Predicting soft robot's locomotion fitness

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ABSTRACT

Organisms with different body morphology and movement dynamics have distinct abilities to move through the environment. Despite such truism, there is a lack of general principles that predict which shapes and dynamics make the organisms more fit to move. Studying a minimal yet embodied soft robot model under the influence of gravity, we find three features that predict robot locomotion fitness: (1) A larger body is better. (2) Two-point contact with the ground is better than one-point contact. (3) Out-of-phase oscillating body parts increase locomotion fitness. These design principles can guide the selection rules for evolutionary algorithms to obtain robots with higher locomotion fitness.

CCS CONCEPTS

• **Complex system** → **Evolutionary robotics**;

KEYWORDS

evolutionary robotics, fitness evaluation, heuristics, complex systems, theory

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1 INTRODUCTION

Optimizing soft robot's shape and dynamics using embodied simulation coupled with evolutionary algorithms is a promising strategy to obtain good robot candidates in physical applications [4, 6]. Most recent efforts have been concentrated on developing better search algorithms [1, 2]. Nevertheless, evolutionary algorithms do not immediately provide the features of the morphology or dynamics that explain why the algorithm selected a specific robot, other than the fact that the robot had good fitness. Knowing which characteristics make a robot more fit could lead to better evolutionary algorithms.

In this work, we use a simple embodied voxel-based soft robots (VSRs) model to study morphological and dynamical features predictive of the robot fitness on a flat ground with no obstacles . The simplicity of the model allows us to investigate the robot's characteristics and the corresponding fitness exhaustively. We show that relatively simple rules correlate with higher locomotion fitness.

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2 METHODS

We performed the experiments in the soft-robot physics engine Voxelyze [3], using a genetic encoding, evolutionary design, and simulation parameters based on Kriegman et al. [4]. We created the genotype networks via Compositional Pattern Producing Networks (CPPNs) [4, 7] with Age-Fitness-Pareto Optimization (AFPO) evolutionary algorithm [5]. CPPNs mutations include addition, modification or removal of a node or edge. The 2×2×2 workspace restricted the robot's possible design configurations (voxels type and position in space). It is the minimal space to start analyzing movements. We expect that results achieved in this minimal setup can be generalized in larger dimensions. Each one of the 50 independent experiments (random seeds 1-50) started with a population of 50 robots and evolved through 2000 generations. In each new generation five new random individuals compete with the previous population and their mutations to increase variability in the search space. The simulation time consists of 1s for the robot settles under gravity and 50s for fitness evaluation. For the 2^3 workspace, 50s is sufficient time to evaluate their steady behavior. Robot's fitness is the distance of its center of mass in the x-y plane between its initial and final position divided by the evaluation time.

The voxels type can be tissue (a flexible but passive material) or muscle (a flexible and actuated material). A global signal controls actuation in the muscle voxels at 2Hz sinusoidal signal. The robot's genotype is composed of two independent CPPN networks: one for the design and one for the phase offset of each voxel with respect to the global signal. Each robot generated in the simulation was grouped in shapes. Each shape contains robots that have the same voxels after reflection and rotations (90°, 180° and 270°) in the x-y plane. Next, we grouped the shapes in structures. Each structure includes shapes that are the same up to a rotation in the z-direction.

3 RESULTS

Understanding why some shapes are more fit to move compared to others is essential given that such simulations and their outcomes are already used in physical environments [4]. We hypothesize the existence of morphological and dynamical control parameters that predict the fitness success of locomotion.

Each shape can have different fitness depending on the phase offset of the oscillating elements. We selected each shape's maximal fitness (by varying the phase offset) to analyze the relationship between shape characteristics and locomotion fitness (Fig.1). The horizontal axis in Fig.1 measures the number of voxels. Each column corresponds to different structures. The vertical axis measures

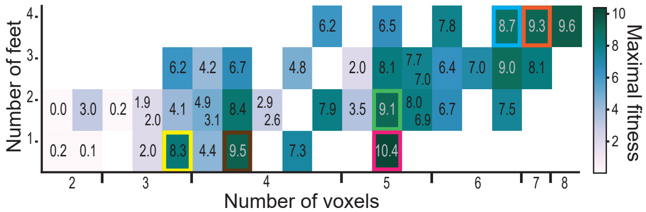

Figure 1: Relationship between shape characteristics and fitness. Color codes and numbers inside each square indicate the corresponding fitness.

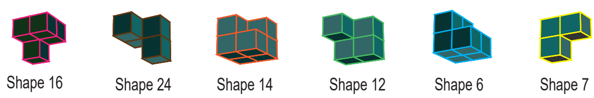

Figure 2: Robots with largest fitness. The selected robots exhibit Fit$_{<0G}$ 8 and Fit$_{<43\theta 0=}$ 6. The robots are ordered by maximal fitness value from left to right. Color code is the same as in Fig.1.

the number of voxels in contact with the ground (feet) at the beginning of the simulation, before any gravity-related movement. Fig.1 shows that shapes with many voxels were more fit for a given number of feet (see, for example, shapes 14, 12, and 6 in Fig.2). Fig.1 also shows that shapes with one foot were overall more fit than other shapes (see shapes 16, 24, and 7 in Fig.2). The movement of shapes with more than one foot and many voxels produces a larger displacement than the small ones. The one-foot shapes with an unbalanced distribution of voxels tumble as the simulation begins and have two contact points with the ground, maximizing the distance between them. The results indicate that these shapes with two-point contact in the ground are the fittest.

A locomotion behavior depends on the distribution of phase offset values in the voxels. To investigate if shapes with larger fitness (Fit$_{<0G}$ 8 and Fit$_{<43\theta 0=}$ 6) have similar actuation policies, we analyzed the absolute difference q between the phase offset of the two most distant voxels in their body. Fig.2 represents a subset of the selected shapes with larger fitness. Fig.3 shows the influence of q on fitness for the corresponding robots in Fig.2. Shapes that are not shown exhibit a similar relationship between q and fitness. For each one of the six shapes, we plotted the distribution of all the robots created during the 2000 generations. An alternate phase, q 0"5 (*i.e.*, phase difference c radius), between the most distant voxels, predicts the fittest robots for all selected shapes (Fig.3). In particular, the alternating phase is optimal even for shapes as distinct as 6 and 24. When the phase offset difference between these extreme voxels tends to zero, the robot's fitness also tends to zero (Fig.3). Therefore, the robots with better performance in locomotion, independently of their shapes, have at least two distant voxels (or groups of voxels) moving out of phase.

Our results indicate that locomotion success is related to having a sufficient number of voxels to structure a body with at least two voxels in contact with the ground. Moreover, the two voxels (or groups of voxels) should oscillate in alternating phases at the body's extreme locations.

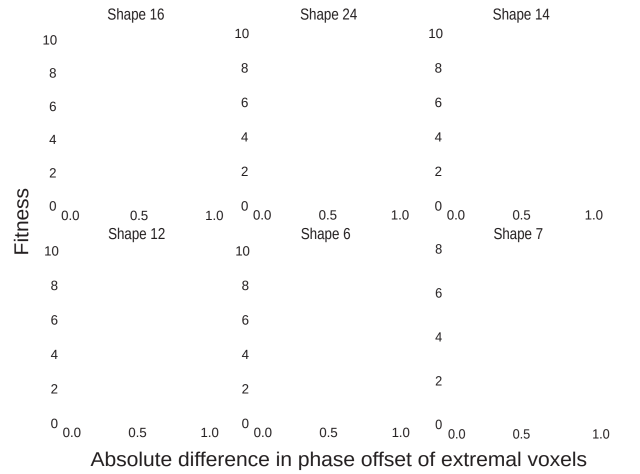

Figure 3: The phase offset difference (q) of the most distant voxels in the robot predicts fitness success. Even for different shapes, high fitness is concentrated around q = 0"5.

4 CONCLUSION

Soft-robots' locomotion behavior depends in a complex way on the entangled body-environment system. Despite that, this work in the minimal space 2^3 shows that there are relatively simple morphological and dynamical characteristics that can predict locomotion fitness. These results indicate which are the features that the evolutionary algorithm selects during its optimization in our simulations. However, it is not yet clear whether they can be generalized to other physical setups and dimensions.

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REFERENCES

[1] Matteo D. Carlo, Daan Zeeuwe, Eliseo Ferrante, Gerben Meynen, Jacintha Ellers, and Agoston E. Eiben. 2020. Influences of Artificial Speciation on Morphological Robot Evolution. In *2020 IEEE Symposium Series on Computational Intelligence (SSCI)*. 2272–2279.

[2] Daniele Gravina, Antonios Liapis, and Georgios N. Yannakakis. 2017. Exploring Divergence in Soft Robot Evolution. *In Proceedings of GECCO '17 Companion* (2017).

[3] Jonathan Hiller and Hod Lipson. 2014. Dynamic Simulation of Soft Multimaterial 3D-Printed Objects. *Soft Robotics* 1, 1 (2014), 88–101.

[4] Sam Kriegman, Douglas Blackiston, Michael Levin, and Josh Bongard. 2020. A scalable pipeline for designing reconfigurable organisms. 117, 4 (2020), 1853–1859.

[5] Michael Schmidt and Hod Lipson. 2011. *Age-Fitness Pareto Optimization.* Springer New York, New York, NY, 129–146.

[6] Dylan S. Shah, Joshua P. Powers, Liana G. Tilton, Sam Kriegman, Josh Bongard, and Rebecca Kramer-Bottiglio. 2021. A soft robot that adapts to environments through shape change. *Nature Machine Intelligence* 3 (2021), 51–59.

[7] Kenneth O. Stanley. 2007. Compositional Pattern Producing Networks: A Novel Abstraction of Development. 8, 2 (2007).