A Method for Neural Network-based Sensor Augmentation via Sensor Data Intercept in CARLA Simulator

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Abstract

This paper introduces a method for enhancing sensor data augmentation within the CARLA simulator, a popular tool for developing AI-based autonomous control agents. Our approach intercepts sensor data in the CARLA Leaderboard framework, integrating neural networks to modify the data before it reaches the autonomous agent, which allows for data enrichment without disruption of scenario execution.

Ⅰ. Introduction

The simulation of virtual environments for the purposes of testing real-life problems has been a growing area of interest in the fields of autonomous driving as well as robotics for some time now, with a particular focus on increasing the fidelity of generated synthetic data for better adaptation to real-world scenarios. For autonomous driving in particular, CARLA simulator exists as an open-source, highly customizable alternative to commercially licensed software for developing and testing artificial intelligence-based autonomous control agents [1].

Sensor data augmentation is a technique for the artificial generation or modification of sensor data, which allows for enrichment of datasets with comparatively little usable collected data [6]. Primary fields of usage for this technique include computer vision and audio processing, where the former typically uses simple operations such as rotation or scaling of images to improve generalization [5]. A newer branch of this technique involves the usage of GANs [3] applied to existing datasets to create synthetic data used alongside real data for training neural networks, which has seen some success when applied to image data [2].

CARLA provides a set of tools collectively referred to as the Leaderboard, which shares a name with the autonomous driving challenge hosted by the CARLA Team for competitive validation of autonomous agents via preset tracks. In this paper, we propose a method of defining a neural network within this framework such that sensor data obtained from CARLA is directly modified before being accessed by the autonomous agent.

Ⅱ. Intercepting CARLA data

The CARLA Leaderboard framework by default uses the ScenarioRunner library, which allows for preset environment definition files- typically consisting of scenario variables such as pedestrian or car spawn locations, map selection, and ego vehicle route- and spawns a specified agent to participate in this environment. This is an expression of CARLA's client-and-server design, where operations such as collision calculation and rendering are conducted on the server, and a client can access data from the server via a Python-based API. For the Leaderboard, this leads to an architecture as depicted in Figure 1.

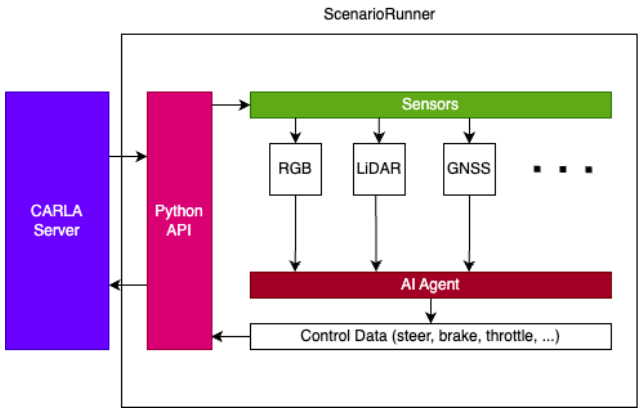

Figure 1. Sensor data is directly processed for input to autonomous driving agent.

Our proposed method defines a number of neural networks at client start time. This leverages the CARLA agent's persistent property- the instantiated client lasts until simulation termination, and so defining the networks alongside client variable initialization allows for avoidance of constant network load/unload overhead. It is assumed that the structure of the neural networks used is suitable for the sensor it is intended for.

These networks are then applied to the sensors. To do this we define a callback function for each sensor

where the retrieved data is fed into the neural network, and the output is placed inside an input buffer for usage in the tick-wise control function. The reason we do this instead of simply applying the neural network inline before the agent code is to allow for data augmentation at the point of data retrieval, not at the point of processing (by a predefined simulation tick rate). Additionally, utilizing a callback function here allows for easy output for debugging or data collection purposes. See Figure 2 for further explanation.

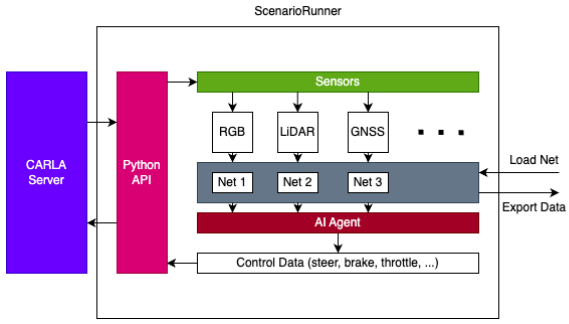

Figure 2. Sensor data is sent via callback to augmentation networks, before being placed in buffer for use by AI agent.

This architecture allows for any externally-trained neural network- such as the CycleGAN-based image translation network previously developed by the authors [4]- to be used to augment input sensor data without interrupting the flow of scenario execution, allowing for efficient testing of data augmentation networks in conjunction with other AI control agents.

Ⅲ. Conclusion

This paper has presented a method by which data augmentation through neural networks is applied directly to sensor data within the CARLA Leaderboard framework. The process is conducted at the point of data retrieval rather than during data processing, enabling complementary use during validation testing of autonomous agents. One key limitation of this technique is that this slows down the processing of a single time-step, enough to slow down the simulation to a state unusable for visualization depending on hardware. Future research into a potentially desynced augment network-agent architecture where augmented data and real data are interlaced for continuous data ingestion is required for less impact on semi-real-time simulations.

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