Demo Abstract: C-Shenron- A Realistic Radar Simulation Framework for CARLA

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Abstract

The advancement of self-driving technology is driven by the need for robust and efficient perception systems along with frameworks for End-to-End testing, enabled by the CARLA simulator. We introduce C-Shenron, a novel integration of a realistic radar sensor model within CARLA, enabling researchers to develop and test navigation algorithms using radar data. It is the first realistic radar simulator which utilizes LiDAR and camera sensors to generate high-fidelity radar ADC measurements from physics based modeling of the environment. Utilizing this radar sensor and showcasing its capabilities in simulation, we demonstrate improved performance in end-to-end driving scenarios. Our setup aims to rekindle the interest in radar-based self-driving research and promote the development of algorithms that leverages its strengths.

CCS Concepts

• **Computing methodologies → Modeling and simulation**; *Machine learning*; *Computer vision.*

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1 Introduction

Development of Autonomous Driving (AD) systems rely on robust perception and End-to-End (E2E) pipelines that seamlessly connect perception to downstream tasks like path planning and navigation. Sensors like cameras, LiDAR, and radar provide robust perception under all weather and lighting conditions. While accurate perception is critical for proper functioning of these systems, E2E testing frameworks are essential to confirm that sensor data leads to implementable decisions.

The CARLA simulator [1] excels in enabling both perception and downstream tasks in AD, by facilitating large-scale data collection, varying weather conditions, complex traffic environments and supporting E2E training and testing pipelines, acting as an effective digital twin for AD systems. Researchers have extensively utilized CARLA to train and test perception models under various driving scenarios, as noted in works such as [2, 3].

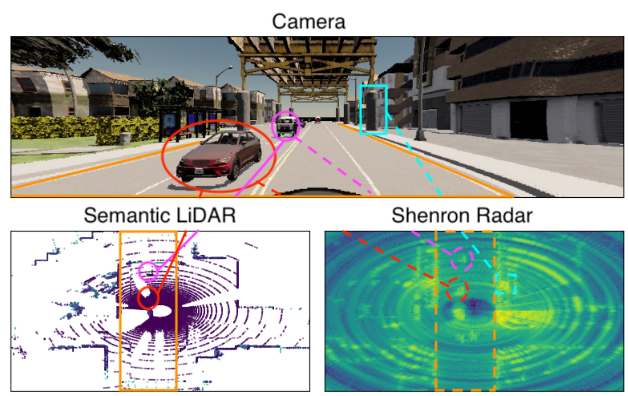

Figure 1: Illustrative image comparing views from Camera, Semantic LiDAR, and Shenron Radar in CARLA. Camera is in First Person View whereas LiDAR and Radar are in Birds Eye View perspective. The orange lines outline the road, red and magenta highlights vehicles, and blue indicates a static object.

Among the three sensors, radar is highly effective in bad weather conditions as it employs millimeter-wave technology. However, the radar model in the CARLA simulator has significant limitations as it lacks detailed physics-based modeling. Building on the works of Shenron [4], we present C-Shenron, a realistic radar simulator for CARLA which utilizes LiDAR and camera data for a highly accurate radar simulation. Shenron uses LiDAR to construct detailed 3D meshes of a scene without the need for complex geometries and camera to extract semantic tags, both of which are fed to a ray-tracing based framework to produce high-fidelity radar

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ADC samples. With the integration of C-Shenron into the CARLA simulator, we aim to enhance simulation accuracy, realism, and versatility, which maximizes the efficacy of AD research.

Using C-Shenron, researchers can also experiment with various radar sensor placements, to explore multiple fusion strategies, and generate high-fidelity datasets for training and testing robust perception models. C-Shenron also allows to simulate radar setups with varying number of antenna arrays, thereby incorporating a comprehensive range of potential setups for AD tasks.

2 Design of C-Shenron

To seamlessly integrate Shenron into CARLA, we devised a hybrid approach by utilizing a custom Raycast Shenron sensor on the server side to capture point cloud data, including semantic segmentation and relative velocity information. The data collected by this Raycast sensor along with metadata is then transmitted to the client side for Shenron to generate the simulated radar data. This is clearly illustrated in Figure 2.

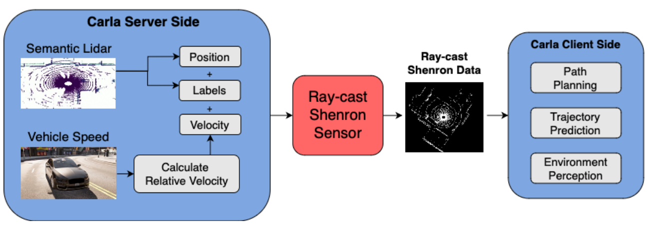


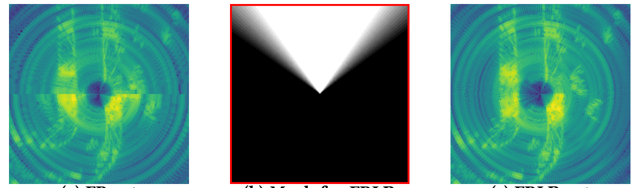
Figure 2: Illustration showing integration of Shenron into CARLA

To mitigate the real-time latency introduced by the Shenron processing, we pause the CARLA simulation during radar processing ensuring that the overall simulation time remains unaffected. The Figure 2 represents the overall picture of the Shenron integration with CARLA. We also implemented the necessary functions required to calculate the relative velocity which is used by Shenron. Additionally, we provide example scripts to simulate and visualize the Shenron radar data within the CARLA environment, demonstrating how to effectively use this radar in simulations.

3 Evaluating C-Shenron

To demonstrate the functionality of this new sensor, we gathered vast amounts of data from a rule-based driver agent that navigated various scenarios and trained a state-of-the-art imitation based model [2] using camera and radar sensor. C-Shenron allows for multiple sensor positions on the ego vehicle such as front, left, back and right, and so we devise a masking technique to stitch the radar views together for providing comprehensive situational awareness. This is demonstrated in Figure 3.

We train multiple models using front only, Front-Back (FB) and Front-Back-Left-Right (FBLR) concatenation of radar and evaluate them on the routes from NEAT [5] paper, which include various settings like highways, urban areas, and residential zones with diverse road layouts and obstacles to simulate urban conditions. The driving proficiency of an autonomous agent is evaluated through various metrics provided by CARLA such as Driving Score, Route Completion and Infraction Penalty.



(a) FB cat (b) Mask for FBLR (c) FBLR cat

Figure 3: Images representing: (a) Radar image after Front-Back (FB) concatenation, (b) Mask for Front-Back-Left-Right (FBLR) concatenation, (c) Radar image after concatenation of all four views.

The findings are presented in Table 1 where LiDAR serves as the baseline for comparison, being the original version from [2] and the Expert model represents statistics from the rule-based driver agent, which sets a theoretical upper limit for driving performance.

Radar View	DS ↑	RC ↑	IS ↑
LiDAR [2]	76.84 ± 5.26	93.93 ± 3.43	0.79 ± 0.05
Front	77.97 ± 5.36	95.52 ± 3.02	0.79 ± 0.06
FB	78.26 ± 2.96	96.51 ± 2.99	0.79 ± 0.02
FBLR	**79.24 ± 1.85**	**97.56 ± 2.75**	**0.84 ± 0.05**
Expert	93.82	97.394	0.964

Table 1: Results for different radar views with Driving Score (DS), Route Completion (RC) and Infraction Score (IS).

As seen from the above table, among all the radar models, FBLR gives the best performance in all three metrics indicating that having multiple views of a scene improves situational awareness of the system. Overall, the radar-based FBLR model outperforms the state-of-the-art LiDAR based perception model indicating the utility of this new integrated sensor.

References

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