

Acknowledgement

The presented work is the result of years of work from the perception lane teams in US and China, and could not have been achieved without the support from infrastructure, localization, hardware, operations teams as well as the rest of the organization.

Why perception lanes?

Generally 2 approaches for driving path generation: HD map and perception

Drawbacks of a map-only solution:

- No real time updates to map data (e.g. construction zones)
- Difficult to scale: a large fleet and a lot of resources are needed to build the maps.
- Maps provided by third parties might not always be accurate

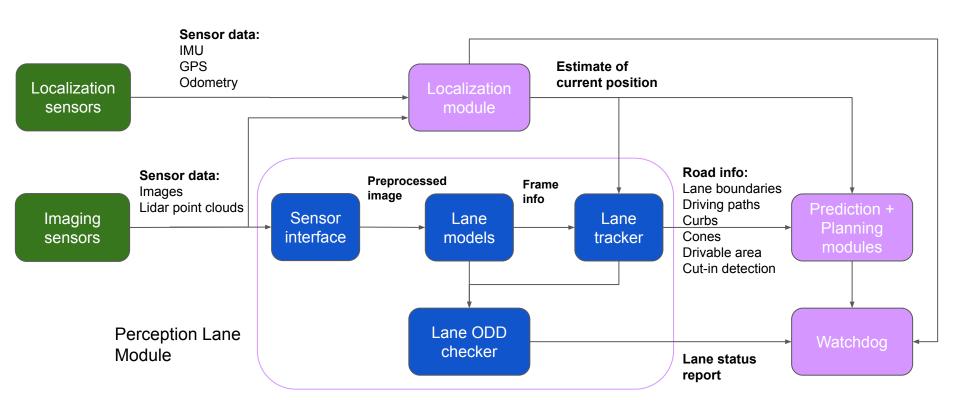
Perception lane detection is critical for a scalable product that doesn't rely on map data

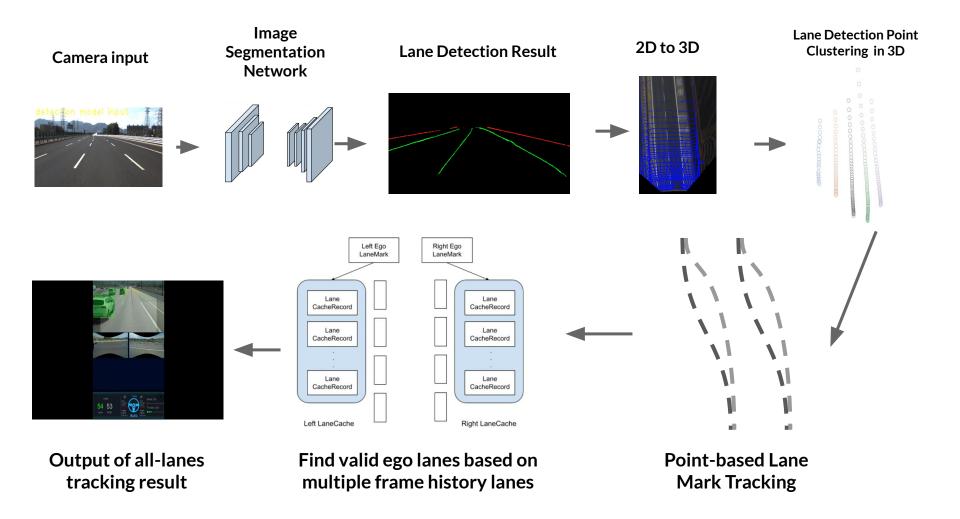
Stable fallback path is essential for a L4 product

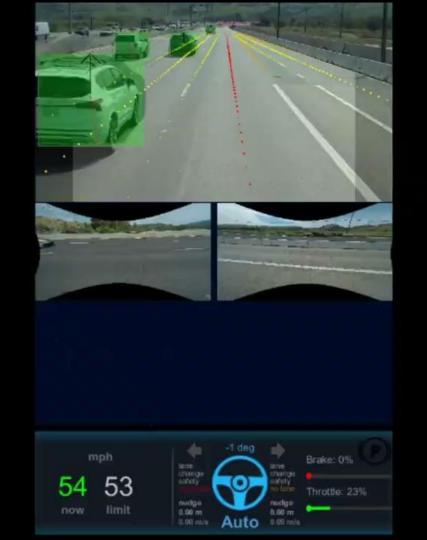
Design requirements



System overview



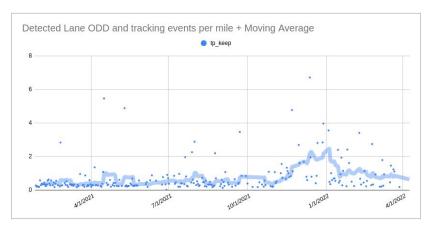




Evaluation and monitoring

Metrics are necessary for performance evaluation:

- Benchmarks for lane models and lane tracking
 - Metrics checked for every code change
 - Some metrics with labeled ground truth
 - Other metrics without labeled ground truth
- Event detection:
 - Online events: e.g. truck didn't follow perception lane path or the lane path was lost
 - Offline events: more thorough analysis which cannot be done online
- Large scale simulation: Selective tests on a large amount of data
- Injection of calibration and detection errors



Example of tracked metric

Metric	Mean		90th Percentile		95th Percentile		99th Percentile	
Date	04/2020	04/2022	04/2020	04/2022	04/2020	04/2022	04/2020	04/2022
RMSE_EGO_DP_IMU_30	0.152	0.118	0.271	0.217	0.331	0.248	0.573	0.333
RMSE_EGO_DP_IMU_50	0.187	0.146	0.344	0.254	0.428	0.297	0.692	0.387
RMSE_EGO_DP_IMU_70	0.248	0.196	0.457	0.349	0.555	0.433	0.866	0.542
RMSE_EGO_DP_IMU_100	0.392	0.318	0.745	0.617	0.981	0.769	1.422	1.09
RMSE_EGO_DP_IMU_150		0.692	1.467	1.439	1.99	1.843	3.254	2.854
HEADING_RANGE	146.8	206.61						

Comparison of some key metrics over a 2 year period

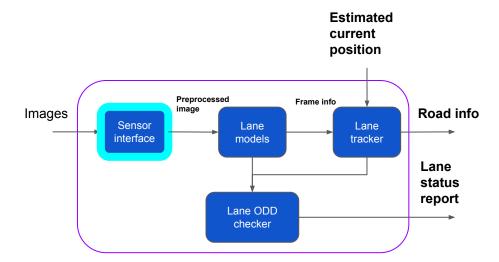
Sensor interface

Current approach:

- Single camera used for detection
- Chosen camera can be changed online in case of camera failure

Future directions:

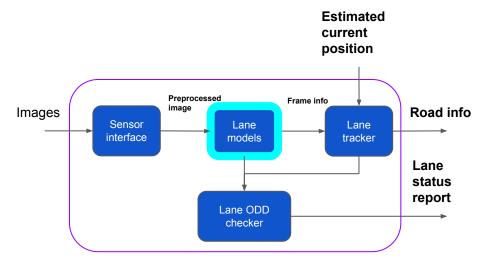
- Fusion of images from multiple cameras
- Use lidar data
- Stereo lane detection
- Common image processing for all perception modules

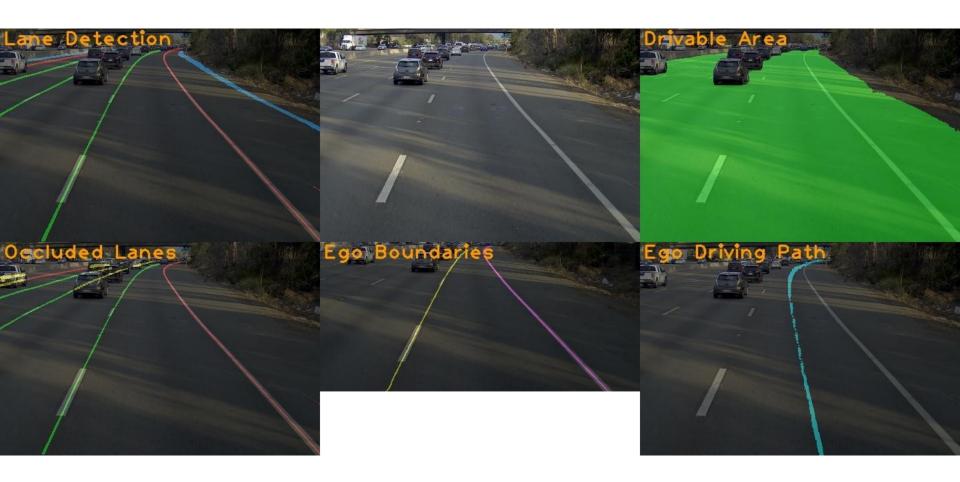


Models

Learning based models for a variety of tasks:

- Lane boundary, road boundary, and cone line detection
- Drivable area detection
- Split/merge detection
- Lane instance segmentation
- Occluded lane detection
- Driving path detection



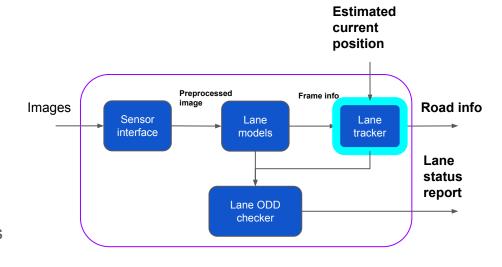


Various learned tasks

Lane Tracker

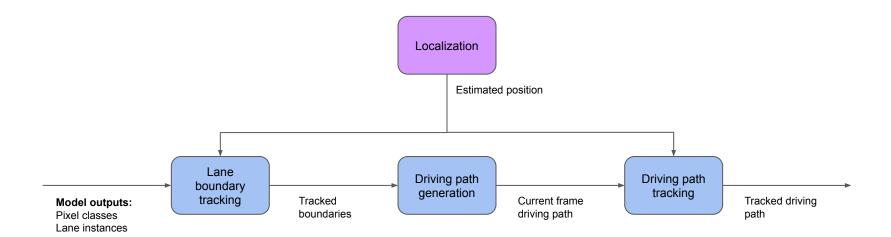
Input: Frame information

- Measurements/detections
- Class information for each pixel
- Instance information for lane boundary pixels
- Driving path



Output: Tracked 3D driving path and lane information (boundaries, curbs, drivable area, splits, merges)

Lane Tracker



ODD Checker

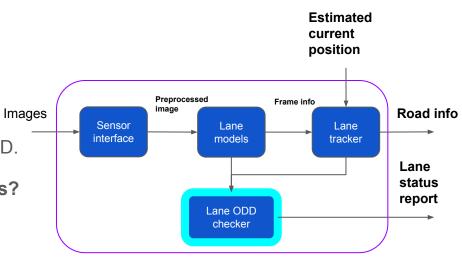
Goal: Monitor outputs and alert system when exiting ODD.

Is it safe to drive autonomously in current conditions?

Checks:

- Lane boundary stability
- Lane width
- Lane boundary and driving path ranges
- Driving path curvature
- Position and heading offsets

Sends signal to watchdog module in case values are not satisfactory



Challenges

- Lighting: difficulty in detecting lane markings
- Missing lane markings and heavy occlusions of lane boundaries
- Large curvature roads (e.g. ramps, interchanges): break road surface assumptions
- Bumps and other large disturbances: break noise and camera positioning assumptions
- Construction zones: cones and rearranged lanes

Future directions

In order to expand the ODD improvements continue across the board:

- Improve models:
 - Neural networks
 - Lane geometry and curve fitting (2D to 3D)
 - Stereo detection
- Better filtering:
 - Noise removal
 - EKF, pitch estimate
 - Road surface tracking
- Higher level logic:
 - Backup driving paths from drivable area
 - Additional consistency checks



Questions?