先端科学技術研究科　修士論文要旨

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要旨

Imitation learning from human demonstrations is an effective approach for enabling robots to acquire complex behaviors without manually designing task-specific controllers. This thesis addresses imitation learning from demonstrations collected through hand-mounted interfaces, where users provide motions through their own hand movements rather than through direct robot teleoperation. Although such interfaces make demonstration collection intuitive, the resulting data may contain robot-infeasible motions due to differences between human and robot physical capabilities. Standard imitation learning methods can be degraded by such infeasible demonstrations because the learned policy may attempt to reproduce motions that violate the robot's physical or dynamic constraints. To address this problem, this thesis proposes Experience-Based Feasibility-Aware Generative Adversarial Imitation Learning (EF-GAIL), an imitation learning framework that estimates demonstration feasibility from the robot's own experience collected during policy learning. Instead of relying on explicit dynamics models or large prior exploration datasets, the proposed method trains a reconstruction model using policy-generated state transitions. Demonstration transitions are then weighted according to their reconstruction error, where transitions similar to the robot's experience receive higher feasibility weights. These weights are incorporated into discriminator training to reduce the influence of infeasible demonstrations. The proposed method is evaluated in a two-dimensional point-mass navigation task and a quadruped robot navigation task using a Unitree Go2 model. The quadruped experiments include both simulation and real-robot evaluation. The results show that infeasible demonstrations degrade conventional adversarial imitation learning, while the proposed method improves task success and final-position accuracy by emphasizing feasible demonstrations during training.