Simulation-Based Testing of Autonomous Ground Vehicles

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How do we study autonomy?

Functionality:

Sensing	Modelling	Planning	Action
Sensor noise Weather effects Sensor placement	Perception Classification Localization	Motion planning Path planning Safety monitor	Vehicle control Actuation Mobility

Sensing → Modelling → Planning → Action

Scenario:

Cross-country navigation
Pedestrian detection & avoidance
4-way intersection

1. Nakhaeinia, Danial, et al. "A review of control architectures for autonomous navigation of mobile robots." *International Journal of Physical Sciences* 6.2 (2011): 169-174.
2. Li, Li, et al. "Intelligence testing for autonomous vehicles: A new approach." *IEEE Transactions on Intelligent Vehicles* 1.2 (2016): 158-166.

Studying Failures

- When a failure happens, we would like to know[1]
  - **Where?**
  - **How**?
  - **What**?
- But there are challenges[2]
  - Built on statistics or AI algorithms
  - Environment is complex and random
  - Failures are (hopefully!) rare

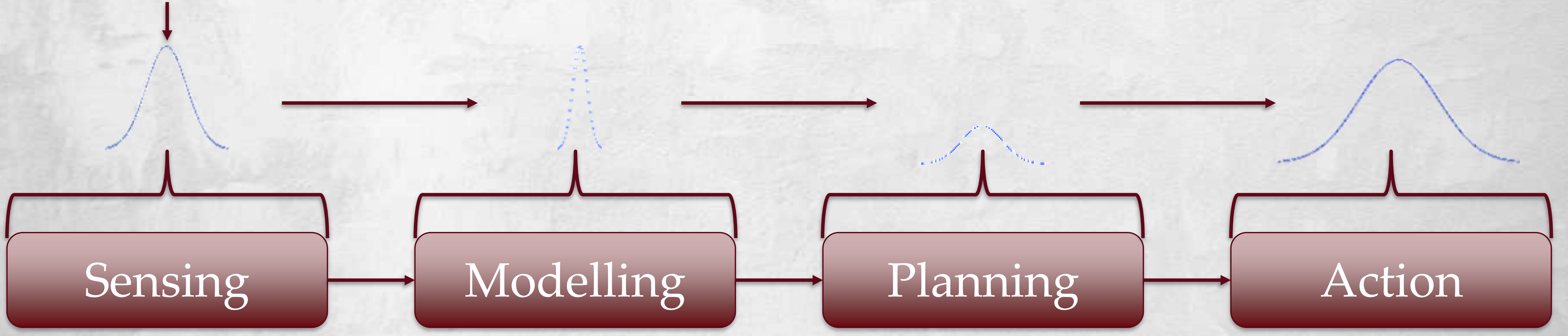
Sensing → Modelling → Planning → Action

1. Falco, Gregory, and Leilani H. Gilpin. "A stress testing framework for autonomous system verification and validation (v&v)." *2021 IEEE International Conference on Autonomous Systems (ICAS)*. IEEE, 2021.
2. Feng, Shuo, et al. "Intelligent driving intelligence test for autonomous vehicles with naturalistic and adversarial environment." *Nature communications* 12.1 (2021): 1-14.

Error Propagation in Autonomous Systems

- How do *external* errors propagate through the *internal* subsystems of the AGV?
- How resilient is each subsystem to errors? What errors cause failures?
- To answer these questions, we need:
  1. Ground truth information about the environment and vehicle state
  2. A way to control the environmental conditions
  3. Metrics for measuring performance/error of each subsystem

Error sources:
- Rain
- Dust
- Sensor noise



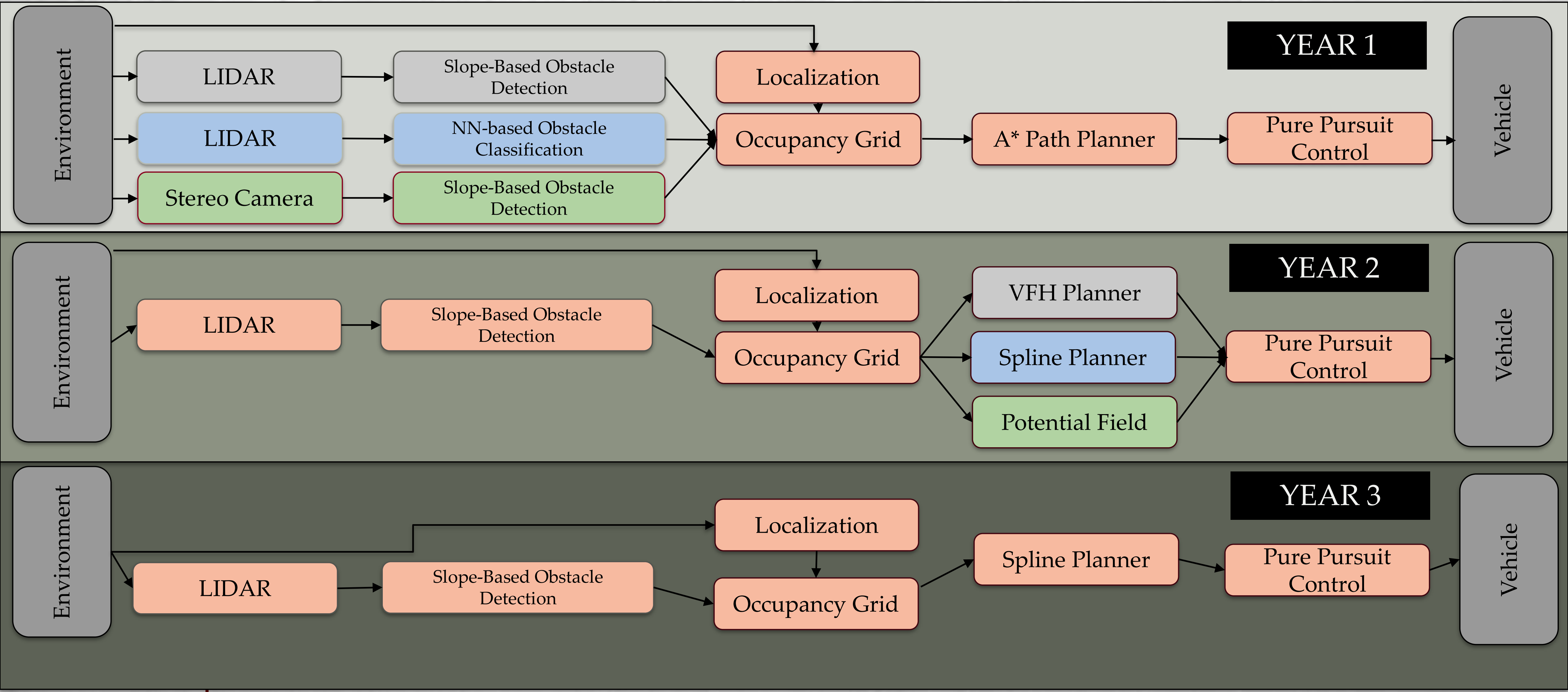
Simulation Based Testing

- Use simulation to mitigate each challenge associated with testing AGV
  - Simulation allows us to measure subsystem level metrics more accurately
  - Simulation offers perfect ground truth
  - Thousands of times more simulated hours than real
- Must constrain with real tests!

Research Overview

- **Goal**: Measure how environmentally induced errors propagate through the subsystems of an Autonomous Ground Vehicle (AGV) and manifest themselves in system-level performance
- **Method**: Use simulation to access ground truth and control environmental conditions
  - Y1: Perception
  - Y2: Planning
  - Y3: Physical Testing / Validation

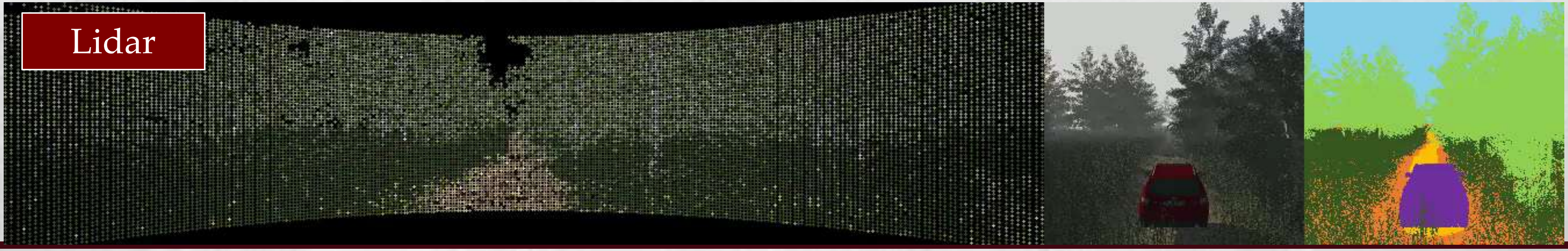
Autonomy Tested



The MSU Autonomous Vehicle Simulator (MAVS)

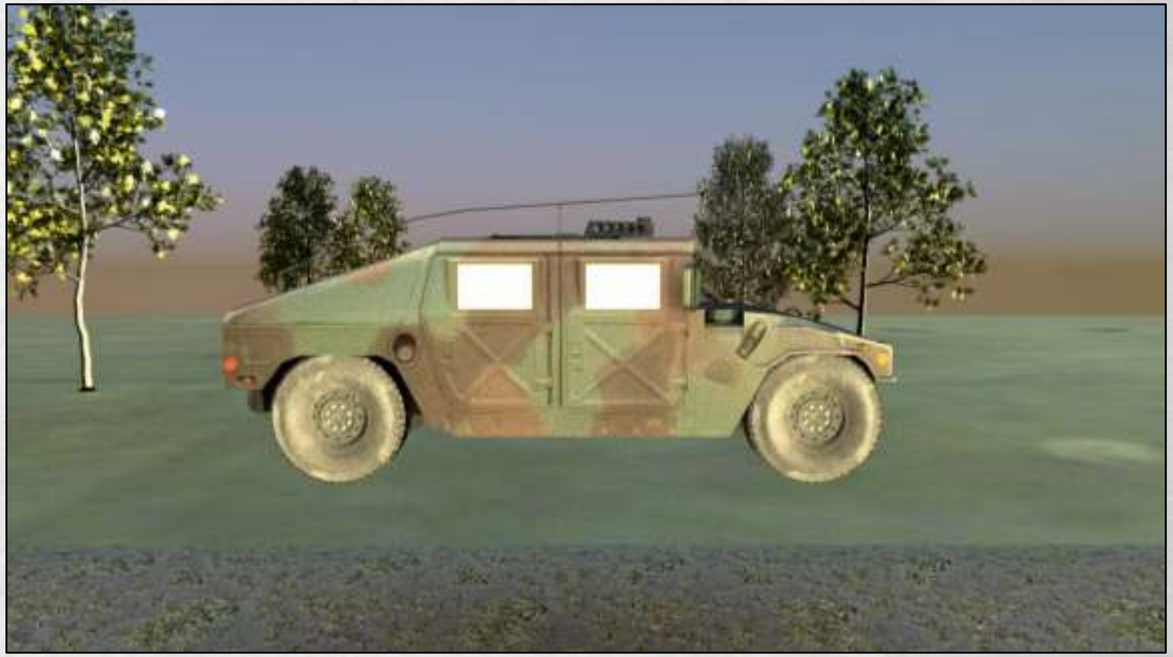
MAVS is:

- A C++ software library for simulating autonomous vehicles in realistic digital terrain.
- A real-time simulator for evaluating the performance of autonomous perception and navigation software.
- A user-friendly Python API for composing custom simulations.
- A physics-based sensor simulator for LIDAR, GPS, cameras, and other sensors.
- A lumped-parameter vehicle-dynamics simulator.
- ROS compatible

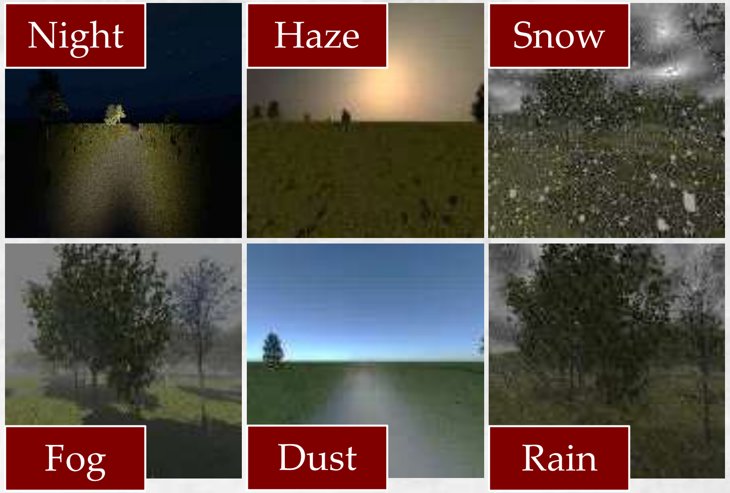


MAVS Vehicle Physics

- MAVS has a variety of vehicle dynamics options, including the default implemented in RP3D and links to Chrono::Engine
- Both physics engines were used at different points in this project



MAVS Sensor-Environment Interaction




electronics

MDPI

Article

Predicting the Influence of Rain on LIDAR in ADAS

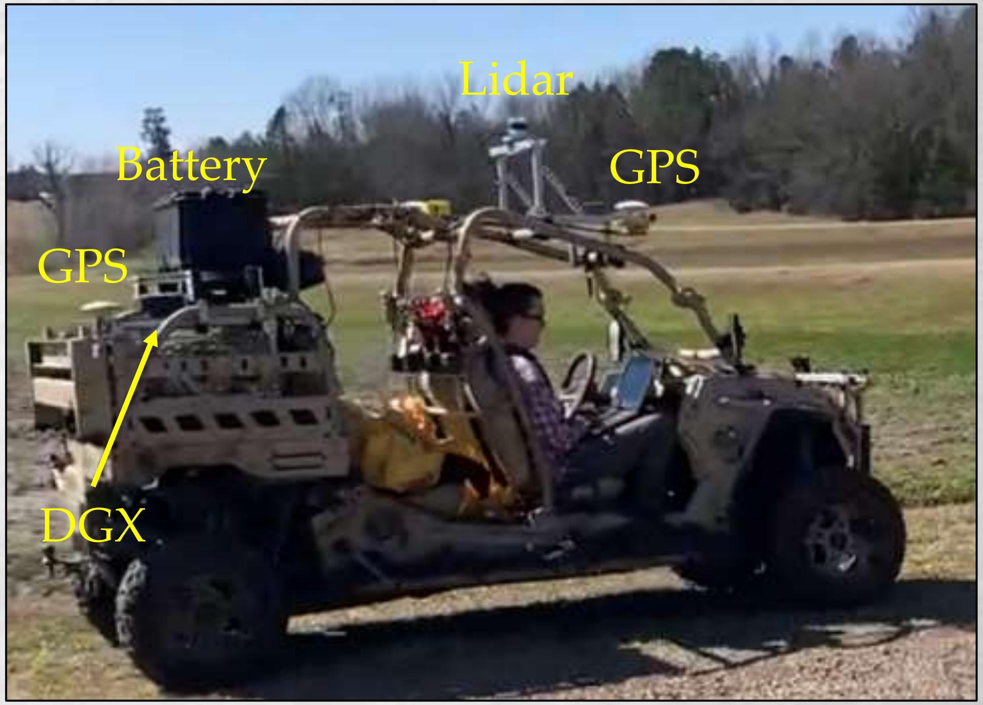
Abstract:

Keywords:

1. Introduction

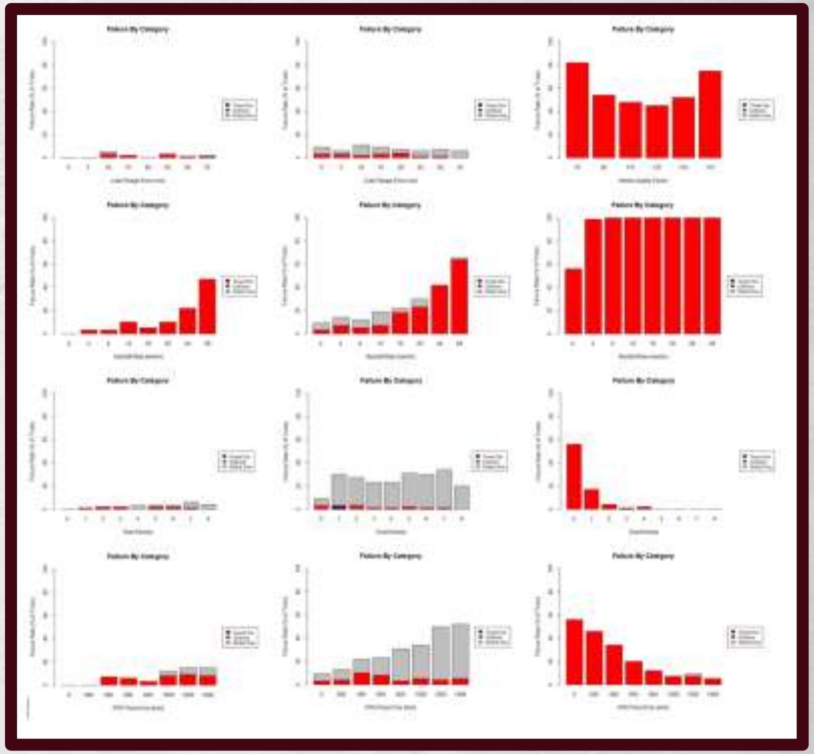
Test Vehicle

- Test vehicle is an MRZR-D4
  - Operated in Low-gear
- Sensors
  - Ouster OS-2 in 64 beam config
  - 2 X Swiftnav Piksi with RTK correction for heading and location
  - 3-axis IMU for pitch & roll
  - NVIDIA DGX interfacing to ROS



Year 1

- Perception: Lidar-slope, lidar-segmentation, stereo camera slope
- Independent Variables : Rain rate, Dust rate, Lidar range error, RTK localization error
- Performance Metrics
  - System level: Failure rate and type, speed
  - Subsystem level: Lidar range error, Occupancy grid error, Localization error, Path planner error
- Results
  - Stereo camera performs very poorly in rain
  - Failure rates increase with rain
  - System is robust to localization and lidar range errors
  - **<u>Subsystem metrics do not correlate well with system level metrics</u>**



Year 2

- Planners: VFH, Potential field, and Spline planner
- Independent Variables: Soil strength, Obstacle size, AGV speed
- Dependent variables:
  - System-level: Failure rate and type, vehicle speed, fuel use
  - Subsystem level: Occupancy grid error, Localization error, Path planner error
- Results:
  - Spline planner was the most robust
  - Softer soil caused increased fuel usage, but did not affect other system level variables
  - Still no correlation between subsystem-level metrics and system-level performance

Year 3

Year 3

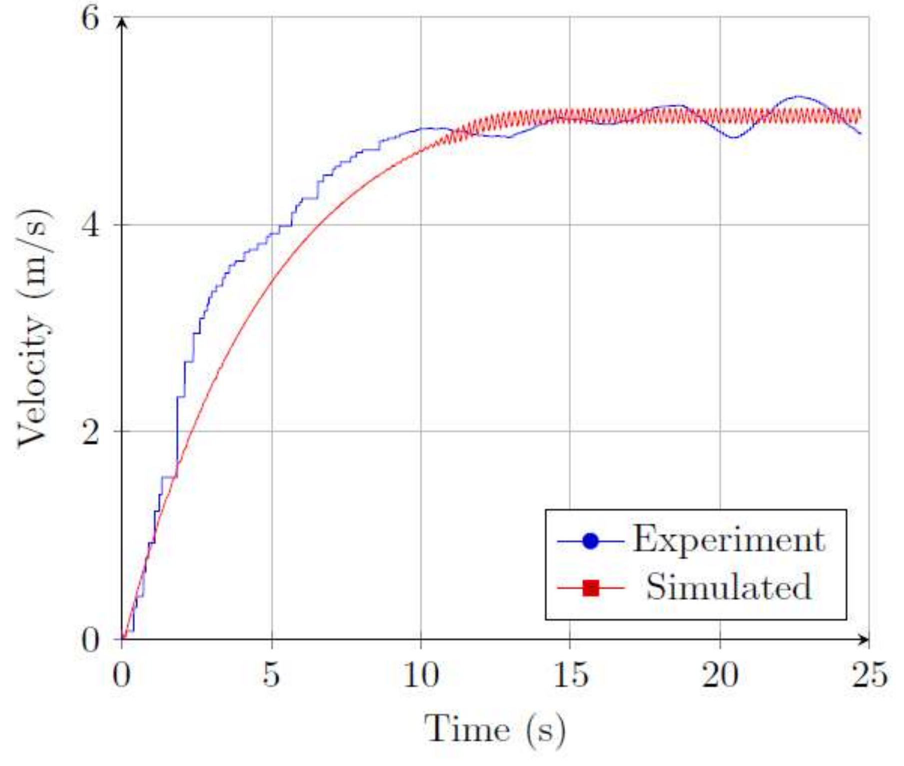
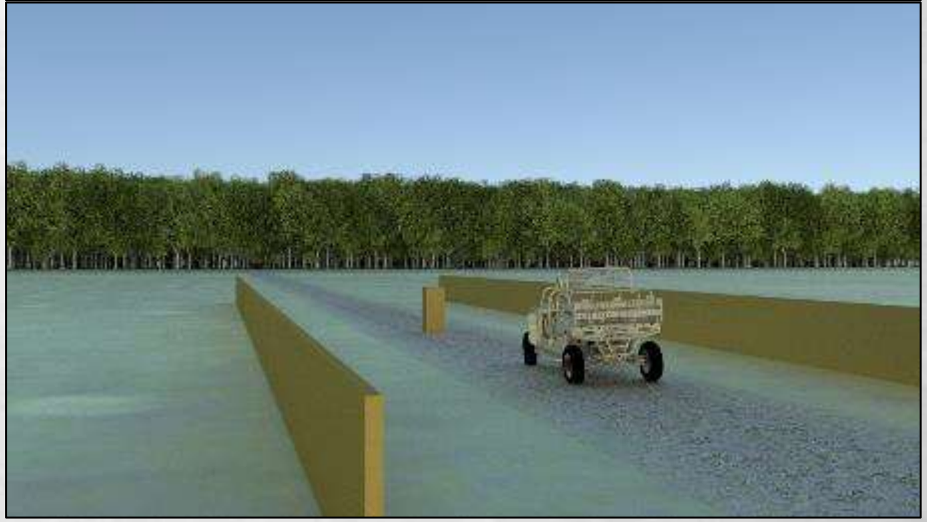


Figure 6. Real vs simulated vehicle speed



Summary / Conclusions

- We are finishing the third year of a 3-year project to study autonomy
- Primary conclusions from first 2 year:
  - Subsystem-level metrics do not correlate well with system-level results
  - Measured affect of rain, dust, sensor error, and soft soil on performance metrics
- Ongoing for year 3 – measuring ODOA with real vehicle for validation of simulation results