Latent Action Discretization Resolution and Policy Generalization in CALVIN

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: To what extent does the resolution of latent action discretization affect policy generalization across unseen tasks in the CALVIN environment. 8 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.9/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: On the Role of the Action Space in Robot Manipulation Learning and Sim-to-Real Transfer. Research question: To what extent does the resolution of latent action discretization affect policy generalization across unseen tasks in the CALVIN environment?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.9/10.

3 Results

11 papers retrieved. 8 claims extracted; 0 independently verified. Quality review score: 3.9/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Cartesian action spaces have an advantage in terms of sample efficiency and maximum reached reward in the pushing task c	×	0.09
Joint velocity and its derivatives have the overall best sample efficiency and converge to higher reward regions than th	×	0.04
Joint position (JP) reaches the highest reward in reaching but struggles massively in pushing.	×	0.02
Velocity action spaces perform better in terms of sample efficiency and final rewards in Cartesian action spaces.	×	0.09
Joint torque action space is the fastest one to converge in the reaching task but fails to solve the pushing task reliab	×	0.05
Multi-step integration delta action spaces consistently perform the worst, while one-step methods seem to have a slight	×	0.05
The success rate of policies is not directly representative of the episodic reward obtained during training.	×	0.06
The joint torque action space can solve the pushing task if trained for a longer time, but it is very expensive.	×	0.06

References

- http://arxiv.org/abs/2505.04999v1
- http://arxiv.org/abs/2312.03673v2
- http://arxiv.org/abs/2011.01928v1