Week 14 Paper Review

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Abstract

This is a brief review of [1], [2].

1 Making Sense of Vision and Touch: Self-Supervised Learning of Multimodal Representations for Contact-Rich Tasks

The authors of this paper introduce a novel methodology to provide a compact multi-modal representation of complimentary sensory raw inputs (haptic, vision, proprioceptive data). These representations remain fixed and provide input to aid policy learning via RL for contact-rich manipulation tasks. The representations are learnt using self-supervised learning. The manipulation task is formulated as a model-free RL problem which acts under uncertainty and is solved via TRPO. The ablation studies show that a combination of complementary multi-modal inputs performs the best by guiding different stages of the robot's trajectory. Moreover, these representations show generalization to tasks with different peg geometry and robustness to perturbation and sensor noise.

Overall, the paper provides a scalable approach to represent high-dimensional / high-modality data into compact forms, however, there is no empirical evidence if the performance would be the same if extremely diverse (non-complementary) sensory inputs are provided.

2 Iterative Residual Policy: for Goal-Conditioned Dynamic Manipulation of Deformable Objects

The authors introduce Iterative Residual Policy (IRP), a novel learning framework for goal-conditioned dynamic manipulation. IRP learns delta dynamics that predict the effects of delta action on the previously-observed trajectory, instead of modelling the entire dynamical system and inferring actions from that model. Combining these learned delta dynamics with visual feedback, they achieve high accuracy by iteratively adjusting actions.

Moreover, the authors have emphasized that they use the same model trained in simulation on a fixed robot setup for testing several variations of the deformable object in the real world. The experiments in both simulation and the real- world have been carried out on 1-D (ropes) and 2-D (tablecloths) deformable objects. They demonstrate IRP's adaptability to many aspects of the system, including object parameters (such as length and density in ropes), real-world dynamics (multi-modal aspect of the solution-space), and even robot hardware embodiment (by changing the end-effector length). Additionally, the goal is reached in just 3 iterations in the real world after fine-tuning which shows significant performance gains over the Sim2Real gap.

Overall, it is an extremely simple, yet robust approach to solving extremely complex tasks. However, the method assumes action repeatability which can not be guaranteed in many applications. They also assume full observability of the manipuland throughout the trajectory, which makes direct application of this approach difficult in highly cluttered scenarios.

Preprint. Under review.

References

[1] Lee, M. A., Zhu, Y., Srinivasan, K., Shah, P., Savarese, S., Garg, A., & Bohg, J. (2018). Making Sense of Vision and Touch: Self-Supervised Learning of Multimodal Representations for Contact-Rich Tasks. ArXiv. /abs/1810.10191

[2] Chi, C., Burchfiel, B., Cousineau, E., Feng, S., & Song, S. (2022). Iterative Residual Policy: For Goal-Conditioned Dynamic Manipulation of Deformable Objects. ArXiv. /abs/2203.00663