ABSTRACT

Motion planning for Autonomous Vehicles (AVs) and Connected Autonomous Vehicles (CAVs) involves the crucial task of translating road environmental data obtained from sensors and connectivity devices into a sequence of executable vehicle actions. This task is critical for AVs and CAVs, because the efficacy of their driving decisions and overall performance depend on the quality of motion planning.

In the context of motion planning technologies, several fundamental questions and challenges remain despite the widespread adoption of advanced learning-based methods, including deep learning (DL) and deep reinforcement learning (DRL). In this regard, the following critical questions need to be answered: 1) How to design suitable DL architectures to comprehensively understand the driving scenario by integrating data from diverse sources including sensors and connectivity devices? 2) How to effectively use the fused information to make improved driving decisions, accounting for various optimality criteria? 3) How to leverage vehicle connectivity to generate cooperative decisions for multiple CAVs, in a manner that optimizes system-wide utility? 4) How to address the inherent interpretability limitations of DL-based methods to enhance user trust in AVs and CAVs? 5) Is it possible to extend learning-based approaches to operational-level decisions in a way that overcomes the inherent disadvantage of low explainability and lack of safety guarantee?

In an effort to address these questions and expand the existing knowledge in this domain, this dissertation introduces several learning-based motion planning frameworks tailored towards different driving scenarios of AV and CAV. Technically, these efforts target on developing trustworthy AI systems with a focus on the information fusion, "explainable AI" or XAI and safety critical AI. From a computational perspective, these frameworks introduce new learning-based models with state-of-the-art (SOTA) structures, including Convolutional Neural Network (CNN). Recurrent Neural Networks (RNN), Graph Neural Networks (GNN), Attention networks, and Transformers. They also incorporate reinforcement learning (RL) agents, such as Deep Q Networks (DQN) and Model-based RL. From an application standpoint, these developed frameworks can be deployed directly in AVs and CAVs at Level 3 and above. This can enhance the AV/CAV performance in terms of individual and system performance metrics, including safety, mobility, efficiency, and driving comfort.

Defense Information:

Date: November 13th (Monday)

Time: 10:00 am to 12:00 pm (Eastern Time)

Room: Hamp 4158

Meeting link:

https://purdue-edu.zoom.us/j/98461640561?pwd=RS93TmtXNE1HN0dJYWw0UTd4ajE3UT09