

Statement of Purpose

My name is Hongyi Chen and I have untraditional experience before doing robotics research: I majored in math and economics in undergraduate college. But I was fascinated by the robotics and AI technology which have changed society, and was determined to build smart robotics for manufacturing applications and daily household assistants. In detail, my research brings together ideas from motion and task planning, language model, machine learning, reinforcement learning (RL), and control theory to solve three major challenges: (1) design reconfigurable robots that can reason and plan themselves from task descriptions, (2) learn to accumulate new skills by conducting experiments over their lifetimes and (3) guarantee safe execution under uncertainty.

Past Research Experience

For challenge (1), to reduce human's burden of programming robots for varied tasks, we designed a neuro-symbolic planner for home assistant robots allowing them to automatically plan the action sequence based on human instruction. The task planning from natural language is challenging as rule-based parsing can't well capture the semantic meaning of language and learning-based networks suffer from error propagation. Instead, our approach combines the benefits of both approaches: the vision-and-language learning network predicts its goal representation, which is sent to a symbolic planner using Planning Domain Definition Language (PDDL) for producing a task-completing action sequence.

However, we still need to define the predicates and rules in PDDL and assume the robots have a complete set of pre-trained skills. To relax these two constraints, we exploit the pre-trained large language models (LLMs) as they can effectively decompose high-level tasks into mid-level plans if the pre-trained LLMs are large enough and prompted appropriately, and learn the new skills during task planning and execution. As LLMs have randomness and can not map the generated plans precisely to admissible actions, we aim to build a tighter bi-directional connection between high-level planning and low-level skill learning, which is also beneficial to solve the challenge (2).

In top-down design, we regard the high-level LLMs planner as an autonomous curriculum to schedule skill learning in a progressive manner, which would continuously grow the agent's capability and the set of tasks that it can solve. Most previous skill learning works rely on RL-based manual reward designs or supervised learning requiring huge amounts of training data which is not available in many tasks. Therefore, I would like to minimize human involvement and learn the skills in a self-supervised manner. In detail, we use LLMs to describe the details of target goal state, perform scene graph abstraction on the goal description and the current world observation, and guide the skill learning by bridging the two scene graphs. In bottom-up design, we inform the LLMs what skills the robot is capable of now and what skills are still in the learning process, letting LLMs plan in a more structural way accordingly.

For challenge (3), robots should not make unwanted contact with the objects in the environment and learn to adapt trajectories to ensure safe execution under uncertainty. To solve this problem, I used the energy-based safe set algorithm (SSA) to enable safe and sample-efficient reinforcement learning. Although navigation in clustered dynamic environments is challenging to be solved by existing RL algorithms, we can guarantee safety by using SSA to monitor and modify the nominal controls during policy training and execution. Furthermore, by encouraging policy exploration with safety constraints and treating SSA as expert demonstrations, we can improve the sample efficiency and speedup the policy training. Later, to offset the myopic problem in single-step reactive SSA, I investigated designing a hierarchical solution consisting of a multi-phase planner on top of the low-level SSA. The planner employs dynamic gap analysis and trajectory optimization to achieve collision avoidance with respect to the dynamic agents. The robust SSA is adopted to address uncertainty by adjusting the safety distance over the planning horizon.

Future Research Plan

Besides the challenges I mentioned above, I am also interested in using robotics to realize a flexible additive manufacturing (AM) process. For example, traditional AM constructs a part using only planar horizontal layers. While performing material deposition using 6 DOF robot arms can significantly expand the capabilities by allowing material deposition on complex non-planar layers and reduce overall fabrication time in printing of large parts. Moreover, the conventional material extrusion AM builds part using a constant bead size, which requires the user to make a tradeoff between surface quality and build time of the part. Instead, we could utilize the robot manipulator with a multi-nozzle extrusion tool and advanced computer vision methods to adjust the deposition rate to achieve short build time and good surface finish.