Using evolution to design modular robots: An empirical approach to select module designs

Rodrigo Moreno[1[0000−0003−3738−010X]] and Andres Faina[2[0000−0001−7288−6988]]

[1] Universidad Nacional de Colombia, Bogota, Colombia unal.edu.co
[2] IT University of Copenhagen, Copenhagen, Denmark itu.dk

Abstract. In modular robots, the shape of the building blocks (robotic modules) greatly influences the end result. By changing the physical properties of the module, different robotic structures with better performance for a given task can be found. In this paper, we modify the modules of a modular robot platform, the EMERGE modular robot, in two different ways: changing the length of the module and changing the shape of the starting module (base). We use artificial evolution to optimize robots for a locomotion task using each different module length and base, and also evolve robots with combinations of modules of different length. Results show that, as the length of the module increases, the best robots obtained use fewer modules and fewer connections per module. However, the increase in length results also in a decrease in locomotion performance for large length increases. Interestingly, very few of the best robots found show symmetric structures, which can be attributed to their tendency to roll over as their main means of locomotion. Modular robot designers can use the information about the effectiveness of modules with different lengths, and the use of different starting bases, to reach trade-offs between the desired number of modules in a robot and their effectiveness for a given task.

Keywords: Modular robots · Evolutionary algorithms · Design optimization.

1 Introduction

In physical structures, the shape of the building blocks greatly influences the end result. Therefore, the design of the building blocks should be carefully optimized. However, there are many areas where these building blocks are difficult to analyse in isolation, that is, when they are not part of an structure. This is the case of modular robots.

Robots are usually designed and built for a specific task, normally without reusing components developed for other kind of robots. In contrast with this approach, modular robots are built by connecting reusable robotic units, called modules, together. Modules are autonomous and encapsulate functionality (sensors, actuation, computational resources and energy).

Over the last decades, multiple modular robot designs have been proposed [22, 26, 8]. Modular robot systems have been demonstrated for locomotion and manipulation tasks and studied for their use in space exploration, among other tasks. In most modular robot works, an engineer decides the configuration of the robot for a task, given a module design, and then focus on how to control and coordinate individual modules, usually by using gait tables [27], hormone-inspired methods [19] or central pattern generators [11].

Some works have addressed the problem of enumerating all the different configurations that can be generated by using a module design [21]. However, knowing how many configurations are possible does not shed light on their performance for a specific task. Artificial evolution has been proposed as a method to find suitable combinations of morphologies and controllers for different tasks [22].

The simultaneous evolution of morphology and control was first proposed by Karl Sims [20]. In his work he evolves morphologies and controllers for virtual creatures which, however, are very difficult to be built physically. Similar techniques have been applied to modular robots [13, 6, 9, 7, 23], with the advantage being that designed robots can be easily built by joining modules together.

In this paper, we address how can we optimize robotic modules to maximize the performance of modular robots for a given task and how the different types of modules give way to different robotic structures that have advantages and disadvantages when solving the task at hand. We will focus on changing modules in two different ways: (1) changing the length of the module and (2) changing the shape of the starting (base) module. Two bases will be tested: a cuboid base, similar in size to a normal length module, and a bigger and heavier flat base. A test with robots that combine modules with different lengths is also performed. Changing the length of the module allows the module to perform wider movements while reducing the strength of that movement. Therefore, selecting the length of the module imposes a trade-off that is worth studying.

Similar questions have been studied before. In [14], Miras et al. studied how codification of the morphology of a modular robot (direct encoding or generative encoding) influences the morphological features of evolved robots. Their results indicate that there are no differences in the diversity of morphological features of the resulting robots when using either encoding. Additionally, Liu et al. [12] researched how the number of faces in the module influences the resulting evolved morphology for a given task. The results showed that a lower number of connection faces could help the evolutionary algorithm to get better results as long as the faces removed are chosen carefully.

This paper is organized as follows: Section 2 describes the methodology, including brief descriptions of the modular robot prototype and the evolutionary framework used. Section 3 describes the experimental setup and section 4 details the tests results. The paper follows with a discussion of the results and a conclusion.

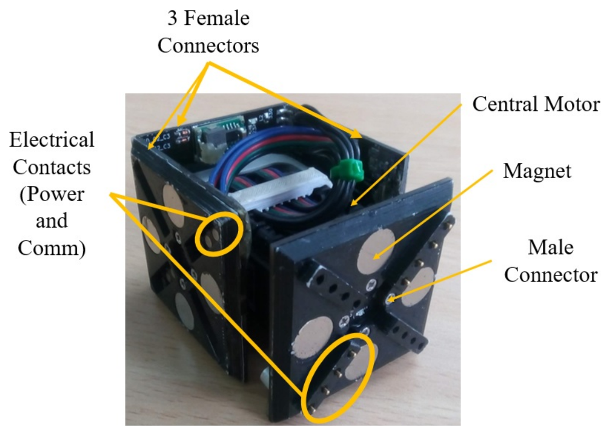


Fig. 1. EMERGE Module: The magnetic connections in their faces allows a quick assembly of the modules to build a robot, which is useful to test evolved morphologies and controllers.

2 Methodology

The methodology employed makes use of the EDHMOR system which is an evolutionary framework specifically designed to evolve morphologies and controllers for modular robots. In this paper, we evolve robots from modified versions of the EMERGE modular robot prototype. This section describes both of these tools.

2.1 EMERGE Modules

The EMERGE (Easy Modular Embodied Robot Generator) modular robot is a robotic platform designed to be easy to build, maintain and modify [16]. This enables us to quickly assemble morphologies, be it using homogeneous modules [15] or heterogeneous modules [12].

Each module has only one hinge, comprised of a servo motor attached to a pair of brackets, and resembles a small cube. Attached to the brackets are PCBs (Printed Circuit Boards) and 3D printed mating magnetic connector faces. A male connector has protrusions that match holes in three female connectors. The connector assembly maintains mechanical and electrical connections between any two modules (Figure 1). Magnetic connectors provide a quick and practical way of assembling evolved robot morphologies and controllers. The simple design of the module also allows for an uncomplicated simulation model (See table 1), which can be easily modified for the purposes of this work.

2.2 EDHMOR

The Evolutionary Designer of Heterogeneous Modular Robots (EDHMOR) [7] has been selected as the evolutionary framework to evolve the robotic structures in this work. It is based on the Java Evolutionary Algorithm Framework (JEAF) [4], but specifically designed to evolve modular robots.

EDHMOR generates a direct encoding that represents the modular robot and its controller. Specifically designed mutation operators are applied to individual robot solutions. After an initial population of robots has been generated, EDHMOR performs the following phases in a loop, until the stop criteria is met:

1. Growing phase: Add a module in a random position.
2. Morphological adaptation phase: Change some of the connections of the robot (the place a module is attached to or its orientation).
3. Control adaptation phase: Change some of the control parameters.
4. Pruning phase: Remove all the modules that do not contribute to the fitness
5. Replacement phase: Remove the worst N individuals and replace them with N/2 random individuals and N/2 variations of the best individuals of the population after applying a symmetry mutation.

In all these phases, the resulting individual only replaces its parent if it can beat the parent fitness, except in the growing phase. This means that the growing phase always adds modules, even if the fitness gets worse. This is done to protect innovations and give them some time to be tested and adapt (morphological and control adaptation phase) before the pruning phase. For a more detailed explanation of EDHMOR, see [7]. The EDHMOR system can be adapted to different kind of modules and it has already been used in conjunction with EMERGE modules before [12].

3 Experimental Setup

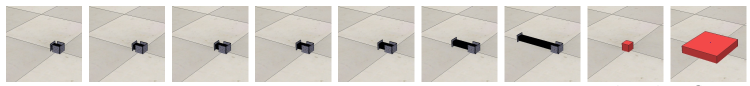
Using the EDHMOR framework, robots are evolved for a locomotion task. The algorithm is configured to use 2 growing phases, 2 morphological adaptation phases, 1 control adaptation phase and 2 pruning phases. Each growing and morphological adaptation phases test 3 different individual variations, while the control adaptation phase tests 10 individual variations for each mutation. A population of 40 individuals is used and 10 robots are replaced in the replacement phase.

Robot morphologies, the number and way in which modules are connected to each other, are encoded using a tree style encoding genotype. The genotype also includes information about the movements of the individual modules: each module joint position (pos) is controlled using a sinusoidal generator as in equation 1.

$$pos = \alpha \cdot A_{max} \cdot sin(\omega \cdot V_{max} \cdot t + \varphi) \quad (1)$$

Where α, the amplitude ($[0,1]$), ω, the angular velocity ($[0,1]$) and φ, the phase shift ($[0,2\pi)$), are control parameters encoded in the individual's chromosome. The quantities A_{max} and V_{max} are fixed and based on the module properties, and t is the simulation time. Individual robot solutions are tested by

Table 1. Different properties of all the modules employed in these work: EMERGE modules, starting with their original size (1xL) and up to 8 times longer (8xL), and two different types of bases, a cuboid base and a flat base, are shown. All EMERGE modules have the same motor and both bases are passive. The cuboid has connectors in all faces except for the upper face (+Z) and the flat base has four connectors pointing in all outward directions at each corner.



	1xL	1.25xL	1.5xL	1.75xL	2xL	4xL	8xL	cuboid base	flat base
Length (mm)	77	86.6	96.2	105.9	115.5	192.5	346.5	55(x3)	270/55
Weight (g)	165	174	183	192	201	275	420	100	250
Connection faces				4				5	16
Torque (Nm)				1.5				-	-

placing them in the center of a simulated flat surface environment and allowing them to move for about 20 seconds. Simulation is carried out in the V-REP simulator [17]. Modules are connected to each other in simulation by using a special element in V-REP called force sensors, these allow modules to break if affected by a force or torque that exceeds a certain value. Using force sensors, individual robots can break, however, they are not penalized for this. Instead, the fitness associated to each evaluation is calculated as the final position of the robot (center of mass) measured in a straight line, in the (x,y) plane, from the position of the robot at $t = 2.5s$ (Equation 2). This starting time guarantees that the transitory effects at the beginning of the movement are not taken into account as all the robots are placed with at least one module in contact with the floor, but can fall if they are not stable.

$$F = d((x_{final}, y_{final}), (x_{t=2.5}, y_{t=2.5})) \tag{2}$$

3.1 Modifying module length

For the different tests performed, the distance between the motor axle and the male face of the EMERGE module is varied by adding a extension to the base of the motor (Table 1). Each different module type portrays a different distance, or length, from the motor to the male face: Starting with their original length (1xL), modules are extended to have 1.25, 1.5, 1.75, 2, 4 and 8 times (8xL) the original module length. In this way, the effect of the added length can be measured for small changes (1.25xL, 1.5xL, 1.75xL, 2xL) and for extreme values (4xL and 8xL). In the real world, the extension can also be added to the module by means of a part attached between the male face and the base of the motor.

The increase in length also implies an increase in the overall weight of the module and changes the weight distribution, which in turn makes bigger forces and torques appear in the module connectors, possibly increasing the number of disconnections. The central motor is also required to use bigger torque values when lifting a chain of modules, reducing the overall strength of the robot.

3.2 Different starting base modules

Tests are also performed using two different types of base modules as the first building block for each robot: A cuboid base and a flat base (Table 1). The main difference between both bases is their size: the cuboid base is similar in dimensions and weight to a normal EMERGE module while the flat base is bigger and heavier, the number of connectors each base has is also different: the cuboid base has 5 connectors and the flat base has 16 connectors.

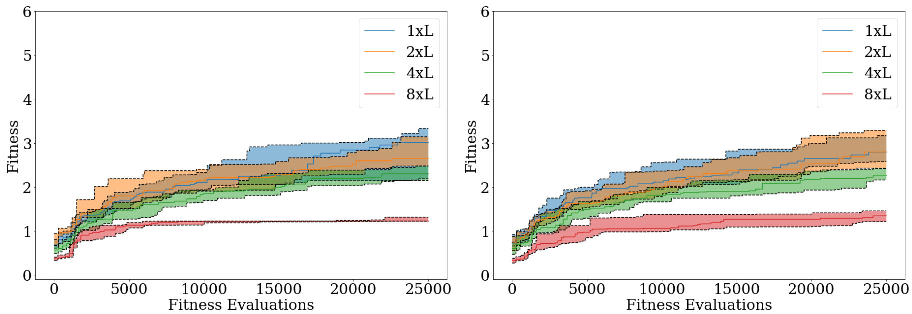
Using these two bases, robots are evolved using only one type of module at the same time and results are compared to determine whether there is a difference through various measures: fitness obtained by the best individuals, which provides an estimate of locomotion performance, number of modules and average number of connections per module, which provide a look into the shape of the robot, and number of broken connections (See section 4). A final evolutionary run is performed for each base, combining modules of all different types. Evolutionary runs are repeated 20 times and configured to perform a total of 25000 fitness evaluations.

4 Results

As mentioned in the last section, the increase in module dimensions strains the module motor and connections. Bigger forces and torques lead to a decrease in the fitness of the best individuals obtained as length is increased, which can be seen on figure 2. This effect can also be seen in figure 3, in which the best individual fitnesses at the end of each evolutionary run are grouped in box-plots.

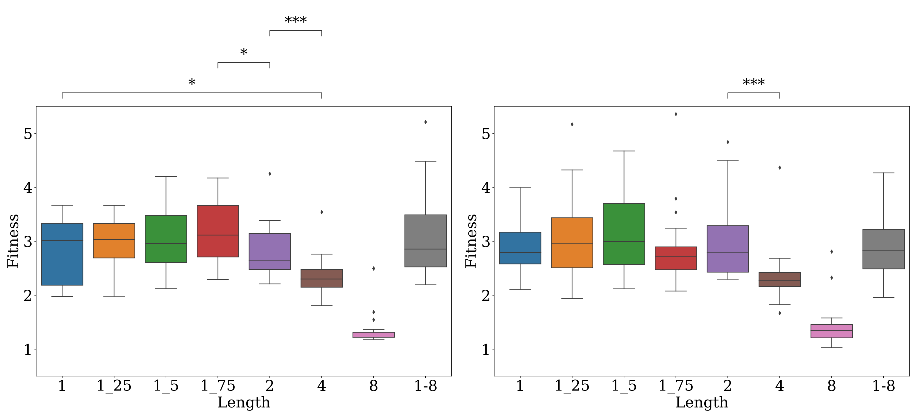
The fitness of the best individuals for modules of length 1xL, 1.25xL, 1.5xL, 1.75xL, 2xL and combined module robots (1-8xL) are very similar to each other, whereas fitness of individuals using modules of length 4xL an 8xL are statistically significantly different from other lengths and present a sharp decrease of fitness ($p = 2.33e^{-12}$ in the case of figure 3a and $p = 9.87e^{-12}$ in the case of figure 3b). In the cuboid base case, modules of length 2xL and 1.75xL also present a statistically significant difference ($p = 2.22e^{-2}$). Statistically significant differences for these and subsequent comparisons, are tested using a Kruskal-Wallis non parametric test for multiple samples, and pairwise statistically significant differences are verified using a post-hoc Mann-Whitney-Wilcoxon test.

The number of modules also shows a sharp decrease as the length of the module goes over 2 times the length (2xL) of the original (See figure 4) for the best individuals of each evolutionary run. In this case, robots using combinations of modules of different length (1-8xL) also have a lower measure than robots built with modules of length below 2xL. The number of modules present a statistically significant difference between robots built using modules of length 1xL and 2xL, between modules of length 4xL, 8xL and all other lengths, and between combined



(a) (b)

Fig. 2. Evolution of the best individuals fitness for (a) a cuboid base, (b) a flat base. For the sake of clarity, only evolution plots corresponding to robots with modules of lengths 1xL, 2xL, 4xL and 8xL are shown in each graph, the plots corresponding to robots with modules of lengths 1.25xL, 1.5xL and 1.75xL overlap with 1xL.



(a) (b)

Fig. 3. Fitness obtained by the best individuals at the end of each evolutionary run, when using (a) a cuboid base, (b) a flat base. Fitness values for robots with combined modules (1-8) are similar to those of robots built with modules of lengths below 2xL. Stars indicate the level of statistical significance: * $p < 0.05$,**$p < 0.01$,***$p < 0.001$,****$p < 0.0001$.

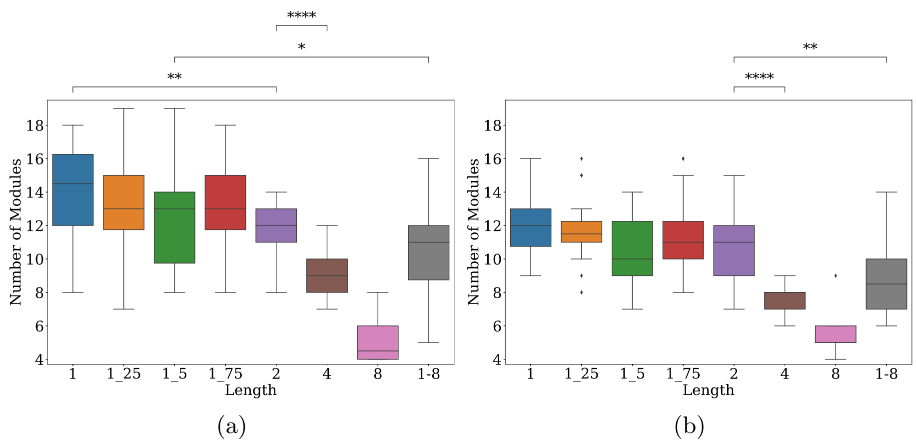


Fig. 4. Number of modules of the best individuals at the end of each evolutionary run, when using (a) a cuboid base, (b) a flat base. The number of modules decreases sharply for extreme length values (4xL and 8xL) as well as for robots with combined modules (1-8xL). Stars indicate the level of statistical significance: * $p < 0.05$,**$p < 0.01$,***$p < 0.001$,****$p < 0.0001$.

module robots (1-8xL) and robots with modules below 1.75xL ($p = 9.05e^{-15}$) for the cuboid base. For the flat base, statistically significant differences also arise between robots built using modules of lengths 4xL and 8xL and robots built with modules of length below 2xL, and between combined module robots (1-8xL) and robots built with modules of length below 2xL ($p = 6.43e^{-16}$)).

A similar phenomenon appears for the average number of connections per module (See figures 5): Robots built with modules of length 1xL, 1.25xL, 1.5xL and 1.75xL show similar average number of connections per module and there is a decrease in this measure for robots built using modules of length 2xL, 4xL, 8xL and 1-8xL, in the case of the cuboid base. In the case of the flat base, robots built using modules of length 1xL, 1.25xL, 1.5xL, 1.75xL and 2xL present a similar behavior, while robots built using modules of length 4xL, 8xL and 1-8xL show a decrease. Statistically significant differences reappear between robots built using modules of length 1xL and 2xL and between robots built using modules of length 4xL, 8xL, 1-8xL and robots built using modules of length below 1.75xL($p = 8.88e^{-13}$) for the cuboid base, and between modules of length 4xL, 8xL, 1-8xL and robots built modules of length below 2xL ($p = 6.43e^{-16}$) for the flat base.

These two measures indicate that robots tend to maintain a small form factor by using less modules and less connections per modules as module length increases. This leads to robots that resemble long chains more and more and can be seen in figures 7 and 8. Robots built using a combination of modules of different length also show this behavior, although less pronounced, as can also be seen on figures 4 and 5. The increase in connector strain also leads to more broken connections as module length increases. When using the cuboid base and lengths 1xL to 2xL, most of the best individuals obtained in each evolutionary

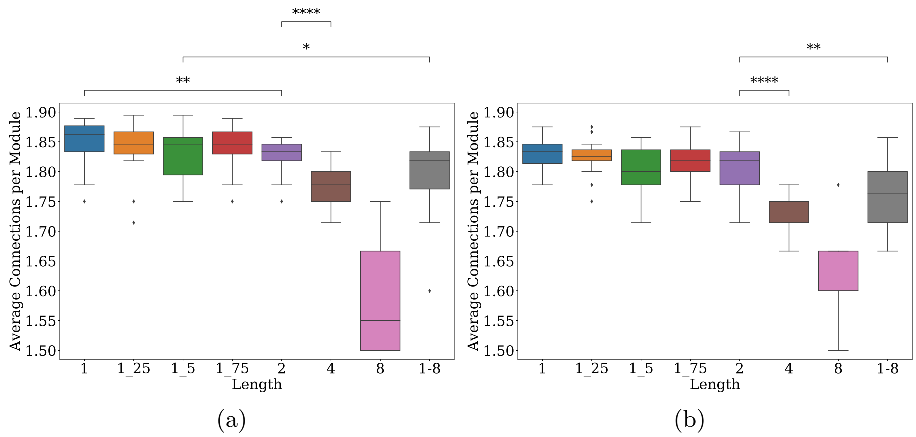
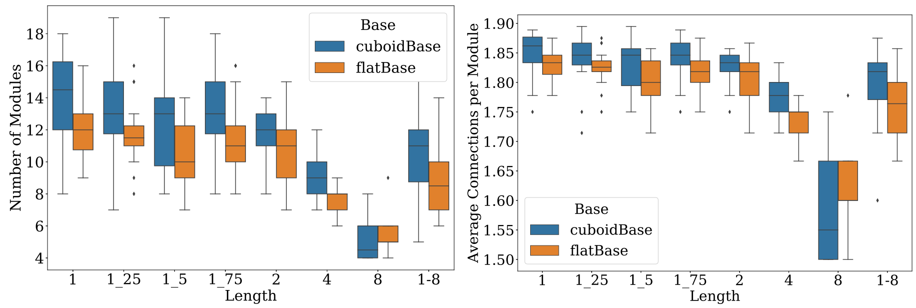


Fig. 5. Average connections per module of the best individuals at the end of each evolutionary run, when using (a) a cuboid base, (b) a flat base. The average number of connections per module decreases sharply for extreme length values (4xL and 8xL) as well as for robots with combined modules (1-8xL). Stars indicate the level of statistical significance: * $p < 0.05$,**$p < 0.01$,***$p < 0.001$,****$p < 0.0001$.

run did not break connections, by contrast, the majority of the best individuals of lengths 4xL and 8xL broke at least 1 connection. In the case of using the flat base, most of the best individuals using lengths 1xL to 1.75xL did not break connections, while the majority of the best individuals of lengths 2xL to 8xL broke at least one connection, with some 8xL individuals breaking up to three connections. When mixing modules of different lengths, most of the best individuals tested did not break connections when using the cuboid base, and most of the individuals using the flat base broke at least 1 connection. The number of broken connections presents a statistically significant difference between groups in the case of both starting bases ($p = 6.75e^{-20}$ cuboid base and $p = 7.58e^{-20}$ flat base).

The type of base also influences the final number of modules and number of connections that the evolutionary algorithm finds. A direct comparison of these measures between base types can be seen on figure 6. A statistically significant difference is found between the number of modules that robots evolved with the cuboid base end up with and the number of modules that robots evolved with the flat base have at the end of the run ($p = 3.1e^{-4}$), a statistically significant difference can also be found in the case of the average number of connections per module ($p = 3.1e^{-4}$). In both measures, the flat base presents the lower values, something that can be attributed to robots trying to maintain a small shape given the bigger dimensions of the flat base. In these figures is also noticeable the sharp drop in the number of modules, and connections per module when module length exceeds 2 times the original value.

In all of the best robot obtained, mainly two types of movement arise: a rolling movement in which the whole robot structure rolls over, taking advantage



(a) (b)

Fig. 6. Comparison of (a) the number of modules and (b) the average connections per module of the best individuals at the end of each evolutionary run, when using a cuboid base and a flat base. The smaller number of modules and average connections per module in the flat base case can be attributed to robots trying to maintain a small shape given the bigger dimensions of the base.

of the small shape in the case of robots made of modules of lengths below 2xL or the thin shape in the case of robots with modules of lengths 4xL and 8xL, and an oscillatory movement in which part of the structure oscillates or tumbles to generate traction, this last movement type can be seen specially in robots built using the flat base as a starting point. Examples of this movements can be seen on figures 7 and 8. A third type of movement is also observed, in which some parts of the structure move almost independently, in a fashion similar to wheels, while the rest remains somewhat stable.

5 Discussion

Evolving modular robots with different module lengths sheds lights on the influence of module dimensions on the final performance of the robots obtained. This is beneficial from the point of view of modular robot designers since they can explore the limitations and advantages that each type of module offers. Furthermore, using easy to build modules of predefined lengths provides an easier and quicker alternative to approaches in which modular robots have to be fabricated from scratch [2]. In this case, results clearly show a drop in the performance of the best robots as length goes past 2xL with both bases (Figures 3 and 6), but also a decrease in the number of modules used. This means the designer can choose for module designs that produce robots with fewer modules at the cost of losing some performance in the locomotion task. Interestingly, the module lengths at which evolved robots show the best performance (115.5 mm and below) roughly match with human designed module dimensions, which usually reach between 100 and 150mm of length [3], with a tendency to use smaller dimensions in the latest prototypes [5].However, a direct comparison with human designed lengths must take into account the maximum torque of the chosen actuator and the

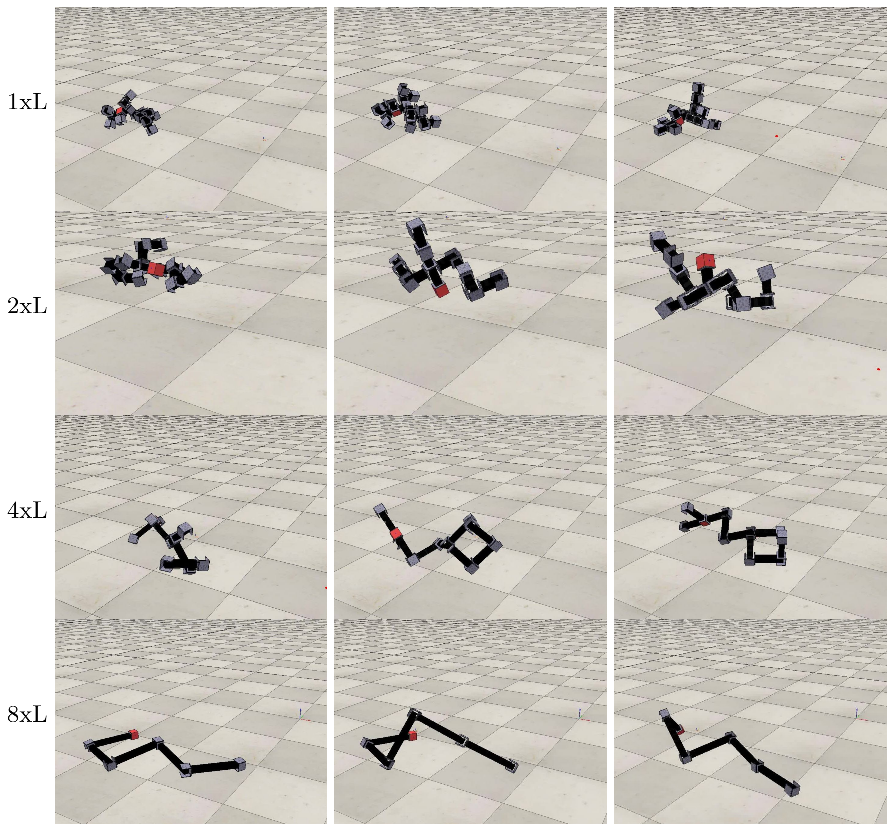


Fig. 7. Examples of the movement of some of the best robots obtained for each module length with the cuboid base. Each row shows a different robot. Robots with longer modules tend to have fewer modules and module connections, which make them resemble a long chain.

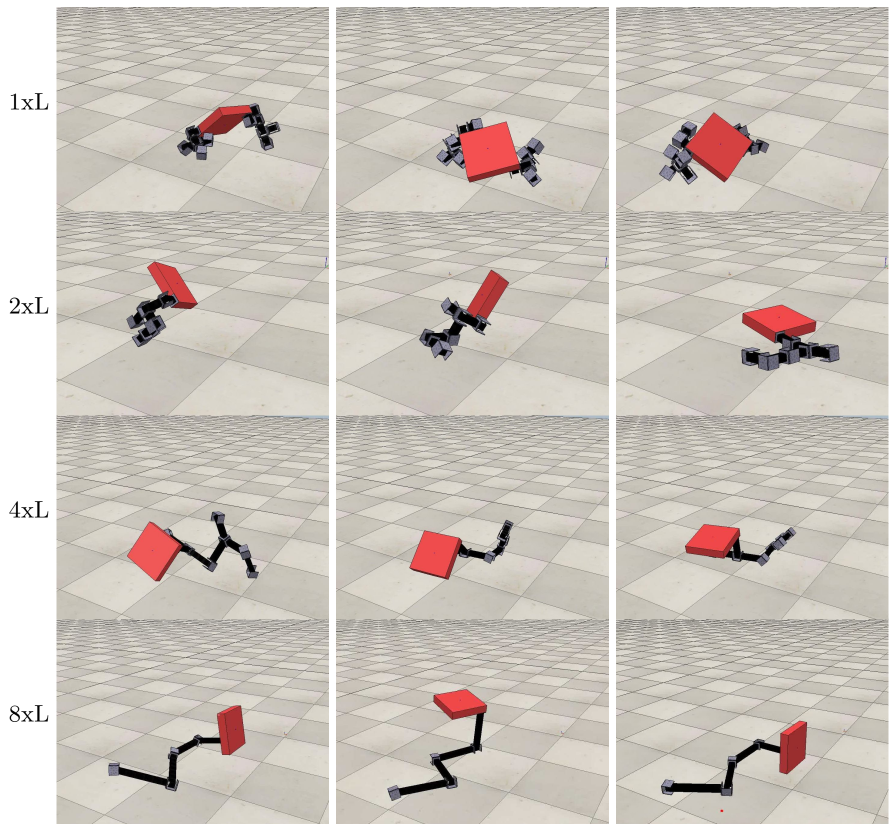


Fig. 8. Examples of the movement of some of the best robots obtained for each module length with the flat base. Each row shows a different robot. Robots with longer modules tend to have fewer modules and module connections, which make them resemble a long chain.

strength of the module connectors. Furthermore, results show that evolution is also able to find robots with good locomotion performance, and fewer modules than if they used only one length, in the case of evolving robots that mix different lengths. This is similar to the results in [1], in which robots evolved using modules of mixed sizes are also able to perform a locomotion task. Thus making evolution a good automatic aid when selecting among module designs.

The decrease in the number of modules and module connections can be attributed to the increase in weight: As the forces exerted on the module connectors increase and the maximum torque of the motor remains constant for bigger module lengths, moving the weight of more modules becomes less advantageous for the locomotion task defined. This loss in strength due to an increase in the number of modules is characteristic of modular robots [18, 1]. And this helps maintain a small form factor (fewer modules with fewer connections per module as the length of the module increases, see figure 6) of the best robots found throughout all module lengths. It also leads to more broken connections in robot evaluations. The decrease in the number of modules and the average connections per module is even more visible for robots using the flat base. As this base is heavier, robots tend to have fewer modules to be able to move with the extra weight. This is also seen on morphologies found in [10], in which a set of predefined parts containing a big core component is used to build robots.

Velde et al. [24], also in a locomotion experiment, found a correlation between the maximum fitness and the average symmetry of a population of modular robots. Surprisingly, very few of the best robots found have symmetric properties in our results, despite the evolutionary algorithm using symmetry operators as in the original EDMHOR work [7]. Nevertheless, symmetric structures were only found in [7] when robots were tested in environments with rough terrains or while they were made to carry loads. A rolling non-symmetric structure is probably a more efficient way of locomotion in flat terrains. Similar experiments in rough terrains are needed to determine whether symmetry would appear in the robots used in here. Finally, this work concentrates only on modules with fixed shape, but there are also modules that can change shape, for example soft modular robots [25]. Checking the validity of the results presented here with this kind of modules is still pending.

6 Conclusions and Future Work

In this work, we present a way of optimizing robotic modules to maximize the performance of modular robots for a locomotion task. Different types of modules give way to different robotic structures that have advantages and disadvantages when solving the task at hand. We focused on changing modules in two different ways: (1) changing the length of the module and (2) changing the shape of the base module. Two bases are available: a cuboid base, similar in size to a normal module, and a bigger and heavier flat base. An evolutionary run with robots that combine modules of different lengths is also performed.

Changing the length of the module, in this case enlarging it, implies an increase not only in the range of its movements but also in its overall weight, which reduces the effective force of the module actuator. This reduction in the strength of the module movements results in a decrease in the number of modules and average connections per module in the best robots found, and an increase in the number of broken connections, as the length of the module increases (Figures 6). Consequently, resulting robots tend to have similar sizes across module lengths and robots become thinner (resembling long chains) as module length increases (Figures 7 and 8). The strength reduction even makes robots with big module lengths (4xL, 8xL) less effective in the locomotion task compared to their shorter counterparts (Figures 2 and 3).

Furthermore, the shape of the base module, used as a starting point for the robot, also influences the morphological configuration of the best robots obtained. As the flat base is heavier and bigger than the cuboid base, robots using the former are inclined to use fewer modules than robots using the latter one (Figure 6). Additionally, although robots combining modules of different lengths also present the same reduction in strength, they are able to achieve fitness values on par with robots built using modules between 1xL and 2xL (Figure 3). Future work includes further testing of evolution as an automatic aid for the modular robot designer to select among module designs with different advantages and disadvantages for a given task.

Interestingly, very few of the best robots found show symmetric structures. This can be attributed to the tendency of resulting robots to produce rolling movements, which may be more efficient in flat terrains. Experiments in different kinds of terrains must be performed in future works to study when symmetry could be an advantage.

As a final conclusion, modular robot designers can use the information about the effectiveness of modules with different length, and the use of different starting bases, presented in this work to strike trade-offs between the desired number of modules in a robot and their effectiveness for a given task. Future work will focus on other module properties, like motor strength or movement speed, for different tasks.

References

1. Akrour, D., Cussat-blanc, S., Sanchez, S., Djedi, N., Akrour, D., Cussat-blanc, S., Sanchez, S., Djedi, N., Joint, H.L.: Joint evolution of morphologies and controllers for realistic modular robots. In: 22nd Symposium on Artificial Life And Robotics (AROB 2017). pp. 57–62. hal-01782566 (2017), https://hal.archives-ouvertes.fr/hal-01782566
2. Alattas, R.J., Patel, S., Sobh, T.M.: Evolutionary Modular Robotics: Survey and Analysis. Journal of Intelligent and Robotic Systems: Theory and Applications **95**(3), 1–14 (2018). https://doi.org/10.1007/s10846-018-0902-9
3. Brunete, A., Ranganath, A., Segovia, S., de Frutos, J.P., Hernando, M., Gambao, E.: Current trends in reconfigurable modular robots design. International Journal of Advanced Robotic Systems **14**(3), 1–21 (2017). https://doi.org/10.1177/1729881417710457

4. Caamaño, P., Tedín, R., Paz-Lopez, A., Becerra, J.A.: Jeaf: A java evolutionary algorithm framework. In: IEEE Congress on Evolutionary Computation. pp. 1–8. IEEE (2010)
5. Chennareddy, S.S.R., Agrawal, A., Karuppiah, A.: Modular Self-Reconfigurable Robotic Systems: A Survey on Hardware Architectures. Journal of Robotics **2017** (2017). https://doi.org/10.1155/2017/5013532
6. Chocron, O.: Evolving modular robots for rough terrain exploration. In: Mobile Robots: The Evolutionary Approach, pp. 23–46. Springer (2007)
7. Faíña, A., Bellas, F., López-Peña, F., Duro, R.J.: Edhmor: Evolutionary designer of heterogeneous modular robots. Engineering Applications of Artificial Intelligence **26**(10), 2408–2423 (2013)
8. Faina, A., Bellas, F., Orjales, F., Souto, D., Duro, R.J.: An evolution friendly modular architecture to produce feasible robots. Robotics and Autonomous Systems **63**, 195–205 (2015)
9. Haasdijk, E., Rusu, A.A., Eiben, A.: Hyperneat for locomotion control in modular robots. In: International Conference on Evolvable Systems. pp. 169–180. Springer (2010)
10. Jelisavcic, M., de Carlo, M., Hupkes, E., Eustratiadis, P., Orlowski, J., Haasdijk, E., Auerbach, J.E., Eiben, A.E.: Real-World Evolution of Robot Morphologies: A Proof of Concept. Artificial Life **23**(2), 206–235 (may 2017). https://doi.org/10.1162/ARTL_a_00231, http://www.mitpressjournals.org/doi/abs/10.1162/ARTL_a_00231
11. Kamimura, A., Kurokawa, H., Yoshida, E., Murata, S., Tomita, K., Kokaji, S.: Automatic locomotion design and experiments for a modular robotic system. IEEE/ASME Transactions on mechatronics **10**(3), 314–325 (2005)
12. Liu, C., Liu, J., Moreno, R., Veenstra, F., Faina, A.: The impact of module morphologies on modular robots. In: 2017 18th International Conference on Advanced Robotics (ICAR). pp. 237–243 (July 2017). https://doi.org/10.1109/ICAR.2017.8023524
13. Marbach, D., Ijspeert, A.J.: Online optimization of modular robot locomotion. In: IEEE International Conference Mechatronics and Automation, 2005. vol. 1, pp. 248–253. IEEE (2005)
14. Miras, K., Haasdijk, E., Glette, K., Eiben, A.: Search space analysis of evolvable robot morphologies. In: International Conference on the Applications of Evolutionary Computation. pp. 703–718. Springer (2018)
15. Moreno, R., Veenstra, F., Silvera, D., Franco, J., Gracia, O., Cordoba, E., Gomez, J., Faina, A.: Automated reconfiguration of modular robots using robot manipulators. In: 2018 IEEE Symposium Series on Computational Intelligence (SSCI). pp. 884–891 (Nov 2018). https://doi.org/10.1109/SSCI.2018.8628628
16. Moreno, R., Liu, C., Faina, A., Hernandez, H., Gomez, J.: The emerge modular robot, an open platform for quick testing of evolved robot morphologies. In: Proceedings of the Genetic and Evolutionary Computation Conference Companion. pp. 71–72. ACM (2017)
17. Rohmer, E., Singh, S.P.N., Freese, M.: V-REP: A versatile and scalable robot simulation framework. In: IROS '13. pp. 1321–1326. IEEE, Tokyo (nov 2013). https://doi.org/10.1109/IROS.2013.6696520, http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6696520
18. Seo, J., Paik, J., Yim, M.: Modular Reconfigurable Robotics. Annual Review of Control, Robotics, and Autonomous Systems **2**(1), 63–88 (2019). https://doi.org/10.1146/annurev-control-053018-023834

19. Shen, W.M., Salemi, B., Will, P.: Hormone-inspired adaptive communication and distributed control for conro self-reconfigurable robots. IEEE transactions on Robotics and Automation **18**(5), 700–712 (2002)
20. Sims, K.: Evolving 3d morphology and behavior by competition. Artificial life **1**(4), 353–372 (1994)
21. Stoy, K., Brandt, D.: Efficient enumeration of modular robot configurations and shapes. In: 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 4296–4301. IEEE (2013)
22. Stoy, K., Brandt, D., Christensen, D.J.: Self-reconfigurable robots: an introduction. Mit Press (2010)
23. Veenstra, F., Faina, A., Risi, S., Stoy, K.: Evolution and morphogenesis of simulated modular robots: a comparison between a direct and generative encoding. In: European Conference on the Applications of Evolutionary Computation. pp. 870–885. Springer (2017)
24. van de Velde, T., Rossi, C., Eiben, A.: Body symmetry in morphologically evolving modular robots. In: International Conference on the Applications of Evolutionary Computation (Part of EvoStar). pp. 583–598. Springer (2019)
25. Vergara, A., Lau, Y.S., Mendoza-Garcia, R.F., Zagal, J.C.: Soft modular robotic cubes: Toward replicating morphogenetic movements of the embryo. PLoS ONE **12**(1), 1–17 (2017). https://doi.org/10.1371/journal.pone.0169179
26. Yim, M., Shen, W.M., Salemi, B., Rus, D., Moll, M., Lipson, H., Klavins, E., Chirikjian, G.S.: Modular self-reconfigurable robot systems [grand challenges of robotics]. IEEE Robotics & Automation Magazine **14**(1), 43–52 (2007)
27. Yim, M., Zhang, Y., Duff, D.: Modular robots. IEEE Spectrum **39**(2), 30–34 (2002)