AutonoVi-Sim: Autonomous Vehicle Simulation Platform with Weather, Sensing, and Traffic control

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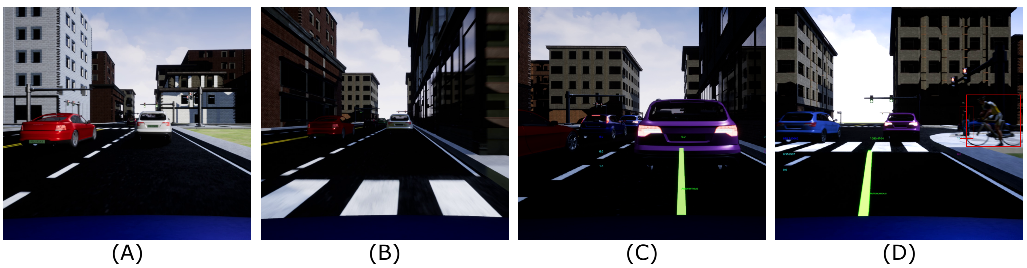

Figure 1: **Training Data Sequence from a Simulated Vehicle**: Data gathered from a vehicle navigating in traffic among other vehicles, cyclists and pedestrians. **(B)**: The visual profile changes as the vehicle enters the building's shadow. **(C)** Image annotated with the vehicle's steering decision in traffic. **(D)**: The vehicle passes a pedestrian and cyclist (highlighted in red) at an intersection.

Abstract

We present AutonoVi-Sim, a novel high-fidelity simulation platform for autonomous driving data generation and driving strategy testing. AutonoVi-Sim is a collection of high-level extensible modules which allows the rapid development and testing of vehicle configurations and facilitates construction of complex traffic scenarios. Autonovi-Sim supports multiple vehicles with unique steering or acceleration limits, as well as unique tire parameters and dynamics profiles. Engineers can specify the specific vehicle sensor systems and vary time of day and weather conditions to generate robust data and gain insight into how conditions affect the performance of a particular algorithm. In addition, AutonoVi-Sim supports navigation for non-vehicle traffic participants such as cyclists and pedestrians, allowing engineers to specify routes for these actors, or to create scripted scenarios which place the vehicle in dangerous reactive situations. Autonovi-Sim facilitates training of deep-learning algorithms by enabling data export from the vehicle's sensors, including camera data, LIDAR, relative positions of traffic participants, and detection and classification results. Thus, AutonoVi-Sim allows for the rapid prototyping, development and testing of autonomous driving algorithms under varying vehicle, road, traffic, and weather conditions.

1 Introduction

Autonomous driving represents an imminent challenge encompassing a number of domains including robotics, computer vision, motion planning, civil engineering, and simulation. Central to this challenge are the safety considerations of autonomous vehicles navigating the roads surrounded by unpredictable actors. Humans, whether drivers, pedestrians, or cyclists, often behave erratically,

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inconsistently, or dangerously, forcing other vehicles (including autonomous vehicles) to react quickly to avoid hazards. In order to facilitate acceptance and guarantee safety, vehicles must be tested not only in typical, relatively safe scenarios, but also in dangerous, less frequent scenarios.

Aside from safety concerns, costs pose an additional challenge to the testing of autonomous driving algorithms. Each new configuration of a vehicle or new sensor requires re-calibration of a physical vehicle, which is labor intensive. Furthermore, the vehicle can only be tested under conditions limited either by a testing track, or the current traffic conditions if a road test is being performed. This means the vehicle can be tested no faster than real-time and without any speedups or parallel testing.

Many recent approaches to autonomous driving rely on machine-learning via Bayesian networks or deep-learning to provide entity detection [1], entity prediction [2], and end-to-end control [3]. However, such approaches rely on substantial amounts of annotated data in safe, as well as dangerous scenarios. The dataset must also encompass varied weather and lighting conditions. In addition, not all autonomous vehicles are equipped with identical or equivalent sensing capability; training data must be available for the specific configuration or sensors of the vehicle being tested. Gathering such data by physical tests can be expensive, difficult and even dangerous. In contrast, a high-fidelity simulator can augment and improve training of algorithms, and allow for testing safely and efficiently.

Insights gained from simulation could provide critical training data and information on algorithmic inefficiencies before actual vehicle testing. In an effort to facilitate progress in these areas, we present AutonoVi-Sim, a simulation framework for training and testing autonomous driving algorithms and sensors. AutonoVi-Sim is a collection of high-level, extensible modules designed to allow researchers and engineers to rapidly configure novel road networks, driving scenarios, and vehicle configurations, and to test these in a variety of weather and lighting conditions. AutonoVi-Sim captures a variety of autonomous driving phenomena and testing requirements including:

- **Data Generation**: Autonovi-Sim facilitates data analysis by allowing exports of relevant data for traffic proximate to the autonomous vehicle as well as data from each virtual sensor on the vehicle. Sensor and local traffic data can be used in training deep-learning approaches by generating automatically labelled classification and decision data efficiently.
- **Varying vehicle, cyclist, pedestrian, and traffic conditions**: AutonoVi-Sim includes various vehicle and sensor models, pedestrians, and cyclists. Diversity of these traffic entities allows for training classification on differing shapes, sizes, colors, and behaviors of cyclists, pedestrians, and other drivers.
- **Dynamic Traffic, Weather and Lighting Conditions**: AutonoVi-Sim provides high fidelity traffic simulation, supporting dynamic changes in traffic density, time of day, lighting, and weather including rain and fog.
- **Rapid Scenario Construction**: Typical road networks can be easily laid out using spline painting and are automatically connected for routing and navigation purposes. AutonoVi-Sim supports many lane configurations and atypical road geometry such as cloverleaf overpasses. In addition, other vehicles and entities can be scripted to generate repeatable erratic behavior, e.g. cutting in front of the ego-vehicle, walking into the road.

The rest of the paper is organized as follows. In section 2, we motivate simulation as a tool for advancing autonomous driving and detail related work in the field. In section 3, we detail the core modules provided by AutonoVi-Sim. We reserve discussion of the *Drivers* and *Vehicles* modules for section 4 and offer demonstrations of the simulator.

2 RELATED WORK

Simulation has been an integral tool in the development of controllers for autonomous vehicles. [4], [5], and [6] offer in-depth surveys of the current state of the art and the role simulation has played. Many successful vehicle demonstrations of autonomy were first tested in simulation [7, 8, 9]. Recent work in traffic modelling has sought to increase the fidelity of the modelled drivers and vehicles; a survey is provided in [10].

Recent studies support the use of high-fidelity microscopic simulation for data-gathering and training of vision systems. [11] and [12] and leveraged Grand Theft Auto 5 to train a deep-learning classifier at comparable performance to manually annotated real-world images. Several recent projects seek

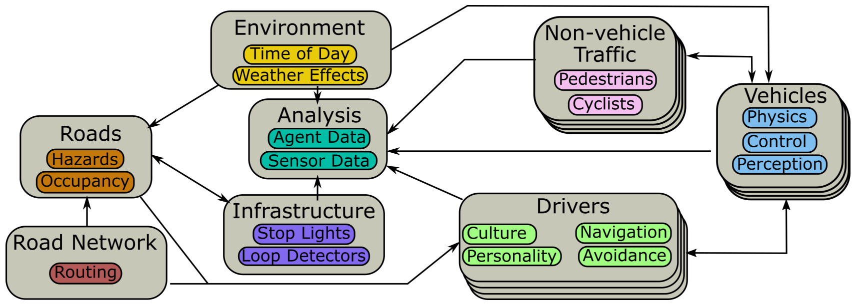

Figure 2: **AutonoVi-Sim Platform Overview:** The eight modules composing AutonoVi-Sim encompass varying aspects of autonomous driving. The *Road*, *Road Network*, and *Infrastructure* modules define the driving environment. The *Environment* module allows engineers to specify specific environment conditions including time of day and weather. The *Non-vehicle Traffic* module allows engineers to specify navigation goals for pedestrians and cyclists, or setup specific triggered behaviors. The *Drivers* and *Vehicles* modules work as a pair to define current traffic conditions and specific driving destinations and decisions for the vehicles in the simulation. Each vehicle in the simulation has a unique set of sensing capabilities and a single driver which operates the vehicle during the simulation. Finally, the *Analysis* module is used to catalog and export data, including agent positions and sensor readings, for analysis.

to enable video games to train end-to-end driving systems, including ChosenTruck and DeepDrive-Universe which leverages the OpenAi Universe system. Using video game data provides benefits in the fidelity of the vehicle models but limits the ability to implement sensing systems and access data beyond visual data. A fully dedicated high-fidelity simulator can address these limitations and provide access to point-cloud data, visual data, and other vehicle sensors without the limitations imposed by adapting gaming software. Research in this area has begun to emerge [13]. Our work is complimentary to such systems and can be combined with generated data from other simulators to increase robustness of training data.

3 SIMULATION MODULES

Drawing from recent work in crowd simulation, [14], AutonoVi-Sim is divided into eight extensible modules, each with various sub-components. The modules are Environment, Road Network, Road, Drivers, Infrastructure, Vehicles, Non-vehicle Traffic, and Analysis. Each module captures some aspect of autonomous driving simulation and can be extended and modified to suit the specific needs of a particular algorithm. Figure 2 shows the connection between components in AutonoVi-Sim. In this section, we will detail the modules which make up the basic simulation system, reserving discussion of the vehicle and driving strategy modules for section 4.

3.1 Roads

Roads in AutonoVi-Sim are represented by their center line, a number of lanes and directions thereof, and the surface friction of the road. Roads are placed interactively by drawing splines on a landscape which allows quick construction. Each road maintains occupancy information, average flow, and can maintain hazard information. The road module also maintains the set of hazards such as potholes or debris, which can be specified by density (number of hazards per km) or interactively by placing them on the road.

Alternately, roads can be specific pieces of geometry as in the case of intersections. This provides the flexibility to place specific intersections and model atypical road constructions for modelling specific environments. Figure 3(A) shows an example of road placement in AutonoVi-Sim.

3.2 Infrastructure

Infrastructure controllers represent traffic lights, signage, and any other entity which modifies the behaviors of vehicles on the road. These controllers can be added specifically to roads, as in the case

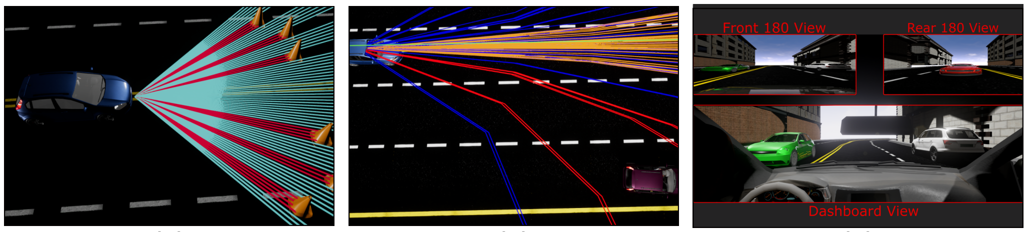

Figure 3: **AutonoVi-Sim Modules: (A):** Sensors on the vehicle are placed interactively. This configuration demonstrates a hatchback with a laser rangefinder navigating around traffic cones. Returned beams are illustrated in red. Beams which do not return data are illustrated in cyan for debugging. **(B)**: Once sensors are placed, the vehicle's navigation algorithm can be tested and examined interactively. The AutonoVi driving algorithm samples potential controls and projects forward in time. Red control paths indicate predicted collisions with the nearby vehicle. **(C)**: The data analysis module allows for exporting sensor data as the vehicle navigation. This test vehicle is equipped with a 180 degree forward facing camera, a 180 degree rear-facing camera, and a dashboard camera.

of intersections, or placed independently as in signage or loop detectors. Vehicles implement their own detection of these entities as is described in section 4.1.2.

3.3 Road Network

The road network in AutonoVi-Sim provides the basic connectivity information for the traffic infrastructure to the vehicles in the simulation. At run-time, the network is automatically constructed by connecting roads into a directed graph. The road network provides GPS style routing to vehicles and localization for mapping purposes. Coupled with the road and infrastructure modules, the Road Network also provides information about upcoming traffic and current road conditions.

3.4 Environment

The environment module allows engineers to specify the specific environmental conditions for a given driving scenario. This currently includes time of day and weather. The system implements varying levels of fog and rain conditions. Environmental effects such as road friction reduction are controlled by the environment module.

3.5 Non-Vehicle Traffic

AutonoVi-Sim implements two non-vehicle traffic participants: pedestrians and cyclists. Pedestrians operate separately from the road network and can be given specific destinations. By default, pedestrians follow safe traffic rules to navigate to their goal. They can also be setup to trigger specific occurrences. For example, as the ego-vehicle nears, a pedestrian can be triggered to walk into the street in front of the vehicle to test its reaction time.

Cyclists operate similarly to vehicles in AutonoVi-Sim. Cyclists are given destinations and route over the road network. Similarly to pedestrians, cyclists can be programmed to trigger erratic behavior under specified conditions. For example, as the ego-vehicle approaches, a cyclist can be triggered to stop in the road, suddenly change direction, or enter the road in an unsafe fashion.

3.6 Analysis and Data Capture

AutonoVi-Sim implements a module for logging positions, velocities, and behaviors of the various traffic participants. It also supports logging egocentric data from the vehicle, such as relative positions of nearby entities at varying times during simulation. Camera-based sensors can record out the video data captured during simulation as can LIDAR based sensors Section 4.1.2 describes sensors in more detail.

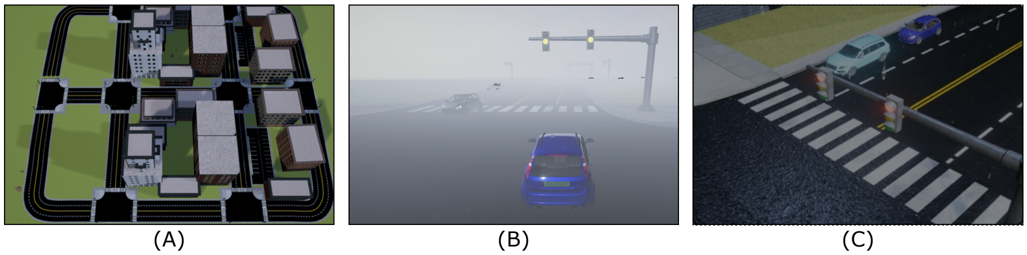

Figure 4: **Simulated scenarios and conditions in Autonovi-Sim: (A)**: A simulated city modelled in AutonoVi-Sim. Closed circuit road networks allow engineers to test driving algorithms over long timescales by assigning new navigation goals periodically. **(B)**: Heavy fog obstructs the view of the vehicle. **(C)**: Vehicles pass through a slick intersection during rainy conditions.

4 AUTONOMOUS DRIVING MODULES

The simulation modules described in section 3 serve as the basis for AutonoVi-Sim. This section describes the two core modules which allow for testing autonomous driving and sensing algorithms under varying conditions, the Drivers and Vehicles modules.

4.1 Vehicles

The vehicle in AutonoVi-Sim is represented as a physics-driven entity with specific tire, steering, and sensor parameters. Physics parameters include the base tire coefficient of friction, the mass of the vehicle, engine properties such as gear ratios, and the physical model for the vehicle. Each of these parameters can vary between vehicles and relevant properties such as tire friction or mass can vary at runtime as needed.

4.1.1 Control and Dynamics

Vehicle control is provided on three axes: steering, throttle, and brake inputs. The specific inputs are chosen each simulation step by the driver model, described in section 4.2. The vehicle's dynamics are implemented in the NVidia PhysX engine. This allows the simulator to model the vehicle's dynamics and communicate relevant features such as slipping as needed by the driving algorithm.

4.1.2 Perception

The perception module of a vehicle provides the interface for information about surroundings to be gathered and stored in the vehicle. The basic sensing module in AutonoVi-Sim employs a ray-cast with configurable uncertainty, detection time, classification error rate, and sensor angle / range. This module is sufficient to test scenarios such as late detection or misclassification of pedestrians with minimal intervention. A vehicle can be equipped with multiple sensors with varying angles and fidelity, allowing the vehicle to simulate high-fidelity sensors in the longitudinal directions and broader, less accurate sensors in lateral directions. In addition, interaction with environmental conditions can be specified for the basic sensors, including performance impacts and uncertainty caused by weather effects.

In addition, the perception module provides interfaces to a generic camera interface and Monte-Carlo scanning ray-casts to simulate various sensor types. These interfaces can be extended to implement LIDAR or camera-based neural network classifiers in simulation. The LIDAR can be configured to change the scanning range, angle, and resolution. Similarly, the camera resolution, color parameters, and refresh rate can be configured for each camera sensor. Figure 3 shows an example of a camera-based sensor and simple LIDAR.

4.2 Drivers

Driving decisions in AutonoVi-Sim, including routing and control inputs, are made by driver models. A driver model fuses information from the road network and the vehicle's sensors to make appropriate decisions for the vehicle. The specific update rate of the driver model can be configured as well as what sensors the model supports and prefers. Each model can implement any necessary parameters needed for the specific approach.

AutonoVi-Sim currently implements three driver models. The first is a simple lane-following approach which employs control methods similar to a driver assistance lane-keeping system. This driver is used to generate passive vehicles travelling along their destinations without aberrant or egocentric behavior. These vehicles are capable of lane-changes and turns, but follow simple rules for these maneuvers and rely on perfect sensing models to accomplish them.

The more extensive driving model, AutonoVi, is described in detail in [15]. This model uses optimization-based maneuvering with traffic constraints to generate behaviors such as overtaking and combines steering and braking maneuvers through a data-driven vehicle dynamics prediction model.

Finally, the simulator implements a manual driving mode, which can be activated from any autonomous driver. Manual mode allows an engineer to drive the vehicle using a keyboard, game-pad, or steering wheel and pedal combination. As described in [16], this manual operation is being employed to test vehicle signalling and connected vehicle operation. It can also be used to collect data for neural-network methods, as shown in figure 4(F).

Figures 3 and 4 detail several example scenarios and configurations we have tested in AutonoVi-Sim. Additional details on AutonoVi and additional simulations and testing environments can be found in [15].

4.3 Generating Training Data

AutonoVi-Sim can be used to generate labelled training data for typical as well as dangerous situations. We can simulate many scenarios involving pedestrians, cyclists, and other vehicles, such as jaywalking or passing in traffic [15]. The vehicle can be driven automatically using the driver models, or manually by an engineer. Camera, LIDAR, relative position, detection, and control data are exported from each trial of the simulation. The controls of the vehicle combined with local conditions can be used for reinforcement learning in the autonomous driving case or imitation learning in the manual case. These scenarios can be repeatedly run under varying lighting and weather conditions; different surroundings, i.e. buildings, trees, etc; and with different pedestrians, cyclists, and vehicle shapes and sizes.

5 Conclusion

We have presented AutonoVi-Sim, a platform for autonomous vehicle simulation with the capacity to represent various vehicles, sensor configurations, and traffic conditions. We have demonstrated AutonoVi-Sim's applicability to a number of challenging autonomous-driving situations and detailed the ways in which AutonoVi-Sim can be used to generate data for training autonomous-driving approaches. AutonoVi-Sim is a modular, extensible framework. While many modules currently represent preliminary implementations of advanced functionality, the extensible nature of the framework provides the basis for progress in the various disciplines which define autonomous driving.

Our work is in active development and still faces a number of limitations. AutonoVi-Sim contains basic implementations of the various modules such as sensors for perception, a physics engine to simulate dynamics etc. However, each of these modules can be extended to more accurately reflect real world conditions. For example, our sensor models currently do not model noise or uncertainty in the exported data. AutonoVi-Sim currently lacks calibration information to replicate specific sensors and sensor configurations. In the future we hope to model specific sensing packages and algorithms to test specific real-world configurations. In addition, current driver models are limited to hierarchical, rule-based driving approaches. Future work will include exploration of end-to-end approaches, which can be represented by a novel Driver model. The current simulator supports few hundreds of vehicles. By combining our simulator with macroscopic or hybrid traffic simulation approaches, we seek to increase the size of supported traffic conditions. We also intend to explore the transfer between algorithms trained on AutonoVi-Sim and actual test vehicles.

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