

Evolving Soft Robots Via Diffusion models

Bachelor/Master Thesis

Advisor: Erdi Sayar (*erdi.sayar@tum.de*)

Supervisor: Prof. Alois Knoll

Introduction and Problem Description

Both the design and control of a robot play equally important roles in its task performance. This problem can be formulated as a two-level optimization framework (co-optimizing design and control), where the outer loop evolves the physical structures of robots and the inner loop optimizes a controller (i.e reinforcement learning algorithm) for a given proposed structure design. Evolution Gym is the first large-scale benchmark for co-optimizing the design and control of soft robots. Each robot is composed of different types of voxels (e.g., soft, rigid, actuators), resulting in a modular and expressive robot design space. As shown in the overview in Figure 1, Evolution Gym [1] is comprised of a task-specific environment and a back-end soft-body simulator. The gym suite provides seamless interfaces with a user-defined co-design algorithm. The co-design algorithm typically consists of a design optimizer and a control optimizer. The design optimizer can propose a new robot structure to the control optimizer, then the control optimizer will compute an optimized controller for the given structure through interactions with Evolution Gym and finally return the maximum reward that this robot structure can achieve.

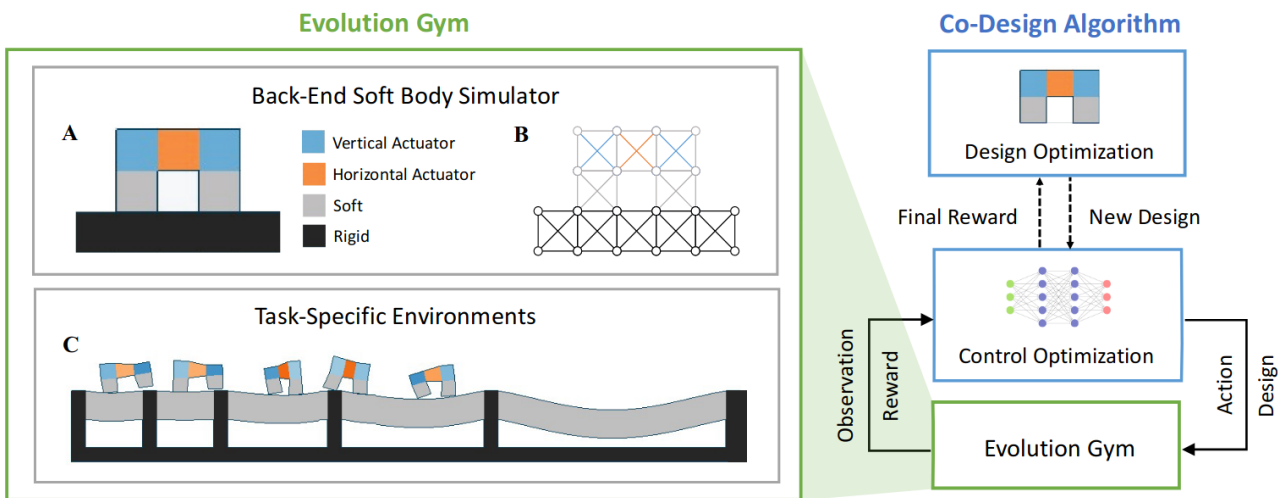


Figure 1: Overview of Evolution Gym and its integration with the co-design algorithms

Evolution Gym benchmark environments span a wide range of tasks, including locomotion on various types of terrains and manipulation. Furthermore, this benchmark includes several robot co-evolution algorithms by combining state-of-the-art design optimization methods and deep reinforcement learning techniques.

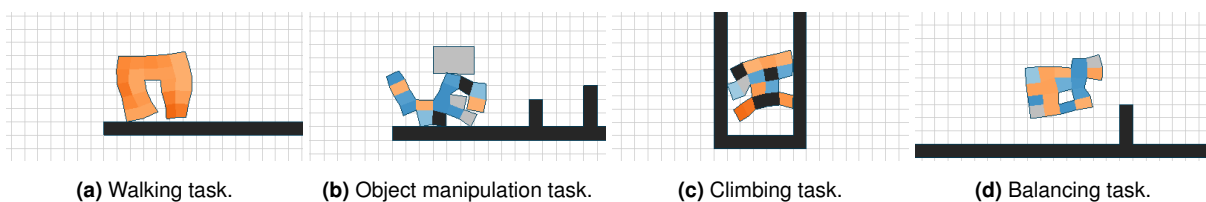


Figure 2: Environment evolution in the PickAndPlace task.

While Evolution Gym utilizes state-of-the-art algorithms, none of the algorithms tested in the benchmark have succeeded in finding robots that can succeed in the most challenging environments.

Task Description

In this thesis, your task will be to learn state-of-the-art algorithms in Evolution Gym, as well as how to use the Evolution Gym benchmark, and develop your design algorithm using Generative AI, such as diffusion models [3], and compare it with the state-of-the-art methods in the Evolution Gym benchmark.

- You will first learn the basics of state-of-the-art algorithms in Evolution Gym, and you will reproduce the results of Evolution Gym benchmark. By doing this, you will gain an understanding of Evolution Gym and the state-of-the-art research results.
- You will learn how to generate hand designed robots using Evolution Gym environment.
- As the Evogym environment requires high computational resources, you should design a simpler environment to test your future diffusion model approach.
- Test different types of diffusion models, such as the discrete diffusion model [2].
- Utilize reward values in conjunction with diffusion models.

References

- [1] Bhatia, J., Jackson, H., Tian, Y., Xu, J., and Matusik, W. "Evolution gym: A large-scale benchmark for evolving soft robots". In: *Advances in Neural Information Processing Systems* 34 (2021).
- [2] Lou, A., Meng, C., and Ermon, S. "Discrete diffusion language modeling by estimating the ratios of the data distribution". In: *arXiv preprint arXiv:2310.16834* (2023).
- [3] Wang, Z., Hunt, J. J., and Zhou, M. "Diffusion policies as an expressive policy class for offline reinforcement learning". In: *arXiv preprint arXiv:2208.06193* (2022).