Slug Mobile: Test-Bench for RL Testing

Jonathan Wellington Morris
Undergrad
UC Santa Cruz
jowemorr@ucsc.edu

Vishrut Shah
Undergrad
UC Santa Cruz
vsshah@ucsc.edu

Alex Besanceney
Undergrad
UC Santa Cruz
rbesance@ucsc.edu

Daksh Shah
Undergrad
UC Santa Cruz
dakshah@ucsc.edu

Leilani H. Gilpin
Department of Computer Science and Engineering
UC Santa Cruz
lgilpin@ucsc.edu

Abstract

Sim-to real gap in Reinforcement Learning is when a model trained in a simulator does not translate to the real world. This is a problem for Autonomous Vehicles (AVs) as vehicle dynamics can vary from simulation to reality, and also from vehicle to vehicle. Slug Mobile is a one tenth scale autonomous vehicle created to help address the sim-to-real gap for AVs by acting as a test-bench to develop models that can easily scale from one vehicle to another. In addition to traditional sensors found in other one tenth scale AVs, we have also included a Dynamic Vision Sensor so we can train Spiking Neural Networks running on neuromorphic hardware.

1 Introduction

Autonomous Vehicles (AVs) have been promised to make driving safer for all drivers by replacing human drivers with AVs. NHTSA [2024] National Highway Traffic Safety Administration (NHTSA) estimates that 94% of collisions are caused by driver error. NHTSA [2018] The main methods for optimal control include classical motion path planning Ferguson et al. [2008], end-to-end imitation learning Le Mero et al. [2022], and Reinforcement Learning (RL) Aradi [2020]. Typically, a driving simulator such as CARLA Dosovitskiy et al. [2017] is used to evaluate vehicle safety and performance Kaur et al. [2021] However, tests in these simulators do not always translate well to real life, resulting in the sim-to-real gap. The sim-to-real gap is a phenomenon where a model trained on a simulator degrades once applied on the real world. Salvato et al. [2021] Sim-real-gap can result from a difference in sensor configuration and vehicle dynamics between the simulator and real vehicle. In this paper, we propose a modified version of the F1TENTH vehicle O'Kelly et al. [2020] and MIT Racecar Karaman et al. [2017], which we call the *Slug Mobile*, which includes updated compute and sensor array, and a simplified hardware stack. We provide instructions and resources to replicate Slug Mobile here: https://github.com/cruz-control/Slug-Mobile.

2 Hardware

The vehicle's base frame is the Traxxas Ford Fiesta ST Rally E-Maxxdude [2017], the same vehicle specified in O'Kelly et al. [2020]. The sensors we chose for our car are as follows: RGB Camera, 2D LiDAR, Dynamic Vision Sensor (DVS) also known as Event Cameras Gallego et al. [2022], and an Inertial Measurement Unit (IMU). We also designed a new mounting solution for the sensors, compute module, and a custom Printed Circuit Board (PCB) which distributes power and signal to the various sensors and the servos.
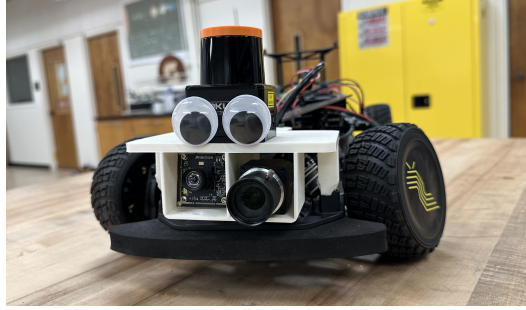
Figure 1: Slug Mobile: One Tenth Autonomous Vehicle for sim-to-real testing

Figure 2: Example visualization of CARLA environment

Most notable change is the inclusion of a DVS camera. We added a DVS camera due to the growing popularity of Spiking Neural Networks (SNN). Eshraghian et al. [2023] The outputs from DVS cameras are sparse and time-variant, which SNNs can take full advantage to increase efficiency of the driving model.

Another change was a switch from a digital Electronic Speed Controller (ESC) to a PWM ESC. The ESC is then connected to an I2C Servo Driver, PCA9685, which in turn is connected to the NVIDIA Jetson Orin Nano. This was done to simplify the software solution for control.

The custom PCB has an XT-60 battery connection for a 12V LiPo, which distributes power to each of the sensors. The Jetson Orin Nano's pinout is connected to a pin header on the PCB, enabling sensor communication across the board in addition to power. Signal from the ESC as well as the data and clock signals for I2C communication are routed between the Jetson, IMU, and I2C servo driver. This hardware solution will aid greatly in training and troubleshooting the RL algorithm by reducing complexity of the car.

3 Software

We deviated from O'Kelly et al. [2020], Karaman et al. [2017] by choosing to avoid using ROS and ROS 2. Our software solution for control relies on the NVIDIA jetson-gpio library to communicate with the I2C Servo Driver. This results in code that is easier to read, easier to change, and easier to run. We also have an OpenAI Gym environment, built off of the gym_carla library Chen [2020] which works in conjunction with the CARLA simulator. This allows us to simplify running and testing RL algorithms, such as those from Stable Baselines. We customized this environment for compatibility and to train and visualize our results in a virtual environment with a car with a top down LIDAR view and several camera sensors, shown in Figure 2. We aim to train a model on our gym enviorment and transfer it to our Slug Mobile and evaluate the performance.

4 Future Works and Conclusion

One of the roadblocks in Reinforcement Learning for Autonomous Vehicles is the Sim-to-real gap. We aim to use a modified version of the F1Tenth car, called Slug Mobile, to test diffent RL algorithms trained in CARLA to then gauge how well these models transfer from simulation to real vehicles to bridge the sim-to-real gap. We also aim to create a dataset using all the sensors in the car to train models using Imitation Learning, notably with the event camera and neuromorphic hardware to take full advantage of it.

5 Acknowledgments

References

NHTSA. Automated vehicles for safety. https://www.nhtsa.gov/vehicle-safety/automated-vehicles-safety, 2024.

NHTSA. Traffic safety facts. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812115, 2018.

Dave Ferguson, Thomas M Howard, and Maxim Likhachev. Motion planning in urban environments. *Journal of Field Robotics*, 25(11-12):939–960, 2008.

Luc Le Mero, Dewei Yi, Mehrdad Dianati, and Alexandros Mouzakitis. A survey on imitation learning techniques for end-to-end autonomous vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 23(9):14128–14147, 2022.

Szilárd Aradi. Survey of deep reinforcement learning for motion planning of autonomous vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 23(2):740–759, 2020.

Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. Carla: An open urban driving simulator. In *Conference on robot learning*, pages 1–16. PMLR, 2017.

Prabhjot Kaur, Samira Taghavi, Zhaofeng Tian, and Weisong Shi. A survey on simulators for testing self-driving cars. In *2021 Fourth International Conference on Connected and Autonomous Driving (MetroCAD)*, pages 62–70, 2021. doi: 10.1109/MetroCAD51599.2021.00018.

Erica Salvato, Gianfranco Fenu, Eric Medvet, and Felice Andrea Pellegrino. Crossing the reality gap: A survey on sim-to-real transferability of robot controllers in reinforcement learning. *IEEE Access*, 9:153171–153187, 2021.

Matthew O'Kelly, Hongrui Zheng, Dhruv Karthik, and Rahul Mangharam. F1tenth: An open-source evaluation environment for continuous control and reinforcement learning. *Proceedings of Machine Learning Research*, 123, 2020.

Sertac Karaman, Ariel Anders, Michael Boulet, Jane Connor, Kenneth Gregson, Winter Guerra, Owen Guldner, Mubarik Mohamoud, Brian Plancher, Robert Shin, et al. Project-based, collaborative, algorithmic robotics for high school students: Programming self-driving race cars at mit. In *2017 IEEE integrated STEM education conference (ISEC)*, pages 195–203. IEEE, 2017.

E-Maxxdude. Ford® fiesta® st rally: 1/10 scale electric rally racer with tqtm 2.4ghz radio system, Aug 2017. URL https://traxxas.com/products/models/electric/ford-fiesta-st-rally.

Guillermo Gallego, Tobi Delbrück, Garrick Orchard, Chiara Bartolozzi, Brian Taba, Andrea Censi, Stefan Leutenegger, Andrew J. Davison, Jörg Conradt, Kostas Daniilidis, and Davide Scaramuzza. Event-based vision: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(1):154–180, 2022. doi: 10.1109/TPAMI.2020.3008413.

Jason K. Eshraghian, Max Ward, Emre O. Neftci, Xinxin Wang, Gregor Lenz, Girish Dwivedi, Mohammed Bennamoun, Doo Seok Jeong, and Wei D. Lu. Training spiking neural networks using lessons from deep learning. *Proceedings of the IEEE*, 111(9):1016–1054, 2023. doi: 10.1109/JPROC.2023.3308088.

Jianyu Chen. Gym-carla: An openai gym wrapper for carla simulator, 2020. URL https://github.com/cjy1992/gym-carla.git.