Mid-term status report on KISSaF: AI-based situation interpretation for automated driving

A. Stockem Novo1,2, M. Stolpe1, C. Diehl1, T. Osterburg3, T. Bertram3, V. Parsi4, N. Murzyn1, F. Mualla5, G. Schneider1, P. Töws5

1ZF Automotive Germany GmbH, 2Hochschule Ruhr West, 3RST, TU Dortmund, 4ZF Friedrichshafen AG, 5INGgreen GmbH
*anne.stockem-novo@hs-ruhrwest.de

Abstract
KISSaF is a publicly funded project with four project partners from industry and academia. The aim of project KISSaF is the development of a robust scene prediction model for automated driving. State-of-the-art Deep Learning methods are used for a complete and reliable forecasting of the traffic scene with large time horizons. The underlying environment modeling uses a graph-based representation of the scene. A prototype vehicle has been built-up for data recording. This data is the central part for model development, improvement and testing. A framework is currently setup for a scenario-based test approach and performance can be judged under realistic conditions with integrated maneuver planning.

Measurement vehicle

Scene prediction modeling with neural network

Sensor input:
• 4 short-range corner radars
• Forward-facing mid-range radar
• Forward-facing camera
• 360° Lidar system
• GPS
• HD-maps

Environment modeling

Environment representation:
Environment model is a list of polylines.
• Ego vehicle preprocessed as a graph
• Global object lists created by using high-level fusion and tracking [1]
• Combined with HD-map information
• Node connections encode relationships to predecessor, successor and lane assignments

Evaluation
Average (and final) displacement error

\[
ADE = \frac{\sum_{i=1}^{n} \sum_{t=1}^{T_{obs}} \sqrt{(x_{i}^{t} - \hat{x}_{i}^{t})^2 + (y_{i}^{t} - \hat{y}_{i}^{t})^2}}{n \left( T_{pred} - (T_{obs} + 1) \right)}
\]

n: number of trajectories
Tobs and Treld: first and final predicted trajectory points
\(x_{i}^{t}\) and \(x_{i}^{t}\): predicted and real longitudinal coordinates of \(i\)'s trajectory point for trajectory \(t\)
\(y_{i}^{t}\) and \(y_{i}^{t}\): predicted and real lateral coordinates of \(i\)'s trajectory point for trajectory \(t\)

KPIs for Driving Functions
• Automated braking or acceleration
• Automated lane change
→ Evaluation in scenarios

References

Future steps
• Massive data taking campaigns to guarantee wide variety of scenarios
• Meta data labeling for efficient data selection
• Scene prediction modeling on real data
• Evaluation and comparison with reference models

Environment representation:
- HD-maps
- GPS
- LiDAR
- 360° camera
- Forward-facing mid-range radar
- 4 short-range corner radars
- Global object lists created by using high-level fusion and tracking

Vectorized representation
- Subgraph encoder
- Interaction graph and predictor
- Ego-vehicle, other vehicles, history vehicle trajectories, lane segments

Sensor input:
- 4 short-range corner radars
- Forward-facing mid-range radar
- Forward-facing camera
- 360° Lidar system
- GPS
- HD-maps

Scene prediction modeling with neural network
- Trajectories and their probabilities are extracted via a Multi Layer Perceptron (MLP) [2, 3]
- Attention weights for the individual nodes are estimated
- Coupled prediction and planning is evaluated

Evaluation
- Average (and final) displacement error
- KPIs for Driving Functions
- Evaluation in scenarios

References