



Autonomous Parking in an Unknown Dynamic Environment using CARLA

Team 9: SE (4)

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Background & Motivation

- **Autonomous parking** is vital for Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) applications.
- Vehicles must **navigate dynamic, partially unknown environments** with moving obstacles and unknown initial positions.
- Existing open-source solutions often simplify to 2D scenarios, ignore non-holonomic constraints of the vehicle, or neglect possibility of **dynamic obstacles**.
- These assumptions **limit their real-world applicability**.
- This paper overcomes these assumptions using **ROS-integrated Carla** simulation platform.

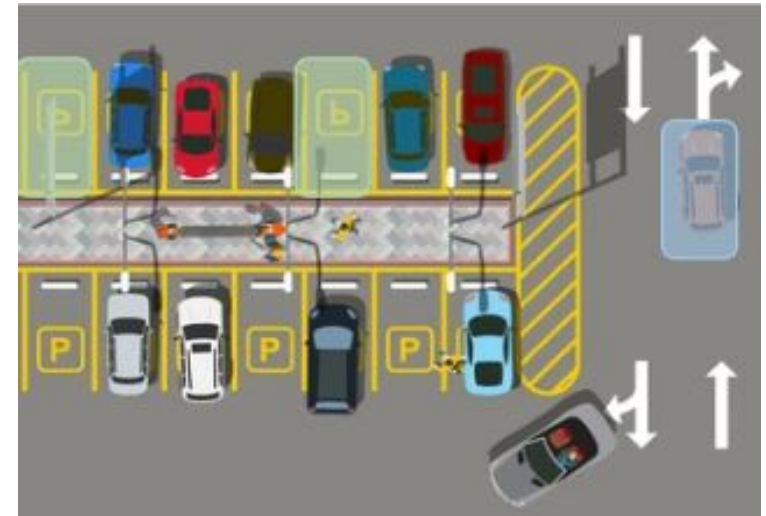
Problem Statement

Autonomous Parking

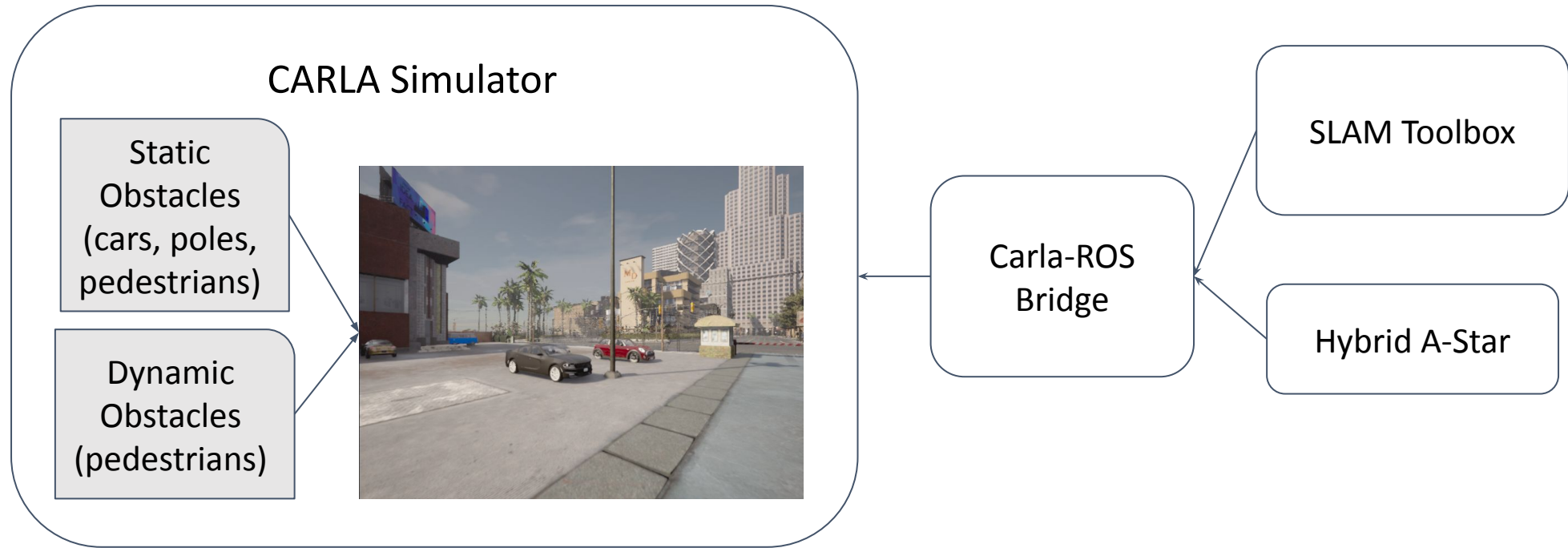
- From an arbitrary starting position in a parking lot, the car searches for an obstacle-free path to the provided parking spot and completes the parking maneuver autonomously.

Assumptions:

- Dynamic objects: Walking pedestrians.
- Goal coordinate and orientation of the parking spot are known.
- There exists at least one open spot.



Proposed Method



Path Planning

Hybrid A*:

- Extension of A* - incorporated non-holonomic constraints - ideal for vehicle navigation.
- Continuous Space Search - Nodes are expanded on possible vehicle motions.
- Ensures path is feasible for vehicles with limited turning ability.
- Uses Reeds-Shepp or Dubins curves to produce drivable paths.
- In our application, Hybrid A* is called every 0.5 second to account for dynamic obstacles.

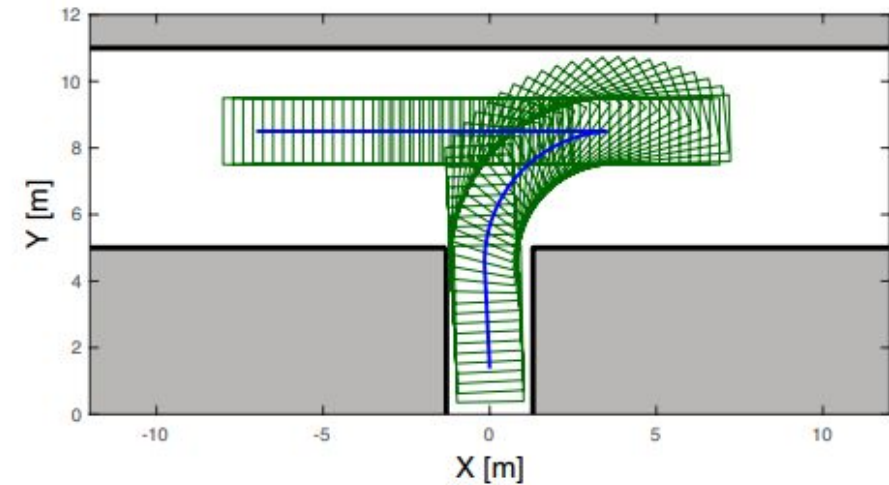


Figure 6: Initial guess provided by Hybrid A* for reverse parking.

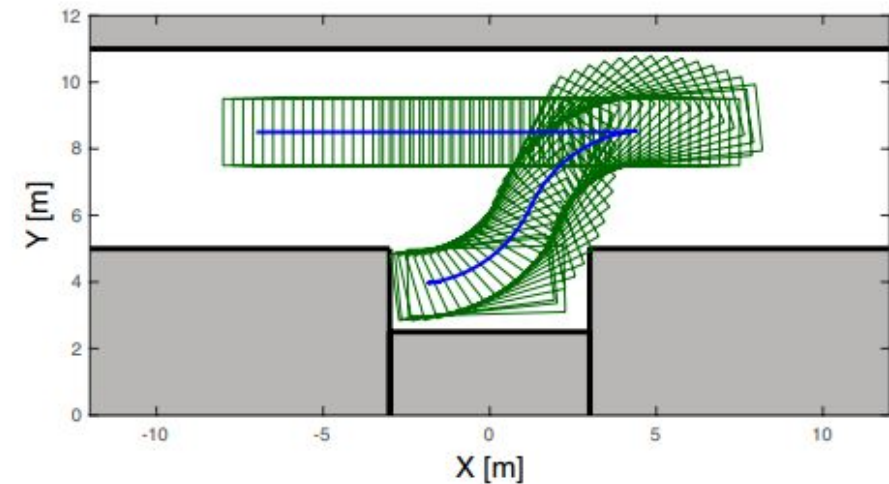
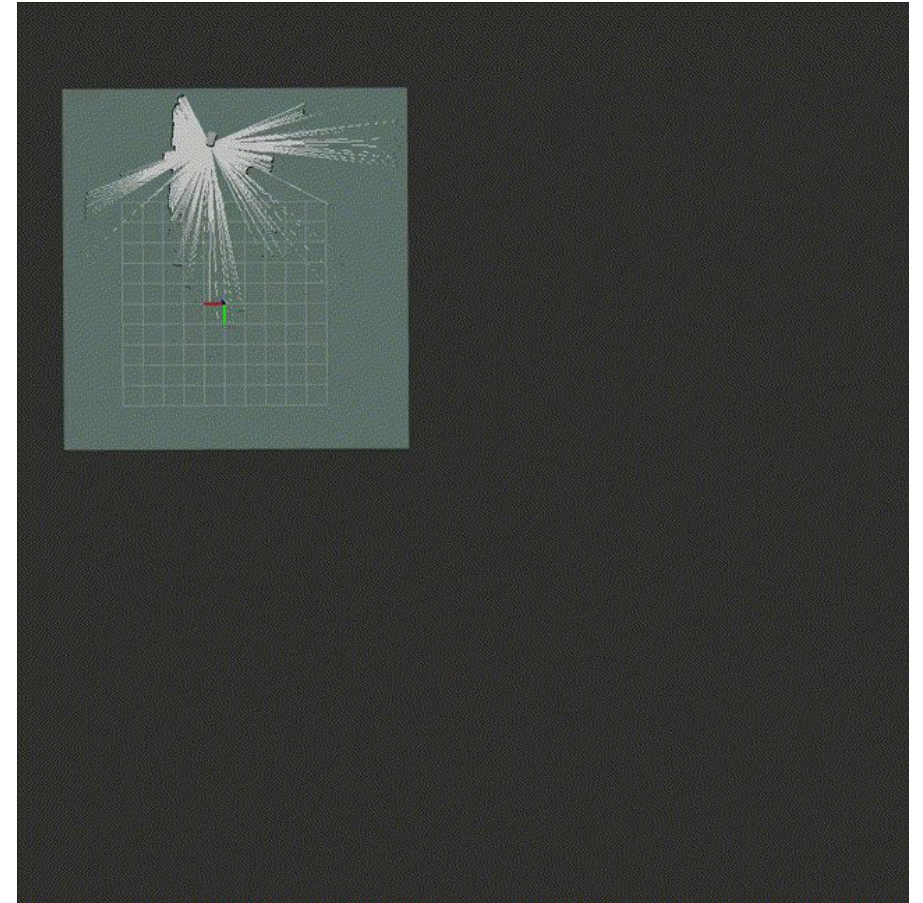


Figure 7: Initial guess provided by Hybrid A* for parallel parking.

SLAM

SLAM Toolbox:

- Lidar Based SLAM method that relies on pose graph estimation using odometry data and lidar scans.
- Builds a 2D occupancy grid to represent surrounding environment.
- Easily integrated into ROS.
- The constructed occupancy grid and vehicle's pose is passed into Hybrid A*.



Our Method in Action

The screenshot displays a ROS environment with three main components:

- Code Editor:** Shows XML configuration for a CARLA connection with arguments for host, port, timeout, and a parameter for using simulation time.
- Terminal Window:** Displays ROS logs for a package named 'carla-ros-bridge'. The logs show the start of a simulation, vehicle initialization (CeresS), and various status messages including location, speed, and gear.
- CARLA ROS manual control Window:** A control interface for the CARLA simulation. It displays real-time vehicle data: Frame (0), Simulation time (0:00:00), FPS (0.0), Vehicle (CeresS), Speed (0 km/h), Heading (0° N), Location (0.0, 0.0), GNSS (0.000000, 0.000000), and Height (0 m). It also includes sliders for Throttle, Steer, and Brake, checkboxes for Reverse, Hand brake, and Manual, and a Gear selector set to 'N'. A 'Manual ctrl' checkbox is also present.

The terminal window also shows a warning about deprecated resources and a message indicating that the vehicle control manual override is set to False.

Dynamic Obstacles

How do we avoid pedestrians in the environment?

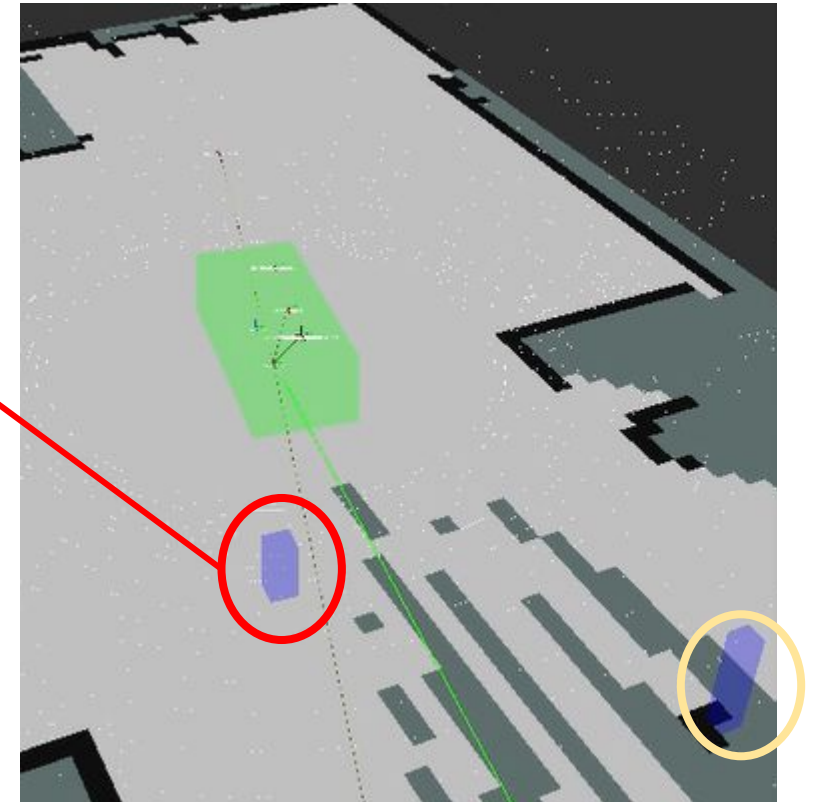
2 Scenarios

Dynamic Pedestrians

- Wait for pedestrian to pass out of the current path

Static Pedestrians

- Consider them an obstacle to path plan around

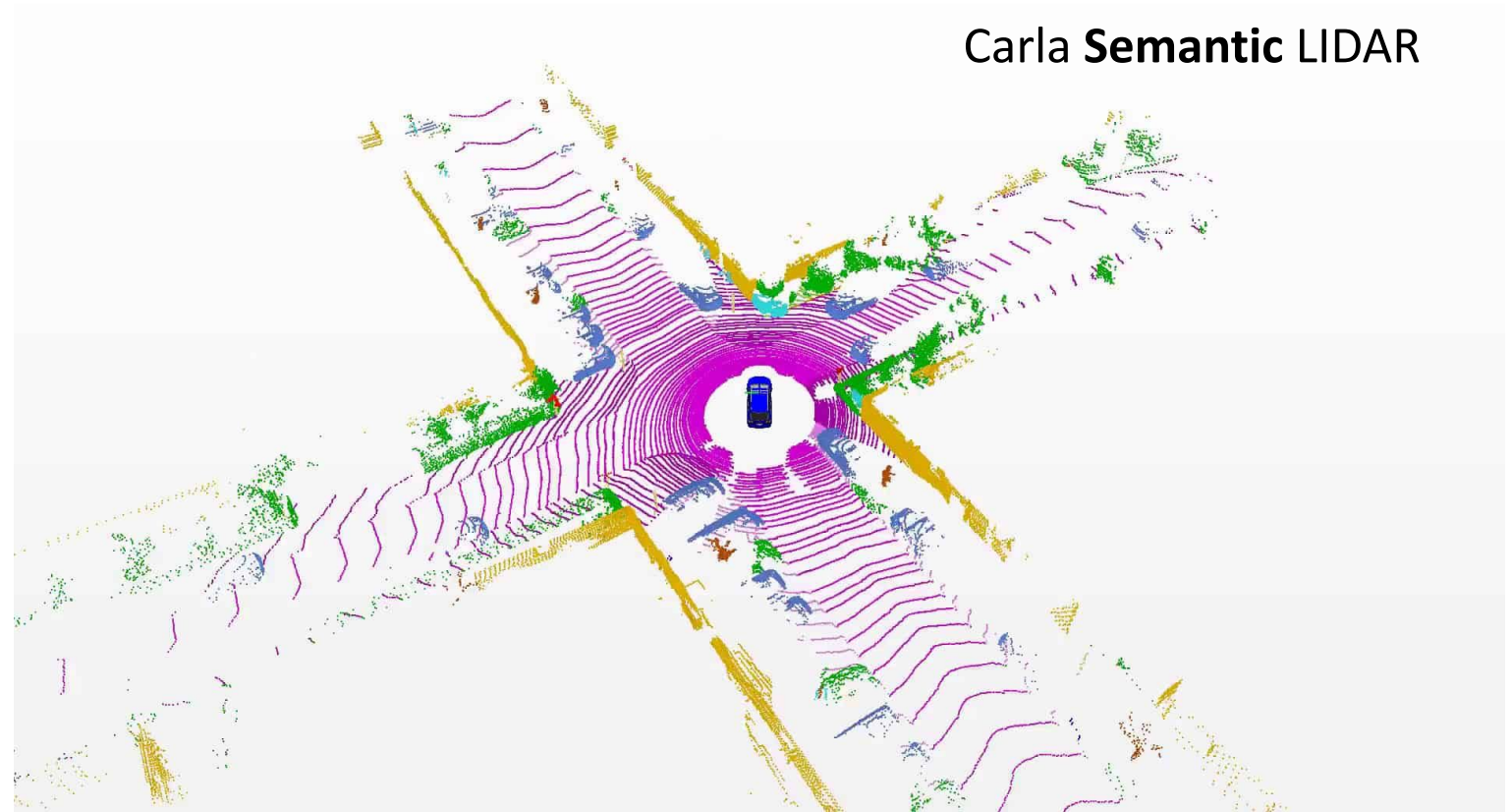


Pedestrian Detection

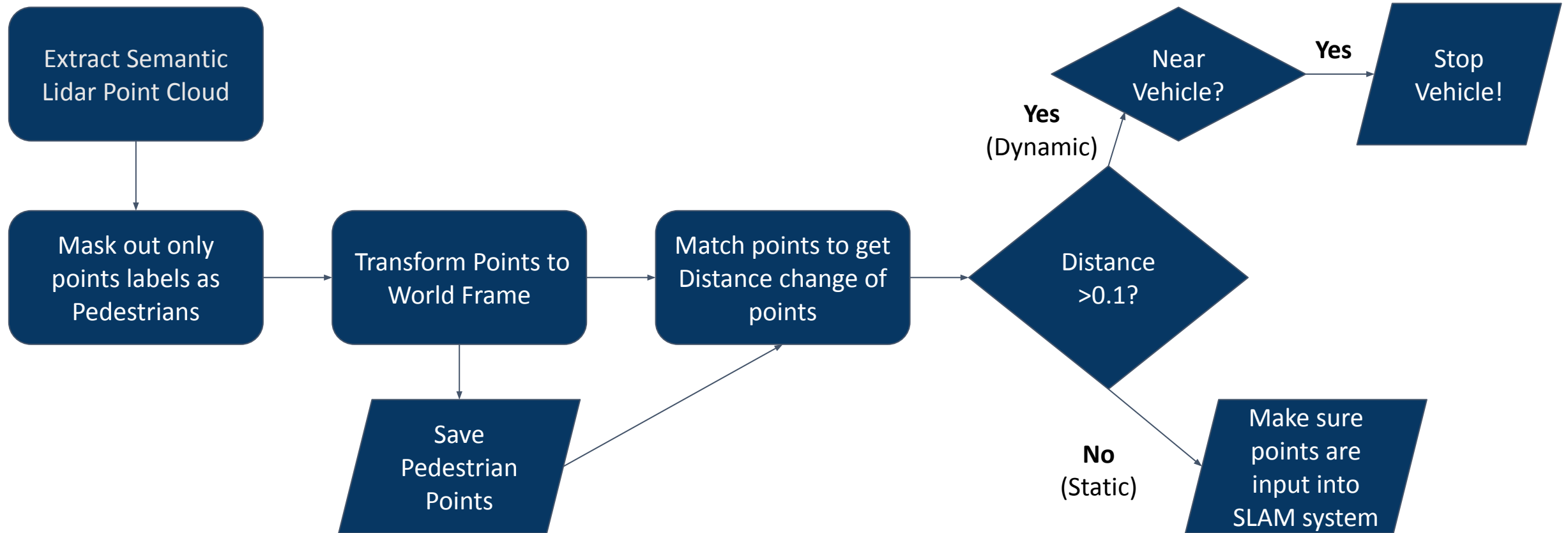
How can we **detect** pedestrians?

Segmentation!

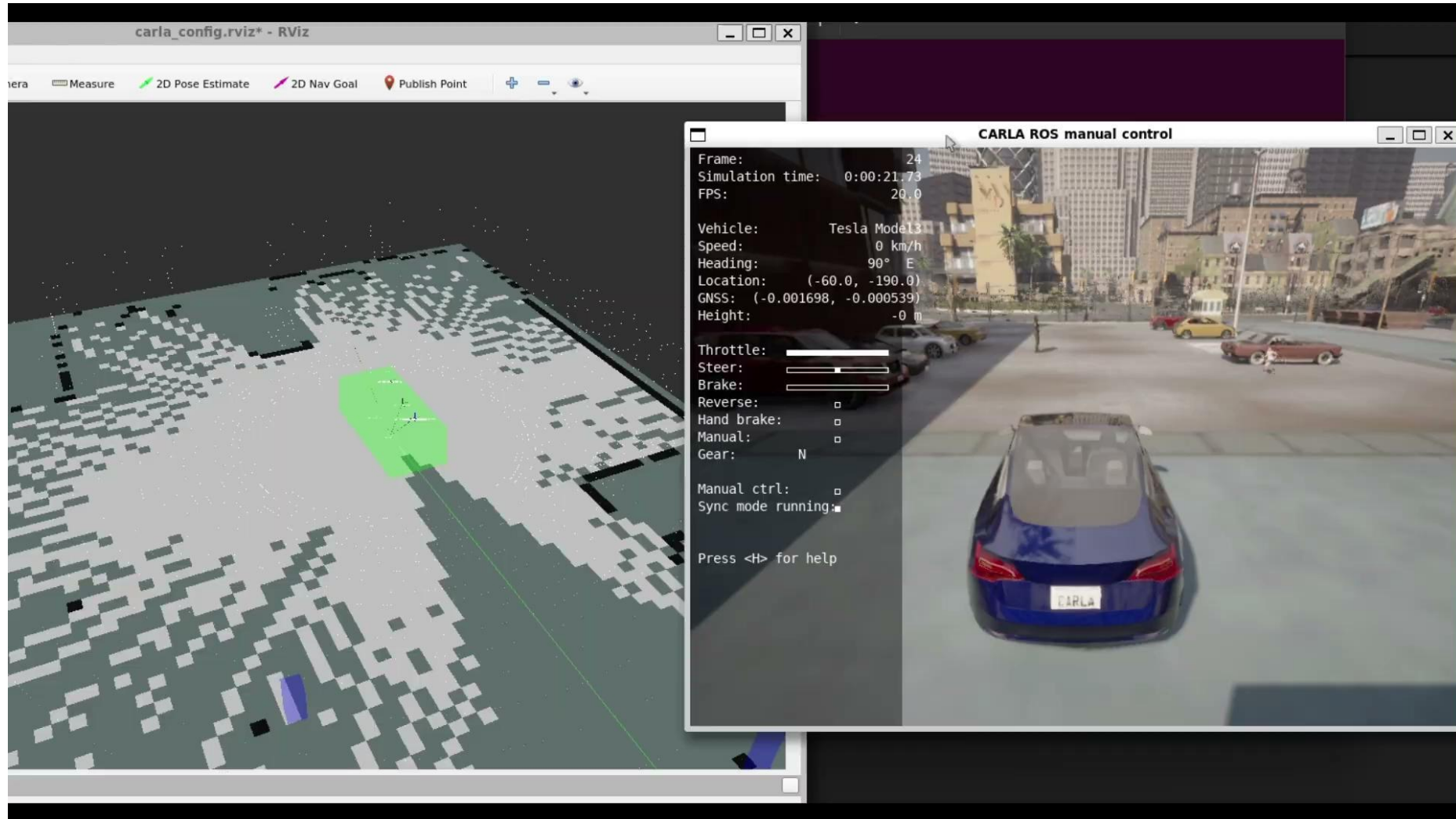
By segmenting the lidar pointcloud, we can determine the position of pedestrians relative to the vehicle.



Pedestrian Avoidance Pipeline



Pedestrian Avoidance in Action



Evaluation

- Conducted eight different experiments.
- All metrics are averaged over 10 drives per Test Case.



Results - Parking Error

Test	Avg Position Error (m)	Avg Rotation Error (°)	Parking Success Rate
T1P1	0.3239	0.61	100%
T1P2	0.2941	0.83	100%
T1P3	0.7997	-12.10	100%
T1P4	0.8261	8.14	90%
T2P1	1.8338	-5.92	100%
T2P2	1.2744	-7.89	90%
T2P3	0.7135	-11.1196	100%
T2P4	1.0035	12.22	80%

Table 1: Evaluation of ground truth position of car vs desired goal position. We also note the success rate of each trial and only evaluate metrics for trials that did not crash.

Results - Localization and Path Planning

Test case name	Avg RMSE APE (m)	Avg RMSE RPE (m)	Avg Path Length (m)	Avg Time taken (s)	Avg Speed (m/s)
T1P1	0.2064	0.0430	23.7868	31.3521	0.7587
T1P2	0.1792	0.0437	24.0780	47.1209	0.5109
T1P3	0.2077	0.0469	21.9027	30.0062	0.7299
T1P4	0.1739	0.0485	23.3763	62.8197	0.3721
T2P1	0.2203	0.0410	33.8590	47.1093	0.7187
T2P2	0.1907	0.0484	35.0442	60.9986	0.5745
T2P3	0.1861	0.0580	37.3519	81.8936	0.4561
T2P4	0.1716	0.0547	48.5644	194.2658	0.2499

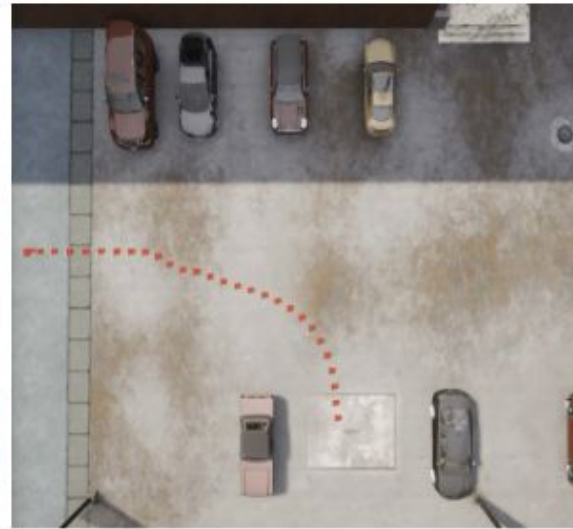
Table 2: Evaluation of time taken for car to park and RMSE APE and RPE of localization error vs ground truth error. We also include the average speed since T1 and T2 have different goal positions.



(a) T1P1



(b) T1P2



(c) T1P3



(d) T1P4



(e) T2P1



(f) T2P2



(g) T2P3



(h) T2P4

Future Work

- **Parking Spot Detection:** Use Computer Vision to detect open parking spots and integrate with current system to allow end-to-end parking.
- **Other SLAM Methods:** Exploit the strengths of newer SLAM methods to improve pedestrian detection and localization accuracy.
- **Incorporate More Dynamic Obstacles:** Current pedestrians move at walking speeds. The environment can become more challenging with faster moving and larger obstacles.

Thank you!

