Adaptive Neuroevolutionary Control for Soft Robots Under Morphological Degradation

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Abstract

This paper presents the implementation and analysis of...

Index Terms

Genetic Algorithms, Binary Encoding, Optimization, Evolutionary Computing

I. Introduction

Evolutionary algorithms (EAs) have shown great promise in solving complex optimization problems across various domains. Recent work in EvolutionGym [1] has demonstrated the potential for evolutionary approaches in robotics and control tasks. This research builds upon these foundations to explore new methodologies.

A. Motivation

The motivation behind this work is to explore...

B. Problem Statement

The primary problem addressed in this study is...

C. Contributions

The contributions of this paper include...

D. Overview

This paper is organized as follows...

II. Related Work

In this section, we review prior applications of evolutionary algorithms to control tasks and highlight key benchmarks, including those relevant to EvolutionGym.

A. Evolutionary Approaches to Control

Previous research has demonstrated...

B. Benchmarking and Simulation Environments

Frameworks such as OpenAI Gym, PyBullet, and EvolutionGym have been used to evaluate...

C. Multi-Objective and Morphological Evolution

Recent works exploring multi-objective optimization and morphology evolution have shown...

III. Methodology

This section details our genome representation, evolutionary process, and implementation within the EvolutionGym environment.

A. Problem Formulation

Our objective is to evolve controllers/morphologies that maximize performance in...

B. Genome Representation

We define each individual as a...

C. Evolutionary Operators

Selection, crossover, and mutation are applied as follows...

D. Fitness Function

The fitness function rewards agents that...

E. Implementation Details

All experiments were implemented using...

IV. Experimental Setup

We describe the selected environments, experimental parameters, and evaluation protocol.

A. Environment Selection

Tasks were chosen from EvolutionGym to provide coverage across locomotion, manipulation, and mixed-behavior challenges...

B. Evaluation Metrics

We measured performance using average reward, success rate, and behavior diversity...

C. Hyperparameters

We used a population size of..., mutation rate of..., over N generations...

V. Results

The results of our experiments demonstrate the effectiveness of...

A. Performance Across Environments

The evolved agents achieved...

B. Comparison to Baselines

Compared to baseline controllers, our approach...

C. Ablation Study

To assess the contribution of each component, we...

VI. Discussion

We discuss the implications, limitations, and potential for future work.

A. Insights from Evolved Behavior

Analysis of behavior reveals that...

B. Generalization and Overfitting

Agents were evaluated in perturbed environments to assess...

C. Limitations

This work is limited by...

VII. Conclusion and Future Work

In this study, we presented... In future work, we aim to...

References

[1] J. Bhatia, H. Jackson, Y. Tian, J. Xu, and W. Matusik, "Evolution gym: A large-scale benchmark for evolving soft robots," in *Advances in Neural Information Processing Systems*, 2021, pp. 2201–2214.