Evolving Folding Bodies and Brains in Origami Robots

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Introduction

Evolutionary robotics (Doncieux et al., 2015) has produced a vast array of adaptive design paradigms applicable to body-brain (controller-morphology) adaptation. However, within the purview of adaptive body-brain evolutionary robotic architectures, folding (origami) robotics (Felton et al., 2014) has received relatively little research attention. An open problem in evolutionary robotics, and more broadly embodied evolution (Eiben and Smith, 2015), is how to automatically design robots that are general problem-solvers across various task environments. Proposals include *AutoFacs*: self-designing methods for producing novel robot (body-brain) designs for given environments, evaluated as problem-solvers in such environments and then re-configured (with adapted body-brain designs) for the next generation of robots (Nitschke and Howard, 2022).

The potential benefits of origami-robots capable of rapid body-brain artificial evolution, folding into many forms with varying functionalities (Rus and Sung, 2018), has been supported by advances in *4D printing* (de Marco et al., 2018), using multi-material (soft-robotics) and directed-assembly approaches (Cichos et al., 2020). Such advances in 4D multi-material printing are hypothesized to lead to the development of future origami-robot actuators printed with forms and functions specific to their task and environment (Fischer et al., 2018). Such advances in intelligent materials have recently been demonstrated for adaptive form and function in physical origami robots (Yan et al., 2023).

To address such challenges, we investigate evolutionary methods to automate the programming of origami-robot form and function. The difficultly of envisaging how robotic forms may adapt, from one beneficial body-brain coupling to another (Buresch et al., 2005), makes pre-programming folded designs impractical for general environment adaptation. Evolutionary robotics is thus a natural pairing, as artificial evolution does not follow conventional design logic, which is a limiting factor for adaptive origami robot design and development (Belke and Paik, 2017).

In this study, body-brain adaptation (self-folding) is driven by distance covered in ambulation tasks. Basic movement comprises a significant portion of an origami-robot's controller, where multiple controllers distributed across robotic modules enables potential refolding to handle varying task environment constraints (in this study, varying surface types). Our study also incorporates evolutionary transfer learning (Nitschke and Didi, 2017) to leverage basic learned (evolved) behaviour in order that robots can function across increasingly complex tasks (Hua et al., 2021).

Research Objectives and Contributions

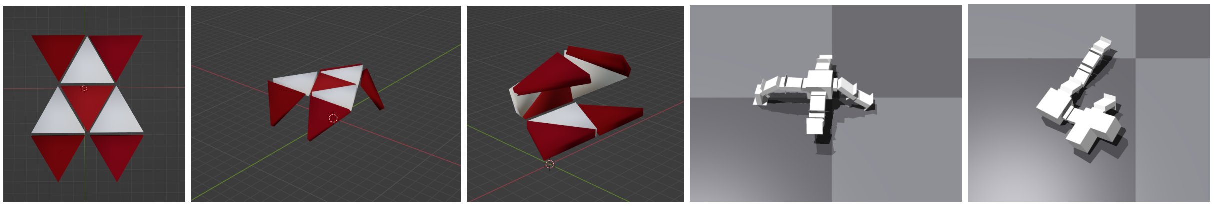
We thus formulate this study's research objectives as:

- Evaluate and compare the evolutionary adaptation (Eiben and Smith, 2015) of folding-robot body-brain designs (Miyashita et al., 2015; Zhakypov et al., 2015) when applied to different ambulation tasks across environments, using both brick and triangle based designs.

- Compare this evolutionary adaptation of folding-robots coupled with evolutionary transfer learning (Nitschke and Didi, 2017; Hua et al., 2021) to performance on specific evolution for tasks and environments.

These objectives are motivated by a lack of research on evolutionary controllers (to adapt robot body-brain configurations) in origami-robotics (Prabhu et al., 2018). Similarly, transfer learning in evolutionary folding robotics lacks significant demonstrated work, despite showing value in other evolutionary robotic applications (Didi and Nitschke, 2016; Nitschke and Didi, 2017; Hua et al., 2021).

We envisage our evolutionary folding (body-brain) robot design and simulation framework will provide an automated design methodology for future work within modular origami-robotics (Felton et al., 2014; de Marco et al., 2018). We anticipate our methodology will constitute an automated design platform and provide a comparative benchmark for future work within adaptive folding-robotics.



(a) All appendages laid flat. (b) Some appendages angled down for walking. (c) Lower appendages folded up as a gripper. (d) Robot and block folds adapted for walking. (e) Robot and block folds adapted for catapulting.

Figure 1: (a, b, c): An example of a modular re-configurable origami robot using triangular modules. Red modules are active modules with active hinges to manipulate edges. White modules are passive modules, with no active control function. (d, e): Simulator screenshots presenting robot designs evolved for different forms of locomotion, (*walking* vs *launching*).

Methods

Our automated folding design methodology extends the artificial evolution of adaptive modular configurations (Belke and Paik, 2017; Spanellis et al., 2021). This includes controller adaptation within each module to control individual module behavior and module connection behavior and thus the *folding-behavior* of specific module subsets and thus the overall body-brain configuration (behavior) of complete robots. Our current experimental system only uses brick-shaped modules, given the versatility and many behaviors observed in previous work (Belke and Paik, 2017). However our evolutionary design method and computational framework accommodates use of various modular shapes[1]. Our simulation framework uses NVIDIA's *Isaac Gym*[2] simulation environments and API (Makoviychuk et al., 2023) coupled with the *Revolve 2* robotics simulator[3] to implement our evolutionary folding methods.

Current experiments focus on the evolution of modular (*foldable*) robot configurations for various ambulation tasks. These experiments compare the efficacy of robot designs with brick-based folds, akin to modular triangular folds observed in previous work (Belke and Paik, 2017). Similarly, a single centralised controller currently controls the behavior of all modules comprising a robot, though future work will use distributed controllers, where individual robot modules each have their own controller and controllers (modules) evolve to work in concert to elicit overall (robot) task accomplishing behaviors. The fitness function driving evolutionary design within each ambulation task minimises the time taken for evolved robots to move from a start position to a goal position in each environment. The efficacy of our evolutionary design method is tested across various terrain types, for example, degree surface traction and surface slope. Figure 1d, 1e shows simulator screenshots presenting robot designs evolved for two forms of motion. Also, an example robot to perform a traversal and manipulation task with a sensor configuration for future experiments is shown in Figure 1. Such a robot should be able to perform multiple tasks (not specifically evolved for) via reforming its body for the task, moving with the form shown in Figure 1b and manipulation in Figure 1c, using adapted controllers.

[1]https://github.com/Rhett-Flanagan/revolve2-isaac-sim.git
[2]https://developer.nvidia.com/isaac-gym
[3]https://github.com/ci-group/revolve2

Results and Future Work

Preliminary experiments on various motion task environments, without sensor modules, have demonstrated a range of evolved robot designs that successfully ambulate to desired locations. In such cases, the fitness function is only given robot coordinate information and the goal location. Evolved robots also generalised when trained on flat terrain, and transferred to rough terrain to perform tasks, and vice versa, where such evolved robots successfully completed their ambulation tasks in new environments. However, there was degraded task performance with environment transference. For example, robots trained on flat terrains struggled with rough terrains, often barely lifting a *folded-leg* to move forward, which resulting in robots being caught on the terrain. However, the reverse appears much more successful, though robots exhibited less efficient movement. These preliminary results indicate that our design paradigm has promise for such tasks, and similar work on retrieval and ball balancing tasks (Belke and Paik, 2017) indicate that our automated folding robot design method has potential to adapt to other tasks. Particularly, if controllers (distributed across modules) evolve generalised behavior that enables evolving robot (body-brain) configurations to suitably *refold* in response to sensor input in varying task environments.

Further experiments will incorporate these concepts into a broad range of tasks including motion across environments of increasing difficulty (with obstacles and disjointed terrain), and transport of object types (of varying shape, size and weight thus transport difficulty). Future work will also investigate the generalisation ability of robots evolved for different tasks using evolutionary transfer learning.

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