Deductive Synthesis and Verification for Robotics Systems

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Project Summary

Overview:

In robotics domains, decision-making often involves dealing with complex continuous state and action spaces, long horizons, and sparse reward feedback. Hierarchical planning and learning with temporally extended state and action abstractions have emerged as promising solutions that use a high-level search for abstract control plans to guide low-level robot execution in the original state transition space. However, these techniques are limited in several ways. They often struggle to generalize across multiple tasks and to large problems that are intractable for modern planners, rely on hand-crafted and possibly suboptimal state and action abstractions, and cannot formally guarantee that high-level abstract control plans are correct and downward executable in low-level continuous spaces. To overcome these challenges, this proposal aims to develop a novel hierarchical learning paradigm for robotics controllers based on program synthesis. The project will explore (*a*) bi-level program synthesis frameworks for learning robot execution programs that can generalize in multi-task settings and operate in noisy, inconsistent environments, (*b*) automatically learning temporally extended state and action abstractions to induce a desirable domain-specific language for robot-control program synthesis, and (*c*) compositional verification techniques for ensuring that synthesized robot execution programs adhere to desired correctness properties. Overall, this project aims to establish new foundations to enable highly interpretable robotics control systems capable of making reliable decisions with verifiable guarantees.

Intellectual Merit:

The key intellectual merit of the proposal lies in the development of a programming-by-reward synthesis framework to learn robot execution programs in stochastic, goal-based, and multi-task settings for high-dimensional continuous state and action spaces with only partial observability. Synthesized programs are able to conduct high-level abstract reasoning to solve tasks with long horizons and sparse rewards, while integrating neural network-based components for low-level perception and control to scale to continuous spaces. First, this project will advance state-of-the-art reinforcement learning and planning techniques which are traditionally concerned with solving individual tasks. By synergistically combining execution-guided and deductive program synthesis, it will enable learning robot execution programs formed of state-conditioned loops, conditionals, and memory structures that warrant generalization across multiple tasks and uncertain environments. Second, this project will study domain-specific language (DSL) induction. It will automatically discover temporally extended state and action abstractions of continuous spaces in an evolving DSL to form the discrete, factored spaces from which high-level programs can be searched. Third, this project will exploit the bi-level structure of synthesized robot execution programs to develop a scalable verification framework that supports formally reasoning about the correctness of high-level programs and their low-level components in a highly compositional manner.

Broader Impacts:

This project tackles key technical questions at the core of an emerging paradigm for building trustworthy robotics systems. Specifically, it focuses on creating a novel neurosymbolic representation for robotics controllers that promotes generalizability, as well as developing new learning and verification algorithms based on formal methods to guarantee correctness. The resulting research will be impactful, paving the way for the next generation of learning-enabled robotics systems where trustworthiness is a critical consideration. Furthermore, the project aims to develop curriculum materials that will teach undergraduate and graduate students how to build interpretable and verifiable robotics control systems using the technologies developed during this research.