Evolving Modular Robots: Challenges and Opportunities

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Abstract

The body of robots and their controllers need to be adapted to the task that they carry out. While it is possible to design and optimize free-form morphologies, its physical implementation consumes too many resources. In contrast, modular robots provide a feasible approach to design robotic morphologies that can be deployed in minutes, making them a suitable tool to implement virtual creatures. In this article, we tackle the main challenges to consider when evolving modular robots and mention some opportunities that these systems can provide.

Introduction

While robots are usually designed by engineers, some authors have proposed to use artificial evolution to design robots automatically (Sims, 1994; Eiben and Smith, 2015). However, it is not only necessary to design them and evaluate them in simulation. They also need to be tested in a physical setup to validate the solution and avoid the reality gap. In order to build the evolved robots, different approaches have been developed: 3D printing (Hale et al., 2019; Pollack and Lipson, 2000; Samuelsen and Glette, 2015), robots that can self-adjust the length of their limbs (Nygaard et al., 2019), soft robots (Hiller and Lipson, 2011) and modular robots (Stoy et al., 2010; Auerbach et al., 2014; Faiña et al., 2015; Moreno et al., 2017). However, it exists a trade-off between the morphological space that is available for evolution and the deployment time to build a robot, which is linked to the reusability of the robotic components (Moreno and Faina, 2020a).

Modular robots are robots built by connecting simple robotic devices, called modules, between them. Each module has standard interfaces for mechanical and electrical connections. Therefore, robots can be built in minutes by reusing available modules. While the morphological space gets reduced compared to free-form approaches, the different recombination of modules still provides a massive search space.

In this paper, we will review the main issues that one needs to address to evolve modular robots and deploy them in hardware. In addition, we will point at different challenges and opportunities that lie ahead.

Hardware Modules

If we want to produce real robots, we need to design and manufacture robotic modules. Several designs have been proposed (Stoy et al., 2010; Faiña et al., 2015), but most of them, especially self-reconfiguring modular robots, are very difficult to build or do not allow a fast assembling of the modules. Addressing this issue, Moreno et al. (2017) designed Emerge aiming for an easy-to-produce and fast-to-assemble module. It is mostly manufactured by off-the-shelf parts and each module can be assembled in less than half an hour. In addition, its magnetic connector allows us to build and recycle robots in seconds.

Until now, all the module designs have been designed by researchers using their knowledge. One open challenge is to automatically design the modules by evolution in order to find an optimal set of modules. In this line, preliminary works to assess different module designs have been carried out (Liu et al., 2017; Moreno and Faina, 2020b; Pastor et al., 2021).

Controllers for Modular Robots

The most common controllers for modular robots are sinusoidal controllers (Faíña et al., 2013; Brodbeck et al., 2015), Central Pattern Generators (CPGs) (Kamimura et al., 2004) and Central Pattern Neural Networks (CPNNs) (Cheney et al., 2014; Buchanan et al., 2020). However, most of these controllers work on open loop. A new research line is the implementation of controllers that take sensory feedback into account (Moreno, 2020; Ferigo et al., 2021).

Representation of Morphologies

An important aspect is the encoding of the morphology. Direct encodings provide a direct mapping from genotype to phenotype, which allows representing all possible combinations of the modules. Usually, a tree codification is used (Lipson and Pollack, 2000; Auerbach et al., 2014; Faíña et al., 2013). In contrast, generative encodings reuse genotype material to compress the number of parameters in the genotype and the mapping from genotype to phenotype is based on a series of rules or program that produces the morphology. The most common generative encodings are L-systems (Hornby et al., 2001; Veenstra et al., 2017), CPNNs (Cheney et al., 2014; Buchanan et al., 2020) and cellular automata (Horibe et al., 2021). One advantage of generative encodings is that they tend to exploit their internal representation to produce symmetric robots, which usually improve results (van de Velde et al., 2019). As obtaining symmetric robots with direct encodings is difficult, some works have introduced symmetry by using different approaches. For example, Marbach and Ijspeert (2005) used a symmetric genotype to phenotype mapping which 'mirrors' the limbs along the spine, resulting in a symmetric structure for all the robots. And Faíña et al. (2013) implemented a symmetry mutation operator, which selects a branch of a robot and creates its symmetrical branch.

While some papers found that generative encodings produce better results than direct encodings (Veenstra et al., 2017), other works did not find a statistical difference (Veenstra et al., 2019). Thus, more experiments are needed to shed light on what conditions generative encodings can provide an advantage.

Evolution of Morphologies and Controllers

The fitness of a robot depends on its morphology and its controller. When evolving both at the same time, it seems that morphological changes affect the behaviour of the robots more than changes in its controller. This leads to a premature convergence of the morphology (Lipson et al., 2016). In order to overcome this, different approaches can be used. Faíña et al. (2013) built an ad-hoc algorithm that cyclically iterates through a morphological mutation phase and a controller adaptation phase. Cheney et al. (2018) proposed to protect the morphological innovations. And recently, Nordmoen et al. (2021) and Medvet et al. (2021) have employed a quality diversity algorithm to increase the exploration of different morphologies.

Evolution in Hardware

The behaviours of morphologies and controllers evolved in software are usually different from the ones observed when testing them in a physical setup. This problem is called reality gap and comes from bad modelled areas in the simulation, which are exploited by the evolutionary process.

The reality gap can be addressed by evolving directly in hardware or by combining hardware and software evaluations (Howison et al., 2021). As the number of evaluations is high, this requires a physical test bed to automatically assemble the robot, test it and disassemble the modules to reuse them. To the best of our knowledge, this has not been achieved yet. However, there are some works that cover some of these aspects and which use an external robotic arm to perform the assembly. Brodbeck et al. (2015) evolved modular robots which are joint by hot glue adhesive. While it has demonstrated evolution of modular robots in hardware, the robots were disassembled manually. Hale et al. (2019) demonstrated the assembly of robotic structures made of modules and custom 3D-printed structural elements. Finally, my co-authors and I have shown the ability to assemble and disassemble modular robots with an external manipulator in seconds (Moreno et al., 2018), see Figure 1. We did not evolve robots as the markers used for localizing the modules obstructed their connectors. The new version of the modules has addressed this issue and we are currently working towards evolving modular robots in hardware without human assistance.

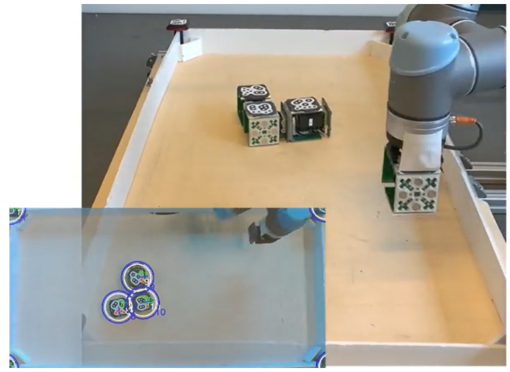

Figure 1: Evolved modular robot (Emerge) being assembled by an UR5 manipulator. The magnetic connector allows the manipulator to assemble and dissemble the modules in seconds. The four modules of the figure have been assembled in less than a minute.

Morphological Development

In developmental psychology, it has been observed that morphological development, which occurs in parallel to cognitive development, provides an advantage for learning. However, the advantages of morphological development in robotics are still not clear, see (Naya-Varela et al., 2021) for a recent survey. This is caused by inconclusive results (Naya-Varela et al., 2020a,b), but also by the low number of experiments performed in robots, motivated by the difficulty of implementing morphological changes. In this sense, modular robots offer a great tool to study the effects of morphological development as they allow morphological changes by reconfiguring the modules. Thus, they could shed light on what conditions and how morphological development could be applied to learn faster.

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