

Neuroevolutionary Control for Soft Robots: A NEAT Implementation Study

Matthew D. Branson
Department of Computer Science
Missouri State University
Springfield, MO
branson773@live.missouristate.edu

Abstract—This paper presents a from-scratch implementation of NeuroEvolution of Augmenting Topologies (NEAT) applied to the coevolution of morphology and control in soft robots within the EvolutionGym framework. The study focuses on walker robots, exploring how simultaneous evolution of body structure and neural network controllers can produce effective locomotion strategies.

Index Terms—NEAT, neuroevolution, soft robotics, coevolution, morphology, neural networks, EvolutionGym

I. INTRODUCTION

The design of effective controllers for soft robots presents unique challenges due to their high-dimensional, non-linear dynamics and complex morphological properties. Traditional control approaches often struggle with the computational complexity and adaptability requirements of soft robotic systems. Neuroevolutionary methods, particularly NeuroEvolution of Augmenting Topologies (NEAT), offer promising alternatives by simultaneously optimizing both neural network topology and parameters.

This study implements NEAT from scratch and applies it to the coevolution of morphology and control in soft robots using the EvolutionGym framework [1]. The focus is on walker robots, examining how the simultaneous evolution of body structure and neural network controllers can discover effective locomotion strategies.

II. RELATED WORK

The EvolutionGym benchmark [1] provides a comprehensive framework for evolving soft robots, supporting both morphological and control optimization. This platform enables researchers to explore the complex interactions between robot structure and behavior in simulated environments.

NEAT [2] revolutionized neuroevolution by introducing topology evolution through complexification, starting with minimal networks and gradually adding nodes and connections. This approach addresses the competing conventions problem and enables the discovery of appropriate network architectures alongside optimal weights.

HyperNEAT [3] extends NEAT's principles by using compositional pattern-producing networks (CPNs) to generate neural network weights based on geometric relationships, showing particular promise for spatially-structured problems.

III. METHODOLOGY

This section describes the implementation of NEAT and its application to soft robot evolution within the EvolutionGym framework.

A. NEAT Implementation

A complete NEAT implementation was developed from scratch, including:

- Genome representation with node and connection genes
- Crossover operators that preserve topological structure
- Mutation operators for adding nodes and connections
- Speciation mechanism to protect topological innovation
- Fitness sharing within species

B. Coevolution Framework

The study focuses on the coevolution of robot morphology and neural network controllers for walker robots.

C. Experimental Setup

Experiments were conducted using walker robots in the EvolutionGym environment.

IV. RESULTS

This section presents the results of applying NEAT to morphology-control coevolution in soft robots.

V. CONCLUSION

This study demonstrates a from-scratch implementation of NEAT applied to the coevolution of soft robot morphology and control. The work provides insights into how neuroevolutionary approaches can discover effective locomotion strategies through simultaneous optimization of body structure and neural network controllers.

ACKNOWLEDGMENT

The author would like to thank the professor for guidance throughout this project and acknowledge that the scope was adjusted from the original proposal due to time and resource constraints.

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.
- [2] K. O. Stanley and R. Miikkulainen, "Evolving neural networks through augmenting topologies," *Evolutionary computation*, vol. 10, no. 2, pp. 99–127, 2002.
- [3] K. O. Stanley, D. B. D'Ambrosio, and J. Gauci, "A hypercube-based encoding for evolving large-scale neural networks," *Artificial life*, vol. 15, no. 2, pp. 185–212, 2009.