

Predicted-Occupancy Grids for Vehicle Safety Applications based on Autoencoders and the Random Forest Algorithm

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Overview

- Prediction of a probabilistic space-time representation of traffic scenarios termed as the Predicted-Occupancy Grid (POG)
- A hierarchical situation classifier to distinguish the different types of traffic scenarios and to identify the safety-relevant traffic participants
- A set of Random Forests (RFs) for each class of the situation classifier to predict the Predicted-Occupancy Grid (POG)
- The input to the RF is an Augmented Occupancy Grid (AOG)
- Dimensionality reduction on the AOG using the Stacked Denoising Autoencoder (SDA) to improve the performance of the RF

Hierarchical Situation Classifier

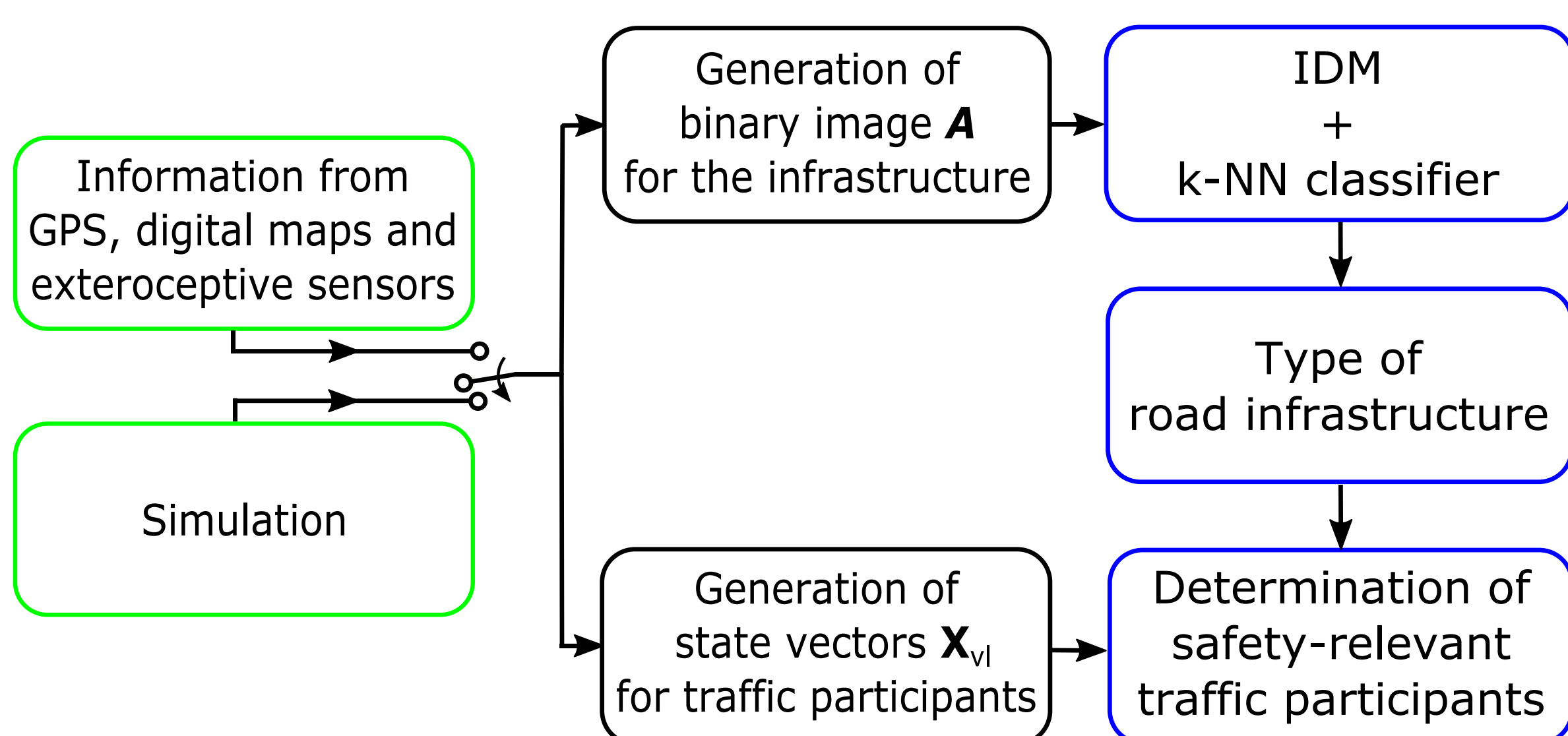


Figure 1: Hierarchical Situation Classifier

- A “Divide and Conquer” approach to identify the different kinds of traffic scenarios and its safety-relevant traffic participants
- The first level of the classifier determines the type of road geometry and it uses the Image Distortion Model (IDM) with k-nearest neighbor (k-NN) classifier
- The second level of the classifier is rule-based and it identifies the safety-relevant traffic participants
- Simulations are carried out in SUMO and MATLAB to validate the methodology

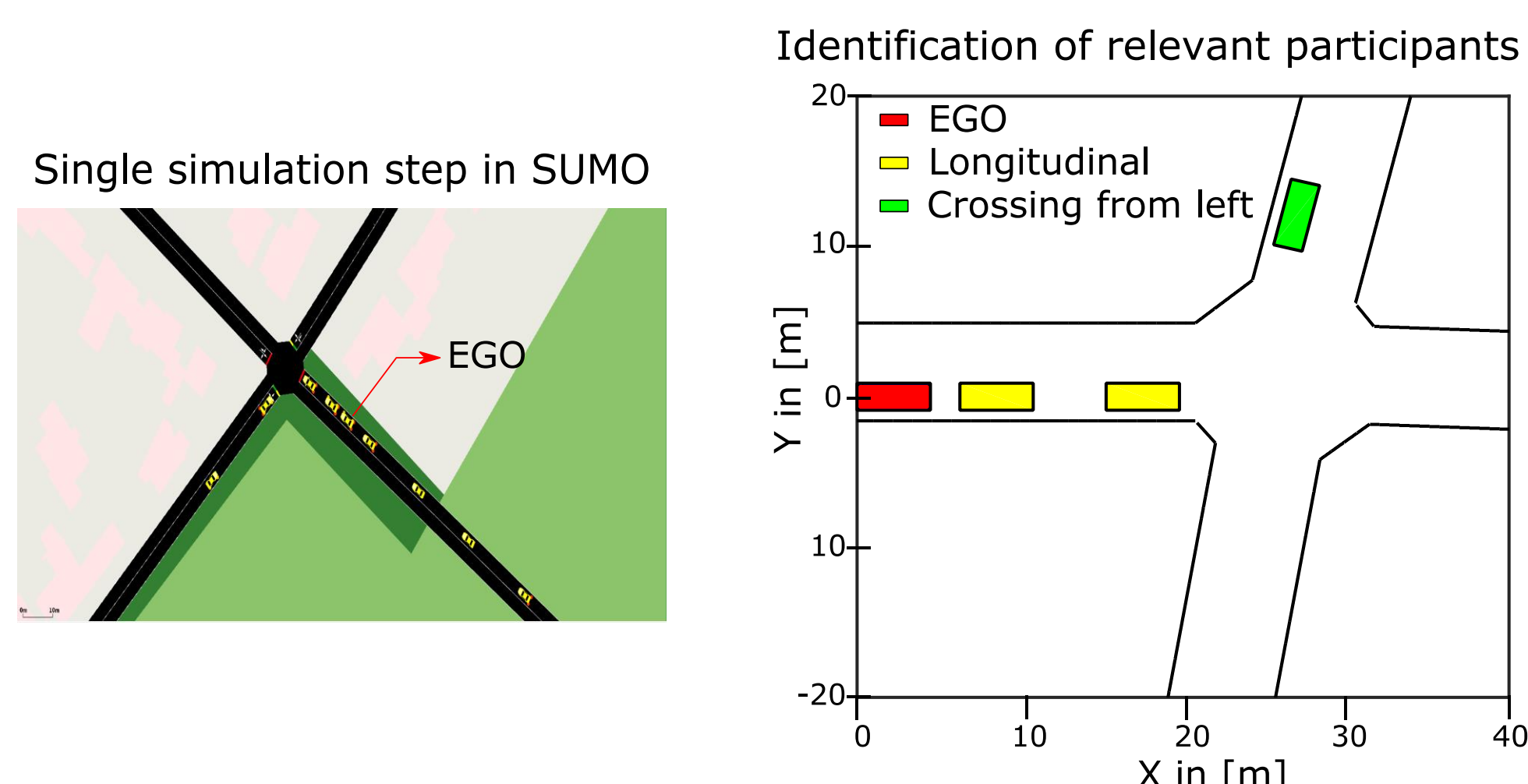


Figure 2: Validation of classifier using SUMO

Augmented Occupancy Grid

- The future behavior of the traffic participants depends on the intention of the drivers and the interaction between them
- The information about the road geometry and the dynamic information about the traffic participants are augmented to the cells of the occupancy grid
- The augmented attributes are the velocity, orientation, longitudinal and lateral acceleration of the vehicle occupying it
- SDA extracts low-dimensional meaningful features from the AOG and this step increases the performance as they remove the noise and the redundant data from the input space

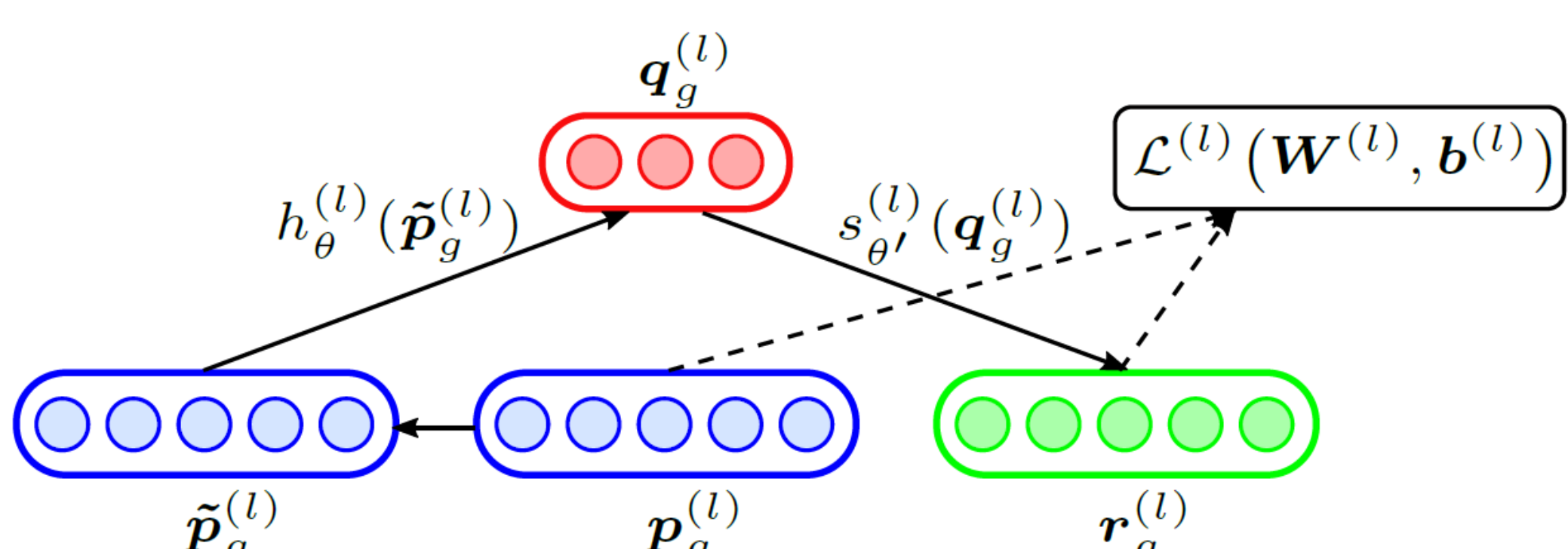


Figure 3: Stacked Denoising Autoencoder

Predicted-Occupancy Grid

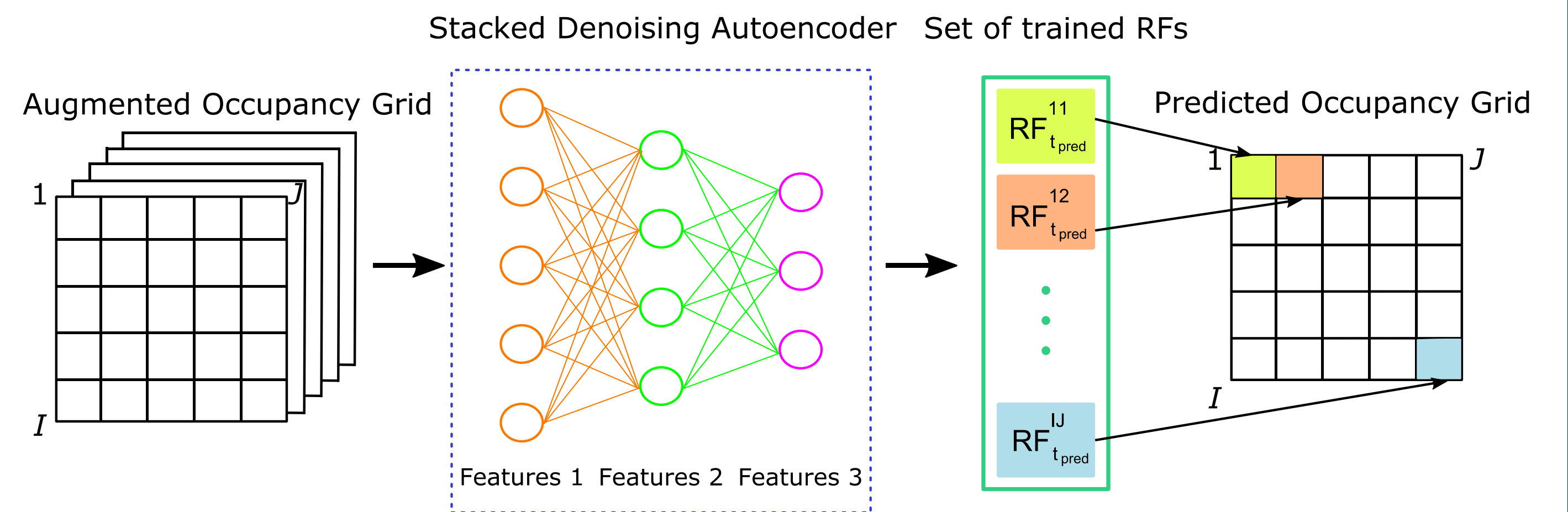


Figure 4: Estimation of Predicted-Occupancy Grid using machine learning

- The RF algorithm maps the low-dimensional input space to the POG
- Probabilities of each cell in the POG are estimated independently by one RF per cell

Simulation

- Simulations are performed to validate:
 - The ability of the SDA to achieve dimensionality reduction on the AOG
 - The quality of the predicted POGs using the low-dimensional features
- A traffic scenario with varying number of traffic participants (maximum 3) is considered
- Number of traffic scenarios for training and testing = 1950 and 900

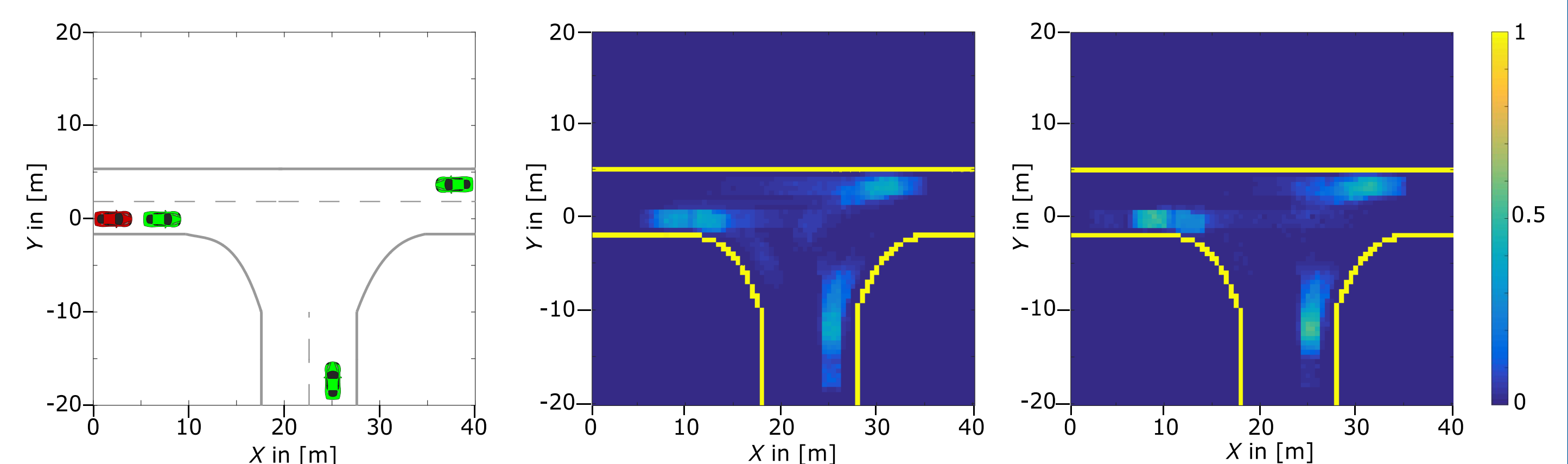


Figure 5: Scenario under consideration, POG using RF and POG using SDA and RF

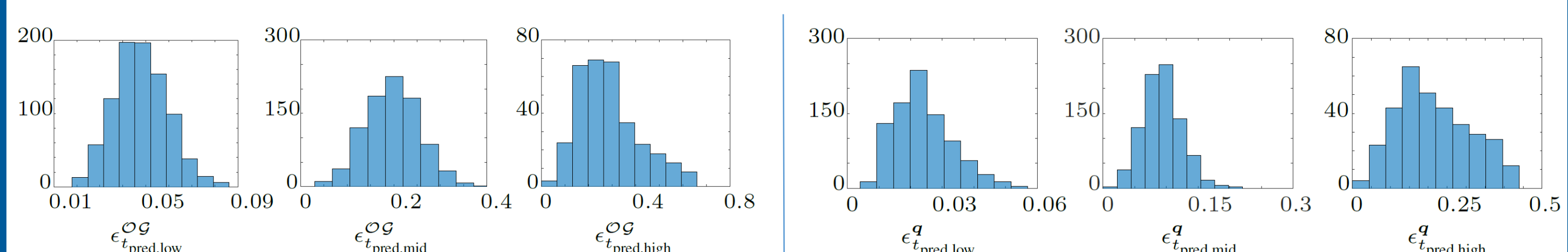


Figure 6: Histogram of error for 900 testing test scenarios using RF

Figure 7: Histogram of error for 900 testing test scenarios using SDA and RF

- Three error estimates low, mid and high are computed for low, mid and high values of the probability of occupancy
- Experiments with real vehicles are carried out at the outdoor test facility of CARISSMA
- A Local Position Measurement (LPM) system provides the reference state information of the traffic participants

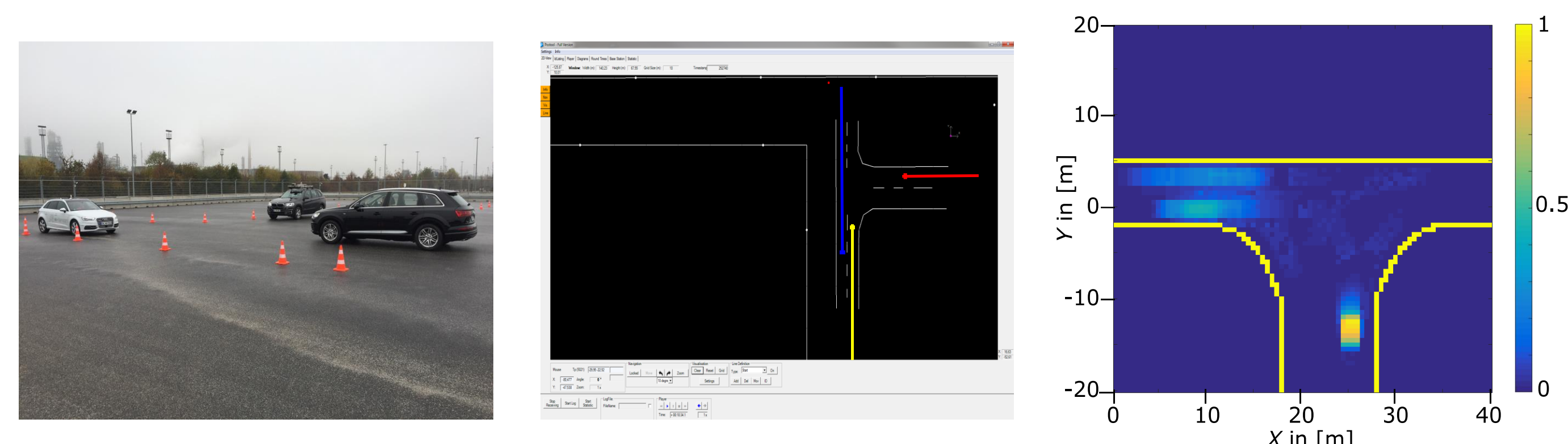


Figure 8: Experiments with real vehicles at the outdoor test facility

Conclusion

- A methodology for predicting the evolution of different kinds of traffic scenarios is presented
- A hierarchical situation classifier distinguishes the different traffic scenarios based on road geometry and also identifies the safety-relevant traffic participants
- The unsupervised dimensionality reduction using SDA is performed on the AOG
- The low-dimensional features increase the learning and the prediction accuracy of the RFs and also lead to a significant reduction in the training time of the RFs