Synthetic Image Generation in CARLA for Evaluating AI-based L3 Automated Driving Systems

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ABSTRACT: The automotive industry is undergoing a significant transformation, moving towards a future where drivers will have a diminishing role in operating their vehicles, eventually being completely prohibited. As we transition from driver assistance to automated driving, a crucial challenge arises—ensuring autonomous systems can handle all situations in their environment independently, without relying on human intervention. Likewise, verifying AI-based video perception, which aims to identify objects in camera images, is becoming increasingly complex. Researchers are conducting extensive research and proof-of-concept (POC) studies to address the verification of AI-based systems in the industry. One critical aspect of verifying AI-based video perception is the ability to generate synthetic images with various parameters that simulate different use cases. In this proposed work, the focus is on utilizing CARLA—a highly realistic, open-source simulation platform for autonomous driving research. CARLA provides a three-dimensional environment that faithfully replicates real-world driving scenarios, ranging from simple lane changes to complex situations like intersection navigation and emergency braking. The platform's modularity allows researchers to customize it by incorporating their own sensors, controllers, and components into the simulation. CARLA also offers pre-built environments, vehicle models, and a suite of tools for data visualization and analysis. With its user-friendly Python API, CARLA facilitates quick setup and execution of simulations. CARLA has gained popularity as a valuable tool for autonomous driving research, attracting a vibrant community of users and contributors. Its realistic simulation environment and flexible customization options make it an ideal platform for testing and developing autonomous driving algorithms and systems. The aim of this proposed work is to establish a proof-of-concept (POC) validation framework for testing Level 3 Automated Driving Systems (ADS) using the CARLA simulator. Various features of the CARLA simulator are explored to create edge case scenarios, enabling thorough testing and evaluation of ADS capabilities.

Keywords*: CARLA, ADAS, segmentation, image, autonomous*

1 INTRODUCTION

ADAS, short for Advanced Driver Assistance Systems, refers to a collection of technologies designed to enhance vehicle safety and efficiency by assisting drivers in various driving scenarios. These systems rely on sensors, cameras, and other technologies to detect potential hazards or risky situations on the road. ADAS aims to prevent accidents, reduce driver fatigue, and improve overall driving experience. Some examples of ADAS features include:

- Adaptive Cruise Control (ACC): ACC adjusts the vehicle's speed to maintain a safe distance from the vehicle ahead, ensuring a consistent and controlled driving experience.
- Lane Departure Warning (LDW): LDW uses cameras or sensors to monitor lane markings and alerts the driver if the vehicle drifts out of its lane without signalling.
- Automatic Emergency Braking (AEB): AEB systems detect imminent collisions and automatically apply the brakes to prevent or mitigate the impact.
- Blind Spot Monitoring (BSM): BSM uses sensors to detect vehicles in the driver's blind spots and provides warnings or alerts to avoid potential collisions during lane changes.
- Rear-view Cameras: Rear-view cameras provide a clear view of the area behind the vehicle, aiding in parking and reversing manoeuvres while enhancing overall visibility.

ADAS technologies act as a stepping stone towards fully autonomous vehicles. They assist drivers and enhance their situational awareness, but they still require human intervention and do not fully replace the need for an attentive driver. ADAS systems often work in tandem with advanced control systems, which interpret sensor data and make decisions based on the environment and vehicle dynamics. On the other hand, self-driving vehicles, also known as autonomous vehicles (AVs), rely on an array of sensors, such as thermo graphic cameras, radar, lidar, sonar, GPS, odometer, and inertial estimation units, to perceive and understand the surrounding environment. Advanced control systems analyse the sensor data to assess acceptable manoeuvring actions, obstacles, and necessary traffic information. An autonomous driving system encompasses multiple subsystems, including environmental sensing, decision-making, and motion control. It performs all necessary driving functions without real-time input from a human driver, with the ability to navigate and operate a vehicle in real-world conditions.

Challenges of ADAS

In March 2016, a self-driving Google vehicle, now known as Waymo, collided with the side of a bus while attempting to change lanes, moving into the path of the bus to maneuverer around an obstacle. This incident serves as an example of the challenges in predicting the behaviour of all vehicles before they occur. Additionally, there have been other notable incidents involving autonomous vehicles, such as an Uber Level 3 autonomous vehicle striking and killing a pedestrian in Arizona in March 2018, and Tesla vehicles in Level 2 autonomous mode being associated with two fatal accidents in Florida and California. It's important to note that in these accidents, a human driver was in control of the vehicle at the time. These occurrences highlight the significance of integrating robustness into control systems and conducting exploratory testing that covers as many foreseeable situations as possible. When transitioning from driver assistance to automated driving, the primary challenge lies in handling real-world environments. Autonomous systems need to be capable of handling any conditions that arise in their surroundings without relying on a human driver. It is crucial to ensure that such systems undergo thorough testing before being deployed in series production. One approach to assessing the safety of autonomous vehicles is testing them in real traffic conditions, which provide situations that closely resemble the real world. However, the unpredictability and randomness of real traffic make it necessary to have a substantial dataset to ensure the validity of experimental results. Due to the high costs involved, this approach is primarily feasible for large enterprises or institutions. Another significant challenge is anticipating the various scenarios that can arise during automated driving, which has implications for safety engineering tasks ranging from design to verification. Given the complexity and uncertainty of the driving environment and the intricacy of the driving task itself, the number of situations that an Automated Driving System (ADS) or Advanced Driving-Assistance System (ADAS) may encounter is virtually limitless. Virtual testing offers a solution to address these challenges. Methods such as Model-in-the-Loop (MIL), Software-in-the-Loop (SIL), Hardware-in-the-Loop (HIL), Vehicles-in-the-Loop (VIL), and other techniques can be utilized to test and validate systems at various stages of development. This has sparked considerable interest in virtual assessment and verification, enabling "safe testing" and exploration, as well as potentially realistic validation based on the evidence provided. However, this raises additional issues, such as selecting crucial tests, developing them effectively, and determining coverage and completeness of the security analysis, assuming the existence of a realistic simulation environment (which is a challenge in itself).
Addressing these issues requires careful consideration of test scenarios, the development of suitable methodologies, and establishing criteria for evaluating coverage and completeness in safety analysis. Virtual testing provides an avenue to tackle these challenges, enabling cost-effective and controlled simulations while striving for realistic and comprehensive evaluations of autonomous driving systems.

2. LITERATURE REVIEW

CARLA: an open-source simulator for autonomous driving research, offering three approaches to autonomous driving: specific pipeline, imitation learning, and model reinforcement learning. Its client-server architecture enables simulation running, scene rendering, command transmission, and sensor reading. CARLA serves as a valuable resource for developing, training, and evaluating autonomous systems in controlled scenarios, exploring urban environments with diverse elements. Further advancements in learning algorithms and model structures are essential for notable improvements [1]. [2] Provides a detailed taxonomy defining six levels of driving automation, ranging from no automation (level 0) to full automation (level 5) for motor vehicles. These definitions, along with additional supporting terms, enable a comprehensive and coherent description of driving automation features on vehicles. The levels pertain to the specific automation feature(s) engaged during on-road activities, encompassing various road users. While a vehicle may possess multiple automation features operating at different levels, the specific level exhibited is determined by the engaged features. The article emphasizes the fundamental concepts of automation levels and the challenges encountered in this field. [3] introduces Boss, an autonomous vehicle equipped with on-board sensors (GPS, lasers, radars, cameras) for tracking vehicles, detecting obstacles, and navigating urban environments based on a three-layer planning system. The mission planning layer determines the optimal route, while the behaviour layer handles lane changes, intersection priority, and error recovery. The motion planning layer selects actions to avoid obstacles and achieve local objectives. Boss was developed through a rigorous process, emphasizing testing and successfully demonstrated its capabilities in the DARPA Urban Challenge. The article primarily discusses Boss, an autonomous vehicle, and its urban challenges. In reference [4], it is noted that current ADAS systems have limitations in detecting obstacles at high speeds and long distances, particularly in complex intersections and obstructed sight conditions. To overcome these challenges, a CVIS-based ADAS framework is proposed, enabling independent obstacle detection and data integration between vehicles and roadside devices. The framework expands the scope of collision advance notice, enhances ADAS effectiveness, and improves adaptability in complex environments. The paper [5] introduces detailed lanelets for autonomous driving, representing the drivable environment. It describes map creation, the libLanelet library, and their application in the behaviour layer of the Mercedes Benz S 500 Intelligent Drive. Lanelets enable complex road scenarios and strategic maneuverer generation. Future extensions include map refinement and automated derivation from human driver input. [6] Sensors are vital for automated vehicles to detect and interact safely with other road users. The study [6] explores driving scenarios, determines detection requirements, evaluates sensor capabilities, and proposes solutions for enhanced sensing. Current ADAS and autonomous vehicles commonly use RADAR and vision systems, with sensor fusion compensating for limitations. LIDAR is less frequent due to cost and processing requirements, while ultrasonic sensors complement other sensors for parking and short-range obstacles..

[7] Waymo's Level 4 autonomous driving system performs the entire driving task without a human driver and can safely bring the vehicle to a stop in case of system failure. Unlike lower-level systems, it operates independently without constant driver monitoring and incorporates comprehensive safety technologies. This report focuses on Waymo's advanced vehicle and its safety features. [8] Focuses on semantically understanding 3D scenes for applications like autonomous driving. By generating synthetic scenes and training a deep neural network, they achieve accurate scene characterization without relying on real-world datasets. The neural network effectively learns mathematical context and surface signals, and its performance is evaluated on real-world datasets. CARLA facilitates synthetic scene generation and pixel data collection..

[9] Camera-based perception in automated driving requires high-quality datasets, but current solutions lack instance segmentation ground truth. This paper introduces a back projection pipeline for precise instance segmentation maps in CARLA, improving evaluation accuracy for pedestrian depth aggregation. Generating large-scale, high-quality datasets is crucial to address collision risks with pedestrians and objects in urban scenes. [10] Autonomous vehicles offer safety, efficiency, accessibility, and environmental benefits. This paper provides an overview of recent developments in autonomous vehicle software systems, discussing key components and advancements in each area. [11] The paper discusses verifying perception in computer vision for autonomous driving, highlighting the importance of tasks like object identification and semantic segmentation. It emphasizes the need for verification and validation in deep learning-based approaches. [12] The paper provides a literature survey on key concepts, techniques, and approaches in autonomous vehicle systems, focusing on tracking and prediction tasks. It highlights the use of deep neural networks and stochastic processes in these areas. The results suggest that learning-based approaches have become the norm in autonomous driving, while rule-based methods have limitations in handling complex driving scenarios. Evolutionary methods require substantial amounts of data to cover a wide range of driving behaviours.

[13] The paper introduces VATLD, a visual analytics framework for assessing and enhancing the accuracy and robustness of traffic signal identification in autonomous driving. VATLD utilizes simplified representation learning and semantic adversarial learning to provide human-friendly visual summaries and uncover interpretable robustness risks. It offers practical recommendations and demonstrates the effectiveness of performance improvement strategies. [14] The paper introduces a label-free robustness metric for evaluating the robustness of CNN object detectors in autonomous driving applications. The metric assesses the sensitivity of predicted confidences to artificial perturbations without relying on ground truth labels. Extensive evaluations demonstrate the effectiveness of the label-free metric in assessing robustness. The paper highlights the importance of robustness assessment in data-driven models for real-world applications and suggests further exploration of evaluating model robustness using datasets with real atmospheric conditions. [15] This paper proposes methodologies to integrate simulation and testing in verifying highly automated driving capabilities. It explores the plausibility of using virtual tests to verify safety properties and actual tests to validate models. The approach quantitatively analyses the accuracy of models and the system's compliance with requirements. By considering the costs of virtual and actual tests, an optimal trade-off is determined. The paper discusses challenges in modelling, particularly in achieving realistic virtual environments and accurate representations of the real system during virtual testing.

3. METHODOLOGY

Vision plays a crucial role in automated driving and robotics, but it faces the challenge of dealing with diverse and unpredictable visual scenes. Due to the vast variety of possible visual inputs, machine learning has emerged as the predominant approach in computer vision. Machine learning enables the creation of models that can generalize from examples, allowing perception functions to process raw sensor inputs and generate semantic information. For instance, a computer vision function can take an image as input and produce an interpretation of the image content, such as detecting objects, performing semantic segmentation, or estimating 3D depth information. This illustrates the role of perception in transforming raw sensor signals into meaningful and actionable insights as shown in the figure1.

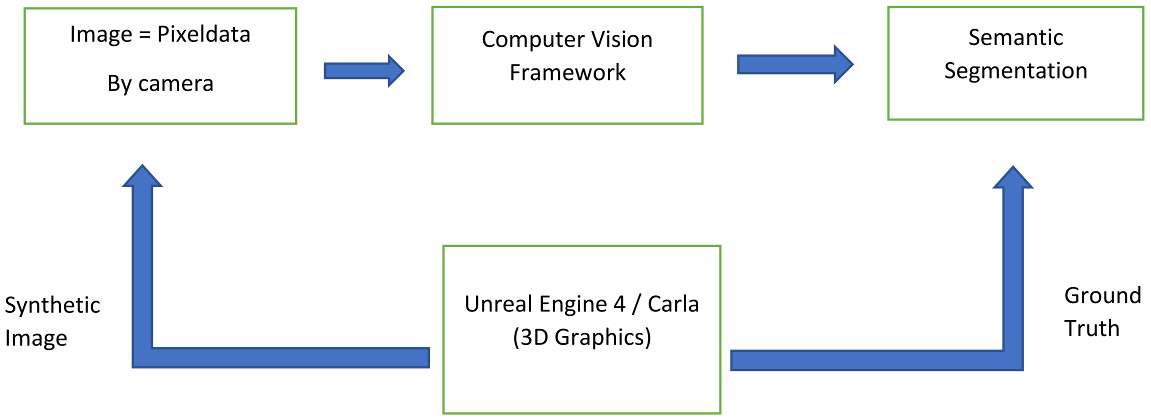


Figure 1. Technical setup to test perception with synthetic data

CARLA / UNREAL ENGINE 4

CARLA, built on the Unreal Engine 4, provides a realistic 3D environment for simulating autonomous driving scenarios as shown in the below figure 2. The Unreal Engine 4 is a powerful game development engine used in the gaming industry. Leveraging its advanced graphics rendering, physics simulation, and game development tools, CARLA creates a highly realistic environment for testing autonomous driving algorithms. It simulates complex lighting, weather conditions, dynamic objects, and pedestrians, enabling realistic and challenging scenarios. The Unreal Editor allows developers to customize the virtual environment, including road networks, buildings, and objects. It also provides tools for creating realistic vehicle physics models and simulating the behavior of pedestrians and other vehicles. CARLA supports the development, training, and validation of autonomous driving systems with open-source code, protocols, and resources. It offers flexible sensor suites, weather conditions, and control over static and dynamic actors. Furthermore, CARLA provides ground truth output generation, RGB input image generation, and programmable control for test generation, and includes free content. It is a popular academic tool supported by companies like Intel, Toyota, and GM.

Figure 2. CARLA / Unreal Engine 4

SEMANTIC SEGMENTATION

Semantic segmentation is a computer vision technique that partitions an image into meaningful segments or regions based on its content. The objective is to classify each pixel in the image into specific categories such as roads, buildings, cars, pedestrians, trees, etc., as depicted in Figure 3 below. Semantic segmentation finds applications in various fields like autonomous driving, robotics, and medical imaging. Unlike object detection or recognition, which identify objects' location and class, semantic segmentation provides a comprehensive understanding of the entire image, including background and non-object regions. Deep learning architectures like Fully Convolutional Networks (FCNs), U-Net, Deep Lab, and Mask R-CNN are commonly employed for semantic segmentation. These models leverage convolutional neural networks (CNNs) to learn image features and representations. Subsequently, a decoder network generates a dense pixel-level output, assigning a class label to each pixel

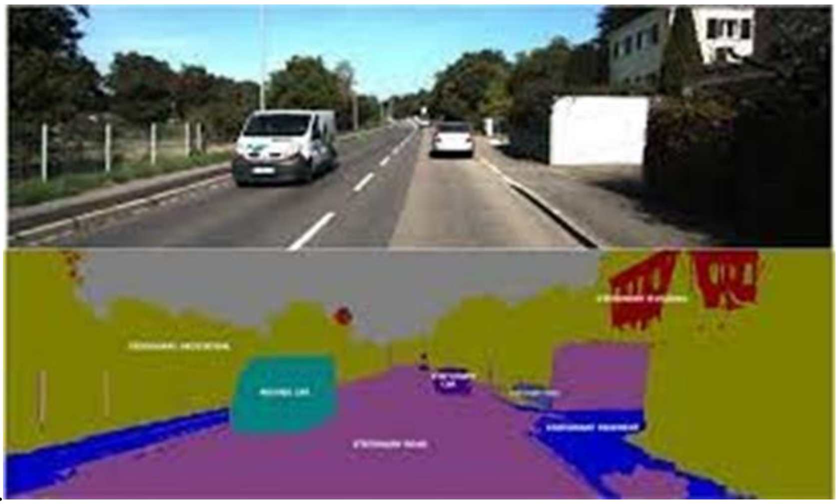
1. 

Figure 3. Semantic Segmentation

AUTOMATIC GENERATION OF CRITICAL TEST CASES

An approach is introduced that utilizes reinforcement learning-based optimization to automatically generate critical test cases and scenarios for automated driving functions. The focus is on the overtaking assistant as an example. The approach employs Q-Learning, which automates the generation of parameters for the test cases, ensuring their effectiveness and relevance.

TEST CASE GENERATION CONCEPT

The process of test case generation involves seven steps, as illustrated in Figure 4.

- Analysis: In this initial phase, the factors that influence autonomous driving functions, such as the ego-speed of the vehicle, are identified and considered for the test.
- Test Case Generation: Parameters for the test cases are generated based on the identified criteria from the analysis phase.
- Test Run Execution: The test execution is conducted through software-in-the-loop testing, using simulation tools to simulate the test scenarios.
- Test Evaluation: The simulation results are evaluated in this phase, using multiple criteria to assess criticality, such as time-to-collision. Based on the evaluation, new test cases may be generated.
- Exploration: After the test evaluation, the environment is further explored or existing knowledge is applied to enhance the testing process. This is achieved through the reinforcement algorithm in conjunction with the test evaluation.
- Parameter Change: In the sixth step, a parameter change occurs. An E-greedy algorithm is used to select a random action that offers the best reward. This action involves modifying a parameter's value, either increasing or decreasing it. Following the parameter change, a new test case is created using the updated parameters, and the cycle repeats.
- Save Critical Test Cases: Finally, critical test cases are saved for future reference and analysis.
- These steps outline the concept for generating test cases in an automated manner, optimizing the testing process for autonomous driving functions.

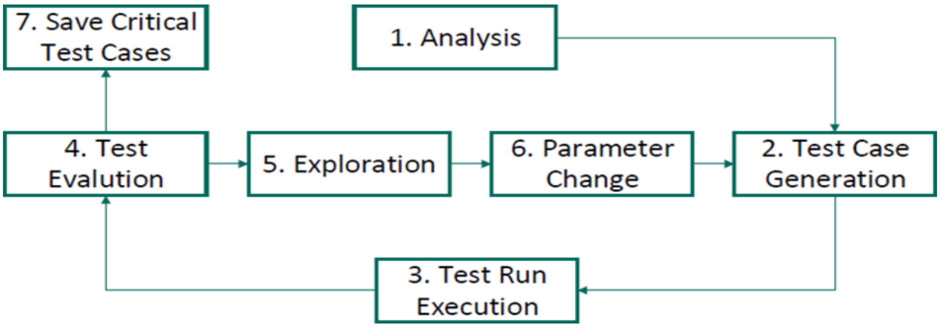


Figure 4. Concept for the generation of Test Cases

CRITICAL SCENARIOS

In the context of system design, safety analysis, verification, and validation, critical scenarios refer to potentially harmful situations that need to be identified and addressed. Discovering and mitigating these unknown critical scenarios is of utmost importance. Such scenarios consist of two main components: triggering conditions and safety-critical operational events. An unknown critical scenario can arise from either an unknown triggering condition or an unknown safety-critical operational situation. Figure 5, Figure 6, and Figure 7 depict examples of critical scenarios that highlight the importance of identifying and managing potential risks and hazards in various contexts. These visuals serve as illustrations to emphasize the significance of addressing critical scenarios to ensure the safety and reliability of systems and operations.

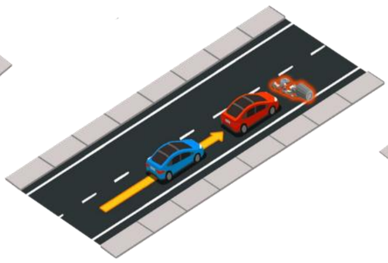




Figure 5. Blind spot in overtaking Figure 6. Construction cones on the road Figure 7. Oncoming vehicle crossing red light at an intersection

4. IMPLEMENTATION AND RESULTS

INTRODUCTION TO SCENARIO BASED TESTING

The validation of SAE Level 3-5 frameworks for safety in complex environments, including varying street and climate conditions, necessitates the development of new systems and processes. Scenario-based testing and approval strategies for automated driving frameworks (ADS) in virtual test environments are gaining momentum and becoming integral to ADS verification and validation. The increasing complexity and costs associated with real-world testing have led to a significant increase in testing efforts. However, these efforts can be efficiently reduced in terms of costs and time by employing scenario and simulation-based approaches. Selecting an appropriate simulation framework and identifying relevant scenarios for the system under test pose as the most challenging tasks. A data-driven strategy is employed to analyse the safety of Automated Vehicles (AVs) to be deployed, with scenarios playing a crucial role. Through a combination of virtual and physical safety validation, carefully selected test scenarios are used to quantitatively evaluate an AV's performance. Real-world driving data is utilized to represent various on-road situations, including traffic movements, typical road layouts, infrastructure characteristics, as well as weather and lighting conditions. The first level of abstraction describes scenarios in a qualitative manner, while the second level of abstraction quantitatively describes scenarios using parameters and models. The scenarios should encompass a wide range of situations that an AV could encounter in real-world traffic. Consequently, a multitude of scenarios is possible.

SYNTHETIC SIMULATION FOR SCENARIO BASED TESTING

To ensure the safety of self-driving technology, extensive testing across diverse driving scenarios is crucial. Simulated synthetic datasets offer a cost-effective and efficient way to gather large amounts of data for deep learning. Simulation plays a vital role in evaluating challenging driving scenarios and assessing the response of self-driving vehicles to real-world conditions. As part of the Proof of Concept, CARLA, an open-source simulator, is utilized for generating synthetic images and advancing the testing process.

CARLA BASED SIMULATION

CARLA is an open simulator specifically designed for autonomous driving research and development. It offers a wide range of digital assets, including city layouts, vehicles, pedestrians, and road signs. With configurable sensor suites, CARLA enables training and validation using data like GPS locations, speed, and acceleration. It also allows customization of environmental parameters such as weather and time of day.

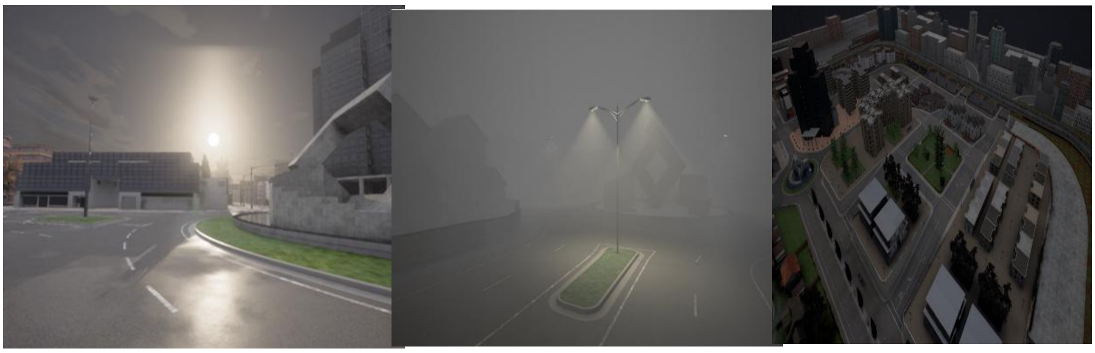
SYNTHETIC SCENE GENERATION USING CARLA

The scenarios in this report cover a variety of traffic situations for AV assessment. Multiple actors are involved, leading to numerous interactions. Critical test situations are identified and simulated using the CARLA simulator within a defined ODD. Key concepts for understanding CARLA are: the below figure 8 shows Synthetic image of Weather Parameters like cloudy sunset, fog and spectator view, and figure 9 shows Synthetic image of spawned walker, spawned vehicle, and spawned waypoints. The sample code snippet for the figure 9 c are mentioned below.

python Copy code

```python
import time

waypoint = map.get_waypoint(vehicle.get_location(), project_to_road=True, la
for _ in range(120):
    world.debug.draw_string(waypoint.transform.location, "*", life_time=120,
    waypoint = waypoint.next(2.0)[1] if len(waypoint.next(2.0)) > 1 else way
    time.sleep(0.5)
```



a b c

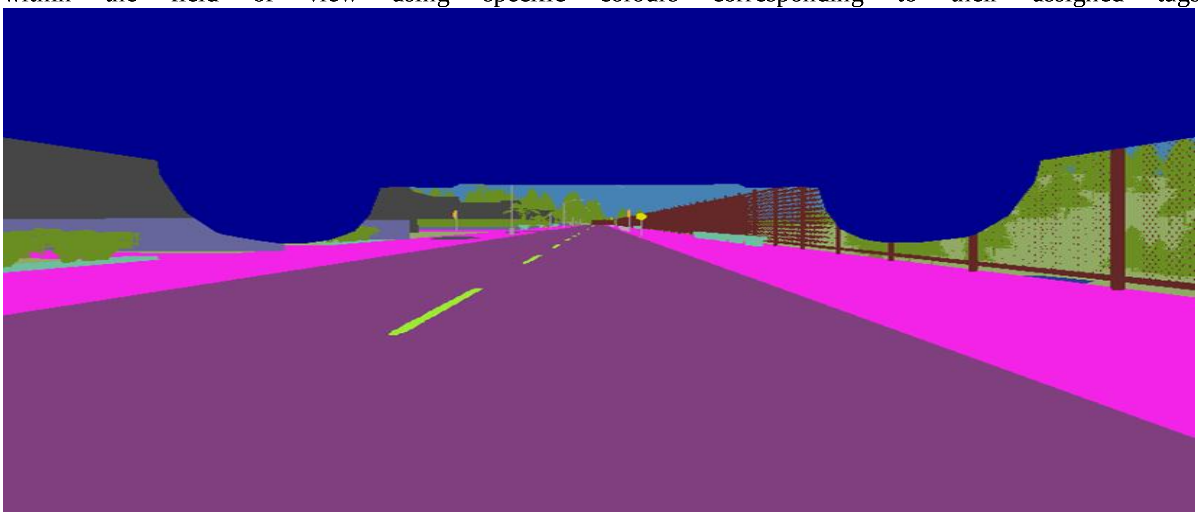
Figure 8: Synthetic image of Weather Parameters (a: Cloudy Sunset b: fog, c, Spectator View)

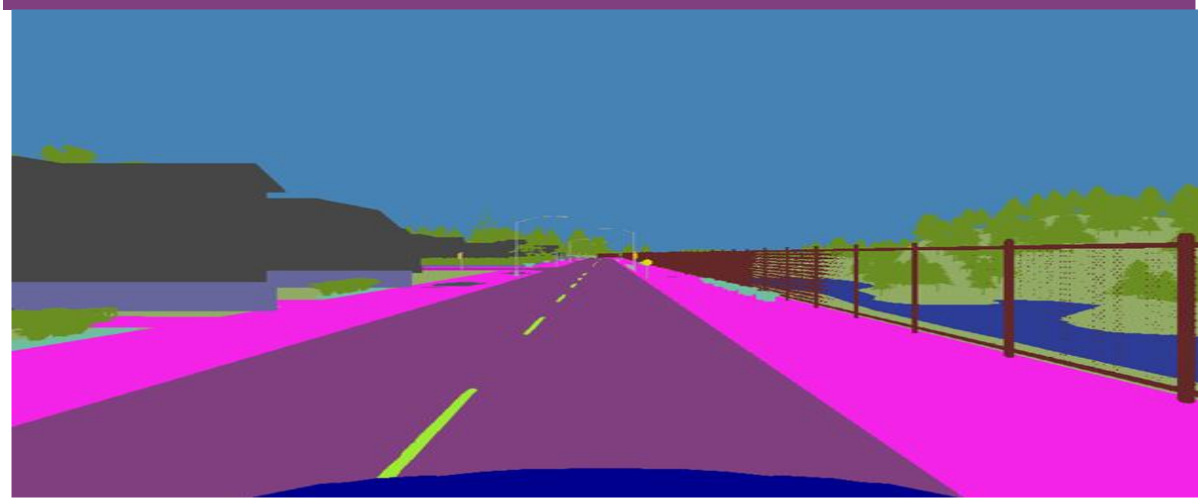
a b c

Figure 9: Synthetic image of (a: spawned walker, b: spawned vehicle, c: spawned waypoints)

SEMATIC SEGMENTATION

The "semantic segmentation" camera distinguishes each object in the field of view by representing them in different colours based on their class, as shown in Figure 9 below. For instance, pedestrians are displayed in a distinct colour from vehicles. This functionality is achieved by assigning labels to each object in the scene beforehand, either during the start of play or upon spawning. When the simulation commences, every element in the scene is tagged accordingly. This tagging occurs when an actor is spawned. Objects are classified based on their general file path within the task. For example, meshes stored in Unreal/CarlaUE4/Content/Static/Pedestrians are labelled as "Pedestrian." The camera then renders elements within the field of view using specific colours corresponding to their assigned tags.





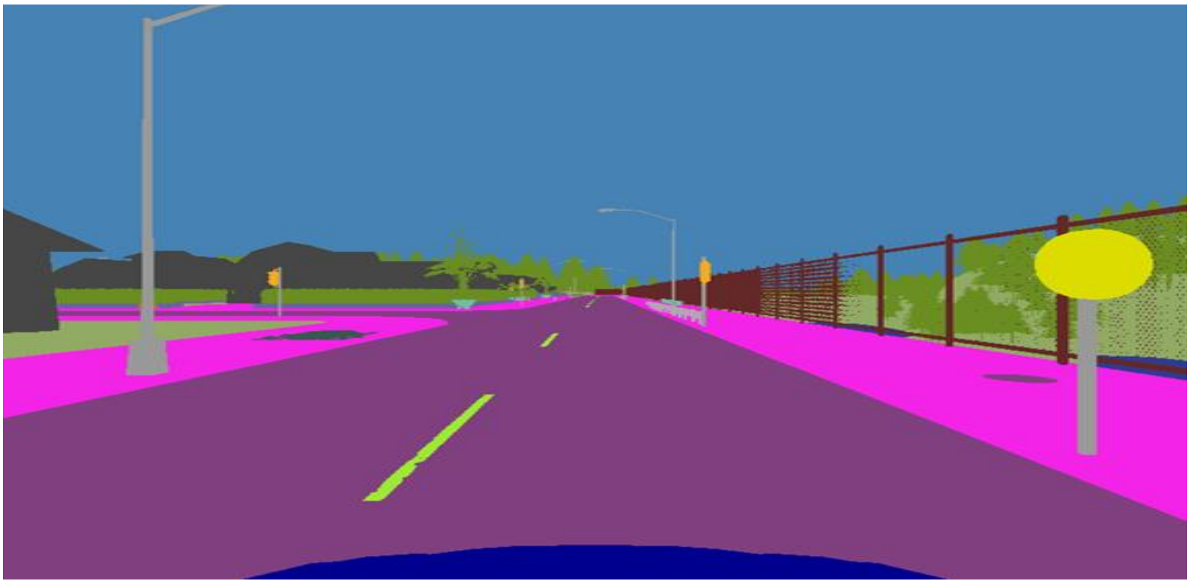


Figure 9. Synthetic images of semantic segmentation

SYNTHETIC SCENE GENERATION USING CARLA

The scenarios outlined in this paper aim to encompass a wide range of situations that vehicles may encounter in traffic. These scenario categories serve as a foundation for developing suitable test cases for assessing autonomous vehicles (AVs). In most scenarios, apart from the ego vehicle, there are at least two additional actors involved. When multiple actors are taken into account, the potential interactions between them increase significantly. In fact, the number of options multiplies exponentially as more actors are introduced. To address critical testing situations, specific test scenarios are identified, and synthetic scenes are generated within a defined Operational Design Domain (ODD) using the CARLA simulator.

SC1: CONSTRUCTION CONES ON THE ROAD

The construction cones on the road schematic diagram is represented below figure 10

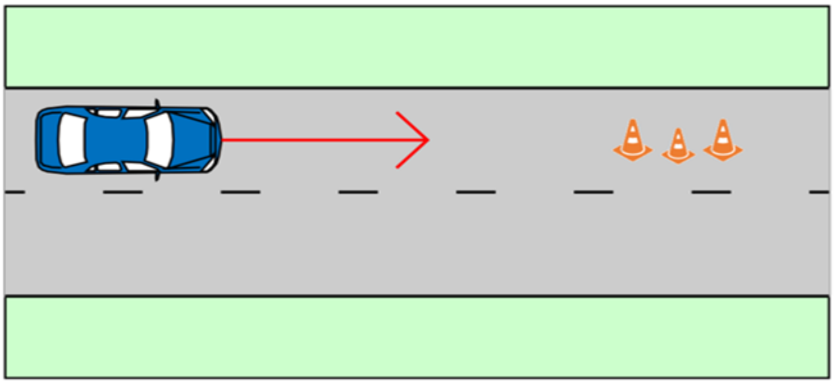


Figure 10. Schematic representation of SC1

GENERAL DESCRIPTION

The scenario depicted in Figure 1 illustrates the following: The ego vehicle is traveling at a high speed, and construction cones are visible in the distance. As the ego vehicle approaches the cones, it is required to decelerate and execute an avoidance maneuverer to avoid colliding with them

PARAMETER DESCRIPTION

Table 1. Parameter description of SC1

Parameters	Description	Value
Vehicle	Carla. Vehicle is a special type of actor that adds Different types of vehicles.	BMW grand tourer
Sensors	A special type of actor to retrieve, measure and stream data.	RGB Sensor, Collision Sensor
Static Props	Props are the assets such as atm, box, tiles, bus stop, mesh, bench and many more.	Dirt debris Construction cone
Waypoint	A 3D-directed point in the CARLA world.	Blue for Vehicle
Weather	Modifies lighting, affects the impressions of climate such as sun orientation, cloudiness, wind, fog etc.	Cloudy Sunset

ODD DESCRIPTION: odd description is as mentioned in the below figure 11

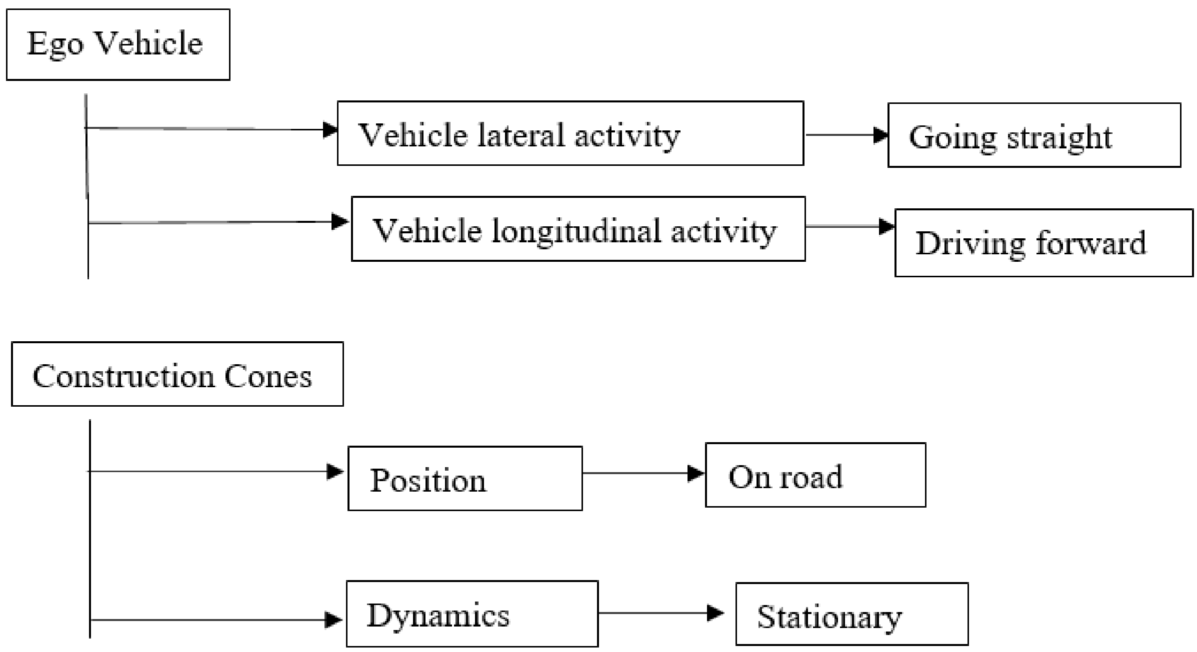


Figure 11. ODD description of SC1

CARLA OUTPUT

Construction cones on the road is as mentioned below figure 12

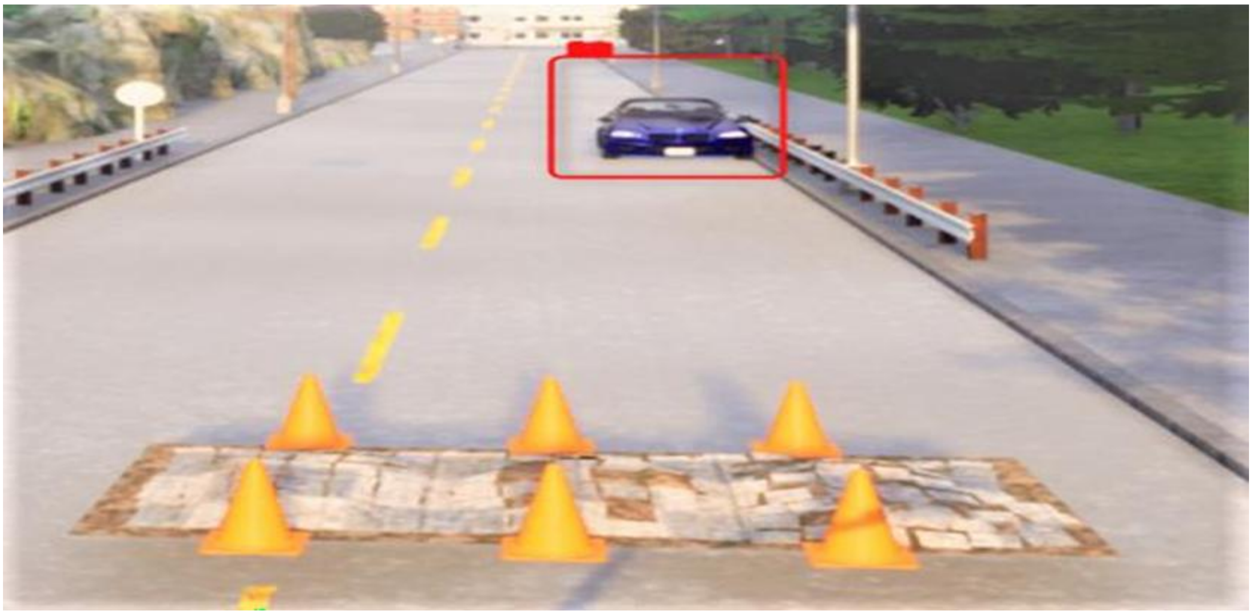


Figure 12. Construction Cones on the road

SC2: VEHICLE WITH HIGH BEAM

Figure 13 below shows the vehicle with high beam.

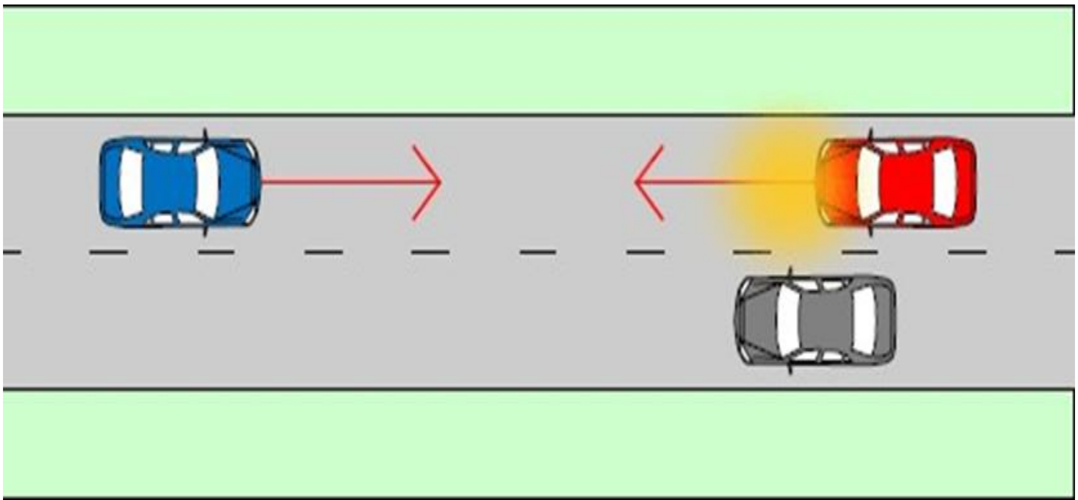


Figure 13. Schematic representation of SC10

GENERAL DESCRIPTION

In this scenario, there is a pile of vehicles ahead, and due to the high beam light from another vehicle, it causes disturbance and disruption. As a result, the vehicle directly in front of the ego vehicle slows down in response to the oncoming vehicle with high beams. Consequently, the ego vehicle must also reduce its speed accordingly to maintain a safe distance and ensure a smooth flow of traffic.

PARAMETER DESCRIPTION

Table 2. Parameter description of SC10

Parameter	Description	Value
Vehicle	Carla. Vehicle is a special type of actor that adds different types of vehicles.	Audi-tt, Harley-Davidson-Lowrider, Audi-Etron
Sensors	A special type of actor to retrieve, measure and stream data.	RGB Sensor, Collision Sensor
Waypoint	A 3D-directed point in the CARLA world.	Red for etron
Weather	Modifies lighting, affects the impressions of climate such as sun orientation, cloudiness, wind, fog etc.	Dark Night

ODD DESCRIPTION

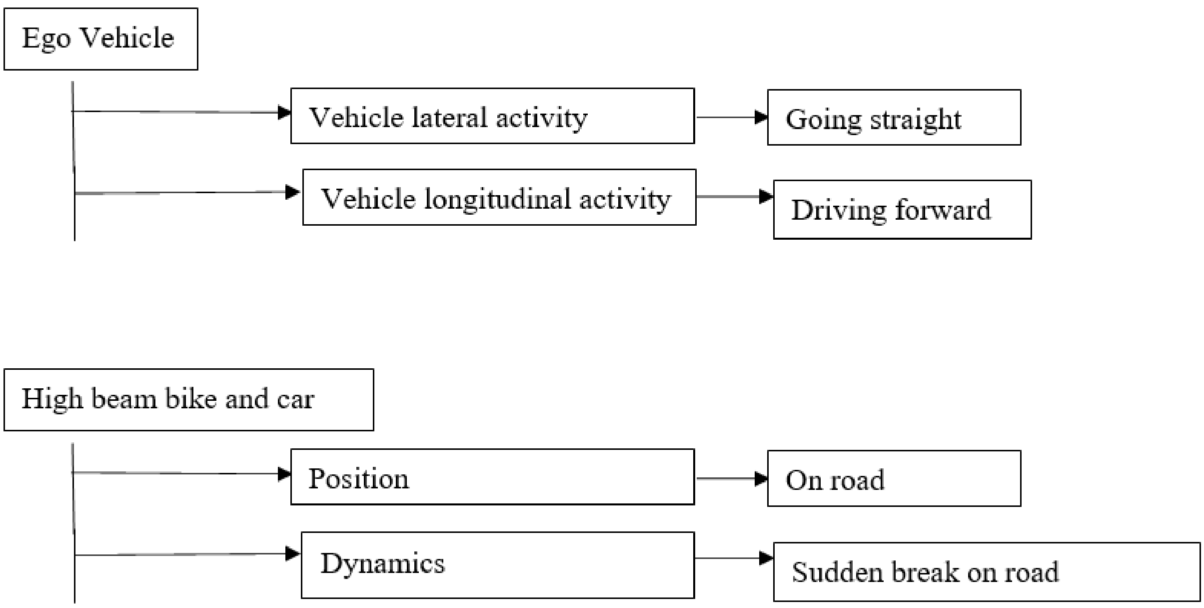


Figure 14. ODD description of SC10

CARLA OUTPUT: figure 15 below shows CARLA output for vehicle with high beam

Figure 15. Vehicle with high beam

5. CONCLUSION

As driving automation reaches higher levels, it introduces numerous unforeseen challenges and incidents. To address these difficulties, the complexity of computing and hardware requirements in today's vehicles is increasing. However, testing these advanced solutions in real-world scenarios is expensive and time-consuming. Consequently, virtual simulation technologies have gained significant attention in the automotive industry. These tools enable Original Equipment Manufacturers (OEMs) to create closed-loop systems that simulate the perception, computation, and action processes. The software under development is tested using simulated sensor data, and the simulated actions are generated based on the software's commands. This allows OEMs to fine-tune vehicle designs before building physical prototypes, leading to cost savings and shorter development cycles. The CARLA simulator, an open-source platform, is used to generate synthetic images for testing purposes. The objective of this project is to develop a proof of concept (POC) validation framework that utilizes the CARLA simulator to test Level 3 Automated Driving Systems (ADS).

6. FUTURE WORK

To address the growing demand for robust testing of Advanced Driver Assistance Systems (ADAS) and overcome the cost challenges associated with testing, an automatic scenario generation method is proposed. This method aims to ensure both effectiveness and coverage in testing by generating test scenarios automatically. The primary focus is on generating more efficient and concise test scenarios for intelligent driving systems. As the functionality and logic of autonomous driving systems become increasingly complex, it becomes evident that manually constructing scenarios, executing simulations, and analysing results will not meet the requirements of present-day testing criteria. To keep pace with the advancements in autonomous driving technology, automating the test and evaluation process is essential. This automation is expected to contribute significantly to increased research and development efficiency by streamlining the testing process and ensuring comprehensive coverage of test scenarios. By leveraging automatic scenario generation methods, researchers and developers can optimize their testing efforts, reduce costs, and enhance the overall quality of ADAS testing. This approach allows for a more systematic and efficient assessment of intelligent driving systems, leading to safer and more reliable autonomous vehicles on the road.

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