Autoware Challenge 2023

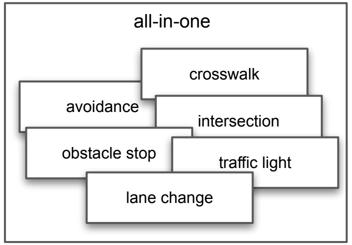
[Planning] A planning architecture that achieves both high module-independent scalability and feasibility of complex use cases

<u>Challenge:</u>

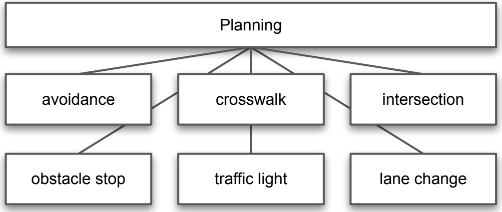
From the perspective of scalability and maintainability, it is desirable to develop functionalities such as intersection, pedestrian crosswalk, traffic light stop planning, and obstacle avoidance, etc. with loose coupling. However, it has difficulty to achieve complex use cases where these functionalities are intricately interconnected. On the other hand, in order to address such complex use cases, all-in-one planning algorithms have been proposed, but they have scalability concerns in that each individual function cannot be independently extended.

This challenge is to propose the appropriate “software architecture and interface design” for the autonomous driving planning system that can address both of these requirements.

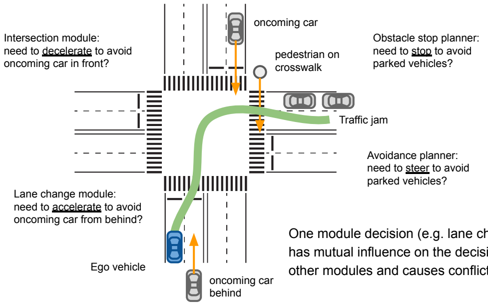
Architecture with intricately interconnected functionalities:
- Implementation of complex use cases: Easy
- Scalability/maintenance: Hard



Architecture with independently designed functionalities:
- Implementation of complex use cases: Hard
- Scalability/maintenance: Easy



Examples of complicated use cases:



One module decision (e.g. lane change) has mutual influence on the decisions of other modules and causes conflicts.

Current planning architecture in autoware.universe:
https://autowarefoundation.github.io/autoware-documentation/main/design/autoware-architecture/planning/

[Planning] Natural driving planning algorithm for complex environments with high density of dynamic objects

Challenge:

This challenge is to propose a “motion planning algorithm” that enables natural and safe driving even in crowded environments with high density of dynamic objects. It is desirable that the algorithm have the following practical features as an autonomous driving system: "to adjust behavior according to object types, similar to how a human driver reacts differently to a car versus a motorcycle", and "to account for recognition errors".

Example Scene 1:
Low-speed zone with mixed traffic including pedestrians, bicycles, and vehicles, with unclear lane boundaries.

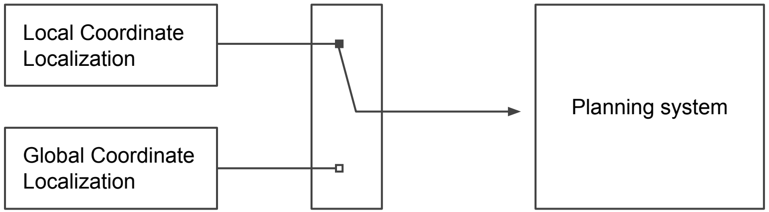
Example Scene 2:
High-speed zone with merging required using rapid acceleration or deceleration. Braking may lead to dangerous situations if there are vehicles approaching from behind the current lane.

[Planning] Planning system capable of handling self-position information from relative and absolute coordinate systems

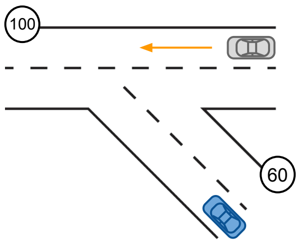
<u>Challenge:</u>

In autonomous driving systems, the self-position is divided into two types: local coordinate and global coordinate. When the global coordinate is available, many information can be obtained through high-precision map information, for example, the position of traffic lights. However, calculating the global self-position can be sometimes difficult in places such as in tunnels in high-speed highway. Moreover, even in urban driving, there are also places where a global localization is difficult. In such cases, planning and control needs to be performed in the local coordinate using a relative position in the driving lane obtained by white line recognition, which can give limited information compared to the global localization. When the characteristics of localization change drastically, handling them seamlessly is not easy, especially for complex planning modules.

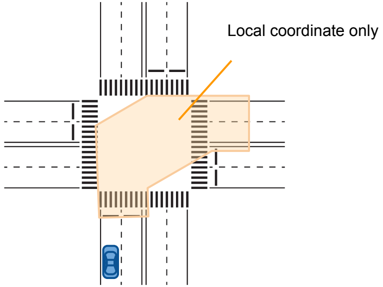
This challenge is to propose a planning system that properly handles switching between local and global coordinate systems when self-position switching occurs.



<u>Expected use case 1:</u>
Approaching Highways from Urban Areas



<u>Expected use case 2:</u>
Global localization is temporarily unavailable in urban area



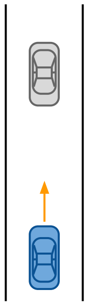
[Planning] Evaluation metrics for planning in autonomous driving

Challenge:

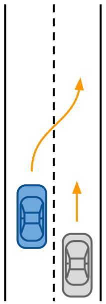
Ensuring safe and appropriate driving in autonomous vehicles requires more than just following traffic rules. It is also important to consider whether the vehicle's actions are dangerous or not, for example, blind spots, pedestrian sidewalk, interactions with other vehicles. The definition of such evaluation metrics is essential for the evaluation of automated driving.
However, list them in all situations considering traffic rules causes a very large number of metrics. "How closely autonomous driving resembles human driving" is one of the metrics, but human driver's behavior sometimes includes an unsafe behavior in mathematical point of view.

This challenge is to propose potential evaluation metrics for identifying "necessary and sufficient" indicators of good autonomous driving.

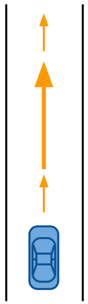
Example 1
Appropriate distance from preceding vehicles



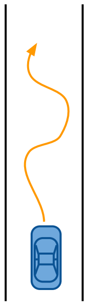
Example 2
Presence of dangerous maneuvers



Example 3
Absence of unnecessary acceleration and deceleration



Example 4
Smooth driving trajectories



[Control] Algorithm for achieving high-precision vehicle control for vehicles with various charactaristics

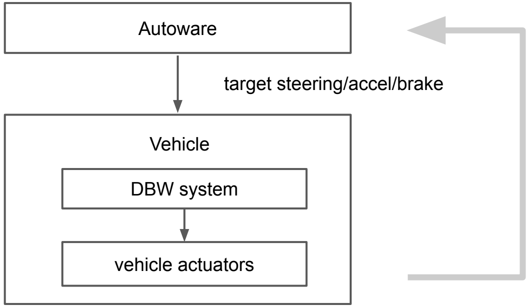
Challenge:

Vehicles equipped with autonomous driving software have various motion characteristics depending on the vehicle type. For example, the Drive-by-Wire (DBW) performance of vehicles varies according to vehicle types such as passenger cars, small cars, large special vehicles, buses, etc. Additionally, in practice, there are many complex elements that make modeling difficult, such as differences in brake response speed, delay in instruction, existence of steering dead zones, insufficient control cycle, and unpredictable behavior due to the intervention of black-box software. To make autonomous driving more widespread, an algorithm that can be quickly applied to such a wide range of vehicles is needed.

This challenge is to propose an algorithm that can achieve optimal control based on the given vehicle's driving data. It is assumed that the vehicle has an ackermann type of steering control mechanism.

It is also desirable to be able to demonstrate the limit of the control performance. For example, if the assumed vehicle performance from this data results in a 50cm tracking error even with the most optimal control. The method of demonstration (theoretical proof / numerical simulation, etc.) is not specified.

various vehicle charactaristics



Analyzing driving data:

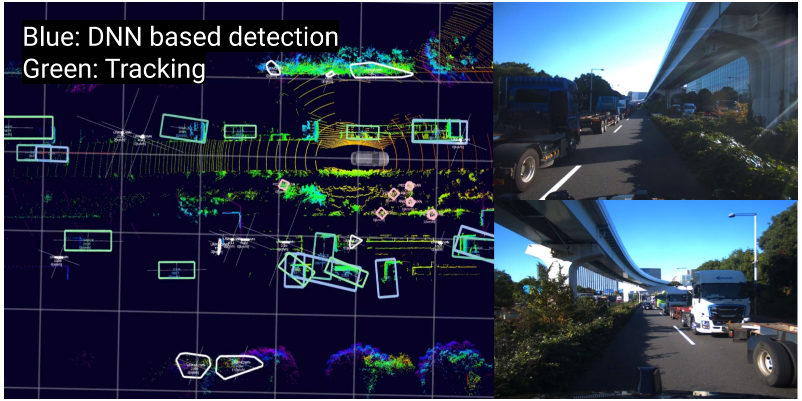
- propose suitable control logic/parameters.
- propose performance limitations.

[Sensing/Perception] Improvement on object recognition in both accuracy and stability

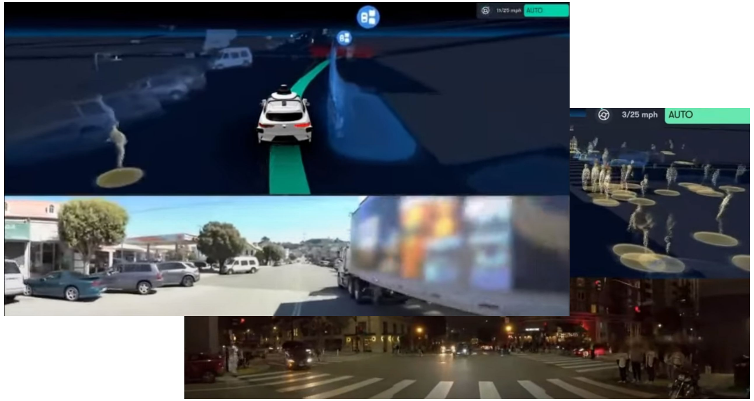
<u>Challenge:</u>

This challenge is to propose online perception algorithms that have accurate/stable detection results as we see in Waymo videos, to solve below issues

- Accuracy of detected position/size/orientation of parked vehicles and large vehicles in close range
- Mis-interpretation of poles or traffic signs as pedestrian
- Detection accuracy of vehicles in long range with occlusions
- Object recognition result is unstable for objects when it is temporarily occluded



<u>Example Scene 1:</u>
Autoware perception result: incorrect vehicle orientation, multiple results being output from one vehicle, insufficient stability over time.



<u>Waymo perception from videos</u>
- https://youtu.be/b84FbSZFJeQ?t=120
- https://youtu.be/ospoTAyEdDQ?t=74

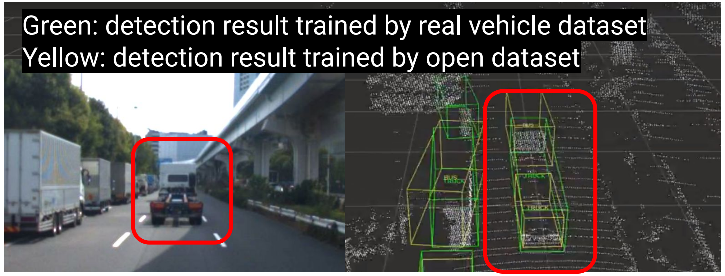
[Sensing/Perception] Improvement on robustness of object recognition

<u>Challenge:</u>

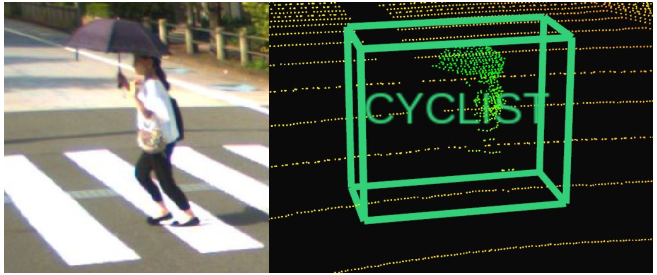
This challenge is to propose online detection algorithms/models that are robust against different environment and different sensors.

Current our detection model's performance deteriorates when:
- driving in different environment where training datasets are collected (e.g., driving Japanese roads using models trained by open datasets)
- Changing sensor configuration (using different lidar model, changing number of lidars)

Some possible approach might include:
- Establish domain adaptation method
- Designing robust DNN model
- Generate enough dataset that includes various sensor configuration and various driving environment



<u>Example Scene 1:</u>
The model trained on the open dataset recognizes trailers in the image as two separate vehicles, but the model trained on real vehicle data can correctly recognize them as a single vehicle.



<u>Example Scene 2:</u>
Detection of pedestrians carrying an umbrella is unstable (recognized as a cyclist, but sometimes cannot be recognized at all).

[Sensing/Perception] Detection of blinkers of surrounding vehicle

<u>Challenge:</u>

Current Autoware does not have a module that can detect blinkers or lamps of vehicles. It only uses vehicle's current motion to predict its future path. Due to latency in detection and tracking, we have large accumulated latency in the prediction result.

This challenge is to propose a detection module to detect the state of blinkers/lamps of surrounding vehicles.

This would allow us to recognize the vehicle states to anticipate its future behavior. It would be nice if the module satisfies the following condition:
- Capable to operate in realtime (10FPS) on an edge device (e.g., Jetson AGX Xavier)
- If the module requires too much computation to detect all the vehicles' blinkers, it is also expected to select appropriate vehicles to detect their blinkers

Source: AC photo

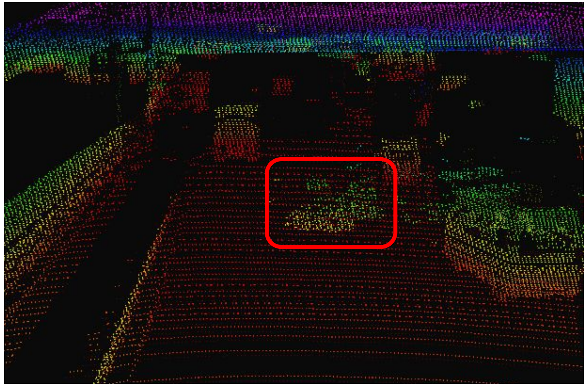
Source: AC photo

[Sensing/Perception] LiDAR filtering false detection suppression

Challenge:

When performing obstacle detection using rule-based LiDAR point cloud filtering, the task of this function is to remove various noise point clouds from the entire point cloud. To avoid sudden braking, it is necessary to remove noise points, but it is also important to keep the points of obstacles that pose a collision risk.

The following challenges arise:
- Unfiltered point clouds of rain, fog, dust, birds, and other objects can remain.
- It is difficult to distinguish between LiDAR reflection points that are not a collision risk (such as plastic bags, water vapor, exhaust gas, noise, and ghost caused by multiple reflections of LiDAR, etc.) and those that pose a collision risk. This can lead to false braking.



Example Scene 1:

The exhaust gas emitted from the vehicle has been detected as a point cloud in the air.

[Localization] Improving Localization in Dynamic Environments with Inconsistent Map

<u>Challenge:</u>

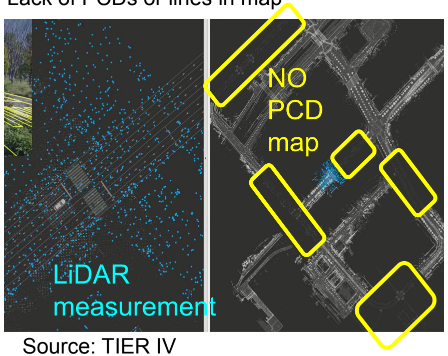
Objective:
There are cases where the map data does not match the real-world environment, such as in parking lots or factories that change over time. Although PCD and LL2 data are provided, they may not be reliable. We want to ensure consistency with the existing map while estimating the position in the missing areas using some method.

Assumption:
PCD and LL2 data are available for the planner.

This challenge is to propose a localization system properly estimating the position in the missing areas.

<u>Ex. Inconsistent Map:</u>

Lack of PCDs or lines in map

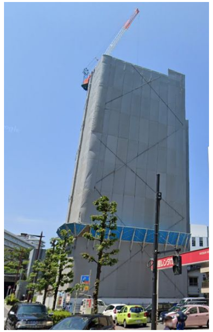


Source: TIER IV

Dynamic occlusions

Source: free-materials.com

Major changes in structure



Source: Google Map The parkhouse Akabane front Aug. 2022

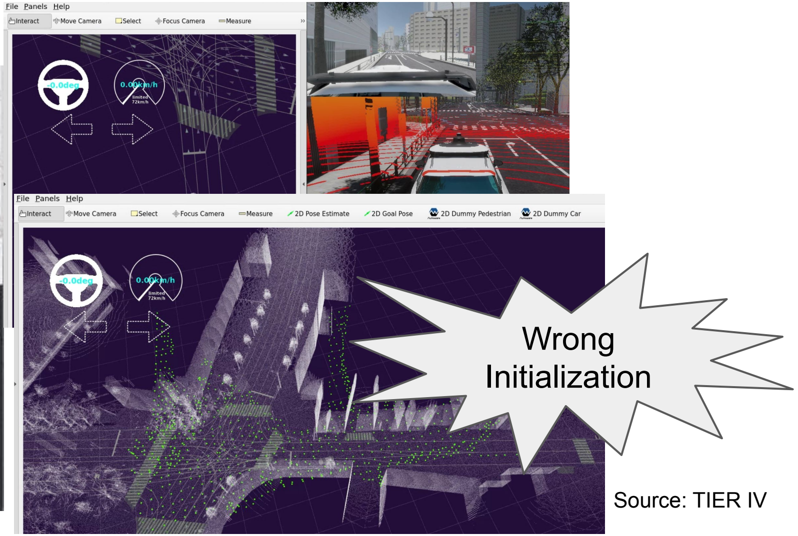
[Localization] Improvements in initialization of localization algorithm

<u>Challenge:</u>

Objective:
Autoware cannot initialize its pose in environments without GNSS signal. Even with GNSS, there is also issues occasionally falling into wrong pose. We would like to have an algorithm to estimate initial pose globally within a given map.

This challenge is to propose a localization initializing the position globally without GNSS and initial values.

<u>Ex. Sample solutions for similar issue:</u>



Source: TIER IV

[Localization] Estimation of errors in the environment hard for localization

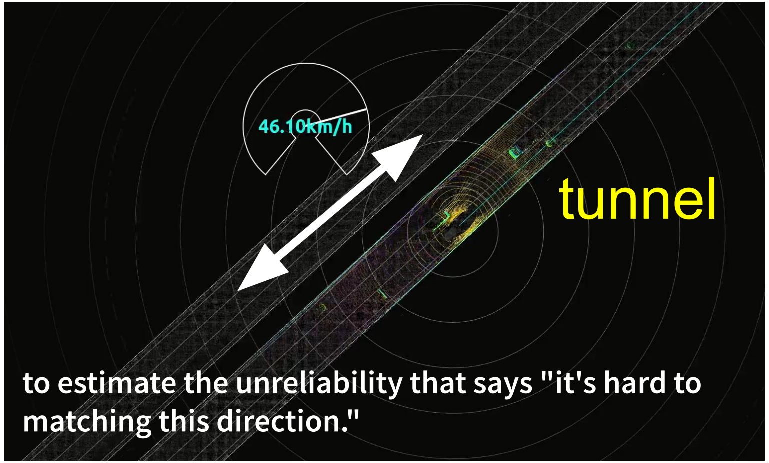
Challenge:

Background: Autoware currently use point cloud matching method to localize its pose. However, It can't detect the suspicious state in the situation where it can be unreliable like the following:
Sample Scenario 1: Vehicle is driving in a tunnel. It might be accurate in lateral direction but not in longitudinal direction.
Sample Scenario 2: Vehicle is driving in an open space. It might be accurate in z/roll/pitch, but not in x/y/yaw

This challenge is to propose an algorithm to detect the unreliability of localization in realtime.

Sample scenario 1:

Related Research



Source: TIER IV