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

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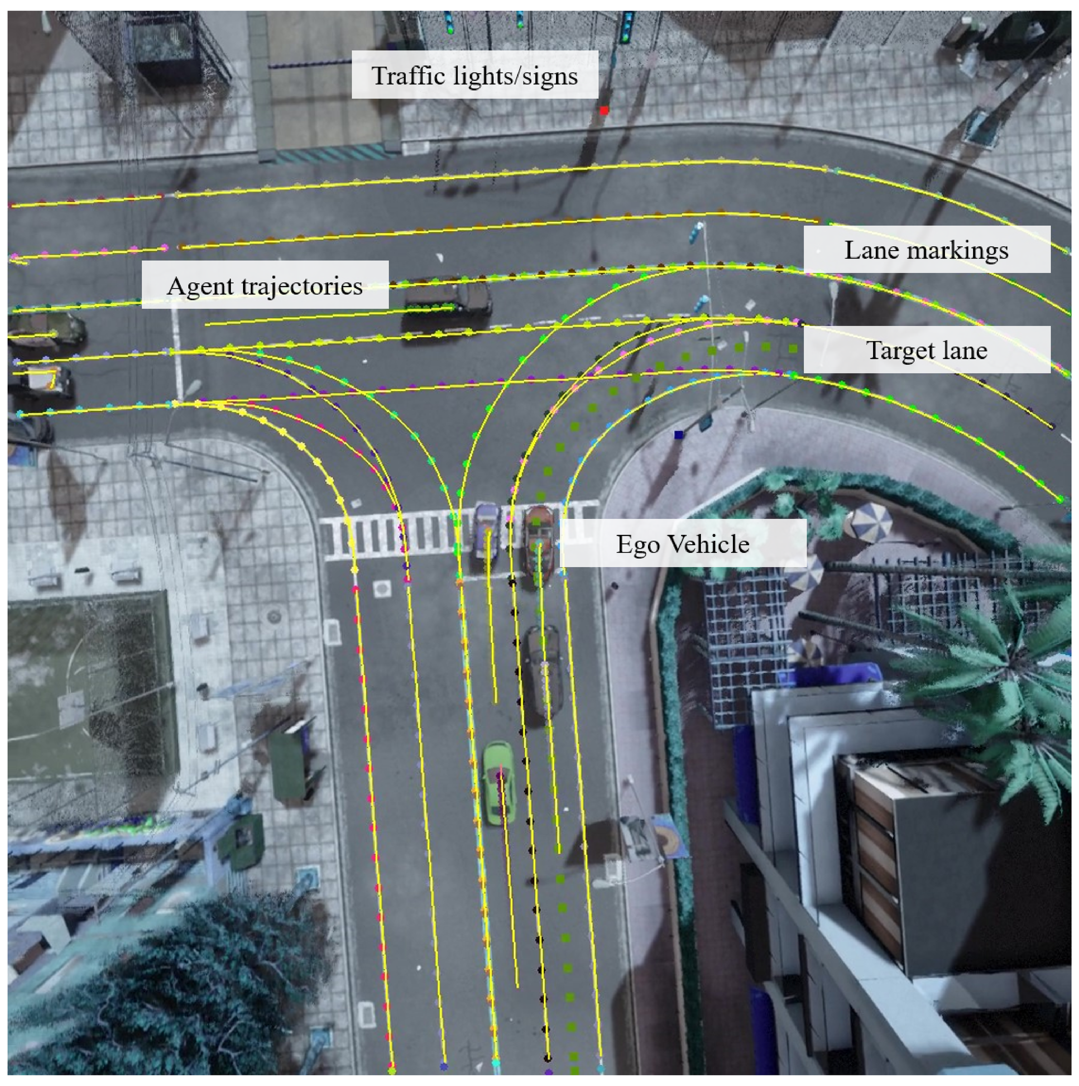
Abstract

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

Enrivonment modeling



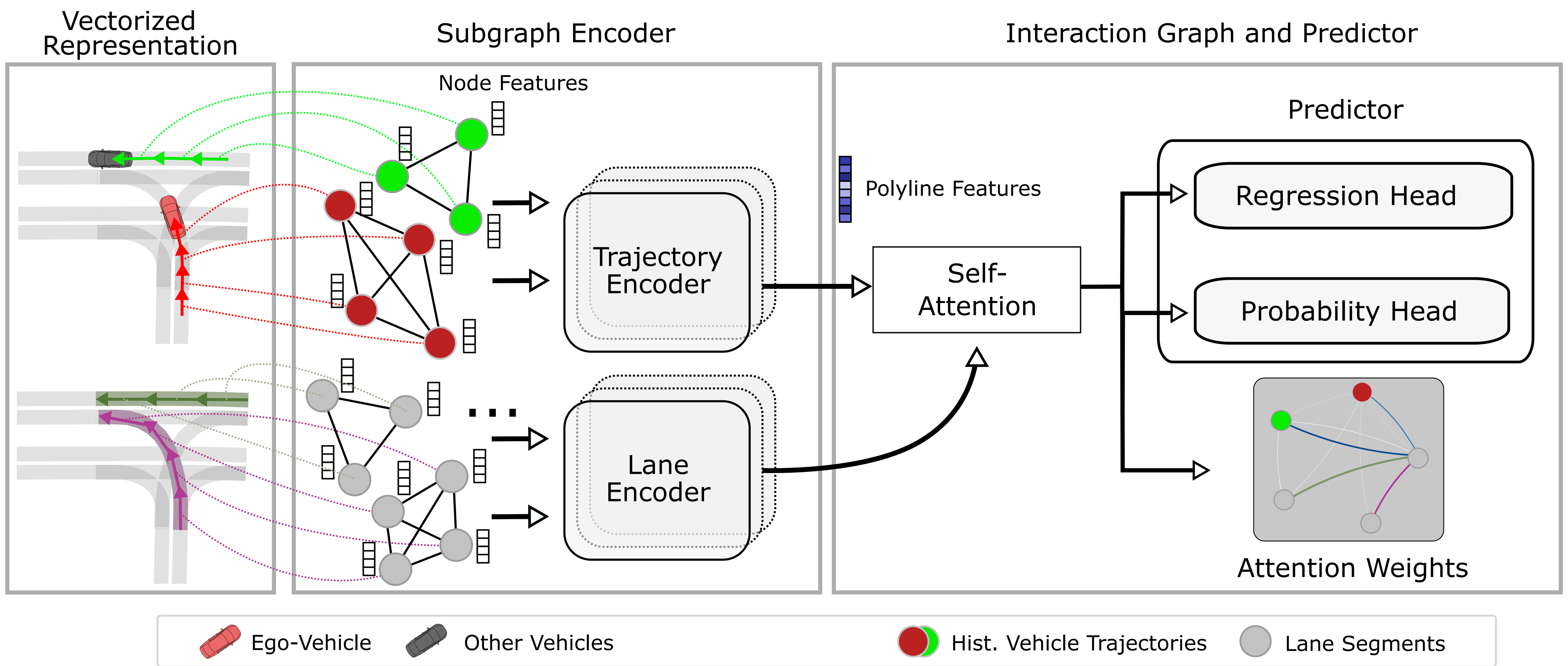
Sensor input:

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

Environment representation:
Environment model is a list of polylines.

- Ego vehicle prepresented 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

Scene prediction modeling with neural network



- Vectorized environment representation is input to the predictor
- 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

$$ADE = \frac{\sum_{i=1}^{n}\sum_{t=T_{obs}+1}^{T_{pred}} \sqrt{\left(\hat{x}_i^t - x_i^t\right)^2 + \left(\hat{y}_i^t - y_i^t\right)^2}}{n\left(T_{pred} - (T_{obs}+1)\right)}$$

- n: number of trajectories
- T_{obs} and T_{pred}: first and final predicted trajectory points
- $\hat{x}_i^t$ and x_i^t: predicted and real longitudinal coordinates of t's trajectory point for trajectory i
- $\hat{y}_i^t$ and y_i^t: predicted and real lateral coordinates of t's trajectory point for trajectory i

KPIs for Driving Functions

- Automated braking or acceleration
- Automated lane change

→ Evaluation in scenarios

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

KISSaF

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