Modular Deep Networks for Visuo-motor Policy Transfer from Simulation to the Real World

Publications


Various approaches have been proposed to learn visuo-motor policies for real-world robotic applications. One solution is first learning in simulation then transferring to the real world. In the transfer, most existing approaches need real-world images with labels. However, the labelling process is often expensive or even impractical in many robotic applications. In this paper, we propose an adversarial discriminative sim-to-real transfer approach to reduce the cost of labelling real data. The effectiveness of the approach is demonstrated with modular networks in a table-top object reaching task where a 7 DoF arm is controlled in velocity mode to reach a blue cuboid in clutter through visual observations. The adversarial transfer approach reduced the labelled real data requirement by 50%. Policies can be transferred to real environments with only 93 labelled and 186 unlabelled real images. The transferred visuo-motor policies are robust to novel (not seen in training) objects in clutter and even a moving target, achieving a 97.8% success rate and 1.8 cm control accuracy.


While deep learning has had significant successes in computer vision thanks to the abundance of visual data, collecting sufficiently large real-world datasets for robot learning can be costly. To increase the practicality of these techniques on real robots, we propose a modular deep reinforcement learning method capable of transferring models trained in simulation to a real-world robotic task. We introduce a bottleneck between perception and control, enabling the networks to be trained independently, but then merged and fine-tuned in an end-to-end manner. On a canonical, planar visually-guided robot reaching task a fine-tuned accuracy of 1.6 pixels is achieved, a significant improvement over naive transfer (17.5 px), showing the potential for more complicated and broader applications. Our method provides a technique for more efficiently improving hand-eye coordination on a real robotic system without relying entirely on large real-world robot datasets.


This paper introduces an end-to-end fine-tuning method to improve hand-eye coordination in modular deep visuo-motor policies (modular networks) where each module is trained independently. Benefiting from weighted losses, the fine-tuning method significantly improves the performance of the policies for a robotic planar reaching task.
