Co-evolution of brain and morphology in a multilegged robot

1. Introduction

In this project, we investigated the impact of evolutionary algorithms on the morphology of a multilegged robot, specifically the number of legs, length of leg segments and length of the torso, and on its controller in a co-evolution setting. Using MuJoCo and the Ant robot environment as a foundation, we modified both the robot's physical structure and the parameters of the MLP controller using an evolved genotype. We used NSGA-II with a maximization of the absolute speed or distance from the origin and a minimization of the control to find the fastest morphology that is also cost efficient, and CMAES with a maximization of absolute speed or distance once again. The project repository can be found at https://github.com/federock02/EPFL-MICRO515-EvolutionaryRobotics-FinalProject.git.

2. Methods

We built on top of MuJoCo's Ant environment by allowing the robot's body to grow longer in a cylindrical shape and by having at most 4 legs per side of the body. A leg is defined as a two segments structure, with both hip and knee actuators. We encoded the robot with a 1028-genes long genotype. The first 1003 genes parametrize the brain of the robot: a MLP controller with 43 inputs, one for each dimensional observation, 17 hidden layers and 16 outputs, the torques for each hip and knee. Absent legs receive zero-torque commands, and their related observations are set to zero. The following 8 genes are scaled to fall within the range of [0, 1] and binarized to determine the presence or absence of the 8 potential legs. The next 16 genes are used to define the leg segment length in the range [0.15, 0.35] meter, while the last gene maps the torso length in the range [0.26, 2.25] meters.

In terms of fitness functions, when using the CMA-ES, the objective is to maximize the average speed. Each candidate is assessed in 5 parallel MuJoCo environments with different random seeds, and fitness is determined by the mean total reward. For NSGA-II, two objectives are considered: maximizing average speed or distance from the origin and minimizing the total control cost.

Each evolutionary algorithm (CMA-ES, NSGA-II) was tried in different runs with distinct random initializations. The mean value and the standard deviation of the objectives and the Pareto-front for NSGA-II were recorded for each run, and the best individual was evaluated empirically.

The hyperparameters for the algorithms were set as follows: population=40, generation=100 for CMA-ES, generation=140 for NSGA-II, crossover probability=0.07, mutation probability=0.05. Furthermore, CMA-ES used a number of parents equal to half the population, i.e. 20.

3. Results

Across all runs, evolved morphologies rarely produced good results: many robots presented awkward leg placements, and the control was not optimal. Even in the best individuals, gaits were jerky or disbalanced, with the robot often doing circles or flipping on its back, leading to an early termination of the episode.

Many NSGA-II runs struggled to make the robot move and considered legless robots the best individuals, as the control cost converged to 0 to ensure a non-negative fitness (Figure 1).

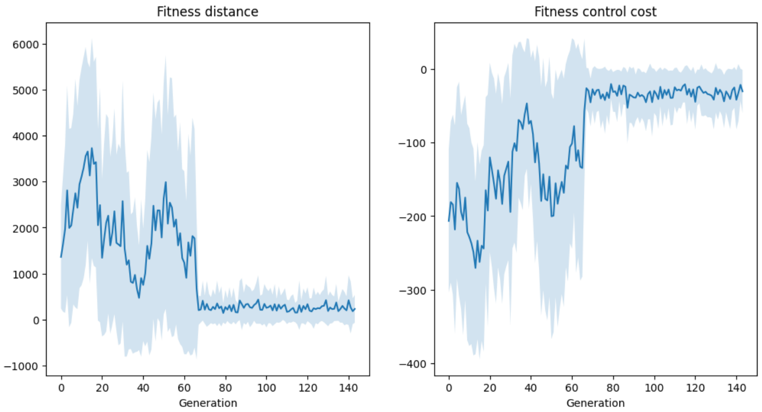

Figure 1 - fitness plot of a NSGA-II run

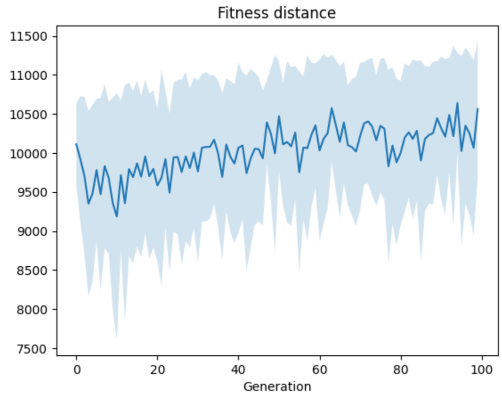

Figure 2 - fitness plot of a CMA-ES run

Even though this phenomenon could also happen with CMA-ES runs, it was not the standard and most run simply yielded robots that would display negligible fitness improvements during training (Figure 22) and that often showed unbalanced, circular motions.

4. Discussion & conclusion

Here we hypothesize the possible causes of failure in our approach:

- Controller-morphology co-optimization: the complexity of co-optimization might lead to premature convergence of the morphology in a local maximum of poor quality [1].
- Poor objectives: our fitness functions measure progress towards an objective, which may limit exploration and consequently prevent said objective from being reached [2].
- Controller not adapted: the high variation in body morphology with a static controller topology can cause a mismatch between the structure of the inherited controller and the new body [3].

Jointly evolving both morphology and controller in a high dimensional space of genes lead us to unstable solutions and bad performance. Future work could improve on the co-optimization implementation, defining better objectives or using a more adapted controller to the task at hand. It may also be interesting to investigate the results of a run with a much larger population and generation count, which requires both computing power and time that we do not have.

5. References *(IEEE)*.

[1] Cheney, N., J. Bongard, V. Sunspiral, and H. Lipson (2016). On the difficulty of co-optimizing morphology and control in evolved virtual creatures. In *Artificial Life Conference Proceedings 13*, Cambridge, MA, pp. 226–233. MIT Press: MIT Press.

[2] Lehman, J., and Stanley, K. (2011). Abandoning Objectives: Evolution through the Search for Novelty Alone. In *Evol. Comput. 19 (2)*, Cambridge, MA, pp. 189–223. MIT Press: MIT Press.

[3] Le Goff, L. K., E. Buchanan, E. Hart, A. E. Eiben, W. Li, M. De Carlo, A. F. Winfield, M. F. Hale, R. Woolley, M. Angus, J. Timmis, and A. M. Tyrrell (2023). Morpho evolution with learning using a controller archive as an inheritance mechanism. *IEEE Transactions on Cognitive and Developmental Systems 15 (2)*, pp. 507–517.