Neural Cellular Automata Enable Self-Discovery of Physical Configuration in Modular Robots Driven by Collective Intelligence

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Abstract

Modular robots are capable of self-assembly and reconfiguration, allowing them to adapt to changing environmental conditions and perform complex tasks. However, these robots typically require controllers that are optimized for their specific shape and intended function. In the event of an assembly failure, even minor discrepancies can lead to significant problems because the controller is designed to operate in a specific scenario. To address this issue, we propose a shape-aware embodied controller that relies on self-discovery driven by Neural Cellular Automata (NCA), which enables the system to identify its own configuration, followed by the selection of the appropriate controller, from a library of pre-trained ones, and its deployment in response to the current situation. As a result, our controller is designed to be able to adapt to unforeseen errors and even damages and continue to operate effectively even in the face of unexpected circumstances.

Introduction

Modular robots offer unique features that make them highly promising for a variety of applications. Ideally, an ensemble of modules could automatically assemble themselves at need to perform a task, without the need for human intervention. This could either be achieved by an external assembly facility (Eiben et al., 2013) or even by the modules themselves (Pathak et al., 2019). Such a capability would be particularly valuable in hazardous situations, where it would be desirable to completely relieve humans from the need to intervene.

However, the assembly and/or reconfiguration phase of modular robots can be a delicate process. With multiple modules involved, arranging and attaching them correctly can be challenging, and mistakes are likely to occur. In fact, if the controller is optimized to deal with a specific shape but the actual configuration is different, even slightly, there will be an inevitable loss in performance (Medvet and Rusin, 2022). This can be a significant problem, particularly in complex or hazardous environments where performance is critical.

Existing approaches to addressing such challenges have focused on online adaptation, e.g., based on unsupervised learning (Ferigo et al., 2022), or damage response (Horibe et al., 2022). Yet, these methods have their limitations and may not be decisive in all scenarios. A potential solution would be to develop modular robots in which the individual modules are able to recognize the shape they are arranged in and adapt their behavior accordingly. Such an approach would be particularly useful when envisioned in combination with a fully embodied and distributed controller paradigm, as it could leverage only local information and no centralized controllers would be required.

To this end, in this paper we describe a fully-distributed shape-aware controller for modular robots, which can be completely embodied. We propose to employ Neural Cellular Automata (NCA) to confer the modules the ability to infer their arrangement exploiting local information, as in (Walker et al., 2022), thus achieving self-discovery. On top of that, we leverage a library of pre-trained controllers to be deployed within the modules, each optimized for a specific shape, from which the NCA is able to select according to the discovered shape. We test our proposal on a class of modular soft robots considering the task of locomotion, and show it can not only effectively detect shape changes, but also react accordingly to prevent performance loss.

An extended version of this work is in (Nadizar et al., 2023), where we give a more detailed description of the approach and discuss the results of a larger set of experiments.

Method

We propose an embodied fully-distributed controller for modular robots, which can perform self-discovery to infer the configuration of modules and thereafter rely on this knowledge to select the most suitable controller from a library of pre-optimized controllers. Figure 1 shows an overview of our approach, where the self-discovery phase corresponds to the two portions in the center.

The self-discovery part of the controller is based on the self-classifying NCA proposed in (Walker et al., 2022): the classification is the result of the update over time of the state of the cell, i.e., of the module, thanks to an update function and the information shared with neighbors. Hence, we use the vector state of cells to store information and to extract the

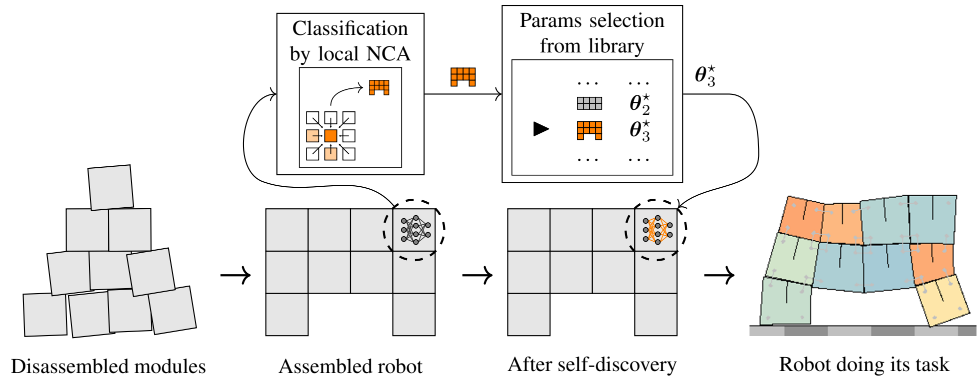

Figure 1: Overview of the proposed approach. (1) modules are assembled (or auto-assemble) into a shape, (2) the NCA inside each module starts the self-discovery phase by exchanging information with adjacent modules, (3) the module selects the controller parameters $\boldsymbol{\theta}^\star$ to be used from a pre-trained library, (4) the robot performs its task.

current self-classification outcome (from the last element of the state). We realize the update function with a Convolutional Neural Network (CNN), operating over the Von Neumann neighborhood of the cell padded with 0 vectors at the corners. We train the weights of the CNN using Stochastic Gradient Descent and the Adam optimizer to minimize a loss $\mathcal{L}$ consisting of the distance between the one-hot encoded class label and the state of the cell, averaged across modules over 25 update steps (discarding the initial 25).

For what concerns the actual controller part, we employ Multi-layer Perceptrons (MLPs), each embodied within a module to control its actions, as in (Medvet et al., 2020). Namely, each module is equipped with an MLP which takes sensory information and information coming from adjacent modules to compute the actuation value(s) and the information to be passed to neighbors. In our case, we deploy the same MLP (in terms of parameters) in each module and we rely on Evolutionary Computation (EC) to optimize its weights $\boldsymbol{\theta}$ for the accomplishment of a task. Clearly, the weights will differ for each robot shape: hence, we can compute a library with the best weights $\boldsymbol{\theta}^\star$ for each configuration.

The shape-aware controller operates by self-discovery first, led by 40 update steps of the NCA, followed by the parameters selection from the pre-optimized library for each module. After the self-discovery phase, the MLPs take control and the robot starts behaving. We remark that there is one NCA cell and one MLP inside each module, and that the modules can communicate (during and after the self-discovery phase) only with neighbor modules. Moreover, all the NCA cells are ruled by the same CNN and they share the same library of optimized MLP weights. The robot is hence an aggregate of modules, rather than a single entity: as such, it constitutes a form *collective intelligence*.

We test the viability of our proposal on simulated Voxel-based Soft Robots (VSRs), a class of modular soft robots, for the task of locomotion. We evaluate the self-discovery capabilities of the NCA, the potential for achieving well-optimized controllers with EC, and the overall performance of the shape-aware controller. We consider 4 sets of shapes with different sizes (ranging from 3 to 39 shapes), to verify if the approach scales when the number of shapes increases.

Set	Size	Accuracy	ρ
C_1	3	1.00	0.00
C_2	9	1.00±0.21	0.00±0.21
C_3	15	1.00	0.00
C_4	39	1.00±0.17	0.00±0.20

Table 1: Median and standard deviation of accuracy and relative performance loss ρ.

Results and discussion

We report in Table 1 the results in term of self-classification accuracy and relative performance loss $\rho = 1 - \frac{v}{v^\star}$ ($v^\star$ being the velocity achieved upon optimization, v being that achieved with the shape-aware controller). We note that for all sets our controller is able to achieve perfect accuracy, corresponding to zero performance loss, in median. This demonstrates the effectiveness of our controller, indicating this as a promising approach within an autonomous robot ecosystem with automatic assembly and reconfiguration.

We also experimentally investigated the robustness of the approach with respect to the number of steps the NCA take to reach a consensus about the shape—for brevity, we do not report the complete results here, see (Nadizar et al., 2021). We found that NCA converge to the correct shape in ≈ 10 steps and tend to diverge away from it after ≈ 80: this observation may be practically relevant if this approach had to be used *online* to react to shape changes, e.g., due to damages.

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