Project Status Report for Berkeley Deep Drive

Motion Generation and Cognition by Combining Learning-based and Conventional Methodologies for Autonomous Driving

submitted by Masayoshi Tomizuka, Mechanical Engineering Department
University of California, Berkeley

1. Project Overview
Autonomous vehicles need to understand the behavior of others, predict their future motions and plan desirable motions which are safe and human-like to execute. In this project, we tackled motion prediction and planning together as a motion generation problem. Learning-based (such as neural networks and Gaussian mixture model) and conventional methodologies (optimization-based planner and controller, as well as Bayesian filtering) were combined to achieve accurate cognition of the behavior of others and to obtain a safe and human-like driving policy for autonomous vehicles.

Two paradigms were proposed for a policy net to learn desirable driving policies from optimization-based expert planners and controllers. Constrained Policy Net (CPN) was proposed in [1] to force a policy net to learn how to generate vehicle motions satisfying safety and feasibility constraints from an optimization-based expert planner. A policy net was trained via imitation learning with dataset aggregation (DAgger) in [2] to learn long-term optimal driving policies from an expert model predictive controller (MPC), and a subsequent layer with MPC guaranteed short-term safety and feasibility.

Adaptive mixture particle filter (AMPF) was proposed for vehicle tracking and prediction by combining Bayes filter and probabilistic learning models. In the proposed framework, vehicle kinematics and dynamics can be incorporated via the Bayesian filtering structure, and the behavioral model can be learned via Gaussian mixture model (GMM) so that accurate probabilistic intention and motion prediction are provided when target vehicles are partially or fully occluded for a long period. A novel approach of GMM-based Mixture Density Network was also developed for intention recognition for surrounding vehicles with semantic descriptions while considering interactions.

2. Publications

3. Summary
3.1. Constrained Policy Net (abstract of Paper [1])
Policy networks have great potential to learn sophisticated driving policy under complicated interaction between human drivers. However, it is hard for policy networks to satisfy safety and feasibility constraints,
which is a standard task for conventional motion generation methods, such as optimization-based approach. In this paper, we propose Constrained Policy Net (CPN), which can learn safe and feasible driving policy from arbitrary inequality-constrained optimization-based expert planners. Instead of supervised learning with $L_2$ norm as the loss, we incorporate the domain knowledge of the expert planner directly into the training loss of the policy net by applying barrier functions to the safety and feasibility constraints of the optimization problem. An exemplar scenario with obstacles on both sides is used to implement the proposed CPN. Test results demonstrate that the policy net can learn to generate motions near boundaries of safety and feasibility constraints to achieve high driving quality as the baseline optimization while the constraints are satisfied.

3.2. Imitation Learning with DAgger (abstract of Paper [2])

For safe and efficient planning and control in autonomous driving, we need a driving policy which can achieve desirable driving quality in long-term horizon with guaranteed safety and feasibility. Optimization-based approaches, such as model predictive control (MPC), can provide such optimal policies, but their computational complexity is generally unacceptable for real-time implementation. To address this problem, we propose a fast integrated planning and control framework that combines learning- and optimization-based approaches in a two-layer hierarchical structure. The first layer, defined as the "policy layer", is established by a neural network which learns the long-term optimal driving policy generated by MPC. The second layer, called the "execution layer", is a short-term optimization-based controller that tracks the reference trajectories given by the "policy layer" with guaranteed short-term safety and feasibility. Moreover, with efficient and highly-representative features, a small-size neural network is sufficient in the "policy layer" to handle many complicated driving scenarios. This renders online imitation learning with dataset aggregation (DAgger) so that the performance of the "policy layer" can be improved rapidly and continuously online. The effectiveness and efficiency of the proposed framework is demonstrated by several driving scenarios.

3.3. Tracking and Prediction via Particle Filter with Gaussian Mixture Model (ongoing work)

Probabilistic learning models can learn the behavior of other road participants to enhance Bayesian tracking when the measurement is noisy or missing due to occlusion or long distance. On the other hand, kinematic and dynamic models can be incorporated via Bayes filter to eliminate infeasible motions to facilitate prediction. Adaptive mixture particle filter (AMPF) is proposed, which is a tracking and prediction framework by combining particle filter and Gaussian Mixture Model (GMM). The tracked vehicle state distribution can be represented uniformly with this framework. The number of components and corresponding particles can be adaptively adjusted to achieve desirable tracking performance with reduced computational cost. When the measurement data is very noisy or even missing due to occlusions, GMM is employed to predict vehicle motions, which is trained by using NGSIM with real-world highway driving data. We also use a Mixture Density Network to predict intentions and motions for surrounding vehicles with semantic descriptions in interactive highway scenarios.