Sim-to-Real Reinforcement Learning with Low-fidelity Simulators and Extensive Domain Randomization for Complex Tasks

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Abstract

Recently, there has been significant attention to sim-to-real reinforcement learning frameworks that focus on training robot control policies in a simulation and then transferring the policies to the real-robot environment in a zero-shot setting. In this framework, it is necessary to obtain policies that are robust to the reality gap that occurs between the real-robot environment and the simulation. Therefore, it is natural to think that if we aim to obtain a transfer policy with higher real-world performance, we should create a simulator that is more fidelity to the real-world environment. Nevertheless, high-fidelity simulators often demand substantial calculation time to replicate the intended phenomena accurately. Additionally, there is a risk that the transfer policy may overfit these phenomena including remaining reality gaps. To cope with this problem, we propose an opposite approach, combining a low-fidelity simulator with policy learning from extensive environmental patterns. Specifically, we reduce calculation time by simplifying the components of the environment (robots and manipulators) without engineering them precisely. We apply Domain Randomization (DR), which learns policies by randomizing combinations of shapes and physical parameters of each component, as extensively as possible to robustly policies to the reality gap. Then, we propose a novel reinforcement learning algorithm that is robust to the instability of policy updates in reinforcement learning occurring by the extensive DR. To evaluate the effectiveness of the proposed approach, Sim-to-Real experiments were conducted on a powder weighing task, a rock removal from sediment task, and a flexible object block collapse task, which are tasks involving physical phenomena that are difficult to reproduce with multiple particles.