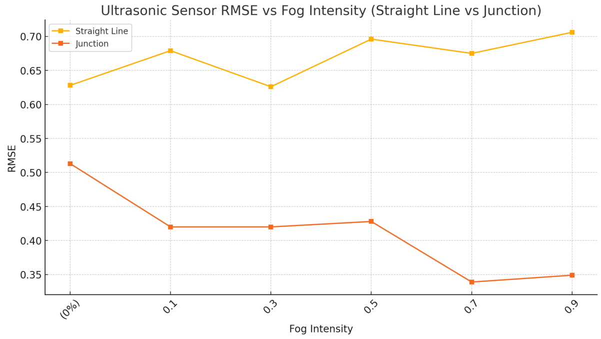


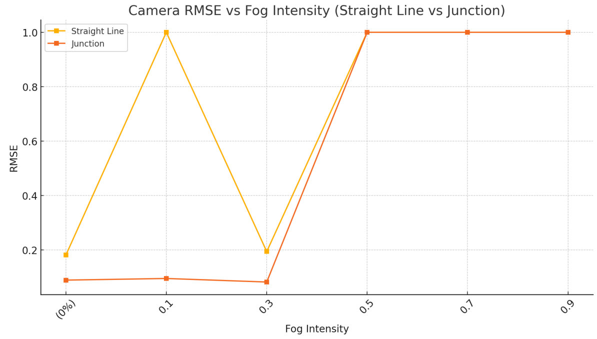
Figure 5.6: Number of points in the point cloud against fog intensity

For 3D acoustic sensor, the RMSE tends to increase in higher fog intensity in straight line scenario while decrease in a more complex junction scenario. However, if we look at the values, the RMSE actually has minor fluctuations only in which we may regard as relatively stable.

Compare to the RMSE of ultrasonics, that of camera demonstrates a sharp and distinct contrast. The camera completely failed to distinguish objects in high fog intensities in both scenarios. Despitein the junction scenario, the camera RMSE remains relatively low at lower fog intensities but also experiences a sharp increase to 1.0 at 0.5 fog intensity, where it remains constant. This result highlights the significant degradation of visual perception under foggy conditions.



(a) RMSE by ultrasonic sensor at different fog intensities



(b) RMSE by camera at different fog intensities

5.2 Summary

These results indicate that ultrasonic sensors are apparently more robust than cameras in foggy conditions, with RMSE values that remain within a reasonable range. However, their performance can be scenario-dependent, as demonstrated by the contrasting RMSE trends in straight-line and junction cases. Cameras, on the other hand, show a drastic loss of accuracy in fog, making them unreliable for distance estimation under such conditions. Additionally, the number of detected points in the ultrasonic sensor data suggests that environmental factors play a crucial role in maintaining accuracy, with junctions offering more stable detection due to additional reflective surfaces.

6 Discussion and Conclusion

6.1 Discussion

The hypothesis of this study posited that an ultrasonic-based 3D perception sensor (Calyo Pulse) would demonstrate superior sensing performance in conditions of rain and fog in comparison to optical sensors, whilst being less susceptible to environmental attenuation. The experimental results lend support to this hypothesis, albeit only to a limited extent. The ultrasonic sensor successfully detected objects in adverse weather conditions, including rain and fog, where camera-based perception exhibited significant degradation due to reduced visibility. However, the sensor failed to detect objects in the simulation scenarios.

However, while the sensor demonstrated robustness to environmental interference, its precision in terms of point cloud density, object dimension estimation, and localization accuracy was lower than that of the camera system.The number of points captured from the ultrasonic sensor was lower than expected, resulting in bounding box inaccuracies when estimating object size and shape. This outcome demonstrates that, despite the ultrasonic sensor demonstrating superior resilience to weather conditions, its spatial resolution is not equivalent to that of the camera, thus resulting in imprecise object size and shape estimation on the road.

In conditions characterised by precipitation and reduced visibility, optical cameras exhibited deficiencies, including blurred images, refraction, and diminished contrast, thereby compromising the reliability of object detection. Conversely, the ultrasonic sensor demonstrated consistent and reliable performance in these conditions. The acoustic wave properties of the ultrasonic sensor enable it to penetrate through droplets and fog particles with minimal scattering and absorption, rendering it a viable alternative for perception in challenging weather conditions.

Notwithstanding this benefit, the precision of the ultrasonic sensor's measurements remains a limiting factor. The point cloud sparsity resulted in inconsistent object contour formation, thereby hindering the acquisition of precise shape and dimension estimations in comparison to camera-based vision, which provides dense and structured data in optimal conditions. This limitation indicates that while ultrasonic sensing is advantageous for detection in unfavourable conditions, it is deficient in the fine-grained resolution required for accurate object classification and dimension estimation.

To answer the question of the potential in implementing the Calyo sensor into automotive perception systems, the novel 3D ultrasonic technology provides a new insight and an additional safety factor. Its environment resilience is outstanding. However, its rough resolution and point cloud sparsity show that it is not a standalone solution or a dominating sensor. A sensor fusion system involving multiple sensors must be applied to ensure the level of safety in automotive industry.

6.2 Limitations

One of the primary limitations of this research is the lack of on-site testing, which restricts direct validation of the sensor's performance in real-world driving conditions. Instead, all experiments were conducted in a simulated environment using CARLA, which, while highly flexible, may not perfectly replicate the complexities of real-world scenarios. The lack of live testing with the actual Calyo sensor also means it remains unknown to prove whether the physics model created in CARLA accurately replicate the actual behaviour of the Calyo sensor.

Furthermore, conducting real-world tests in adverse weather conditions, particularly under heavy rain or dense fog, introduces significant safety risks to both test operators and surrounding road users. Additionally, the high cost of physical testing—including vehicle modifications, sensor integration, and controlled environmental setups—posed financial constraints that made real-world validation impractical within the scope of this study.

Another challenge was time constraints associated with large-scale experimentation. Simulating various environmental conditions and sensor configurations in CARLA required extensive computational resources and careful parameter tuning. While simulation allows for iterative testing in a controlled manner, it cannot fully capture the variability and stochastic nature of real-world weather patterns, which could impact sensor accuracy in ways that were not observable in the simulated experiments. This limitation reduces the ability to generalize findings across all possible driving conditions.

The reproducibility of dynamic scenarios in real-world testing is another significant concern. Unlike simulations, where environmental factors such as rain intensity, fog density, and vehicle trajectories can be precisely controlled and replicated, real-world testing introduces inconsistencies due to natural variations. This lack of reproducibility makes direct performance comparisons across different weather conditions more challenging and complicates data-driven optimizations.

Finally, one of the most critical challenges is the difficulty in generating live sensor data under adverse weather conditions in a controlled manner. In a simulation, conditions such as rainfall rate, fog density, and wind turbulence can be systematically adjusted to evaluate their effects on sensor performance. However, in real-world testing, waiting for naturally occurring adverse weather events introduces unpredictability and potential delays. Even if artificial rain or fog generators were used, ensuring uniformity and repeatability across multiple test cases would remain a significant challenge.

Given these limitations, this research relied on high-fidelity simulation techniques to analyze ultrasonic perception under adverse weather conditions. While the results provide valuable insights, future work should include physical validation studies to verify the sensor's real-world performance and further refine its integration into multi-sensor perception systems for autonomous vehicles.

6.3 Future Work

To build on the findings of this study, several areas for future work are proposed:

- **Sensor Fusion**: One of the most promising approaches to address Calyo sensor's limitations in adverse weather is to integrate it with other sensor modalities. Combining radar with 3D acoustic sensors, LIDAR, and optical cameras can create a multi-sensor system that compensates for the weaknesses of individual sensors.
- **Real-World Testing**: While simulations provide a controlled environment to study sensor performance, real-world testing is crucial to validate the findings. Conducting experiments in various weather conditions will allow for the collection of real sensor data, helping to fine-tune sensor fusion strategies and ensure that the integrated system performs well in practical applications.
- **Improve acoustic signal processing Algorithms**: Another avenue for improving sensing performance is through the development of advanced signal processing techniques. Algorithms that adaptively filter noise, or use machine learning to predict and mitigate signal degradation in adverse weather, could help reducing the need to rely on multiple sensor in a single perception system.

By pursuing these future directions, it will be possible to develop more robust and reliable sensing systems for autonomous vehicles, capable of navigating safely in a wider range of environmental conditions.

6.4 Conclusion

This research has explored the integration of a novel 3D ultrasonic sensor, the Calyo Pulse sensor, into automotive perception systems, evaluating its performance under varying environmental conditions. By simulating the sensor in CARLA, incorporating scattering and attenuation effects, and comparing the point cloud-based object detection against ground truth data, this study has provided a foundation for understanding the feasibility of ultrasonic perception on road.

The results demonstrate that acoustic sensing is a viable alternative to camera in specific scenarios, particularly in adverse weather conditions where optical sensors suffer from visibility degradation. The sensor's ability to detect obstacles with reasonable accuracy, despite signal attenuation due to rain and fog, highlights its potential for robust perception in autonomous navigation. Furthermore, the implementation of point cloud clustering, bounding box generation, and error analysis provides a quantitative assessment of its performance relative to ground truth vehicle positions.

Future work should focus on exploring real-world validation and implement sensor fusion approach to further examine to what extent can Calyo sensor provide sufficient level of weather resilience and spatial resolution at the same time from the generated point cloud. Also, the potential of wider implementation and testing scenarios can be a critical step in verifying the sensor's practical applicability.

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