CS 486 Pre-Proposal

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rEvoLution: RL for learning optimal agent design

Overview Our goal is to create an agent that uses reinforcement learning (RL) to dynamically optimize its physical morphology—such as limb count, joint configuration, and overall shape—to efficiently run. We aim to use Nvidia's **Isaac Lab** for realistic 3D simulations [3], though it doesn't natively support dynamic morphology adjustments during training.

Proposed Approach To address this, we plan to pre-select a set of body designs parameterized by URDF files. Each design will be trained separately, evaluated, and iteratively refined by replacing the lowest-performing morphologies. Over successive generations, we expect convergence toward an optimal design. Hence, the name of our approach is inspired by "evolutionary" algorithms.

Backup Plans and Methodology If the above proves infeasible, we will adopt methods from "Reinforcement Learning for Improving Agent Design" [1], using simpler (2D) but more flexible environments such as **Gymnasium** [5] and automatic training frameworks like **Tianshou** [6]. Alternatively, we may leverage **MuJoCo** [4] for detailed 3D simulations, potentially employing multi-agent RL strategies using **MARL** [2]. Additionally, can use **Weights & Biases** as a monitoring tool with any of the approaches.

We seek feedback on the feasibility and practicality of our proposed solutions, particularly concerning dynamic morphology optimization in the Isaac Lab environment. Please see reference images below 1 2.

Resources

https://mujoco.readthedocs.io/en/stable/overview.html
https://marllib.readthedocs.io/en/latest/
https://github.com/thu-ml/tianshou/tree/master
https://gymnasium.farama.org/
https://designrl.github.io/
https://isaac-sim.github.io/IsaacLab/main/index.html
https://github.com/wandb/wandb

References

[1] David Ha. Reinforcement learning for improving agent design. 2018. https://designrl.github.io.

[2] Siyi Hu, Yifan Zhong, Minquan Gao, Weixun Wang, Hao Dong, Xiaodan Liang, Zhihui Li, Xiaojun Chang, and Yaodong Yang. Marllib: A scalable and efficient multi-agent reinforcement learning library, 2023.

[3] Mayank Mittal, Calvin Yu, Qinxi Yu, Jingzhou Liu, Nikita Rudin, David Hoeller, Jia Lin Yuan, Ritvik Singh, Yunrong Guo, Hammad Mazhar, Ajay Mandlekar, Buck Babich, Gavriel State, Marco Hutter, and Animesh Garg. Orbit: A unified simulation framework for interactive robot learning environments. *IEEE Robotics and Automation Letters*, 8(6):3740–3747, 2023.

[4] Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5026–5033, 2012.

[5] Mark Towers, Ariel Kwiatkowski, Jordan Terry, John U. Balis, Gianluca De Cola, Tristan Deleu, Manuel Goulão, Andreas Kallinteris, Markus Krimmel, Arjun KG, Rodrigo Perez-Vicente, Andrea Pierré, Sander Schulhoff, Jun Jet Tai, Hannah Tan, and Omar G. Younis. Gymnasium: A standard interface for reinforcement learning environments, 2024.

[6] Jiayi Weng, Huayu Chen, Dong Yan, Kaichao You, Alexis Duburcq, Minghao Zhang, Yi Su, Hang Su, and Jun Zhu. Tianshou: a highly modularized deep reinforcement learning library, 2022.

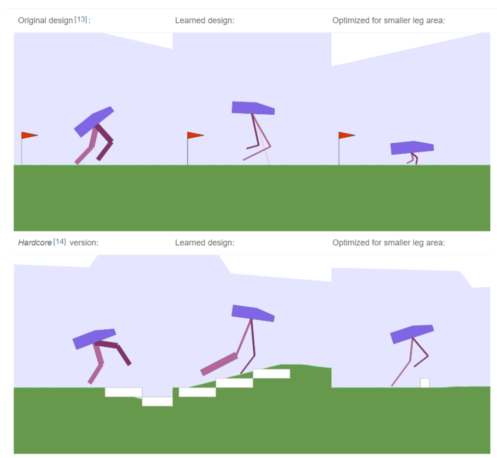
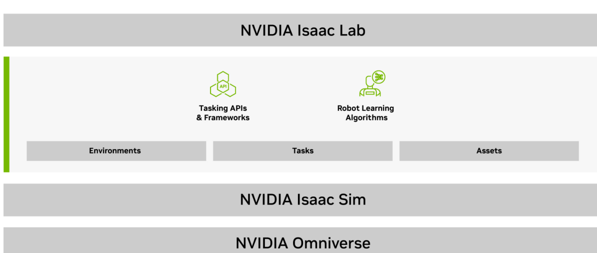


Figure 1: An example of an RL agent learning optimal morphology from "Reinforcement Learning for Improving Agent Design"



Nvidia Isaac Simulation Stack

Rendered simulation environment in Isaac Lab

Figure 2: Our preferred RL simulation environment, Isaac Lab