A Hybrid Contact Dynamics and Residual Reinforcement Learning Framework For Multi-Point Object Pushing

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Abstract

Multi-point object pushing is a fundamental manipulation primitive in robotics, widely applied in industrial automation, warehouse logistics, collaborative robotics, and autonomous material handling. However, accurately modeling the physical interactions involved in multi- contact pushing remains challenging due to nonlinear friction, contact mode transitions (sticking and slipping), torque-force coupling, and unmodeled surface anisotropies. Classical analytical contact dynamics models provide interpretability and computational efficiency but often suffer from systematic prediction errors when real-world effects deviate from simplified assumptions. To address these limitations, this work proposes a Hybrid Contact Dynamics and Residual.RI framework for robust and accurate multi-point object pushing.The proposed framework integrates a physics-inspired quasi-static contact dynamics baseline with a data-driven residual correction model. The baseline component computes net forces and torques from multiple contact points and predicts object pose evolution using friction- damped motion equations. While this analytical model captures core rigid-body mechanics, it does not fully represent nonlinear friction saturation, translation-rotation coupling, and micro- slip behaviors. To compensate for these discrepancies, a neural residual module is introduced to learn the systematic difference between baseline predictions and true object motion. This residual correction enhances predictive accuracy while preserving the interpretability of the underlying physics model.

A key contribution of the framework is the Residual. RI (Residual Refinement Iterative) mechanism, which applies learned corrections iteratively during inference. Instead of performing a single correction step, the system refines the predicted state multiple times using updated intermediate estimates. This iterative residual refinement improves rollout stability in long-horizon simulations and mitigates compounding error accumulation commonly observed in purely learned dynamics models.The framework is validated using a synthetic multi-contact pushing dataset, where hidden nonlinear and anisotropic effects simulate real-world physical complexity. Experimental evaluation demonstrates that the hybrid approach significantly reduces one-step prediction error compared to the analytical baseline. Moreover, multi-step trajectory rollouts show improved stability and accuracy when employing Residual.RI refinement. The results indicate that combining structured physical modeling with learnable residual corrections provides a balanced trade-off between interpretability, generalization, and predictive precision.