CAREER: Safe and Agile Autonomous Cyber-Physical Systems

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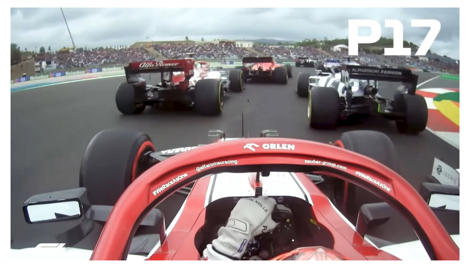
The goal of this project is to develop motion planning and control algorithms, along with safety architectures for autonomous Cyber-Physical Systems like Autonomous Vehicles. This will enhance their safety in complex environments and improve their response to unforeseen events.

Overview

Safety Through Agility

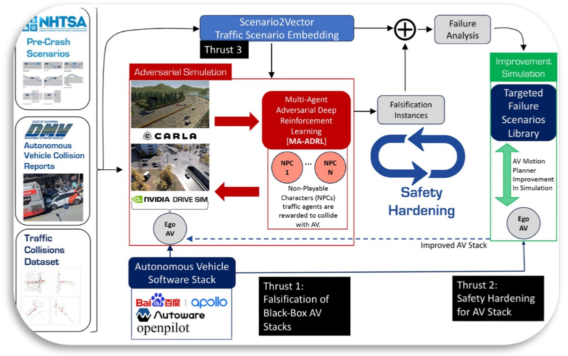
High-speed and close-proximity nature of racing provides a suitable setting for learning, developing, and testing safe and agile autonomous systems.



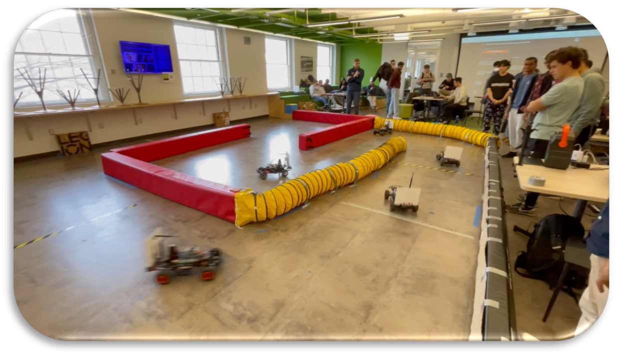
- High-Speed
- Close-Proximity
- Driving at vehicle limits

- Handle Uncertain Dynamic Situations
- Robust Motion Planning
- Improved vehicle handling

Scientific Impact on Cyber-Physical Systems



Improving safety for CPS with learning-enabled components



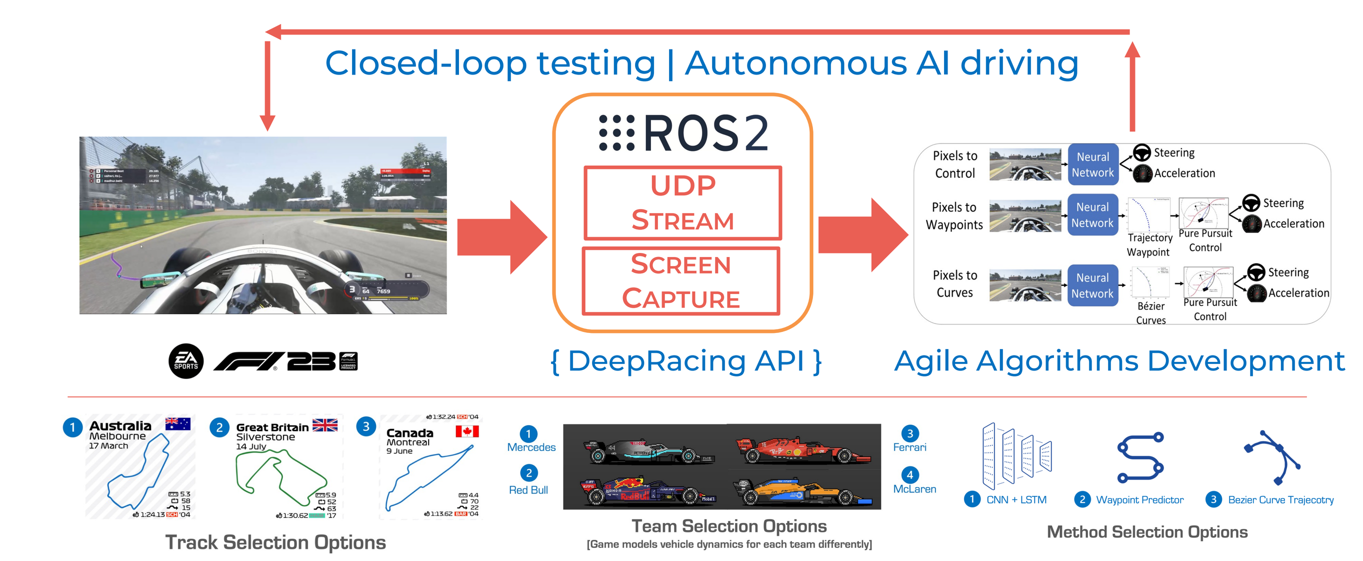
Planning under uncertainty for multi-agent scenarios

Learning from expert demonstrations and addressing Sim-2-Real gaps

Engineering full-scale CPS testbeds

Methodology

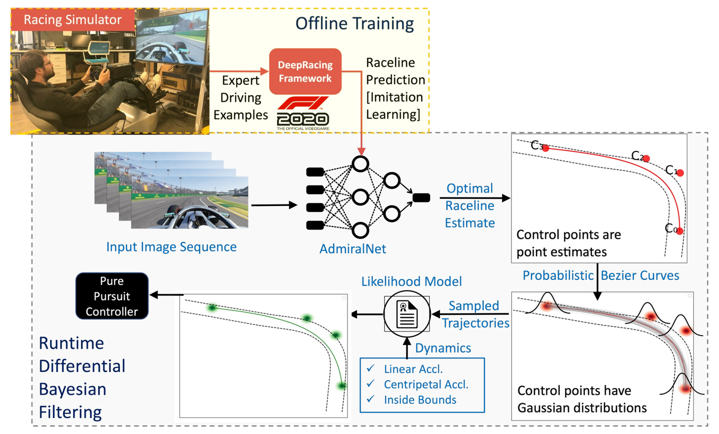
DeepRacing AI



T. Weiss and M. Behl, DeepRacing: A Framework for Autonomous Racing, *IEEE Design, Automation, and Test in Europe. 2020*
T. Weiss and M Behl, DeepRacing AI - Autonomous Motorsport Racing, *NeurIPS 2020.*
T. Weiss and M. Behl, Deepracing: Parameterized trajectories for autonomous racing. arXiv , 2020

Differential Bayesian Filtering

- Trajectories represented as probabilistic Bezier Curves.
- Bayesian inference incorporates vehicle dynamics and safety constraints.
- Monte-Carlo sampling from distribution of trajectories.
- Sequential update, re-weighting, optimal trajectory convergence



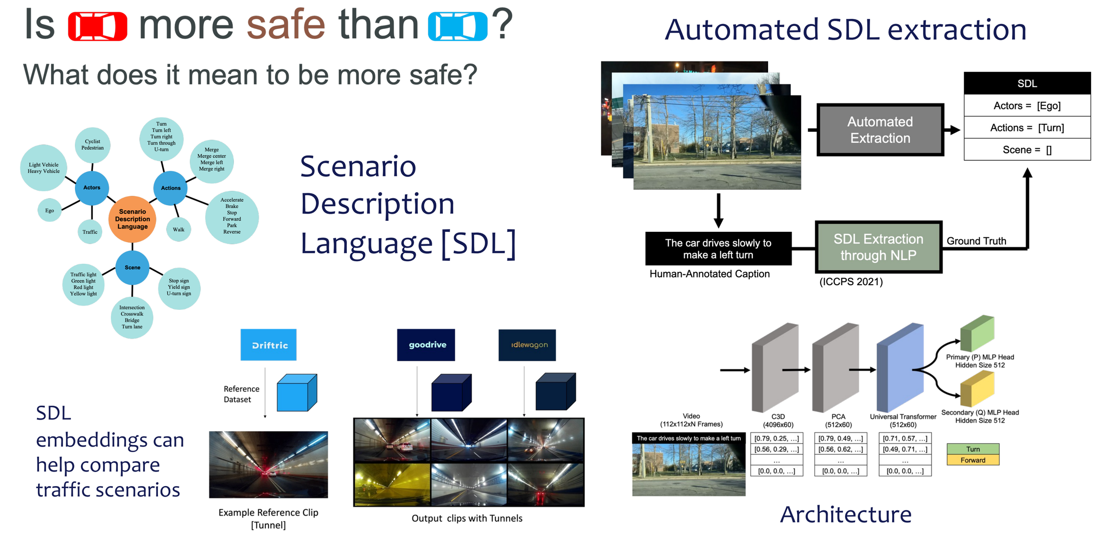
Results

Model Configuration	Lap Time [s]	Overall Speed [m/s]	Number of Boundary Failures
Waypoint Prediction (Behavioral Cloning)	106.683	49.245	5.6
Bézier Curve Prediction (Behavioral Cloning)	101.72	52.193	1.8
Unfiltered Raceline Prediction	91.219	58.109	0
Fastest Human Lap (Training Data)	89.177	59.439	1
Ground-Truth Raceline	88.046	60.186	0
Raceline Prediction w/ Differential Bayesian Filtering (Ours)	**86.761**	**61.092**	**0**
Nicholas Latifi (in real-life 2019 Australian Grand Prix)	86.067	Unknown	0
Lewis Hamilton (in real-life 2019 Australian Grand Prix)	80.486	Unknown	0

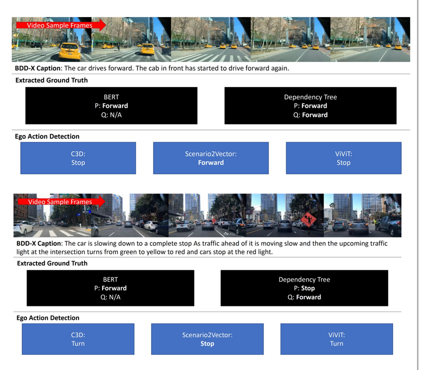
Trent Weiss and Madhur Behl. DeepRacing: Parameterized Trajectories for Autonomous Racing. IROS 2021 Workshop on Perception, Learning, and Control for Autonomous Agile Vehicles, 2021 ***(Best Paper Award)***
Trent Weiss and Madhur Behl. This is the way: Differential Bayesian filtering for agile trajectory synthesis. *IEEE Robotics and Automation Letters, 7(4):10414–10421, 2022. Presented at IROS 2022*
Trent Weiss, John Chrosniak, and Madhur Behl. "Towards multi-agent autonomous racing with the Deepracing framework." *International Conference on Robotics and Automation (ICRA)-Workshop on Opportunities and Challenges with Autonomous Racing.* 2021.

Scenario-2-Vector

Is [car] more safe than [car]?
What does it mean to be more safe?



SDL extraction Examples



Scenario Retrieval

Model	mAP
C3D	0.607
ViViT	0.570
Scenario2Vector	**0.628**

Aron Harder, Jaspreet Ranjit, and Madhur Behl. "Scenario2Vector: scenario description language based embeddings for traffic situations." In *Proceedings of the ACM/IEEE 12th International Conference on Cyber-Physical Systems (ICCPS)*, pp. 167-176. 2021.
Aron Harder and Madhur Behl, "Automated Traffic Scenario Description Extraction Using Video Transformers", *IEEE Design, Automation, and Test in Europe (DATE), 2024.*

Broader Impacts

Real-World | Full-Scale | Fully-Autonomous Racing

One of 9 teams in the world in Indy Autonomous Challenge

50+ students since 2021

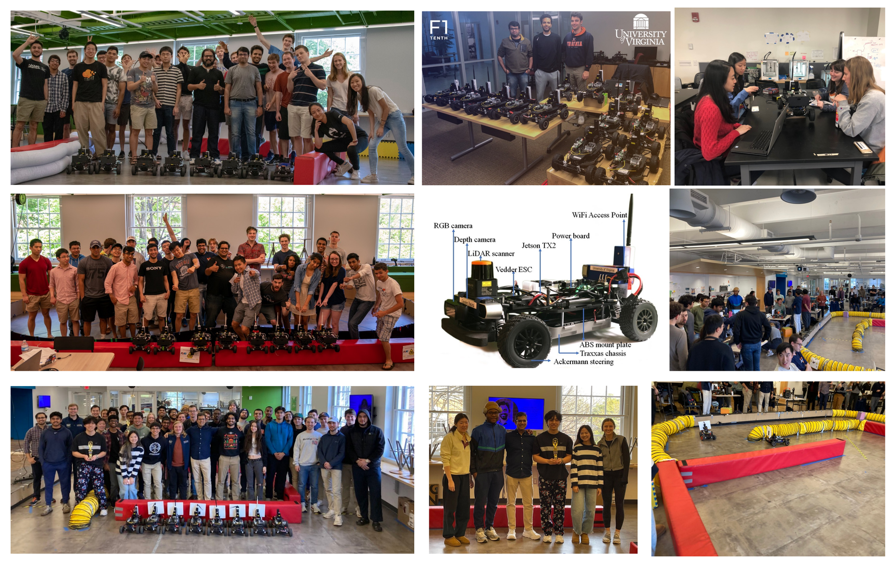
Cavalier Autonomous Racing

Indianapolis Motor Speedway [October 2021]

Las Vegas Motor Speedway [January 2022, 2023]

Texas Motor Speedway [November 2022]

F1TENTH: Undergraduate Curriculum and Autonomous Vehicle Testbed



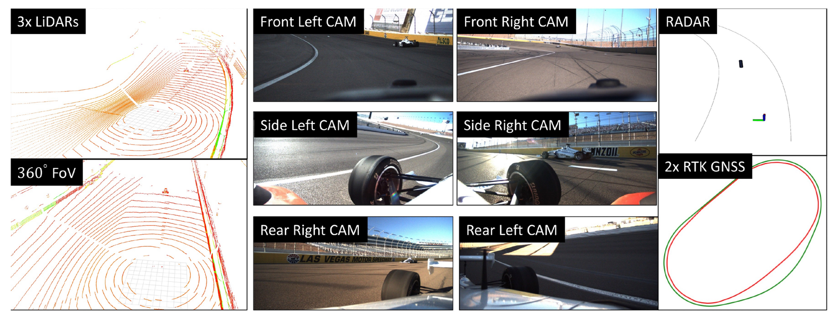
300+ students since 2017

Workshops & Competitions

Opportunities and Challenges with Autonomous Racing Workshops – ICRA 2021/2022

Multiple F1tenth competitions at CPS-IoT Week, ICRA, IROS, and ES-Week

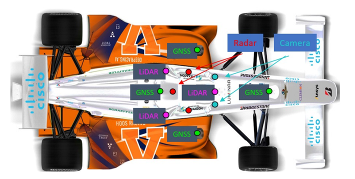
RACECAR: The Dataset for High-Speed Autonomous Racing



https://github.com/linklab-uva/RACECAR_DATA

Dataset and Tutorials

Released in ROS2 and NUSCENES formats



Sensors
- 3 Solid State LiDARs (Luminar)
- 6 Cameras (Allied Vision)
- 3 Radars (Aptiv)
- 2 RTK GNSS Receivers (Novatel)
  - 1 -2 cm level accuracy
  - Built in IMUs

11 Racing Scenarios – 27 Sessions – 6.5 Hours of

Scenario	Track	Description	Speeds
S_1	LVMS	Solo Slow Lap	< 70 mph
S_2	LVMS	Solo Slow Lap	70-100 mph
S_3	LVMS	Solo Fast Lap	100-140 mph
S_4	LVMS	Solo Fast Lap	> 140 mph
S_5	LVMS	Multi-Agent Slow	< 100 mph
S_6	LVMS	Multi-Agent Fast	> 130 mph
S_7	IMS	Solo Slow Lap	< 70 mph
S_8	IMS	Solo Slow Lap	70-100 mph
S_9	IMS	Solo Fast Lap	100-140 mph
S_{10}	IMS	Solo Fast Lap	> 140 mph
S_{11}	IMS	Pylon Avoidance	< 70 mph