Machine Learning-Driven Trajectory Prediction Models and Motion Control Strategies for Connected Automated Vehicles with Human Adaptation

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Vehicles are currently undergoing a digital transformation, increasingly equipped with advanced sensing devices, electronic control units, and communication interfaces that enhance their capabilities. The richness of information generated by these systems fosters the development of data-driven approaches that facilitate context-aware decision-making. The thesis focuses on developing data-driven frameworks in two key research directions: vehicle trajectory prediction and vehicle motion control. The thesis aims to enhance safety, traffic efficiency, comfort, and the overall driving experience through the implementation of these frameworks.

Initially, for vehicle trajectory prediction, a machine learning-aided, uncertainty-aware framework is introduced to detect collisions in complex urban environments. The proposed framework leverages Long Short-Term Memory (LSTM)-based models to predict vehicles' future trajectories and estimate the uncertainties associated with them. Subsequently, a random forest classifier leveraging both the trajectory predictions and their associated uncertainties is employed to detect collisions preemptively. The framework was evaluated using mobility traces from two urban intersections, and the results demonstrated that it could detect all collisions at the intersections preemptively, unlike its alternatives. In addition, it has fewer false positives, emphasizing the framework's effectiveness. The use of prediction intervals along with the predicted trajectories led to a 61% improvement in the median reaction time available for drivers. Given their timely detection, automated vehicles can avoid all collisions at both intersections.

Subsequently, for vehicle motion control, two Deep Reinforcement Learning (DRL)-based frameworks have been introduced: 2-Layer Learning Cooperative Adaptive Cruise Control (2LL-CACC) and Adaptive Autopilot. The 2LL-CACC framework utilizes a two-layer learning strategy designed to tackle challenging maneuvers with the objective of enhancing safety, comfort, and traffic efficiency. The top layer hosts a context recognition model to appropriately weigh the target metrics such as headway, jerk, and longitudinal wheel slip. The bottom layer leverages a

DRL-based control strategy that optimizes vehicle acceleration to achieve the objectives. To evaluate this approach, CoMoVe (Communication, Mobility, and Vehicle dynamics), a virtual validation framework, is employed to realistically simulate the challenging cut-in and cut-out scenarios using domain-specific simulators. The results show that the framework achieved a better trade-off among the objectives and outperformed its counterparts. In terms of traffic efficiency, the approach maintained the desired headway for 73% of the simulation time on average across two scenarios, while its counterparts achieved only 30%. Additionally, SCALEXIO AutoBox is used for rapid control prototyping to experimentally validate the simulation results.

Modern vehicles, despite being equipped with Advanced Driver Assistance Systems (ADAS), often encounter their ADAS functionalities disengaged by drivers due to their limitations in adapting to driver preferences. To tackle the disengagement rate, the adaptive autopilot framework focuses on achieving human-like driving behavior by tailoring control actions according to the driver's preferred driving style. It addresses three interconnected sub-problems in the car-following scenario. Initially, a rule-based (RB) approach categorizes driving styles into three types: aggressive, normal, and conservative. Subsequently, deep neural network-based regressor models are trained on this categorized data to predict human driver-like acceleration values for each driving style. Finally, a Constrained Deep Reinforcement Learning (C-DRL) approach is trained to mimic human-like driving behavior by controlling the vehicle's acceleration. The C-DRL agent is trained to reduce the difference between its action and the predicted human driver-like acceleration, while also guaranteeing safety. Performance assessments show that each sub-problem has achieved its respective objectives. The RB classifier effectively categorizes drivers' driving styles, while the regressor models predict human driver-like accelerations, with 80% of the absolute errors falling below 0.21 m/s^2, outperforming its alternatives. Following that, C-DRL agents can safely mimic human-like driving across all styles, thereby enhancing the driving experience and reducing the disengagement rate of ADAS functionalities.