

## Maps and Scenario Framework in CARLA

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*Article history:* Received: 25/05/2024, Revised: 29/05/2024, Accepted: 29/05/2024, Published Online: 31/05/2024

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### Abstract:

In this research, we explore the use of CARLA, a high-fidelity simulation environment, to train and evaluate machine learning models, particularly reinforcement learning agents, for autonomous driving. CARLA offers a range of realistic 3D maps that replicate urban environments, enabling the simulation of diverse driving scenarios. These maps include detailed roads, intersections, buildings, pedestrians, vehicles, and dynamic elements, creating a comprehensive framework for testing autonomous driving algorithms. The primary objective is to develop and refine algorithms that enable vehicles to autonomously navigate these environments safely and efficiently, exhibiting human-like driving behaviors. This involves tasks such as perception, decision-making, and control, all tested under various challenging conditions including adverse weather, pedestrian interactions, and complex traffic scenarios. Specific testing scenarios include intersection navigation, lane changes, pedestrian crossings, adverse weather conditions, emergency braking, construction zone navigation, and highway merging. These scenarios allow for the systematic assessment of algorithm performance, ensuring robustness and adaptability in various conditions. Ultimately, CARLA maps provide a structured and risk-mitigated environment for iterative experimentation, fostering innovation and collaboration within the autonomous driving community. By enabling comprehensive and realistic testing, CARLA significantly contributes to the advancement of autonomous driving technology, helping to develop robust algorithms capable of handling the complexities of real-world driving. This approach not only accelerates the development process but also ensures that the algorithms are thoroughly tested in diverse and challenging conditions, which is crucial for their deployment in real-world scenarios. CARLA thus serves as an essential tool in the pursuit of safe, efficient, and reliable autonomous vehicles.

**Keywords:** CARLA, autonomous driving, maps, scenarios, perception

### 1. Introduction:

Carla is an open-source simulator for autonomous driving research. It's designed to provide a realistic environment for training and testing various algorithms related to self-driving cars. In Carla, machine learning models, particularly reinforcement learning agents, are trained to

navigate complex urban environments, encountering scenarios. Through interaction with the simulated environment, these agents learn to make decisions akin to human drivers, such as obeying traffic rules, reacting to dynamic obstacles, and adapting to diverse driving conditions. Acting in Carla involves the process of developing and refining algorithms that enable vehicles to autonomously navigate within the simulated environment. This encompasses a wide range of tasks, including perception, decision-making, and control. The ultimate goal is to create agents that can exhibit human-like driving behavior, capable of safely and efficiently navigating complex urban scenarios, thereby advancing the development of autonomous driving technology.

CARLA provides several high-fidelity, realistic 3D environments known as "CARLA maps." These maps serve as virtual environments for testing and training autonomous driving algorithms and systems. Each map is meticulously designed to replicate real-world urban environments, complete with roads, intersections, buildings, pedestrians, vehicles, and various other dynamic elements. CARLA maps are designed to facilitate a wide range of scenarios, providing a framework for testing and developing autonomous driving algorithms. CARLA maps play a crucial role to evaluate the performance of their autonomous driving algorithms in diverse and realistic environments before deploying them in the real world.

Recognizing the multiple challenges in developing self-driving vehicles, CARLA maps offer tailored environments that mimic real-world conditions with precision. By providing researchers and developers with a diverse range of scenarios, CARLA maps empower them to thoroughly evaluate algorithms in various driving contexts, spanning from urban environments with complex intersections to highway settings with high-speed traffic.

This initiative seeks to expedite progress in autonomous driving by offering a structured framework for testing and refining algorithms under simulated conditions. CARLA maps enable to systematically assess algorithm performance across a spectrum of challenges, including adverse weather, pedestrian interactions, and collision avoidance. By facilitating iterative experimentation within a controlled environment, CARLA maps mitigate risks associated with real-world testing while fostering innovation and collaboration within the autonomous driving community. Ultimately, the goal is the development of robust and safe autonomous driving systems, thereby realizing the transformative potential of self-driving technology for safer, more efficient transportation ecosystems [1-5].

## 2. Material and Methods:

### 2.1 Framework Creation Process

The methodology for creating CARLA maps and the scenario framework involves several key steps to ensure realism, versatility, and effectiveness in testing autonomous driving algorithms:

#### 1. Realistic Environment Modeling:

CARLA maps begin with the modeling of real-world environments. This includes accurately replicating road layouts, signage, traffic lights, buildings, terrain features, and other infrastructure elements using advanced 3D modeling techniques.

#### 2. Dynamic Actor Integration:

To simulate realistic driving scenarios, dynamic actors such as vehicles, pedestrians, cyclists,

and other traffic participants are integrated into the maps. These entities exhibit realistic behaviours, including following traffic rules, reacting to environmental stimuli, and interacting with each other and with the autonomous vehicles.

### 3. Scenario Design:

CARLA maps are designed to accommodate a wide range of scenarios relevant to autonomous driving research. Scenario design involves crafting specific driving situations, such as lane changes, merging, intersection navigation, highway driving, adverse weather conditions, pedestrian crossings, and collision avoidance scenarios.

### 4. Scenario Parameters:

Parameters for each scenario, such as traffic density, weather conditions, time of day, and the behavior of dynamic actors are carefully configured to create diverse and challenging test cases. This ensures that algorithms are evaluated under a variety of conditions to assess their robustness and adaptability.

### 5. Evaluation and Iteration:

Autonomous driving algorithms are deployed within the CARLA simulation environment to undergo various testing and evaluation.

### 6. Benchmarking:

CARLA maps serve as a common benchmarking platform to compare the performance of different algorithms.

## 2.2 Map Creation

The process of map generation for the CARLA project involves several steps aimed at creating realistic and environments for testing autonomous driving algorithms:

### 1. Data Acquisition:

The map generation process begins with the acquisition of real-world geospatial data, including satellite imagery, elevation data, and GIS (Geographic Information System) data such as road networks, landmarks, and terrain features. This data serves as the foundation for creating the virtual environment.

### 2. Road Network Generation:

Based on the road network data obtained from GIS sources, roads, highways, intersections, and other infrastructure elements are generated within the virtual environment. Road geometry, lane markings, traffic signs, and traffic lights are meticulously replicated to simulate realistic driving conditions.

### 3. Building and Landmark Placement:

Buildings, landmarks, and other structures identified in the satellite imagery are placed within the virtual environment to recreate the urban landscape accurately. The placement of buildings takes into account factors such as building height, orientation, and proximity to roads.

### 4. Dynamic Element Placement:

Dynamic elements such as vehicles, pedestrians, cyclists, and other traffic participants are placed within the virtual environment to simulate realistic traffic scenarios. Their placement and behaviour are configured to mimic real-world traffic patterns and interactions.

### 5. Terrain Generation:

Using the acquired elevation data, terrain features such as hills, valleys, and slopes are generated to accurately replicate the topography of the real-world location. This ensures that the virtual environment closely matches the real-world terrain.

### 6. Scenario Integration:

Scenarios relevant to autonomous driving research, such as intersection navigation, highway driving, pedestrian crossings, and adverse weather conditions, are integrated into the virtual environment. This allows to test algorithms under diverse and challenging conditions.

## 7. Quality Assurance and Validation:

The generated map undergoes thorough quality assurance and validation processes to ensure accuracy, realism, and consistency. This involves testing the map against real-world data and addressing any discrepancies or anomalies.

## 3.3 Scenario Framework

### 1. Intersection Navigation:

An autonomous vehicle approaches a busy intersection with multiple lanes, traffic lights, and pedestrians crossing. The scenario evaluates the vehicle's ability to accurately detect traffic signals, yield to pedestrians, and navigate through the intersection while following traffic rules.

### 2. Lane Change:

The autonomous vehicle is driving on a highway with heavy traffic. It needs to execute a lane change to overtake a slower-moving vehicle while maintaining safe distances from other vehicles in adjacent lanes. This scenario assesses the vehicle's decision-making and trajectory planning capabilities during lane changes.

### 3. Pedestrian Crossing:

A pedestrian step onto a crosswalk, intending to cross the road. The autonomous vehicle must detect the pedestrian, yield the right-of-way, and safely stop to allow the pedestrian to cross. This scenario tests the vehicle's pedestrian detection, tracking, and interaction capabilities.

### 4. Adverse Weather Conditions:

The simulation environment is set to simulate heavy rain and reduced visibility. The autonomous vehicle encounters slippery road conditions and decreased traction, requiring it to adapt its driving behavior accordingly. This scenario evaluates the vehicle's ability to handle adverse weather conditions safely.

### 5. Emergency Brake:

A vehicle suddenly stops in front of the autonomous vehicle, simulating an emergency braking situation. The autonomous vehicle must detect the obstacle, assess the risk of collision, and execute an emergency brake to avoid a collision while ensuring the safety of occupants and other road users.

### 6. Construction Zone Navigation:

The road is undergoing construction, leading to lane closures, detours, and temporary traffic signs. The autonomous vehicle needs to navigate through the construction zone, follow detour routes, and adhere to temporary traffic regulations. This scenario assesses the vehicle's ability to adapt to dynamic road conditions and construction-related obstacles.

**7. Highway Merge:** The autonomous vehicle approaches a highway on-ramp with merging traffic. It needs to merge seamlessly into the highway traffic flow, adjusting its speed and trajectory to merge safely while minimizing disruptions to the flow of traffic. This scenario evaluates the vehicle's merging strategy and cooperation with other vehicles on the highway. These scenarios represent a subset of the diverse range of test cases that can be generated within the CARLA environment to evaluate and validate autonomous driving algorithms under various driving conditions and scenarios.

## 3. Results and Discussion:

While CARLA provides a highly detailed and versatile simulation environment for

autonomous driving research, several limitations must be acknowledged. Despite the realism of CARLA's maps and scenarios, they cannot fully replicate the unpredictability and variability of real-world conditions. Nuanced human behaviors and unexpected road hazards may not be perfectly captured. However, the insights gained from simulations significantly expedite the refinement of autonomous driving systems by offering a controlled and safe environment for experimentation.

Running high-fidelity simulations with complex scenarios requires substantial computational resources. This can limit extensive testing and slow down the iterative process of algorithm development. Nonetheless, the structured and repeatable nature of CARLA's scenarios allows for systematic testing and iterative refinement, which is essential for progressively improving the performance and safety of autonomous driving systems.

Although CARLA offers a wide range of scenarios, gaps in coverage for specific edge cases or rare events that autonomous vehicles might encounter in the real world remain a challenge. Ensuring comprehensive testing across all possible scenarios is crucial. Additionally, algorithms that perform well in simulated environments may not necessarily translate to equivalent performance in real-world conditions due to the "reality gap."

While CARLA can simulate various weather and lighting conditions, the range and accuracy of these simulations may not fully encompass the extreme or rapidly changing conditions of the real world. Continuous improvements to CARLA, including more diverse scenarios, enhanced dynamic actor behaviors, and better simulation of extreme conditions, will further bolster its utility. Moreover, the behaviors of simulated traffic participants might not fully replicate the complex and often unpredictable nature of human drivers and road users. However, CARLA provides a common platform for benchmarking different algorithms, fostering collaboration and knowledge sharing within the autonomous driving research community.

By enabling extensive testing in a risk-free environment, CARLA significantly contributes to the safety and reliability of autonomous driving systems. This is particularly important as these systems move closer to real-world deployment. Ultimately, CARLA plays a crucial role in the advancement of autonomous vehicle technology, providing a robust framework for the development of safe and efficient autonomous driving algorithms.

#### 4. Conclusion:

Through the creation of diverse test scenarios, ranging from urban driving challenges to adverse weather conditions, CARLA has facilitated comprehensive testing and evaluation of autonomous driving algorithms under various real-world conditions. This facilitates in identifying strengths, weaknesses, and areas for improvement in autonomous driving systems, ultimately driving progress towards safer, more efficient, and more reliable autonomous vehicles.

#### Acknowledgement:

I extend my deep appreciation Vishwakarma University and Energy Research Institute at NTU for supporting this research and providing the opportunity to work under the guidance of Dr. Anshuman Tripathi. I am also grateful to my mentor, Prof. Joseph de Guia Madrid, for his invaluable insights and support. Special thanks to Prof. Kailas Patil for his guidance and contributions. Their guidance has played a vital role, and I am sincerely thankful for their dedication and commitment to my academic and professional growth.

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