The Impact of Different Tasks on Evolved Robot Morphologies

Matteo De Carlo
Vrije Universiteit Amsterdam, NL
m.decarlo@vu.nl

Eliseo Ferrante
Vrije Universiteit Amsterdam, NL
Technology Innovation Institute, UAE
e.ferrante@vu.nl

Jacintha Ellers
Vrije Universiteit Amsterdam, NL
j.ellers@vu.nl

Gerben Meynen
Vrije Universiteit Amsterdam, NL
g.meynen@vu.nl

A. E. Eiben
Vrije Universiteit Amsterdam, NL
a.e.eiben@vu.nl

ABSTRACT

A well-established fact in biology is that the environmental conditions have a paramount impact on the evolved life forms. In this paper we investigate this in an evolutionary robot system where morphologies and controllers evolve together. We evolve robots for two tasks independently and simultaneously and compare the outcomes. The results show that the robots evolved for multiple tasks simultaneously developed new morphologies that were not present in the robots evolved for single tasks independently.

KEYWORDS

Evolutionary Robotics, Morphological Evolution, Robotic Skills, Multi-Objective Optimization

ACM Reference Format:
Matteo De Carlo, Eliseo Ferrante, Jacintha Ellers, Gerben Meynen, and A. E. Eiben. 2021. The Impact of Different Tasks on Evolved Robot Morphologies. In *2021 Genetic and Evolutionary Computation ConferenceCompanion (GECCO '21 Companion), July 10–14, 2021, Lille,France.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3449726.3459562

1 INTRODUCTION

Evolutionary Robotics (ER) is concerned with optimizing robots for performing a given task through algorithms inspired by natural evolution [4, 5]. This paper presents an experimental study to obtain insights into evolutionary robot systems where bodies and brains evolve together and the robots' fitness is based on more than one task. As a motivational example, consider the problem of designing robots for exploring an unknown area. This complex task can be broken down into more simple sub-tasks, e.g., locomotion, searching, homing and the optimal morphology for each of these can be different, e.g., many legs and a low center of mass for locomotion and a long neck and cameras positioned high above the ground for searching abilities. The question is, what kind of morphology (and corresponding controller) can perform all sub-tasks well.

The tasks we consider here are rapid locomotion (i.e., acquiring a good gait such that the robot can move quickly) and rotation (i.e., spinning around as many degrees as possible). The first one is a fundamental skill for any autonomous mobile robot, the second one is chosen to mimic searching behaviour, as in "looking around". Using our evolutionary robot system where bodies and brains evolve simultaneously we investigate the following research question: Can evolution produce generalists (morphologies well performing on both tasks), or will it mainly deliver specialists (good for one task only, and if generalists will evolve, what is the difference in task performance compared to specialists, i.e., what is the price of being a generalist?

Our approach is based on using multi-objective evolution. Related work includes [9] who used Multi-Objective Optimization (MOO) for combining speed and stability, [10] who evolved voxel-based soft robots for locomotion being underwater and on the surface, and [6] where MOO is used to create stepping stones for evolving a complex skillset.

2 EXPERIMENTS

The robot design is based on the modular robots in the RoboGen [1] system, integrated in our evolutionary robot simulator called Revolve [7]. Robots are composed of three different modules: Head, Bricks, and Joints. The brain of a robot contains two different modules, one for each skill and a hard-coded selector for choosing the correct module for the given task. Each controller module is a Central Pattern Generator Network (CPG) where each joint has its own CPG as used in [2].

The evolutionary algorithm is based on a (100 + 50) steady-state algorithm with a population size of 100 and an offspring size of 50 robots. The representation and the variation operators of the evolutionary algorithm are identical to the one we used previously in [2], but for selection we implemented NSGA-II [3], a well known multi-objective evolutionary algorithm.

The outcomes of an evolutionary process are examined by behavioural as well as morphological measures. To quantify behaviour we use the **locomotion speed** (cm/sec) and the **rotation** (radians). Morphological properties are inspected by two of the morphological descriptors introduced in [8], in particular the **proportion** and the **size** of a robot.

We run the experiment 10 times. For each run, we identify the specialists by taking those robots that have the best fitness in one of the two objectives. To select a good generalist candidate, we select the robots that are closest to the maximum achieved in both objectives. We present the fitness of these robots in Table 1. The behaviour of these robots was recorded and can be observed at https://youtu.be/9tN5L3qtRC4.

GECCO '21 Companion, July 10–14, 2021, Lille, France

ACM ISBN 978-1-4503-8351-6/21/07…$15.00
https://doi.org/10.1145/3449726.3459562

Table 1: Fitness of generalists compared to best fitness for each run and loss percentage for generalists vs. specialists

Run	Locomotion		Rotation	
	Best	Generalist	Best	Generalist
1	6.49	4.25	8.01	4.28
2	9.78	6.35	10.10	6.59
3	7.20	5.56	11.75	5.04
4	5.28	2.99	6.20	3.24
5	6.81	3.67	12.39	3.73
6	8.65	6.39	8.60	5.74
7	9.40	8.75	9.52	8.77
8	6.58	4.61	8.82	4.20
9	9.81	6.17	11.38	7.85
10	6.71	4.52	6.88	4.37
Sum	76.71	54.20	93.66	53.82
Loss %		29.35%		42.53%

In our experiments we observed the evolution of generalists consistently across all runs. We measured (Table 1) an overall performance loss of 29% for locomotion skills and 42% in the rotational skill. It is interesting to note that the performance drop for the locomotion skill is lower than the one for the rotation skill. We also observed that robots need more specific morphologies to develop rotational skills, while locomotion skills can be developed on a wider range of morphologies. We deduce that the rotational skill is harder to develop than locomotion.

Another observation on the morphologies can be done when comparing the results with experiments previously done by De Carlo et al. [2] in a single objective evolutionary setting. In this comparison (Figure 1) we observe the differences that developed by the use of a multi-objective optimization compared to evolution driven only by one skill. What we observe is that evolving only locomotion leads to robots that are very disproportionate and big, while evolving only rotation leads to individuals that are very small and proportionate. Interestingly, Figure 1 shows one of the key advantages of using a multi-objective optimization framework: the morphological trait space is explored much more when using multi-objective evolution, with traits (the orange points) spanning a wider area of the trait space compared to single-objective evolved traits (the green and blue points) that are instead confined to much smaller regions.

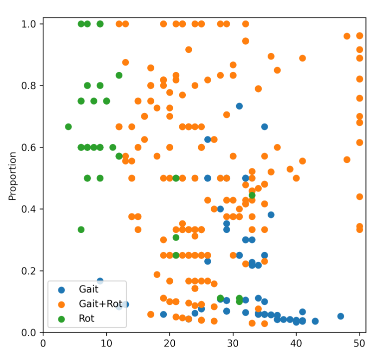

Figure 1: Morphological traits (proportion vs size) of the population in the final generation of all evolutionary runs. The orange dots are produced by NSGA-II, while the blue and green dots are from results published in [2].

3 CONCLUSIONS AND FURTHER WORK

The experiments reported in this paper delivered insights into evolutionary robot systems where bodies and brains evolve together and the robots' fitness is based on more than one task. Evolving robots for two specific tasks, locomotion (needed for navigating a terrain) and rotation (needed for "looking around") we have found interesting and previously unknown effects.

Regarding the evolved morphologies we observed that multi-objective evolution explored the multidimensional space of morphological traits very well. The morphologies of the best generalists were often different from the specialists, but for the most part they tended towards elongated bodies that have been previously found to be optimal for locomotion.

Further work is aiming at consolidating and extending these initial findings. One research direction is to investigate the dependence of the current results on the encoding of morphologies. Preliminary results indicate different regions of attraction in the morphology space when using a tree-based direct encoding instead of an L-system (indirect encoding). Another research line concerns the investigation of different tasks as well as different ways to combine them.

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