Simulation Environment for Testing Autonomous Vehicles

Mojca Komavec[*], Marko Balažic[*], Jaka Sodnik[**]
[*] NERVteh, Ljubljana, Slovenia
[**] University of Ljubljana, Faculty of electrical engineering, Ljubljana, Slovenia
{mojca.komavec, marko.balazic}@nerv-teh.com, jaka.sodnik@fe.uni-lj.si

***Abstract*— The focus of automotive and software industry in the recent years has been in the development of algorithms for autonomous vehicles, whose input depends on various sensor data. Such algorithms which are mostly based on machine learning techniques need a vast amount of data to be trained successfully. Since obtaining data in a real world can be expensive and time-consuming job, one can obtain and train algorithms also in a simulation environment. Vehicles in a simulation also perceive the environment through a set of sensors whose output should replicate the output of real-world sensors as much as possible. This paper describes an example of such professional driving simulation environment for testing self-driving vehicles, gives an overview of a simple autonomous driving algorithm, which is partly based on sensor input, and concludes with an evaluation of our algorithm in comparison with the human-driving data. The results show that autonomous algorithm performed much better than human drivers.**

I. Introduction

With higher speed and larger amount of vehicles on the roads, safety is becoming of high importance. To increase the safety, vehicles are nowadays equipped with driver assistance technologies. These technologies are sensor based, meaning, that they analyze the data obtained from sensors in order to make actions that safe lives and prevent injuries. Such examples are braking automatically if the driver in front of us makes a sudden stop, preventing the driver to drift off the road or to make unsafe lane changes, automatic braking when pedestrians are in front of a vehicle, etc.

Driver assistance technologies have been evolving throughout the years and are helping the driver to automate the driving tasks with the aim to fully automate the driving. National Highway Traffic Safety Administration (NHTSA) [1] defines five levels of automation.

In Level 0 there is zero autonomy, the driver performs all the driving tasks. In Level 1 the vehicle is equipped with advanced driver assistance system (ADAS), which sometimes assist the driver with either steering or accelerating/braking, but not simultaneously.

Partial automation is a part of Level 2. ADAS on the vehicle can control steering and accelerating/braking simultaneously in some cases. Driver must be engaged with the driving task and monitoring the environment all the time.

Level 3 defines conditional automation. Automated driving system (ADS) is integrated into the vehicle, which can perform all aspects of the driving task under some circumstances. The driver must be ready to take control of the vehicle when ADS requests him/her to do so.

Level 4 defines high automation. The ADS can perform all driving functions under certain circumstances, in which the driver does not need to pay attention. The driver may still have the option to control the vehicle.

Last, Level 5, defines full automation. The vehicle can perform the driving in all circumstances. The driver is not needed, but it has an option to control the vehicle.

The fully autonomous vehicle, as NHTSA defines it in Level 5, performs all the driving tasks. These types of vehicles drive according to the algorithms, which command how the vehicle should move in the next step, for example the speed and the steering wheel angle of the vehicle. These algorithms are trained with the data obtained from various sensors, such as LIDAR (Light Detection And Ranging), radar, ultrasonic, etc. Learning solely from the data obtained from the real world requires extremely high number of driven training miles, vast number of situations, possibly also unusual and critical, and is therefore a very time-consuming and expensive task. In order to speed up the process of acquiring the training data, it is possible to use the simulation environment to obtain the data from various sensors in various situations and consequently faster train the algorithms.

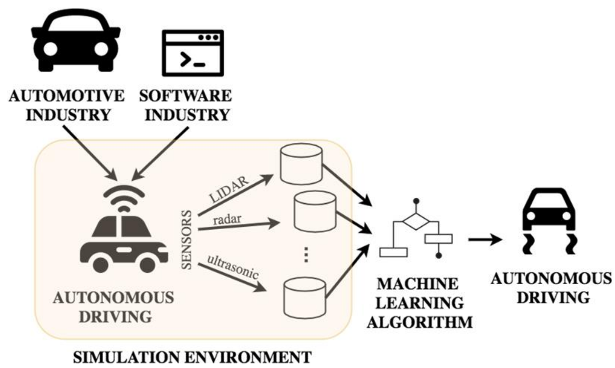

Figure 1. The process of training autonomous vehicles in simulation environment and real environment.

Once the algorithm is successful in simulation environment, it can be applied to the real world driving scenarios, as can be seen in Fig. 1. Such approach of pre-training autonomous vehicles in simulation environment, which is as close as possible to the real environment, is currently gaining high interest in automotive industry due to cheaper, faster, and easier data acquisition. In fact, more than 90% of the algorithm training is performed in simulated environments, which is also a focus of many research groups around the world.

The authors in [7] focus on automatic generation of simulation environment from specified testing criteria that algorithms should met however they only mention the limitations of sensors in testing environment, by example how to have the same output as the sensors in real-world have in different weather conditions.

The authors in [8] create a simulation environment from the camera output, mounted on a physical vehicle in the traffic. This data was then used to create a simulation environment, where the autonomous vehicle was tested particularly for two tasks: obstacle avoidance and self-driving. Since their input was based solely on the camera, their future plans include the inclusion of other sensors, such as LIDAR, radar, and ultrasonic in their simulation environment.

In this research, we implemented a simple autonomous algorithm which makes decisions according to the traffic rules and sensor input. The goal was to successfully apply autonomous algorithm to a vehicle in the simulation platform. In addition, we were interested in how the algorithm performed, therefore we evaluated its driving performance and compare it to the results acquired by human drivers in the same environment.

II. MOTIVATION

Simulation environment is an environment with 3D objects, such as vehicles, pedestrians, bicycles, and other static objects, such buildings, traffic signs, lanes. The task for autonomous vehicle in a simulation environment is to obtain the data from surroundings through sensors and to process it in the same way as they would process the data obtained in the real-world. Simulation environment is also perfect for fast generation of a big variety of events including critical and unpredicted scenarios, road artifacts, weather conditions, etc.

We are presenting a professional simulation platform [3,9] for driving simulation studies and driver training. It can be used also as a test platform for algorithms for autonomous driving. In this paper, we are focusing primarily on autonomous driving features of the platform, more specifically on the features available for acquiring data from a variety of sensors. Screenshot of simulation environment can be seen in Fig. 2.

Figure 2. Screenshot of simulation platform

III. METHODOLOGY

Our simulation platform enables us to create a variety of scenarios, including static and dynamic objects, different roads, building, surroundings, and traffic. All vehicles, pedestrians, and other objects in the simulation are controlled by the AI-based traffic modules, which enable them to move around in the environment and obey the default driving rules. On the other hand, their behavior can also be modified or changed at any time through a scripting language. The latter enables us to create custom interactions among the objects and to create also untypical and critical situations and scenarios.

The simulation environment provides also a set of sensors for detection of the environment: LIDAR, radar, ultrasonic, camera, and GPS. The output of these sensors has been defined and developed based on existing industry solutions [4,5,6] for the sensor used in automotive industry in order to replicate real-world as much as possible. All sensor modules have their own specific configuration options. With those options one can configure the virtual sensor to replicate the same specifications as in reality and provide the same output data with limitations from the environment. An example of the configurations of radar and LIDAR is presented in Fig. 3.

Figure 3: Configuration parameters for radar meter and LIDAR.

In order to test the ability of sensors in simulation environment, we tested our algorithm for autonomous driving with our internal evaluation algorithm, which generates a score for each drive according to traffic compliance, collisions, safety distance, etc. To make the calculated score credible, we compare it to the scores obtained from the human-driving data.

A. *Algorithm For Autonomous Driving*

Our proposed algorithm, which provides fully autonomous driving, works in the following way. It predicts how the vehicle should move in the next step by acquiring and analyzing data obtained directly from the simulation environment as well as sensors. Therefore, it is based on two parts: sensor- and rule-based. The rule-based part takes into account the traffic rules, which are directly obtained from the simulations, whereas the sensor-based part consists of the following four modules:

- Lane keeping algorithm
- Adaptive cruise control algorithm
- Emergency braking algorithm
- Surroundings mapping algorithm

Lane keeping algorithm uses the camera input in order to keep the vehicle in the middle of the lane. The camera detects the road markings and supplies the algorithm with the distances to the sides of the lane and the curvature for the road ahead. From this data we calculate the steering wheel angle needed to maintain the position on the current lane.

In addition, we use this data for lane changing and intersection crossings.

Adaptive cruise control algorithm uses the radar input in order to keep a safety distance to the next vehicle. From the data collected from the radar the algorithm calculates the nearest vehicle in front of us, which is used to maintain the safety distance to it. The range of the radar detection can be modified to any specific distance. We use different distance settings for highway, urban, and rural driving.

Emergency braking algorithm also uses the radar input in order to brake if the safety distance becomes too short.

Surroundings mapping algorithm uses LIDAR to obtain the data about the environment and positions of the objects in it in order to avoid collisions. LIDAR collects data from a 360° radius with 721 horizontal rays and 46 vertical rays. It has a range of 120m and a refresh rate of 60Hz. An example of visualization of LIDAR output is shown in Fig. 4.

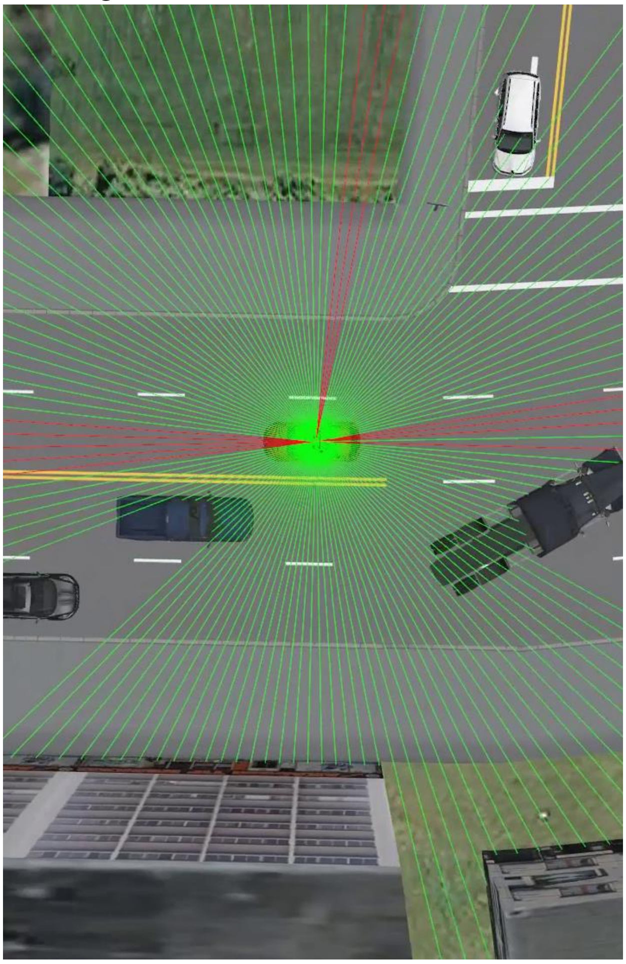

Figure 4: Visualization of LIDAR output, which is used in Surroundings mapping algorithm

B. Evaluation

Once we implemented the algorithm for autonomous driving, we prepared a test-bed for evaluation in the following way.

First, we created a scenario, which consists of two parts. The first part is driving on the highway and the second one is driving in urban environment. Scenario consists of various critical situations, such as vehicle driving in the wrong way on highway, driving in fog, children jumping onto the road, aggressive drivers, and so on.

Next, we let our autonomous vehicle drive 30-times the same scenario. For each trial, we also collected the performance data.

Lastly, we evaluated the driving performance from the gathered data. We developed our own internal mechanism for the evaluation of the driving performance, which first calculates the following sub-scores:

- Aggression score
- Alertness score
- Attention score
- Violation score

Each of these sub-scores is calculated from the data obtained from simulation.

Violation score for example takes into account traffic violations, such as driving through the red light, failure to stop at stop sign, failure to reduce the speed at yield sign, speeding, collisions, penalty points, etc. Due to the IP protection policy of the company NERVteh we cannot provide the details on the calculation of other sub-scores.

Each sub-score has the range from 0 to 100, where 0 is the worst and 100 is the best score. Once the sub-scores are calculated, we calculate the final driving score, which also ranges from 0 to 100, making 0 the worst and 100 the best driving score.

IV. Results

As mentioned, we let the autonomous vehicle repeat the scenario for 30 times. For each time, we calculated the driving score, as described in the previous section.

To make the evaluation results credible, we compared the results obtained by our autonomous vehicle to the real human driving data. We gathered the driving data at New York International Auto Show [2] from more than 300 human drivers which were driving in the same simulation scenario. The results for both, autonomous and human driving are shown in Fig. 5. Human driving is shown with blue and autonomous driving is shown in orange colored bars.

The results show that autonomous driving performs much better than human driving. The average evaluation score of autonomous algorithm is 71, whereas the evaluation score for human driving is 43. Additionally, more than 40% of autonomous driving have score more than 95, whereas most of the human driving evaluation scores are around 35. The evaluation scores lower than 50 are mostly due to the collisions.

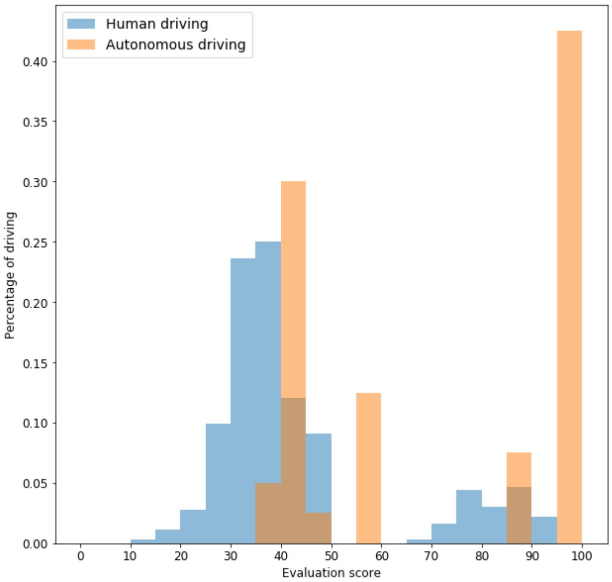

Figure 5: The results of evaluation score for autonomous driving and human driving.

V. Discussion

As the results show our simple autonomous algorithms performs much better than human driving, however there are certain shortcomings which we must be aware off.

The real-world sensors' output can contain noise, which can be presented either due to different weather conditions, inferences with other signals. Such noise has to be further applied in simulation environment to test the limits of real and virtual sensors, suggest possible upgrades, create algorithms that deal with incomplete data and data loss.

Additionally, our algorithms rely on some data gathered directly from the simulation environment, which should be gathered from sensors in order to make the simulation autonomous driving comparable to the real-world autonomous driving.

Acknowledgment

This research was supported by Slovenian Research Agency and NERVteh.

References

[1] Automated Vehicles for Safety. Available at https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety, accessed 25.04.2018

[2] New York International Auto Show. Available at https://www.autoshowny.com/press/#/press-releases, accessed 25.04.2018

[3] SCANeR DT. Available at http://www.oktal.fr/en/news/automotive, accessed 29.11.2017

[4] LIDAR. Available at http://velodynelidar.com/industry.html, accessed 29.11.2017

[5] Ultrasonic sensors. Available at https://www.maxbotix.com/Ultrasonic_Sensors.htm, accessed 29.11.2017

[6] Radar, https://www.nxp.com/applications/solutions/industrial/unmanned-aerial-vehicles-uavs/vision-systems-advanced-sensing-autonomy/automotive-radar-systems:RADAR-SYSTEMS, accessed 29.11.2017

[7] B. Kim, Y. Kashiba, S. Dai and S. Shiraishi, *Testing Autonomous Vehicle Software in the Virtual Prototyping Environment*, IEEE Embedded Systems Letters, vol. 9, no. 1, pp 5-8, March 2017.

[8] C. Zhang, Y. Liu, D. Zhao and Y. Su, *RoadView: A Traffic Scene Simulator for Autonomous Vehicle Simulation Testing*, 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), Qingdao, 2014, pp. 1160-1165.

[9] NERVteh Simulation Technologies. Available at https://www.nerv-teh.com, accessed 29.11.2017