RWR 4015

Traffic Simulation for Planning Applications

Dr. Ahmad Mohammadi

Week 6 | Lecture:

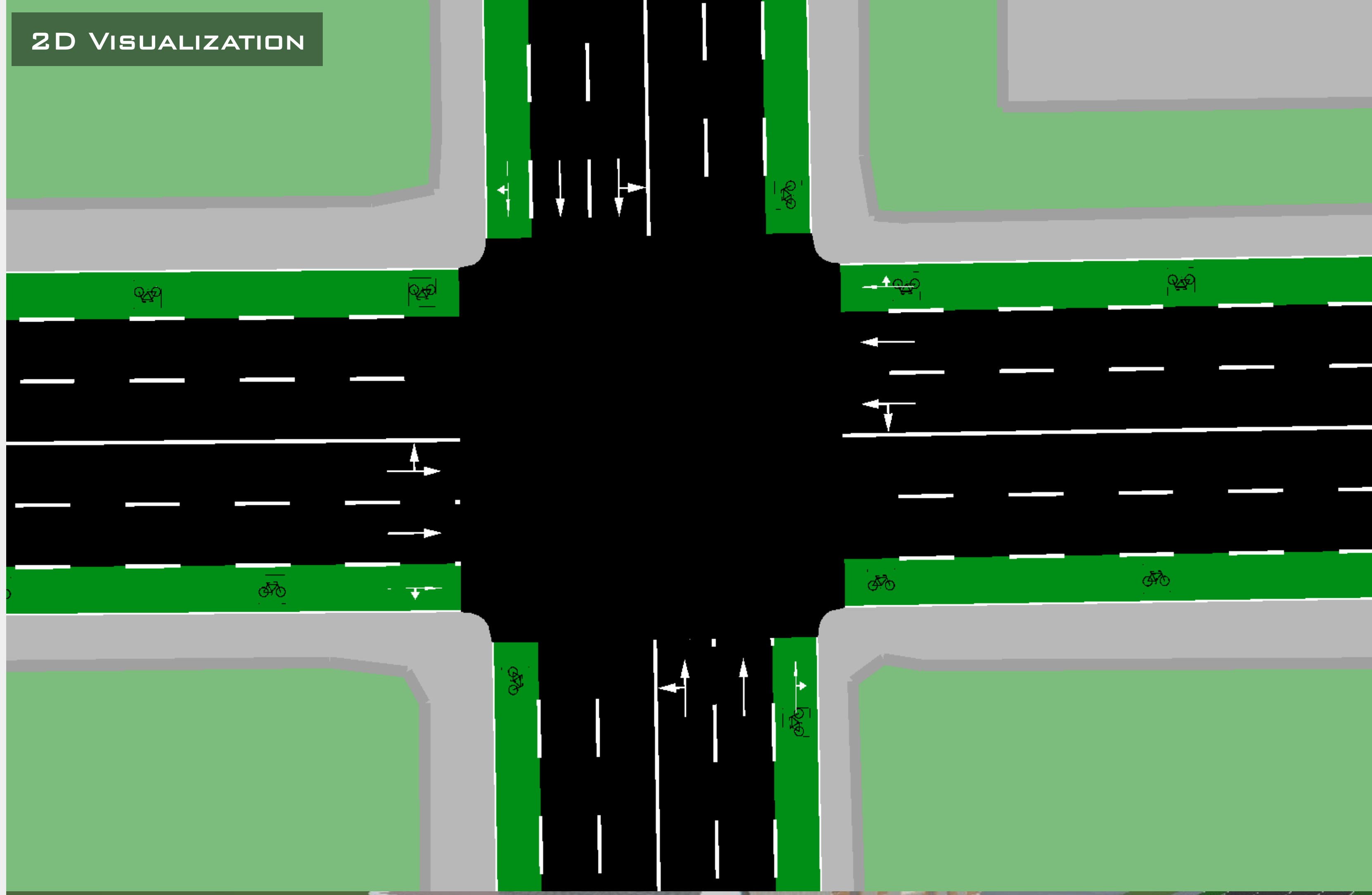
Mixed Traffic Planning:

AVs and Human-Driven Vehicles

Fall 2026

RoadwayVR

roadwayvr.github.io/TrafficSimulationforPlanningApplications



Agenda

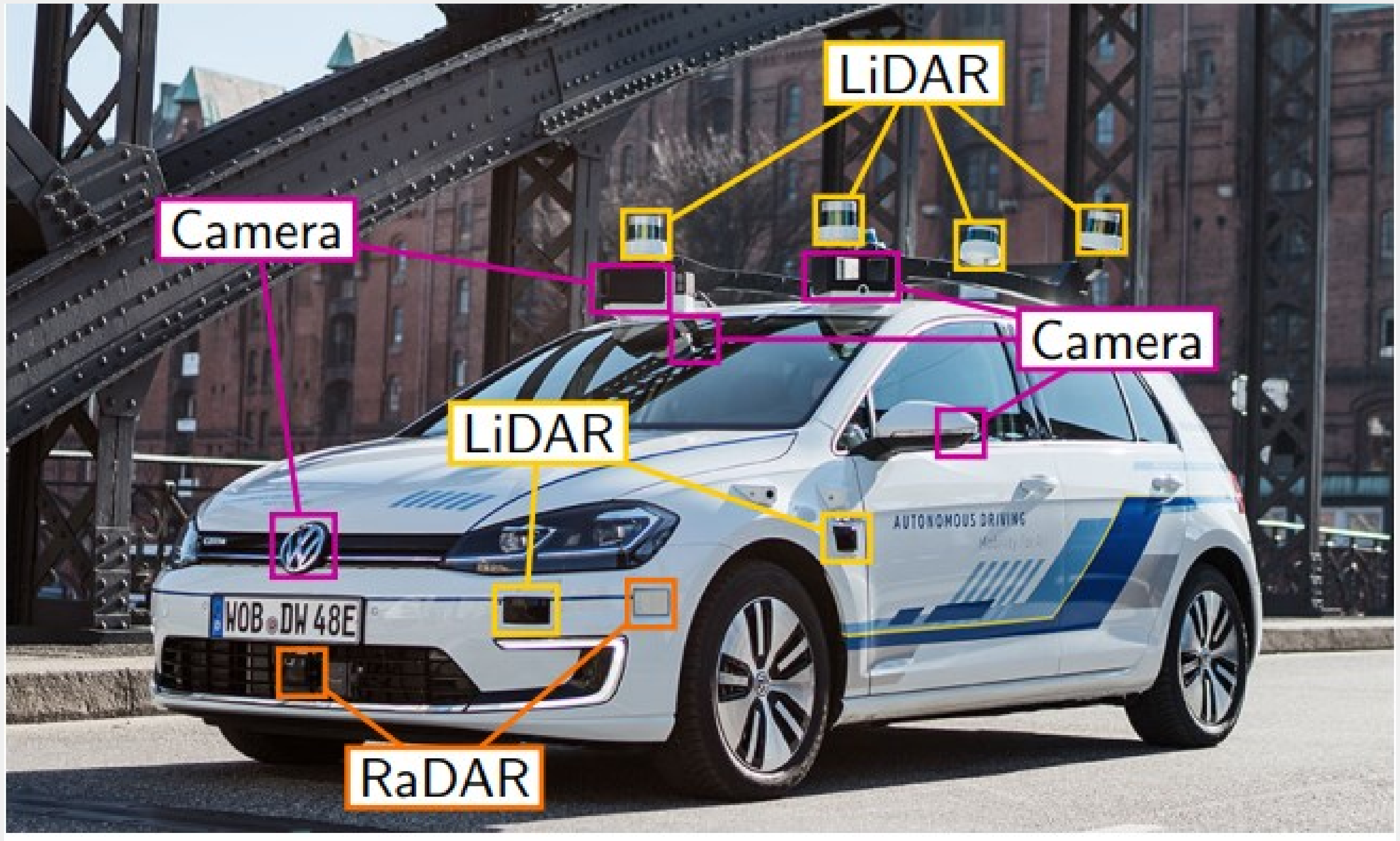
Autonomous *Vehicle (AVs)*

- ❑ Fundamental of Connected and Autonomous Vehicles (CAVs)
- ❑ Automation Levels
- ❑ Simulation Tools for CAVs CARLA, OMNET++/Vein, and SUMO
- ❑ Impact of Mixed Traffic Planning for AVs and HDV

https://www.transportation.gov/sites/dot.gov/files/docs/policy-initiatives/automated-vehicles/320711/preparing-future-transportation-automated-vehicle-30.pdf

Autonomous Vehicle

- **Autonomous Vehicle (AV) Without Connectivity:** Vehicles rely purely on their onboard sensors (for example, radar, Lidar, camera) and artificial intelligence algorithms to handle tasks like steering, braking/acceleration etc.



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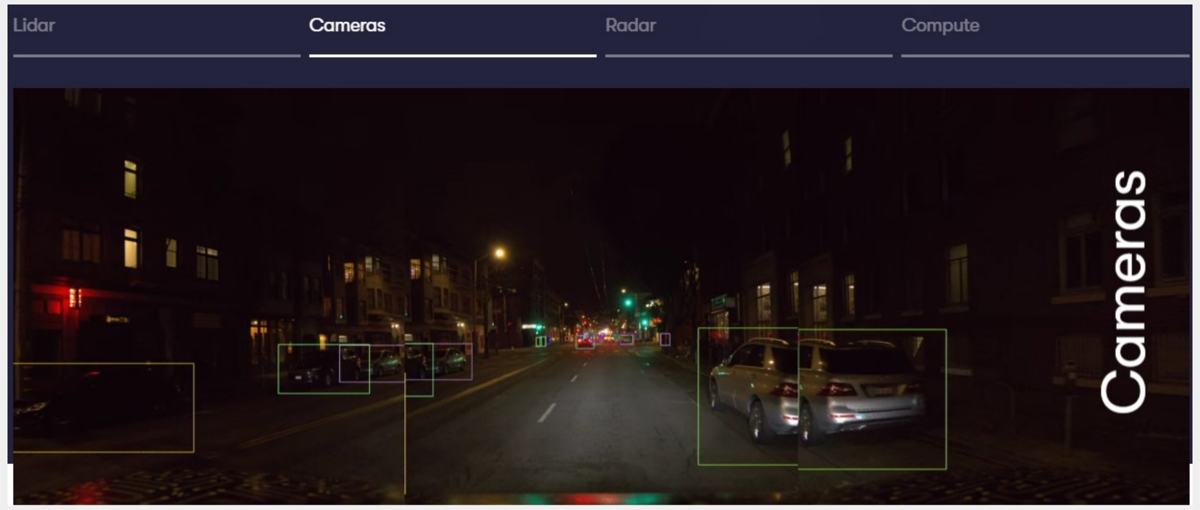
Autonomous Vehicle

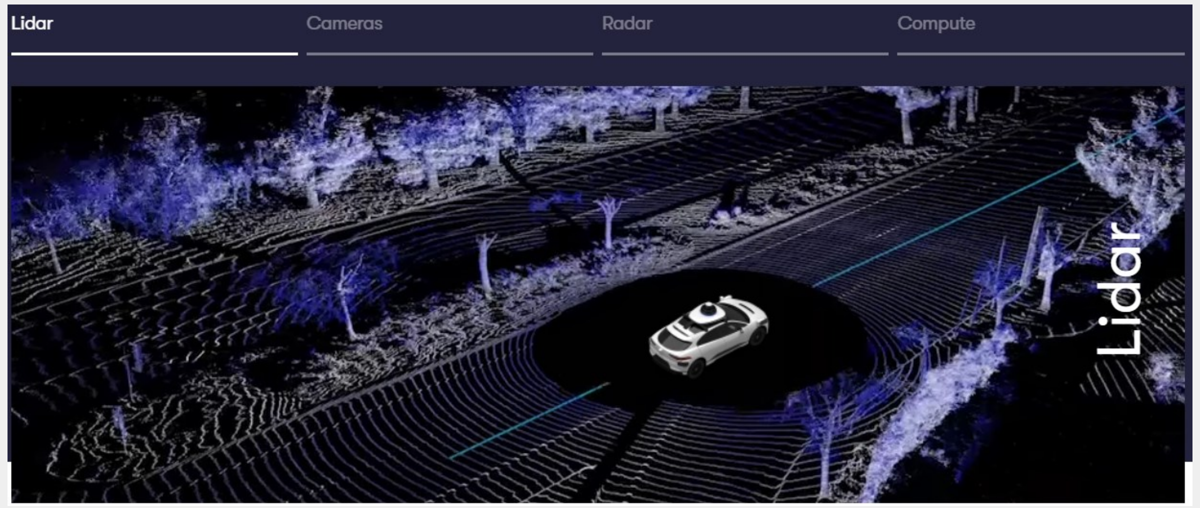
Camera:

❑Recognize lane markings, traffic signals, road signs, and obstacles like pedestrians or other vehicles.



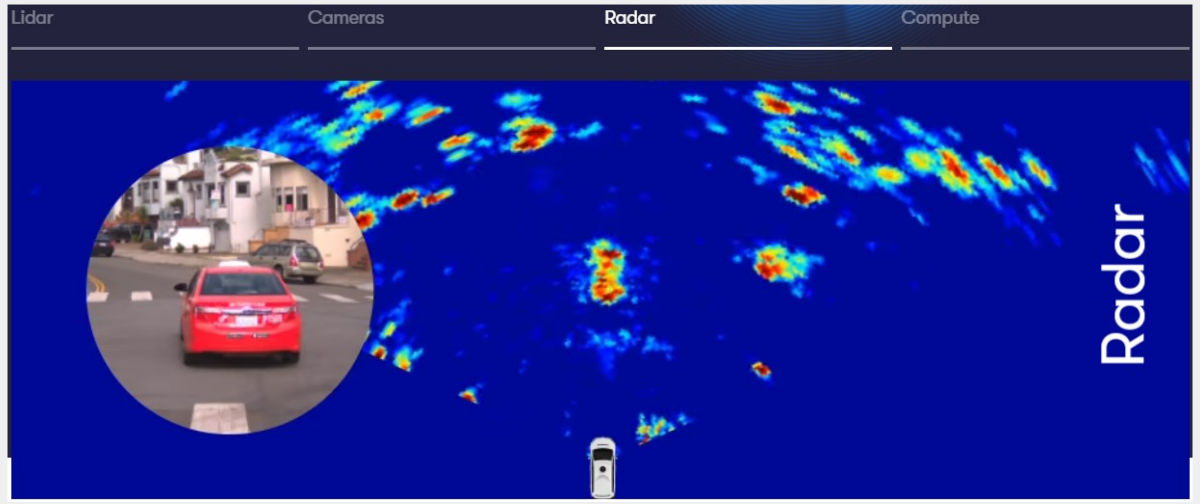
Lidar (light detection and ranging):

❑Measures exact distances to objects and maps the geometry of the scene.



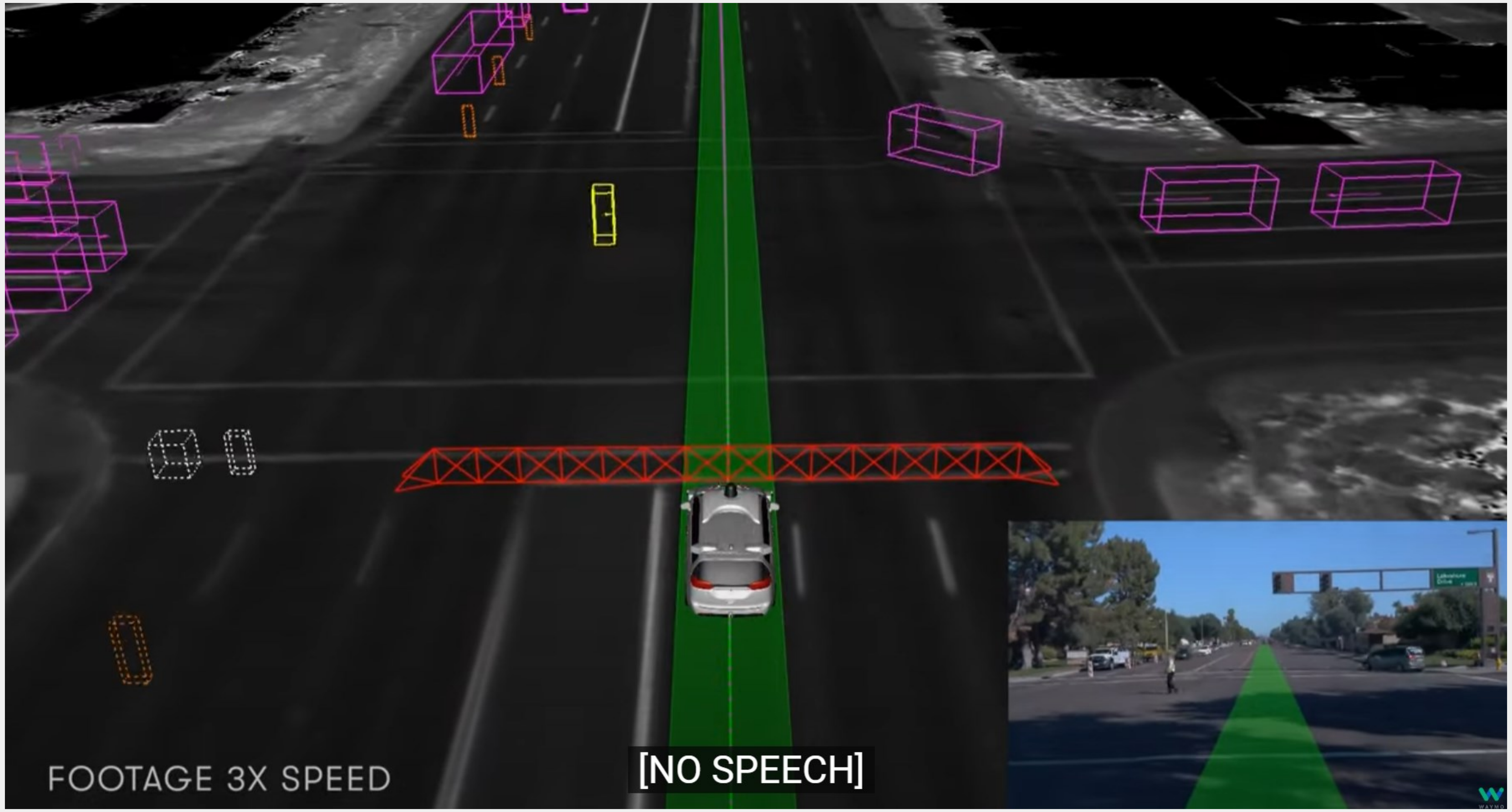
Radar:

❑ Measuring exact distances to objects and their relative speeds. It works well in adverse weather conditions (fog, rain, snow) where cameras and lidar may struggle.



What an AV Sees

- ❑Pause and watch the following video clip: https://www.youtube.com/watch?v=OopTOjnD3qY



Society of Automotive Engineers (SAE) Automation Levels

Level #	Functions	Hands / Feet / Eyes
Level 0 (No Automation)	Steering, accelerating, braking, monitoring environment are handled by drivers	Hands on wheel, foot on pedals, eyes on road at all times
Level 1 (Driver Assistance)	Either steering or accelerating/braking is handled by Driver Assistance Systems	Hands on wheel, foot on pedals, eyes on road at all times
Level 2 (Partial Automation)	Steering and accelerating/braking are handled by Driver Assistance Systems	Hands on wheel, foot on pedals, eyes on road at all times (system assists both steering & acceleration, but driver must stay vigilant)
Level 3 (Conditional Automation)	Steering, accelerating, braking, and monitoring are handled by the automated driving system	Hands/feet/eyes can be off under certain conditions, but driver must be ready to intervene upon system request
Level 4 (High Automation)	Steering, accelerating, braking, monitoring are handled by the automated driving system	Hands/feet/eyes off in the system's operational domain; no driver input needed unless outside that domain (for example, well-mapped urban areas or highways in good weather)
Level 5 (Full Automation)	Steering, accelerating, braking, monitoring are handled by the automated driving system	Hands/feet/eyes off in the system's operational domain

Reference
SAE International. J3016_201806: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles. Warrendale, PA: SAE International, 15 June 2018. https://www.sae.org/standards/content/j3016_201806/

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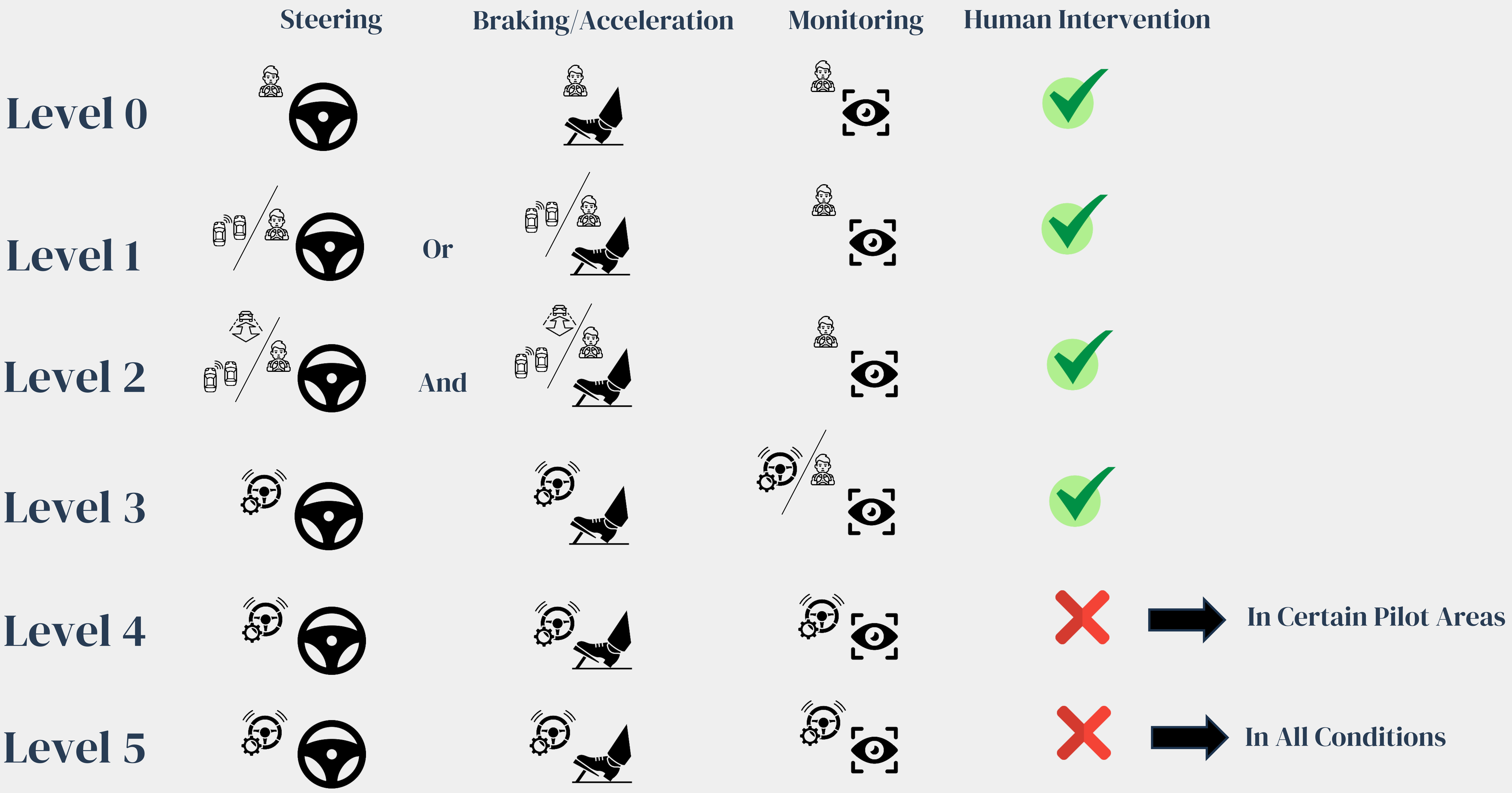

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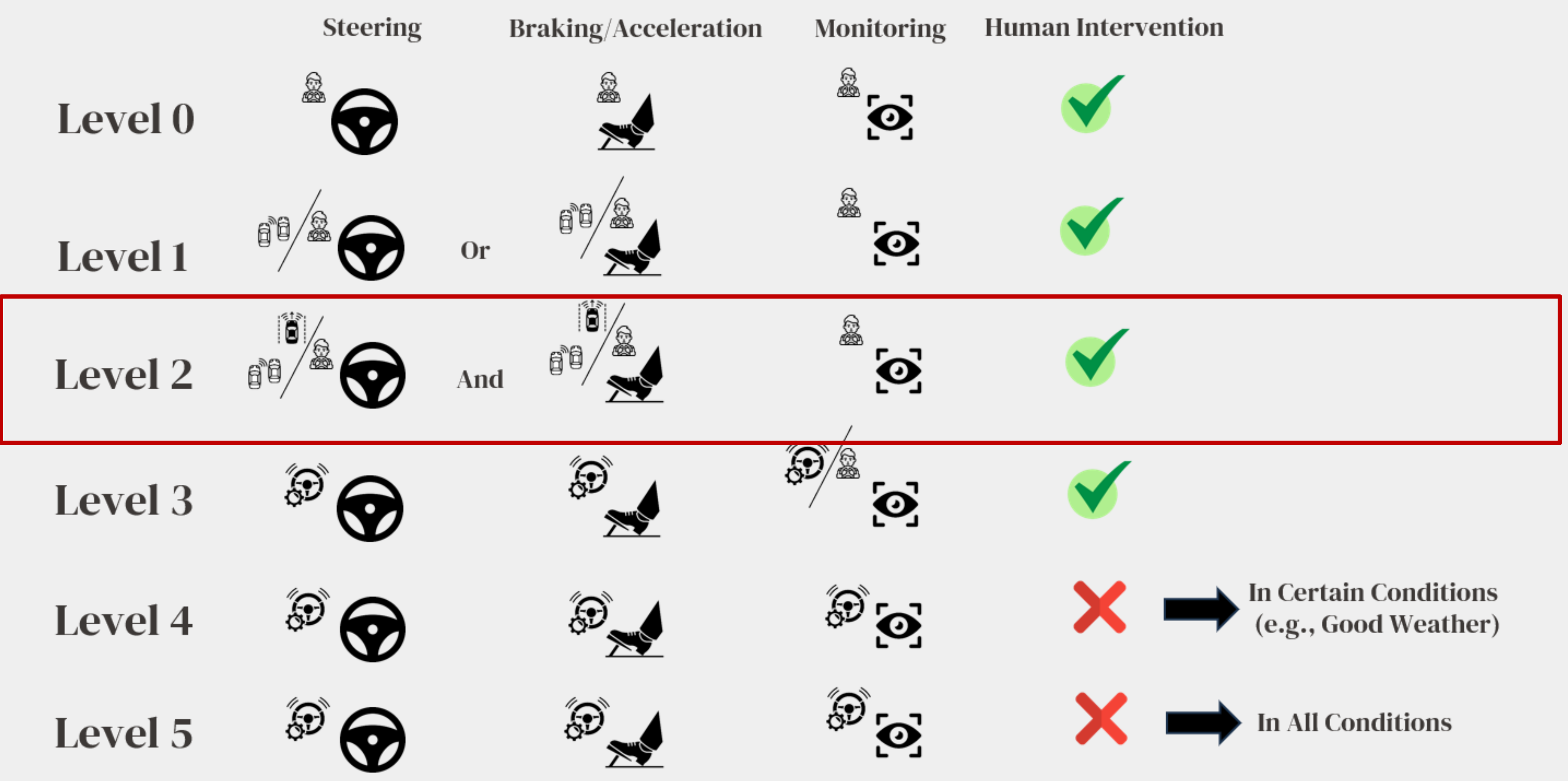

CACC Car Following Models for Acceleration and Braking in SUMO
Only Consider Longitude Movement

Li, H., Li, H., Hu, Y., Xia, T., Miao, Q., & Chu, J. (2023). Evaluation of fuel consumption and emissions benefits of connected and automated vehicles in mixed traffic flow. Frontiers in Energy Research, 11, 1207449.

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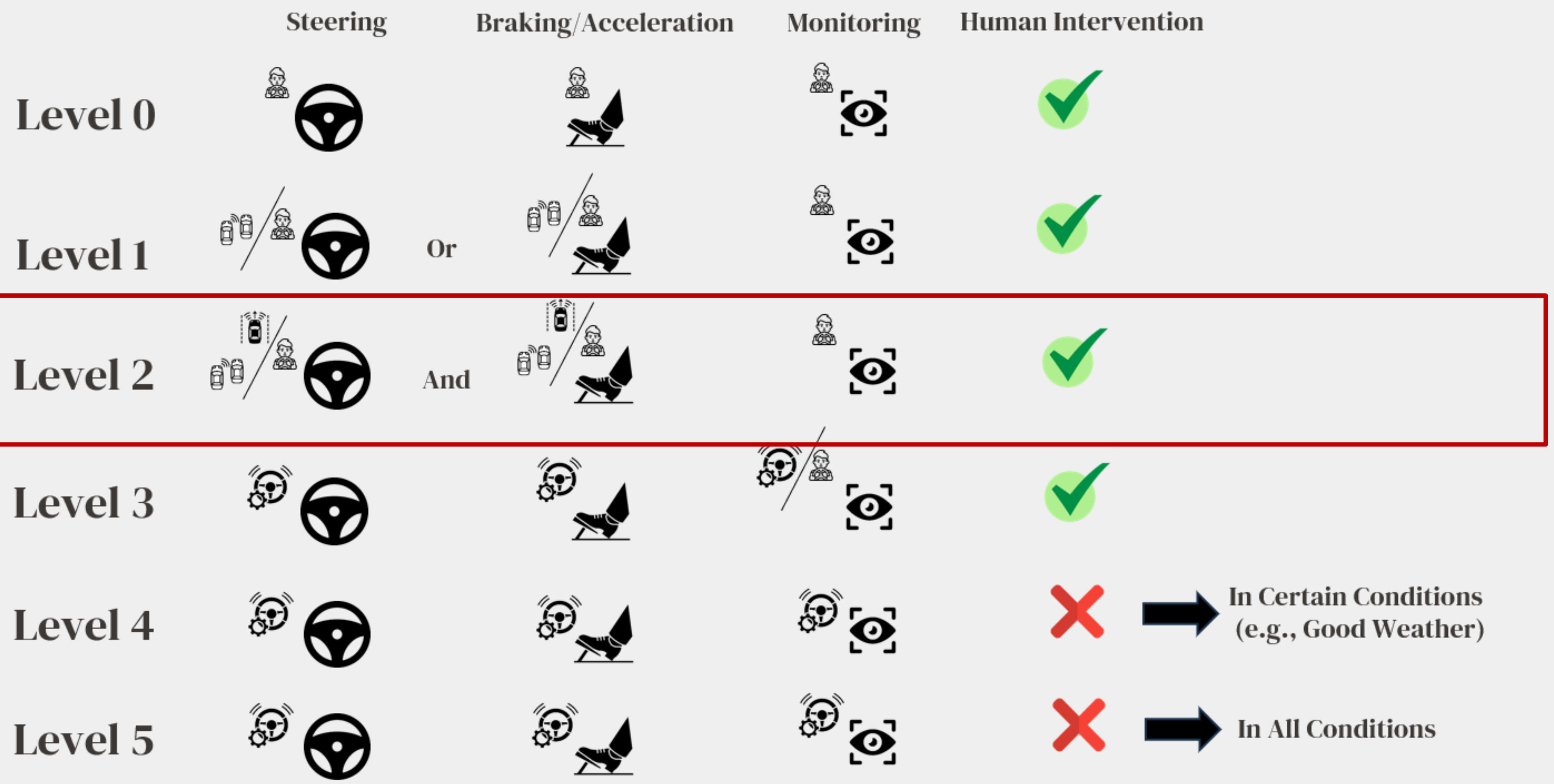

Tesla Autopilot

See video:
https://vimeo.com/192179726

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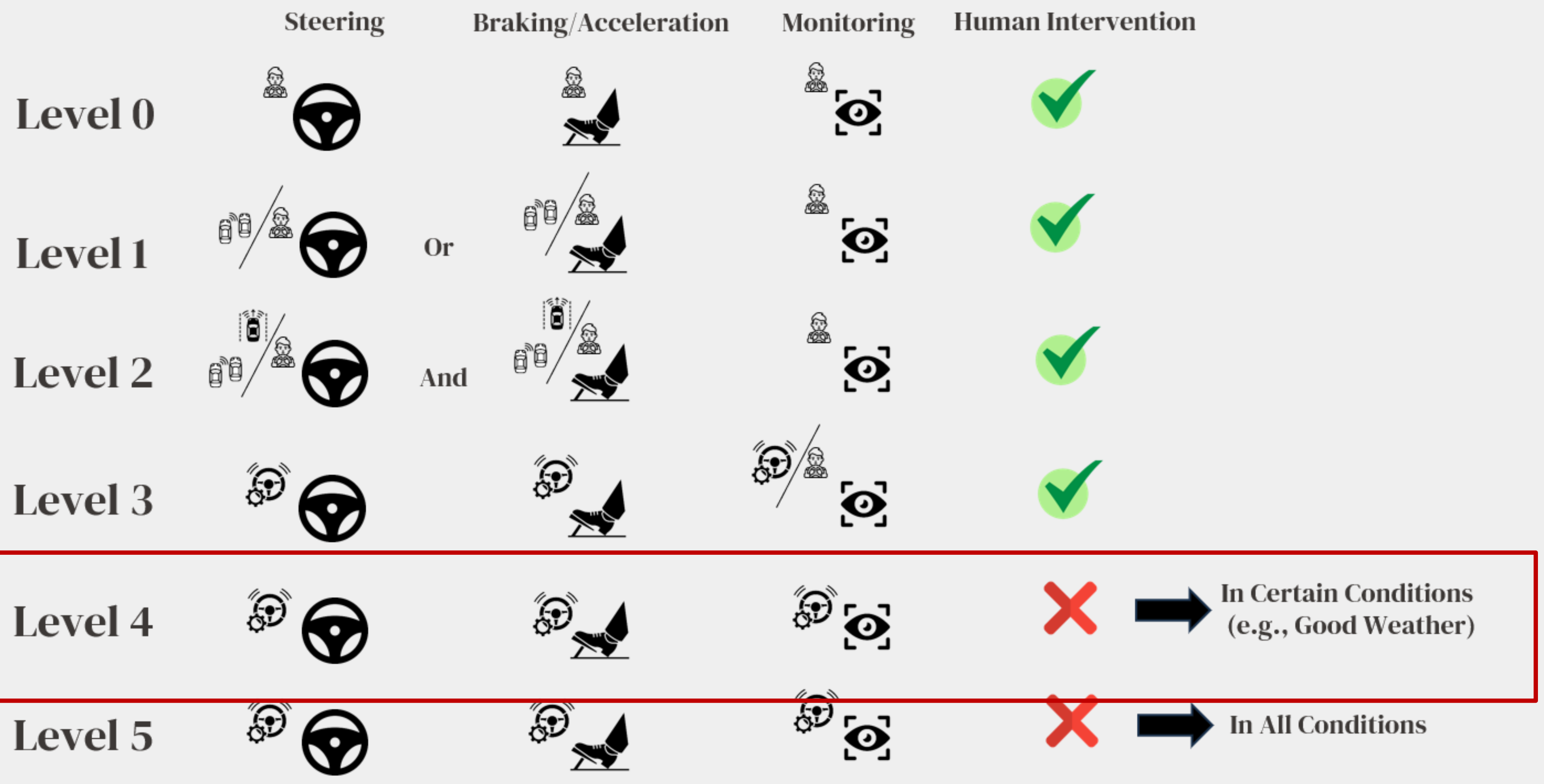
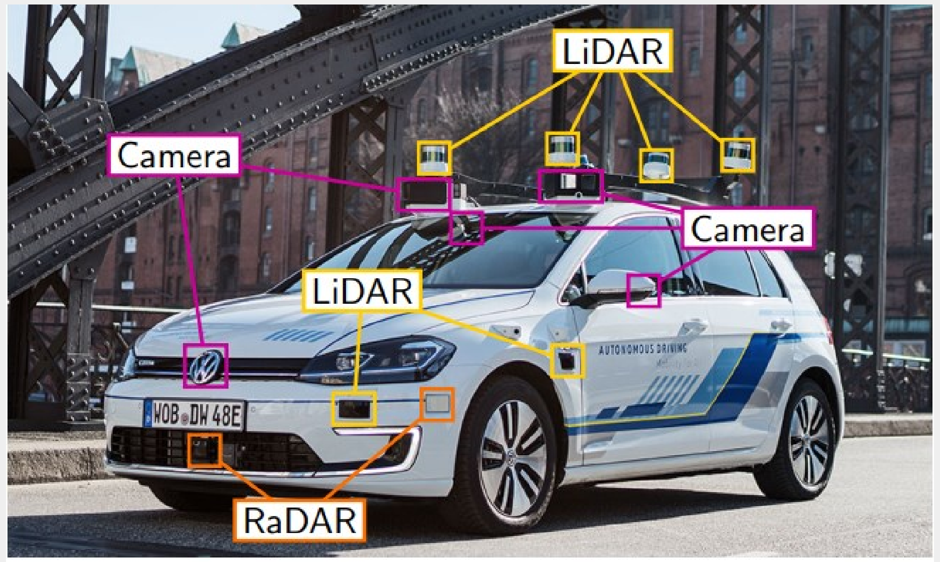


Waymo

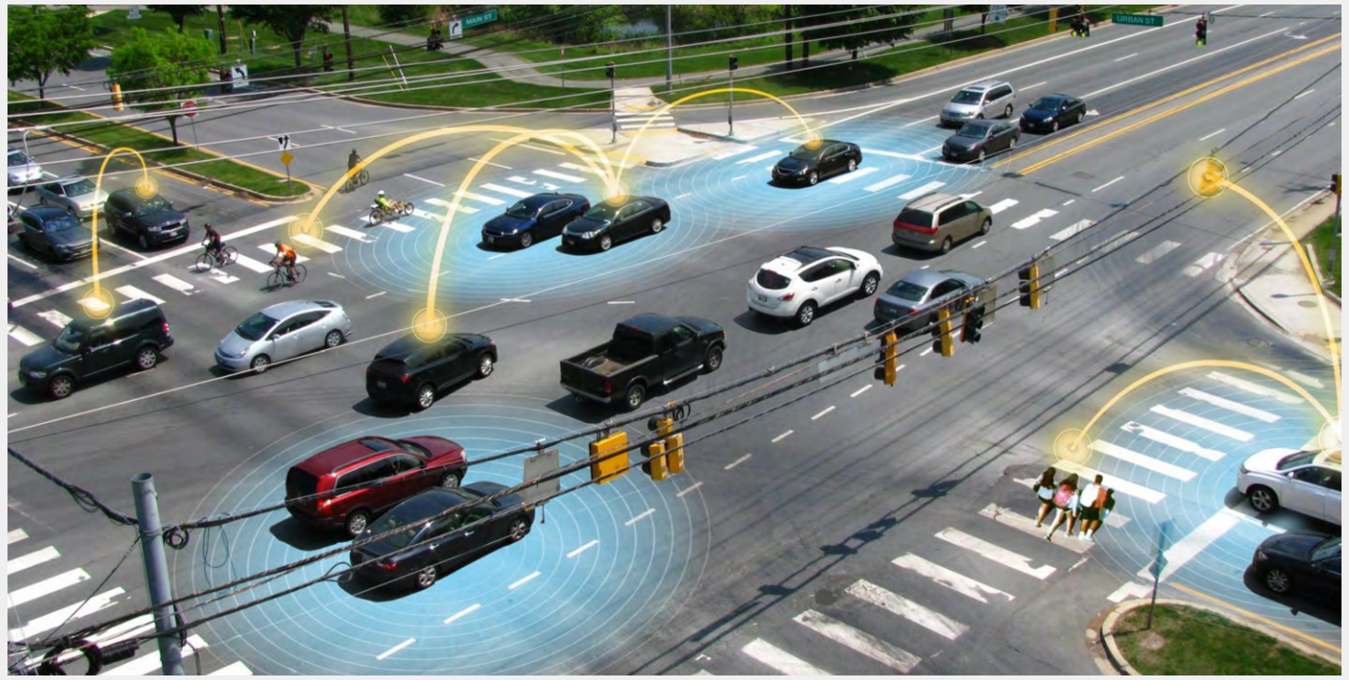
See : https://waymo.com/

Autonomous Vehicle and Connected Vehicles

- **Autonomous Vehicle (AV):** Vehicles rely purely on their onboard sensors (for example, radar, Lidar, camera) and artificial intelligence algorithms to handle tasks like steering, braking/acceleration etc.

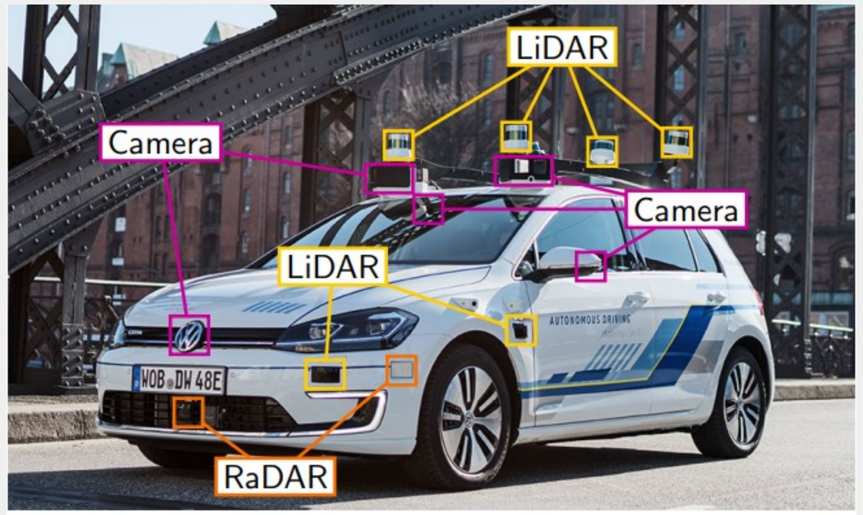


- **Connected Vehicle (CV):** A vehicle equipped with technology that allows it to communicate with other vehicles, the internet, and external devices, offering features like real-time traffic information, emergency assistance, and remote vehicle control.



Cooperative and Connected Autonomous Vehicles (CAVs)

- **Connected and Autonomous Vehicles (CAVs):** Vehicles have **both** onboard sensors and V2X (vehicle-to-everything) capabilities. The vehicle still makes use of local sensor data but also leverages information from other vehicles, and infrastructure such as traffic light information.
- The goal of CAVs: improving traffic flow, safety, and environment (energy and emission)
- V2V: Vehicle-to-Vehicle
- V2I: Vehicle-to-Infrastructure
- V2X: Vehicle-to-Everything (=V2V + V2I)



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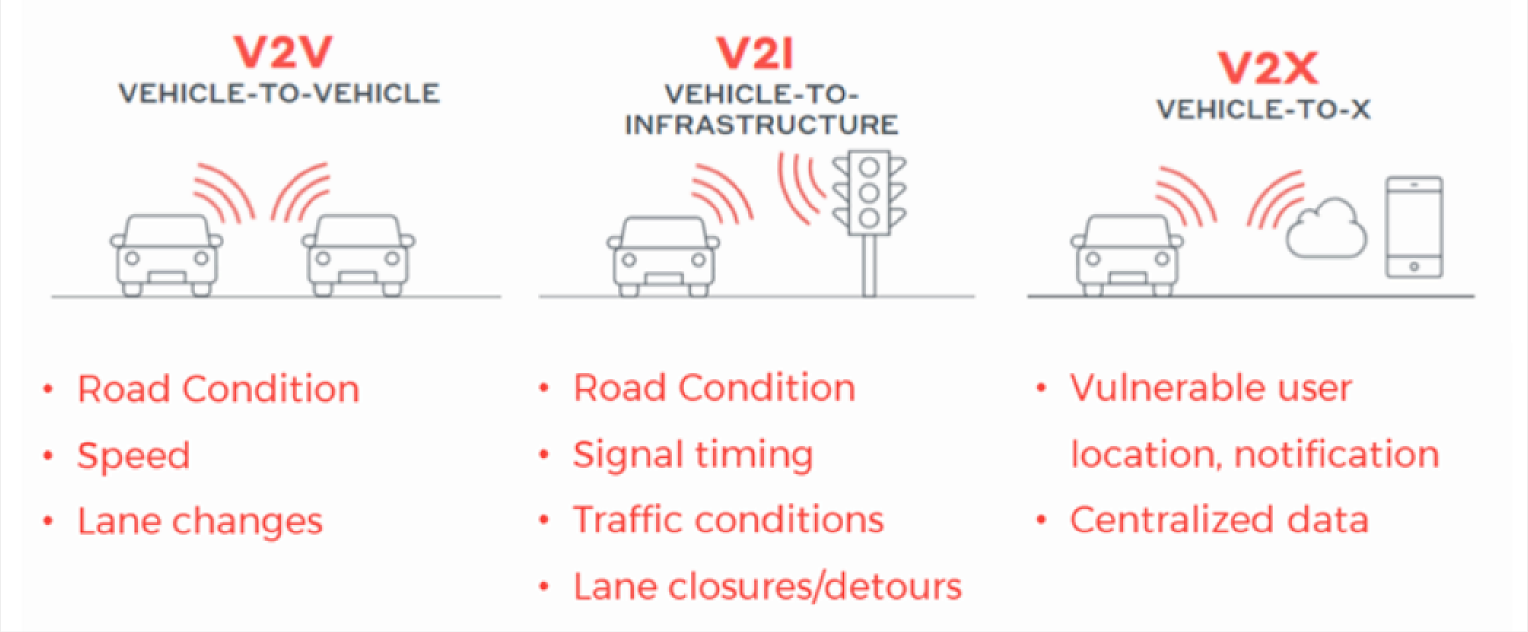


Reference: USDOT, https://www.ovinhub.ca/wp-content/uploads/2020/05/CAV-Readiness-Plan-Final-Report-2020-04-03-1.pdf

Watch The Following Video Clip

https://www.youtube.com/watch?v=Q8Cn47L8FRQ

V2X (Vehicle-to-Everything) Communication

- **V2X:** Lets vehicles exchange data about speed, position, hazards, and more—information that onboard sensors alone might not capture in time.
- How it Works:
- **DSRC (Dedicated Short-Range Communications):** uses a Wi-Fi–based protocol (IEEE 802.11p) to send messages directly between vehicles or between a vehicle and roadside units, typically in the 5.9 GHz band.
- **Cellular V2X (4G/5G):** uses mobile networks to enable direct communication (vehicle to vehicle) and/or network-based communication (vehicle to cloud/infrastructure).

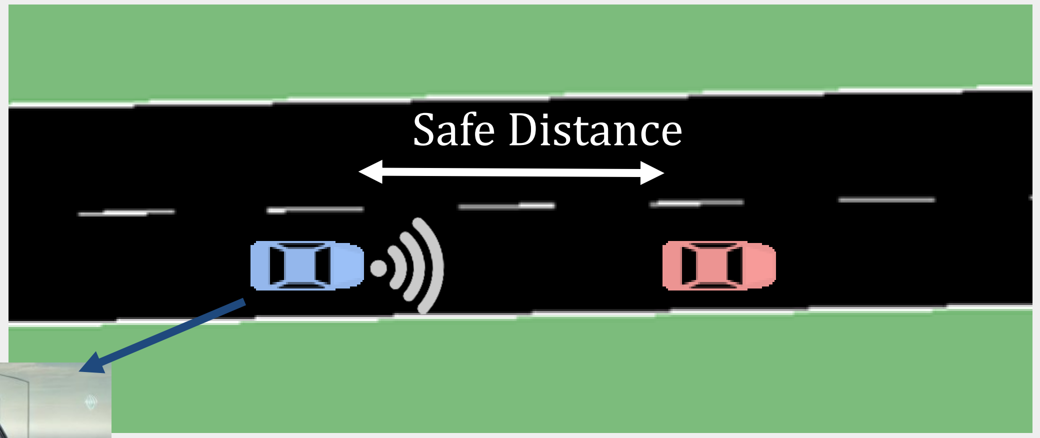
AVs – Technologies

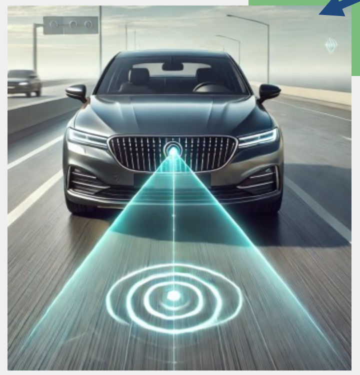
- **Adaptive Cruise Control (ACC):** Each Car use cameras and other sensors to detect surrounding cars and automatically adjusts the vehicle's speed to maintain a safe distance

- **ACC** is one of the foundational technologies in the progression toward self-driving vehicles.

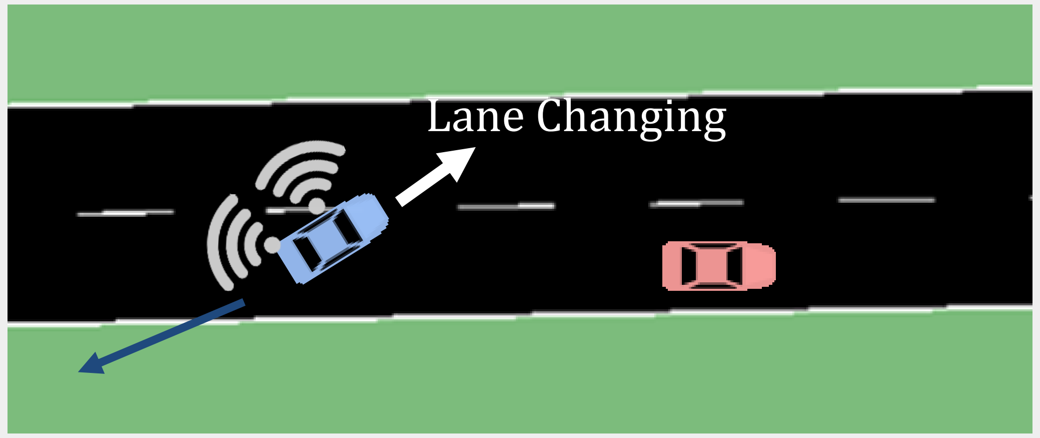
- **Auto Lane Change (Lane Change Assist):** Each Car uses cameras and other sensors to detect gaps in adjacent lanes and help initiate a safe lane change maneuver when conditions are appropriate.

Longitudinal Movement



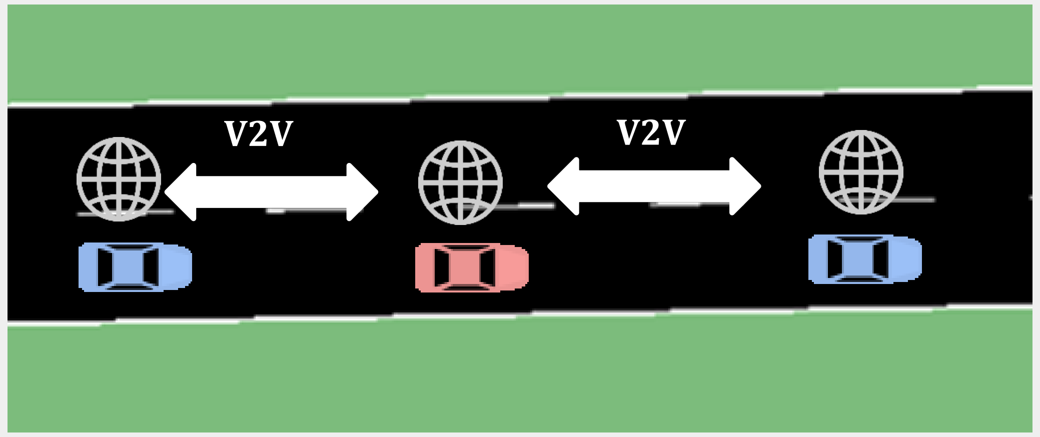


Lateral Movement



CAV - Technology

- **Cooperative Adaptive Cruise Control (CACC):** Each car has ACC and use vehicle-to-vehicle communication (V2V) to share speed and positioning data.



Benefits Over ACC:

- **Extended Awareness:** Sensors typically have a limited range, so a vehicle might only detect the one directly ahead. V2V communication allows vehicles to receive information about speed and acceleration from multiple vehicles further up the platoon, offering a broader view of traffic conditions.

- **Reduced Latency:** Communication between vehicles can deliver real-time data more quickly than sensors that need to process reflected signals, helping vehicles react faster to changes.

- **Enhanced Predictability:** By knowing the exact speed and intended maneuvers of preceding vehicles, a car can anticipate changes (like deceleration or lane changes) earlier, leading to smoother and safer adjustments.

Difference Of
Carla, OMNET ++/Veins, SUMO

Carla Use:

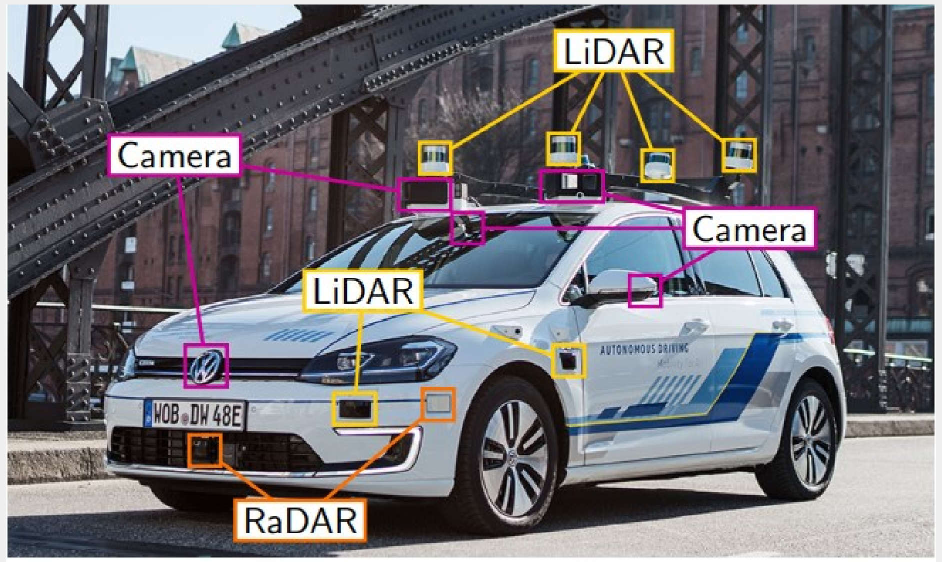
- Computer vision research

OMNET ++/ Veins Use:

- Communication protocols and networking

SUMO Use:

Realistic traffic flows and scenarios, including congestion, traffic lights



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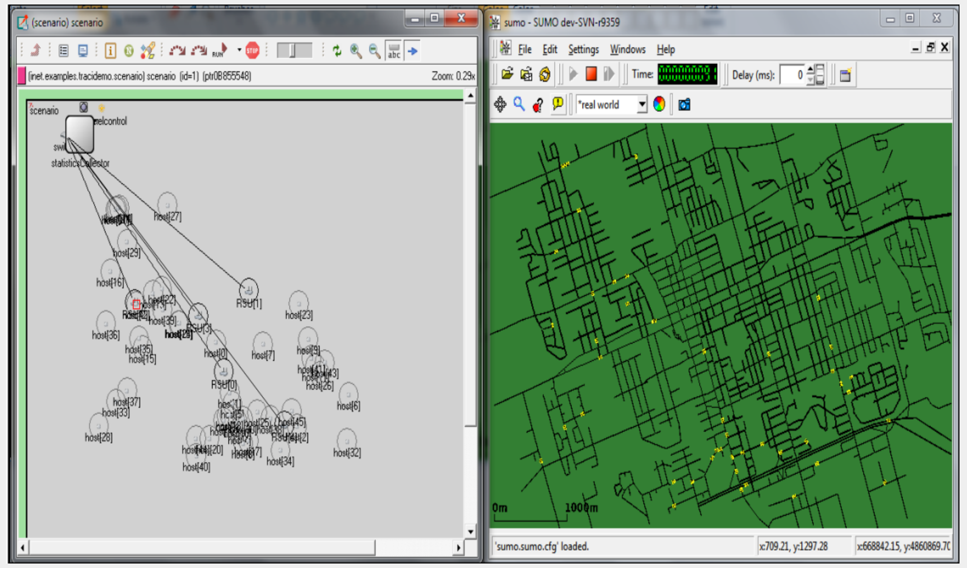

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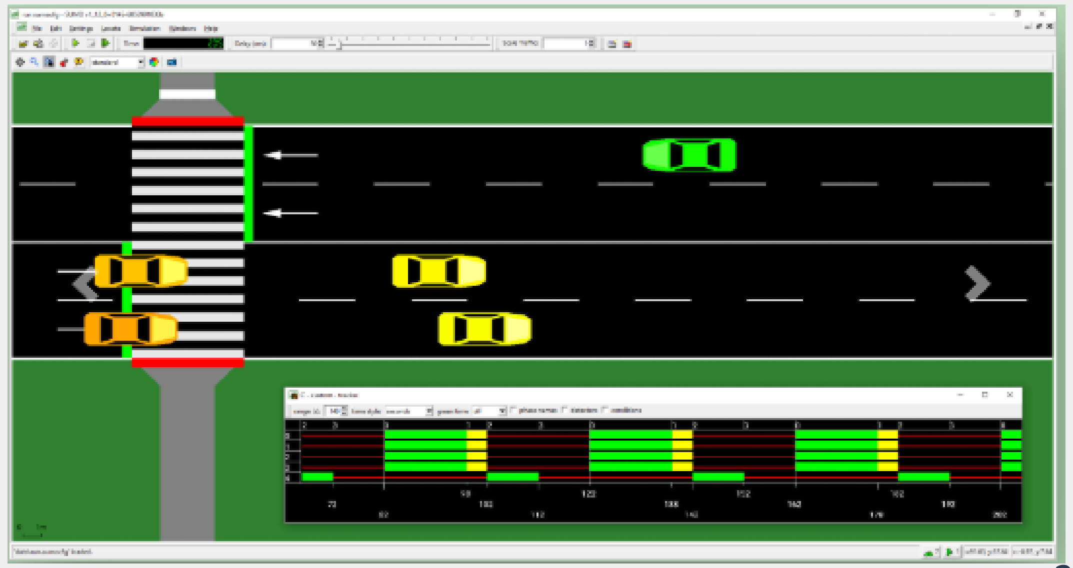


Difference Of
Carla, OMNET ++/Veins, SUMO

Carla Use:

Primary Focus: emphasizing sensor data (cameras, LiDAR, radar)

Key Use Cases:

- Computer vision research
- Testing AV control algorithms for sensor fusion, environment perception, and navigation.

OMNET ++/ Veins Use:

Primary Focus: Network simulations, specifically for vehicular ad-hoc networks (VANETs) and vehicle-to-everything (V2X) communication.

Key Use Cases:

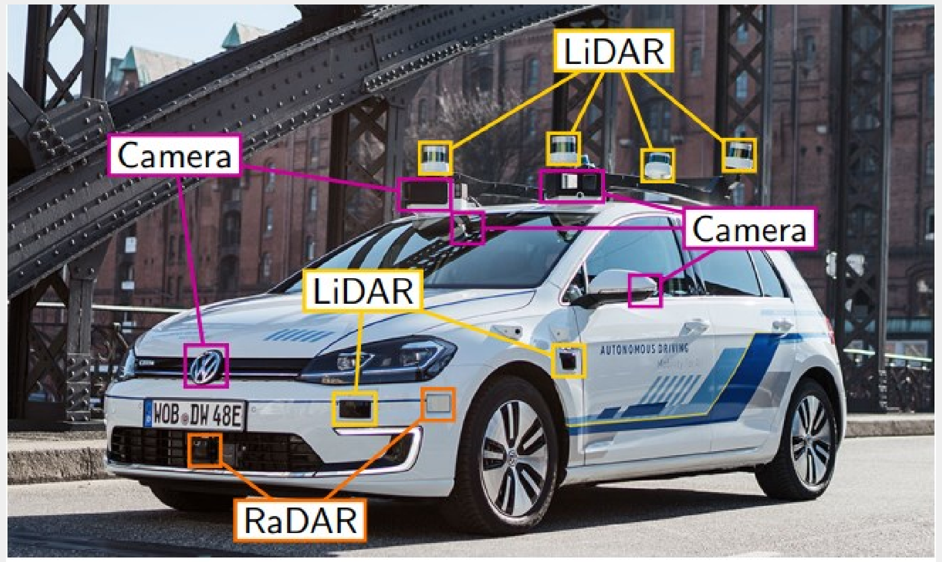
- Evaluating communication protocols and networking strategies among vehicles (e.g., DSRC, IEEE 802.11p, LTE-V).
- Investigating scalability, latency, and reliability of inter-vehicle communication.
- Integrating with SUMO focusing on the network layers.

SUMO Use:

Primary Focus: Traffic simulation and modeling of transportation roads, supporting mixed traffic (cars, trucks, buses, bicycles, pedestrians, AVs etc.).

Key Use Cases:

- Generating realistic traffic flows and scenarios, including congestion, traffic lights,
- Studying cooperative and automated driving strategies in a larger traffic environment (e.g., CACC – Cooperative Adaptive Cruise Control).



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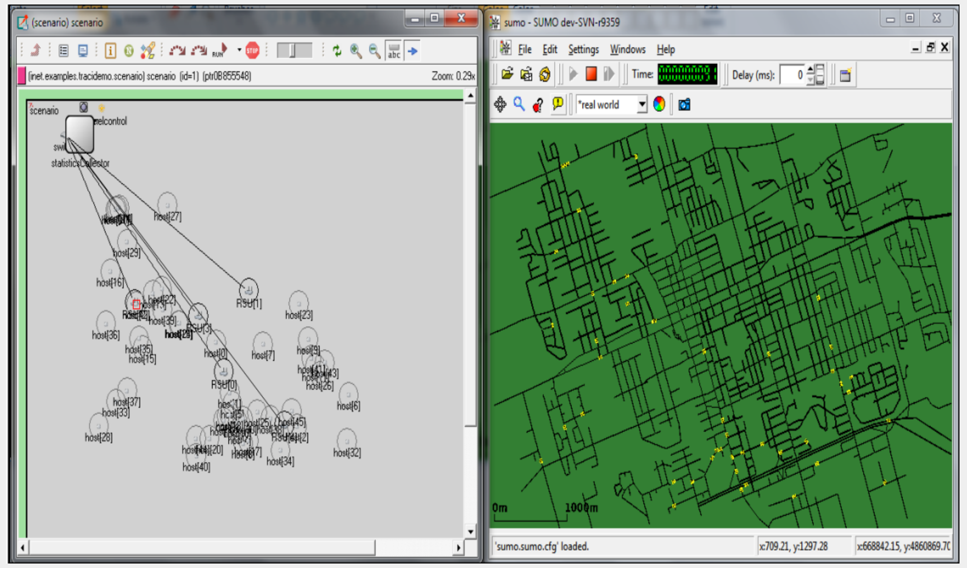

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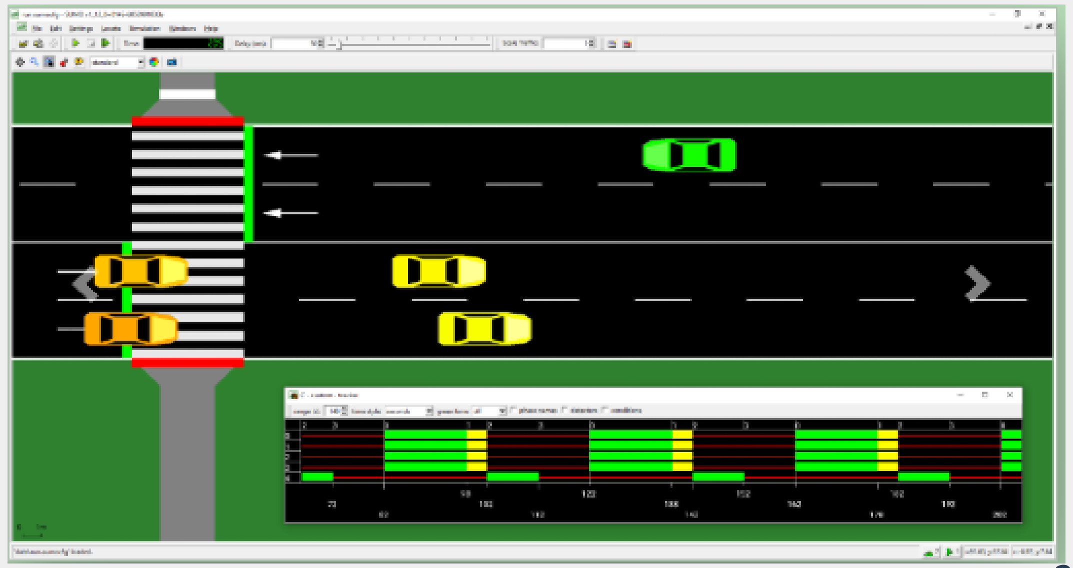

CARLA in Unreal Engine

Carla for Autonomous Vehicle Simulation and Testing (SAE Levels 0-6)

https://www.youtube.com/watch?v=u2TxYhv3UKE&t=14s

Sensors reference

- Collision detector
- Depth camera
- GNSS sensor
- IMU sensor
- Lane invasion detector
- LIDAR sensor
- Obstacle detector
- Radar sensor
- RGB camera
- RSS sensor
- Semantic LIDAR sensor
- Semantic segmentation camera
- Instance segmentation camera
- DVS camera
- Optical Flow camera

AWSIM in Unity

- AWSIM for Autonomous Vehicle Simulation and Testing (SAE Levels 0-6)

A Comprehensive Comparative Analysis of CARLA and AWSIM: Open-Source Autonomous Driving Simulators

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[b] *Western Power, 363 Wellington St, Perth, 6000, WA, Australia*

Abstract

The number of open-source autonomous driving simulators has been increasing in recent years, and many papers have surveyed the most popular options. However, there is a lack of in-depth and comprehensive comparison among the most advanced open-source simulators. This article provides a detailed quantitative and qualitative analysis of two of the most promising simulators for end-to-end testing: CARLA and AWSIM. The analysis focuses on various metrics, including the efficiency of simulation, the realism of physics simulation, scenario creation and testing, user-friendliness, and extendability. Based on our findings, we conclude that CARLA remains the best open-source simulator for end-to-end testing, while AWSIM shows advanced performance in specific areas, such as Lidar-based algorithms and Autoware development.

Keywords: Autonomous driving simulator, Unreal engine, Unity, CARLA, AWSIM

Figure 2.5: CARLA Simulator

Figure 2.6: AWSIM

Table 3: CARLA vs. AWSIM Comparison Table

Criteria	Weight	CARLA			AWSIM Unity		
		Raw	Score	Weighted	Raw	Score	Weighted
GPU Utilization	2	32.52%	1.000	2.000	37.85%	0.859	1.718
GPU Used Dedicated Memory	1	30.21%	0.562	0.562	16.98%	1.000	1.000
Real-time Factor	3	65.50%	0.655	1.965	100.00%	1.000	3.000
CPU Utilization	2	29.56%	1.000	2.000	30.02%	0.985	1.969
CPU Memory	1	22.34%	0.568	0.568	12.68%	1.000	1.000
Tire-Road Interaction	1	-	0.300	0.300	-	0.000	0.000
Multi-body Dynamics	1	-	0.300	0.300	-	0.000	0.000
Actuator and Powertrain Modelling	1	-	0.300	0.300	-	0.000	0.000
Integrated Control System Modeling	1	-	0.300	0.300	-	0.000	0.000
Vehicle Parametrization and Customization	1	-	0.300	0.300	-	0.000	0.000
GNSS	3	✓	1.000	3.000	✓	1.000	3.000
IMU	3	✓	1.000	3.000	✓	1.000	3.000
RGB Camera	10	✓	0.850	8.500	✓	0.950	9.500
Depth Camera	2	✓	1.000	2.000	-	0.000	0.000
Event/DVS Camera	2	✓	1.000	2.000	-	0.000	0.000
LiDAR	10	✓	0.500	5.000	✓	0.750	7.500
Radar	2	✓	1.000	2.000	✓	1.000	2.000
V2X	1	✓	1.000	1.000	✓	1.000	1.000
Night	4	✓	1.000	4.000	-	0.300	1.200
Cloudy	4	✓	1.000	4.000	-	0.300	1.200
Rainy	4	✓	0.800	3.200	-	0.200	0.800
Foggy	2	✓	0.800	1.600	-	0.200	0.400
Snowy	1	-	0.100	0.100	-	0.200	0.200
Lighting Conditions	5	✓	1.000	5.000	✓	0.800	4.000
Pedestrian Lights	4	✓	1.000	4.000	✓	1.000	4.000
Classic Traffclights	5	✓	1.000	5.000	✓	1.000	5.000

Impact of Mixed Traffic Planning for AVs and HDV

- Mixed Traffic Flow
  - Traffic Efficiency
    - Traffic Density
    - Traffic Flow
    - Traffic Speed
  - Traffic Safety
    - Surrogate Safety Measures
    - Time to Collision (TTC)
    - Post Encroachment Time (PET)
  - Energy Consumption and Emissions
    - Fuel
    - CO
    - NO
  - Platooning
    - Traffic Efficiency
    - Traffic Safety
    - Energy Consumption and Emissions