Online Learning Methods for Vehicle Safety in Autonomous Driving (OLAF)

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Overview

- Hierarchical online learning for vehicle applications
- Human as “data generation model” for keeping the criticality below a certain threshold (with approx. 200 mio km per fatal accident humans are “very good drivers”)
  - Input in ML algorithm: compact scenario representation
  - Output of ML algorithm: sequence of actions to reduce the criticality
  - Training data: observations of the drivers behavior (in vehicles with autonomy level <3)
  - Learned sequence of actions are transformed into steering-angle and pedal position signals using model-based trajectory planning
- Method will support the transition to level 4 autonomy by computing vehicle trajectories that keep the criticality low

Hierarchical Machine Learning Architecture

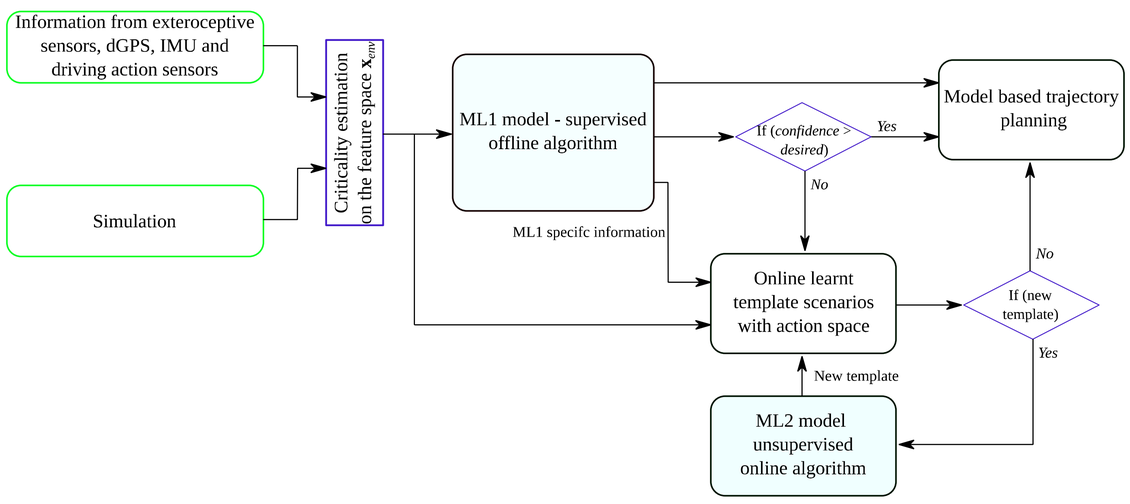

Figure 1: Hierarchical architecture

- A hierarchical architecture combining an offline supervised model (ML1) and an online unsupervised model (ML2) to ensure the changes during online learning happens locally
- The ML1 model has to master as many scenarios as possible before the online learning begins
- ML1 is an ensemble method: Random Forest (RF) algorithm, is used to classify scenarios, generate confidence information, and also to generate features for the ML2 model
- ML2 is an online learning method that is required when the confidence information from ML1 is low
- Before online learning, the new scenario is compared with existing templates created online.
- New templates should be created if the similarity value is low
- The hierarchical architecture assures that the mappings learnt by ML1 are not forgotten. In ML2 only local changes are possible

$$\mathbf{x} = \{\mathbf{x}_{ego},\ \mathbf{x}_{obj_{1:n}},\ \mathbf{x}_{map}\ \cdots\}$$

$$\boldsymbol{act} = \{left,\ right,\ brake\ hard,\ brake\ soft,\ acc\ hard,\ \cdots\}$$

ML1 Specific Information

- The ML1 specific information can be used for similarity measures
- The ML1 specific information can be the pattern emerging from the indices of the terminal nodes in which the new scenario lands in every tree of the RF: “RF activation pattern”

$$\mathbf{x}_{ML1} = \{id_{t1},\ id_{t2},\ id_{t3},\ \cdots,\ id_{tn}\}, n = no.\ of\ trees$$

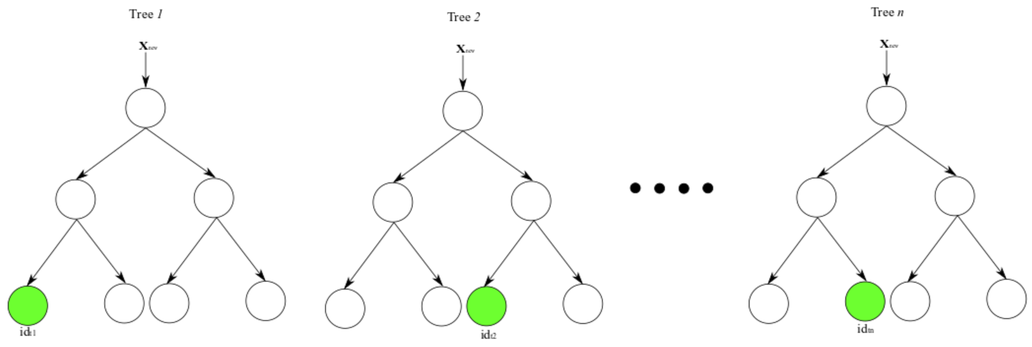

Figure 2: ML1 specific information

Scenarios of Interest

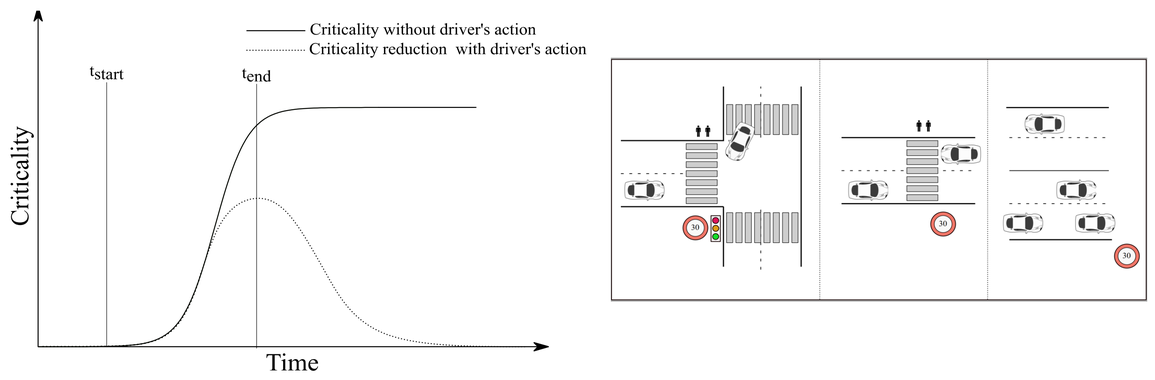

Figure 3: Scenarios of interest

- The focus in this work lies on urban scenarios with a 30km/h speed limit
- Scenario data are generated from: simulations, real vehicles on the test facility, and on-road

Data Generation

- Simulation: a MATLAB based simulation tool is used to create scenarios and generate data

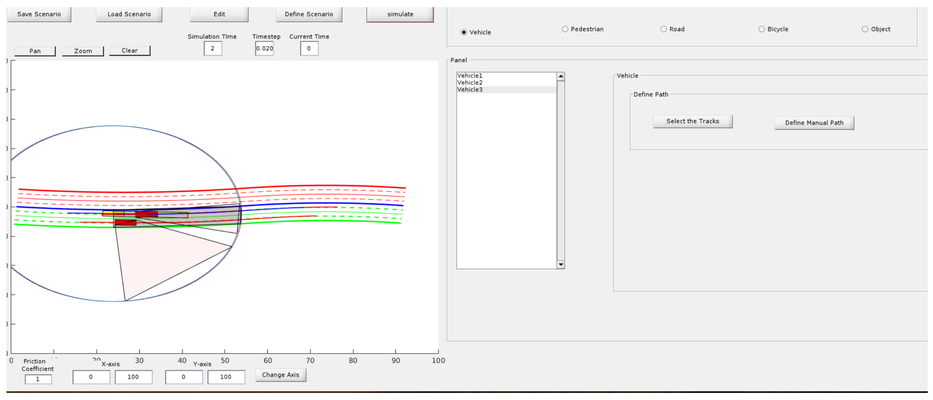

Figure 4: MATLAB based simulation tool developed in the HySLEUS project

- Real vehicles: the environment perception is done with LiDAR, the reference information is taken from INS, and driver actions are recorded with pedal force and steering sensors

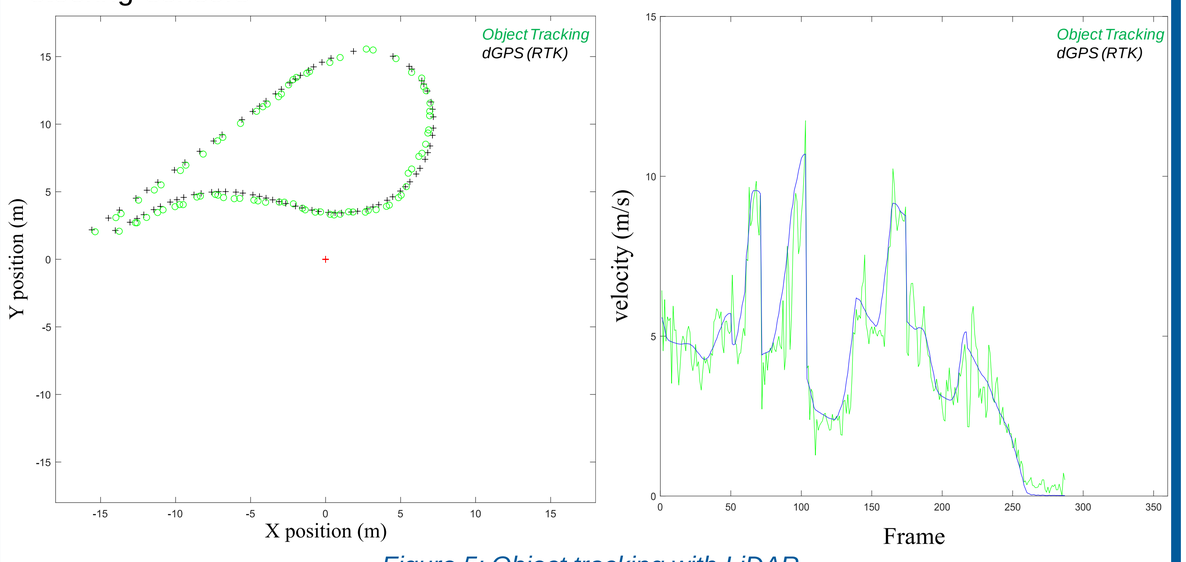

Figure 5: Object tracking with LiDAR

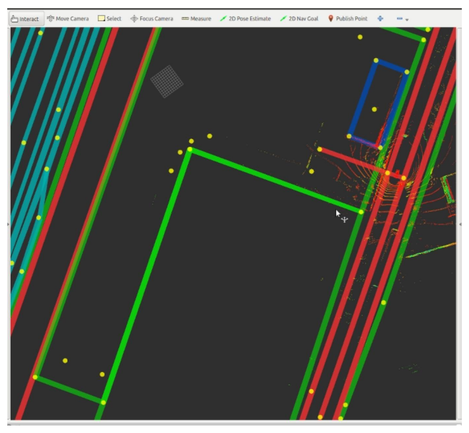

Figure 6: Implementation in ROS: for generation of a map that contains both LiDAR and dGPS information

- Data from simulations and the recordings with real vehicles are transformed into features for machine learning
- The architecture in the real vehicle is based on ROS

Conclusion

- Humans are very good drivers and in most scenarios they are able to reduce the criticality by their actions. The proposed methodology aggregate this knowledge in an offline and an online stage
- The “RF activation pattern” can be used as a feature for computing similarities
- Data are generated by simulations (MATLAB) and with real vehicles (ROS)

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