Task-relevant Model-based Reinforcement Learning for Contact-rich Robotic Tasks

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Abstract

This thesis presents “task-relevant model-based reinforcement learning” to learn complex robot dynamics and perform tasks in contact-rich environments. Model-based Reinforcement Learning (MBRL) offers a promising solution for capturing complex robot dynamics that pose challenges for analytic solutions attempting to capture them accurately. However, controlling the robot with an MBRL-learned dynamics model is limited to the available entries of the robot state, which may not be sufficient for completing the intended task. To enhance standard MBRL's ability, we present the task-relevant MBRL that reformulates the robot state to 1) satisfy the requirements of the intended task, 2) be adequate for dynamics learning with MBRL, and 3) be able to adjust the motion behavior while performing the task. Our method is verified through two contact-rich applications: First, we improve the contact-safety during the learning process of two common kitchen tasks, particle mixing and scooping tasks. The improvement in contact-safety is achieved by accommodating model-uncertainty in a reformulated robot state and utilizing it to constrain the robot’s motion to achieve contact-safe behaviors accordingly. Second, we enable real-time planning for walking acquisition on a spring-loaded bipedal robot. This is achieved by following the law of conservation of energy to reformulate an energy-state that views all springs as energy containers and treats actuators as energy sources. The formulation of the energy-state reduces the model dimension and significantly increases planning speed while sufficiently expressing the robot's dynamics during walking. The success of both applications demonstrates the task-relevant MBRL’s effectiveness and applicability to various robotics applications that require flexibility, robustness, and safety in uncertain and contact-rich environments.