The impact of module morphologies on modular robots

Ceyue Liu and Jiangong Liu
Department of Mechanical Electronic and Information Engineering
China University of Mining & Technology (Beijing)
Beijing 100083,China
liuceyue@163.com, liujg@jzeg.cn

Rodrigo Moreno
Department of Computer and Industrial Engineering
Universidad Nacional de Colombia
Bogotá 111321, Colombia
rmorenoga@unal.edu.co

Frank Veenstra and Andres Faina
Department of Computer Science
IT University of Copenhagen
Copenhagen 2300, Denmark
{frve, anfv }@itu.dk

***Abstract* - Many different types of modular robots have been designed in the last two decades. However, limited research has been done on analyzing which module morphology is able to create better robots for a given task. To address this issue, this paper investigates how the number and position of available connection faces in a module influence the evolvability of the modular robot. In contrast to previous research on modular robots, an analysis of the morphology of the module is done in order to improve and simplify its mechanical design. To this end, we designed a homogeneous module called EMeRGE, and defined the number of connection faces and their relative positions as morphological parameters. Afterwards, we evolved the morphology and control of robots composed of EMeRGE modules in a robotic simulation platform. Simulation results indicate that robots containing modules with only two available connection faces were able to acquire better performance than robots that contained modules using more connection faces for a locomotion task. Finally, the simulated robots were transferred to the real world in the actual modular robot to verify the simulation results.**

Index Terms* – *Module Morphology, Evolutionary design, Modular robot.

I. INTRODUCTION

Modular robots are mechanically connected compositions of autonomous devices, called modules, which encapsulate part of their functionality [1]. Modules can be assembled in various configurations leading to different robot morphologies. Modular robots offer a benefit to robotics, especially evolutionary robotics, since they can easily be reconfigured to form a distinct morphology. Moreover, identical modules are easy to produce. Considering these advantages, modular robots have been applied to many fields, ranging from education and commercial tools to search and rescue [1].

Most modular robot systems that have been physically implemented are designed using a bottom-up approach. First, a module is designed and implemented and later different modular robot aspects are analyzed using different configurations. As has been argued by Pfeifer and Bongard [2], the body, in addition to the brain, is of similar importance for robots. In modular robots, the body is composed of two features: a configuration or how the modules are joined together and the module morphology. The module morphology influences the type of configurations that can be generated which, in turn greatly influences the resulting morphology of the modular robot. Only few studies address this topic. One of them analyzes the different possible configurations of a modular robot [3]. However, the number of different configurations does not convey whether these configurations are useful for a specific task.

This paper explores how the morphological features of the module influence the acquisition of modular robot morphologies. For example, a large number of connection faces on each module will increase the number of configurations that these modules can generate but, on the other hand, the mechanical design will be more complex. Thus, there is a trade-off between the complexity of the module and the reconfigurability that it allows. Also, many of the robot configurations produced by a module with a high number of connectors could be redundant. Therefore, it is important to analyze not only how many configurations can be generated but also whether they are suitable for a task. To this end, we propose an approach to study module morphologies based on an evolutionary design, which uses an evolutionary algorithm to find successful morphologies and controllers without adding human bias.

To estimate the performance of a specific module morphology, an evolutionary algorithm ran several times to find suitable configurations and controllers for locomotion as the objective. We define the performance of the module as the average of the maximum fitness of the robots generated in different evolutionary runs. In evolutionary computation, the ability to generate adaptive genetic diversity is called evolvability [4]. There are several factors that influence the evolvability of a system, such as the genotype to phenotype mapping as well as the parameters of the evolutionary algorithm [5]. However, in this paper these factors are not modified and we use the evolvability as an estimation of the module performance.

The evolution of morphology and control to generate virtual creatures for simple tasks has been explored in the last two decades by many scientists [6], [7], [8], [9]. Most of these approaches have been done in simulation environments where not all dynamic properties and physical features can be taken into account. Therefore, we do not know how easy we could transfer these evolved virtual creatures to reality. Pollack addressed this by evolving robots that were subsequently 3d printed [10]. This approach allowed researchers to easily build the obtained robots in reality. Marback and Ijspeert evolved the locomotion of homogenous modular robots based on Yamor modules, a homogenous architecture implementing only hinge modules [11]. Lund employed Lego parts to build

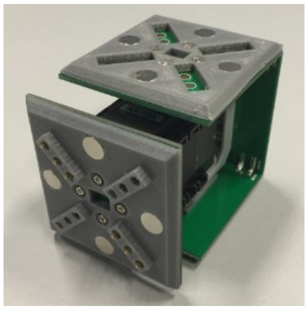

Fig. 1. The EMeRGE module

TABLE I
MAIN CHARACTERISTIC OF THE MODULE

Weight	194.1 g
Num. connection face	4
Max disconnection torque of the module	0.85 N-m
Final Max Holding Torque of the AX-12A	16.5 kgf.cm (at 10V)
Type of movement	Revolute
Stroke	180°
Orientation	4

different morphologies of a modular robot followed by the evolution of the control of the assembled modular robots [12]. Moreover, Faíña et al. evolved morphology and control using a heterogeneous modular architecture to minimize the number of modules in the robot [13]. Though the methodology employed in this paper is similar to previous approaches, our goal is to compare different module morphologies.

In this paper, we investigate how the number and position of available connection faces of individual modules influence the performance of assembled modular robots for a locomotive task. For this purpose, a real robotic module called EMeRGE (Easy Modular Embodied Robot GEeneration) [14] with four connection faces is designed and its main features are described. Then, five different module morphologies are defined by disabling some connection faces of the EMeRGE module. The approach employed to analyze which of these five morphologies produce better robots for locomotion is based on the evolution of the morphologies and their controllers in a simulator. The simulation results are transferred to real modular robots for comparison. Section II summarizes the design of the EMeRGE module, consisting of its basic features, connection mechanism and control. This is followed by the evaluation of the morphologies generated with the different types of modules (Section III). Section IV presents the results of the evolutionary runs followed by a discussion section (Section V) and the conclusion of the paper (Section VI).

II. ROBOTIC MODULE

The EMeRGE[1] module (Fig. 1), is the robotic module used throughout the experiments. It is easy to construct and multiple modules can be assembled into a working modular robot in a matter of seconds. This section outlines the basic features, connection mechanism, and control system of this module.

A. Basic features

The module possesses one degree of freedom and its size is 80mm×61mm×55mm. The module has four connection faces, three of them attached to the motor’s shaft and the other one attached to the motor’s chassis. Each connection face is 3D printed. Under each face there is a Printed Circuit Board (PCB) which routes electrical signals, effectively sharing power and communications among all faces. We number the four connector faces from face 0 to face 3. We employ standard Dynamixel motors (AX-12A or AX-18A) and their accompanying servo brackets. Assembly of the module takes only a few minutes if all components are ready. The main features of the module are displayed on TABLE I.

B. Connection mechanism

In order to join the modules quickly and easily, a magnetic connection mechanism has been designed. Communications and power are shared through the connector, and an assembled robot can be powered and controlled using only one three-core cable. The connection mechanism design is displayed in Fig. 2. Each connector face contains four NdFeB (neodymium, iron and boron) magnets organized such that their poles face in the same direction. The strength of the magnet is approximately 10.72N and the diameter is 12 mm. Face 0 is a male connector and faces 1, 2 and 3 are female connectors. Thus, the polarity of the magnets in face 0 is the opposite from those on the other three faces. To make the connector robust to shear forces, four protrusion parts have been designed in the male connector, and four matching concave parts have been designed in the female ones. Still, faces can disconnect because of a bending moment. The maximum bending moment that the connector can support is 0.85 N-m.

All PCBs contain four symmetrically distributed groups of pads, each group has three pads. In face 0, three spring pins are soldered to the pads, these pins reach the pads in other PCB boards connecting three signals (+11.1V, GND and Data). The face protrusions have three holes through which the spring pins can pass. On the edge of the three contiguous faces, the PCBs are soldered together to provide electrical contact and increase the mechanical strength. The connection between the three contiguous PCBs and the other one as well as with the motor is made by using off-the-shelf cables. The Dynamixel protocol allows several motors to be connected and controlled using the same bus, so all modules are connected to the same three signals.

C. Control

To control the modules, we implement a centralized controller using a PC. The PC uses an USB2AX interface device that receives USB commands and translates them into the Dynamixel bus. Each motor has a unique id and can be

[1] The source is available at https://sites.google.com/view/emergemodular/home

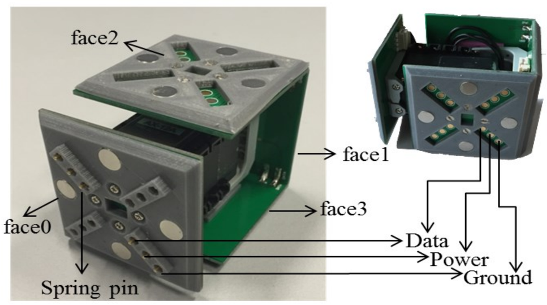

Fig. 2. Connection mechanism description

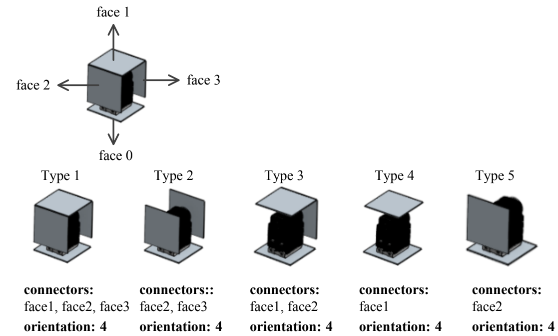

Fig. 3. Classification of the EMeRGE module based on connection faces

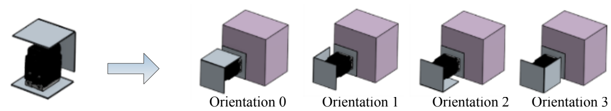

Fig. 4. Connection configurations of the EMeRGE module

controlled independently by setting its speed and position. Motors can also provide their measured position and speed.

III. APPROACH FOR MODULE EVALUATION

To evaluate the modules, we evolve the morphology and control of modular robots for a locomotion task. Thus, evolvability of the different types of modules is analyzed. This section explains the approach employed for evolving modular robots.

A good evolutionary platform design involves many aspects, e.g., solution encoding, realistic evaluations, fitness function as well as many other parameters inherent to evolutionary algorithms. In addition, the integration and coordination of these aspects also plays an important role in the evolutionary tool. To illustrate the influence of module morphologies on the performance of the modular robot, we evolve the robot morphologies using the Evolutionary Designer of Heterogeneous Modular Robots (Edhmor system[2]), which integrates the Java Evolutionary Algorithm Framework (JEAF) [13]. In this paper, we have used the latest version of the Edhmor system, which employs the V-REP (Virtual Robot Experimentation Platform) simulator [15]. The system evolves the morphology, made from predefined modules, and the controller to automatically generate feasible modular robots for one specific task.

The EMeRGE module has been selected as a basic module to form homogeneous modular robots, and different morphologies of the EMeRGE module were produced by using only a limited number of its connection faces. These module morphologies were encoded in the Edhmor system. Different evolutionary runs with the distinct modules were compared to examine the modules performance as building blocks. In this section, the evolutionary parameters, such as the morphology classification, the simulated model, the encoding, and the evaluation, will be described in detail.

A. *Morphology classification*

To analyze how the morphology of the module influences the ability to find good robotic morphologies for a task, we define different types of modules based on the EMeRGE module. Specifically, we have chosen the number of connection faces and their relative positions in a module as the morphological parameters. We classify the morphology of connection faces into five types, as illustrated in Fig. 3. As described in section II.B, face 1, face 2, and face 3 (female connectors) in one module can be connected to face 0 (male connector) in other modules. Thus, modules are always connected to the previous module using male connectors (face 0), and, therefore, face 0 is always connected. In addition, each module type has four possible orientations as the connector allows us to connect two faces after a 90 degrees rotation. As an example, the four different orientations of the Type 3 module are shown in Fig. 4.

B. *Simulated model*

The evaluation of the modular robot is carried out in the V-REP simulator, in which robots are also assembled. Robots move according to their simulated phenotype within a fixed simulation time. Their fitness value is determined at the end of the simulation.

The physical characteristics of the EMeRGE module have been accurately modeled in V-REP (Fig. 5). All modules are controlled by a sinusoidal function, as in (1).

$$y_i = \frac{\pi}{2}\sin\left(2t + \varphi_i\right) \tag{1}$$

Where i is the number of the individual module, y_i is the angle of the actuator, t is the simulation time and φ_i is the phase, which is the only control parameter that can be changed by the evolutionary process.

C. *Encoding*

How modular robots are evolved depends on the encoding, which also has a great influence on the morphological search space [16]. The Ehdmor system uses a direct encoding (Fig. 6) for representing individuals based on a tree structure. The individual's information is stored in an array composed of the module type, number of children per

[2] The source code is available at https://bitbucket.org/afaina/edhmor

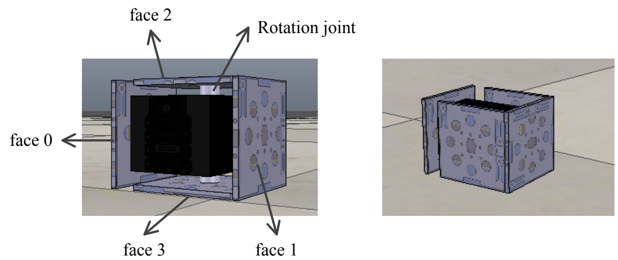

Fig. 5. Simulated model of the EMeRGE module in V-REP

Type	Number of children	Parent connection face	Orientation	Phase control
1	0~3	face1,face2,face3	4	φ

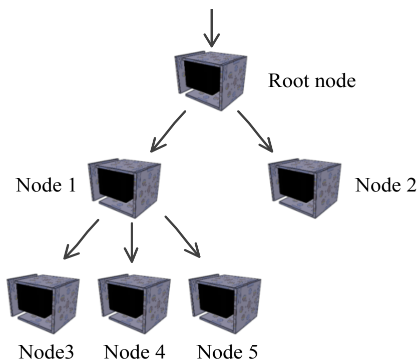

Fig. 6. Schematic diagram of the encoding of one individual modular robot

node, connection face on the parent, orientation and phase control. One individual represents one full robot and one node represents one module. Each node hangs from the parent node according to the encoding information. Only one type of module is used for each evolutionary run.

D. *Evaluation*

The fitness function, or performance measure, is defined as the distance that the robot has moved during a fixed simulation time, using equation 2.

$$f = \text{distance} = \sqrt{\left(x_{m2} - x_{m1}\right)^2 + \left(y_{m2} - y_{m1}\right)^2} \tag{2}$$

Where the values $\left(x_{m1}, y_{m1}\right)$ and $\left(x_{m2}, y_{m2}\right)$ represent the initial and final positions of the center of mass of the robot respectively, as implied in equation (3).

$$\left(x_m, y_m\right) = \sum_i m_i \left(x_i, y_i\right) \Big/ \sum_i^n m_i \tag{3}$$

Where n is the number of modules, m_i is the mass of module i, and $\left(x_i, y_i\right)$ are the coordinates of module i.

IV. Experiment

In order to evaluate the different types of module morphologies, we performed twenty different evolutionary runs for each type of module. Afterwards, we analyzed which

TABLE II
CONFIGURATION PARAMETERS OF THE EVOLUTIONARY ALGORITHM FOR THE LOCOMOTION EXPERIMENT

Evaluation time	30 s
Population	24
Max number of modules	9
Maximum evaluations	20000

type of module produced the best morphologies given the performance measure. As a final check, we built some of the best morphologies obtained in real modules and evaluated them.

A. *Statistical analysis on the influence of the module morphology*

To show the influence of the module´s morphologies on the modular robots generated, we performed 20 evolutionary runs for each type of morphology derived from the EMeRGE module. The configuration parameters of the evolutionary algorithm are shown in TABLE II, the parameters that are not shown are the same as in [13].

The best fitness of the robots assembled by these five module types is plotted against the number of generations in Fig. 7(a) ~ (e). It can be seen from results that feasible modular robots can be obtained for each type of module. Furthermore, Type 4 modules performed better than the other types of module for the locomotion task. To compare this type of module against the default EMeRGE module, we compare the median fitness of the maximum acquired fitness of each run of Type 4 and Type 1 modules and plot error bars using 25% and 75% percentiles (data is not normally distributed). The result is shown in Fig. 7(f).

Two-tailed Mann-Whitney U tests were performed to check whether evolutionary runs were statistically significant. The results of these tests are summarized in TABLE III. It can be seen that there is no statistically significant difference between Type 1 and Type 2 and between Type 1 and Type 3. There is a statistically significant difference between Type 4 and Type 5, and between these two and the rest.

To illustrate the statistically significant difference between these modules and the rest, five boxplots comparing fitness data of the last generation of 20 different runs of each module type are shown in Fig. 8. From the boxplots, it can be seen that the central tendency of Type 4 falls between 2.3 and 3.2 meters, and its median is about 2.6 meters, being both higher than the other types.

This means that only using one female connection face (face 1) of the EMeRGE module can lead to the best morphologies of the modular robot for the locomotion task within the given simulation time. In Fig. 9, the robot morphologies that got the best fitness for all five types of modules in simulation are displayed.

B. *Transferability*

With the aim of comparing the simulation results and the real results, we transferred the best morphologies obtained using the five types of modules to the real modular robots. Afterwards, we transferred the control parameters into the real

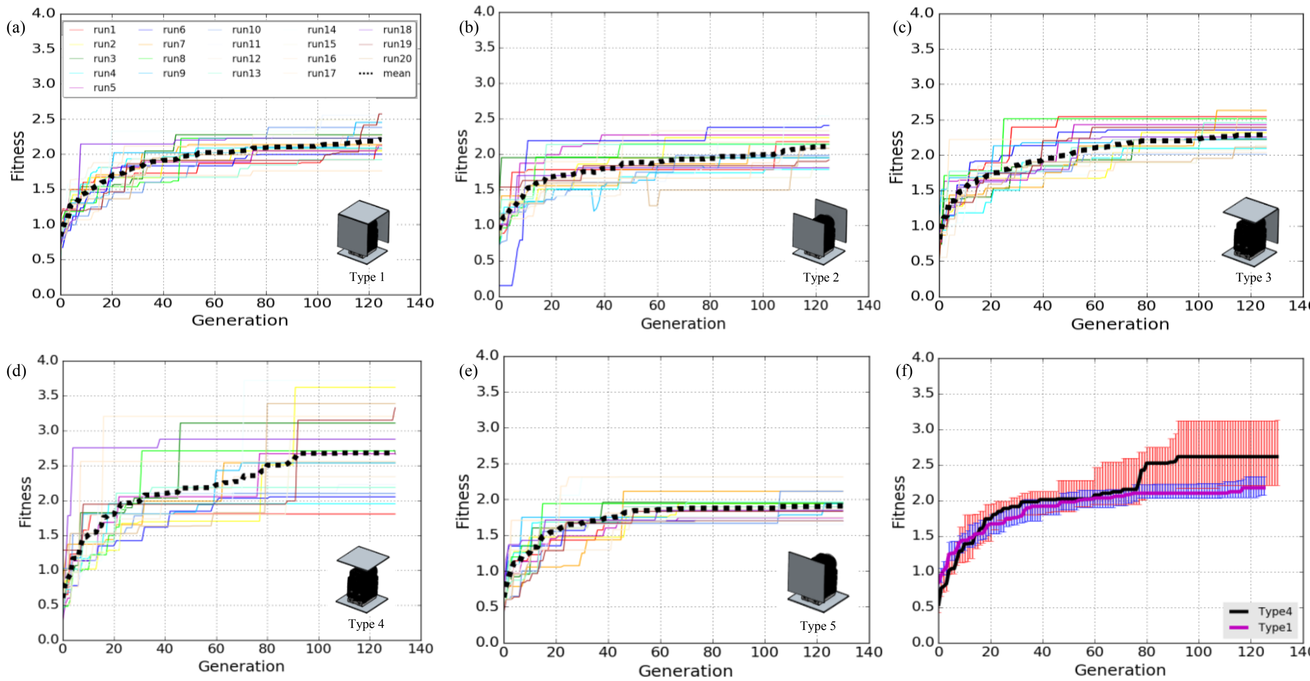

Fig. 7. Graphs (a), (b), (c), (d) and (e) display the fitness of the best robots assembled by modules from Type 1 to Type 5 for 20 independent evolutionary runs for a locomotion task. Graph (f) displays the median fitness with 25% and 75% percentiles as error bars for Type 4 and Type 1 modules.

TABLE II
THE TEST RESULT OF THESE FIVE TYPES BASED ON MANN-WHITNEY U-TEST (SIGNIFICANCE LEVEL IS 5%)

Test number	Two independent samples of module type		p-value	Statically Significance
1	Type 1	Type 2	0.2732	No
2		Type 3	0.2977	No
3		Type 4	0.0051	Yes
4		Type 5	9.200e-05	Yes
5	Type 2	Type 3	0.0144	Yes
6		Type 4	0.0005	Yes
7		Type 5	0.0028	Yes
8	Type 3	Type 4	0.0179	Yes
9		Type 5	5.814e-06	Yes
10	Type 4	Type 5	5.809e-06	Yes

assembled robots to perform the locomotive task using the same time limit as in simulation.

In Fig. 10, five real robot morphologies are displayed, which correspond to the best simulated robots for each type of module. The robot evaluations are performed using the same fitness function as in simulation. There is one meter of measuring tape on the ground as a reference. The measured fitness for these five real robots, from Type 1 to Type 5, are 0.32m, 0.24m, 0.81m, 1.02m, and 0.25m respectively. In contrast, the fitness of the corresponding simulated robots, from Type 1 to Type 5, are 2.57m, 2.41m, 2.62m, 3.72m, 2.31m.

Despite the big difference between the simulated fitness and its real performance, Type 4 modules still perform

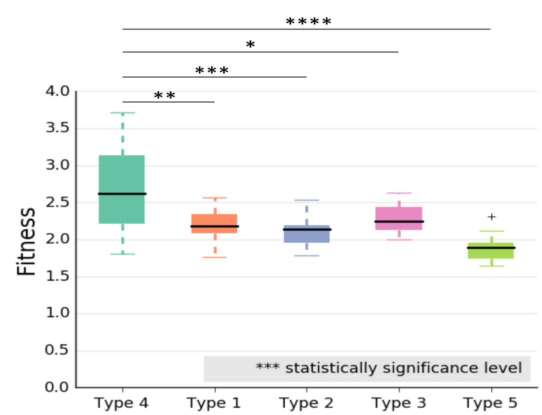

Fig. 8. Boxplot depicting the best fitness for each module type in 20 evolutionary runs. The bottom and top of the box are the first and third quartiles, and the band inside the box is the second quartile (the median), whiskers extend to the most extreme data point within 1.5 * IQR, where IQR is the interquartile range. The number of stars is used to represent the p-value that results from the Mann-Whitney U-test, four stars means p-value <0.0001, three stars means 0.0001 ≤ p-value < 0.001, two stars means 0.001 ≤ p-value < 0.01, one stars means 0.01 ≤ p-value < 0.05. Outlier represented as +.

significantly better than the others. Therefore, this result verifies the simulated result to some degree.

V. DISCUSSION

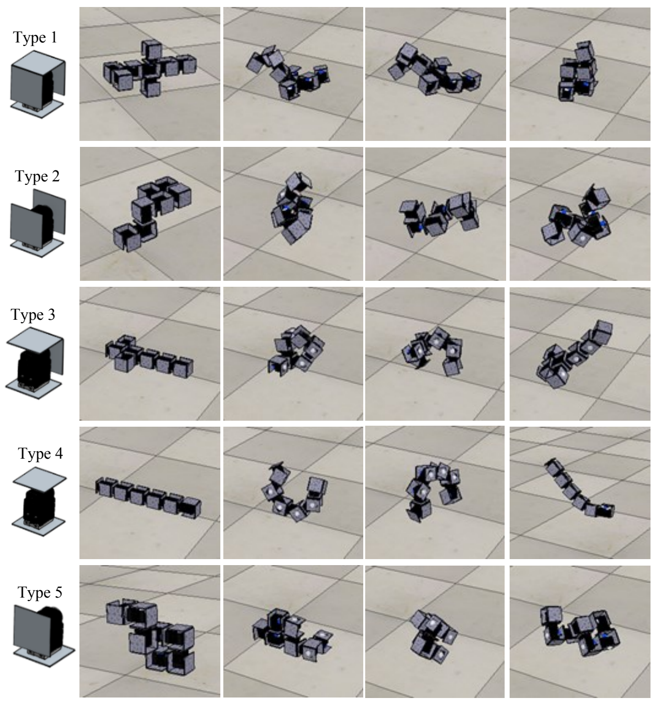

Fig. 9. Examples of the five best simulated robot morphologies using Type 1 to Type 5 modules obtained in the locomotion task experiment.

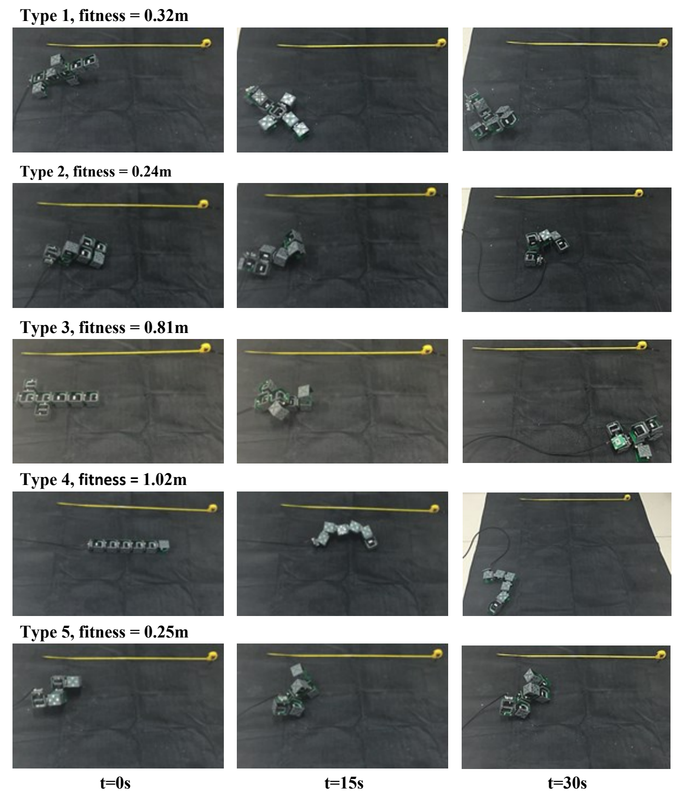

Fig. 10. Examples of the five best real robot morphologies using Type 1 to Type 5 modules transferred from the locomotion experiment.

A different number of connection faces for each module type means that the results from the evolution are not directly comparable as the search space is not the same. For example, Type 4 and Type 5 modules have only one female connection face so they have a smaller search space compared to other types. As the number of evaluations for every evolutionary run is fixed to 20,000, a fair comparison between these types of module cannot be made. However, we can compare Type 2 to Type 3 and Type 4 to Type 5 modules. In addition, the search space of Type 1 modules is bigger than Type 2 and 3 and if it still gets statistically significant better performances compared to Type 2 and 3, we can conclude that the reconfiguration space contributes to the overall performance in modular robots. However, we do not know if the search space is more rugged or smoother for each different module type. The resulting behavior of Type 4 modules might imply a more rugged search space as indicated by the large disparity between evolutionary runs compared to the other module types. But since the results of the Type 4 modules could potentially also be acquired by Type 1 and Type 3 modules we suspect that the search space is actually smoother and that Type 1 and Type 3 modules do not lead to the same performance of Type 4 modules due to an increased ruggedness in the search space. This makes it less likely for evolved modular robots including Type 1 and 3 modules to transition to the more efficient behaviors seen in Type 4 modules.

This experiment only focuses on the simple case which evaluates the robot moving on a flat surface. In order to get more results on the influence of module morphology on the evolvability of modular robots, different tasks should be defined to evaluate the robot. As there are no sensors on the first version of the EMeRGE module, another task which would evaluate the robot moving with a payload on a flat or rugged surface can be considered.

Regarding the transferability of the robots, results show that the fitness of real robots is much lower than the fitness in simulation. In addition, movements obtained in simulation are also slightly different from the real robots movements. Thus, the evolutionary algorithm exploits the badly modelled phenomena to achieve better fitness. However, our approach is still promising, due the fact that the obtained robots can be built in seconds by connecting the modules together.

From an evolutionary point of view, we have shown that evolutionary approaches can be drastically more efficient when the morphological search space is reduced. Reducing this search space minimizes computational time but might limit performance when longer evolutionary runs are done. Through limiting the morphological search space an evolutionary algorithm can more quickly acquire decent locomotive strategies in evolved modular robots. However, the speed of the acquisition of behavior could also be influenced by altering the parameters of the evolutionary algorithms. Other researchers have proposed using speciation [17], novelty search [18] or age layered evolutionary algorithms [19], [20] that have all been shown to enhance the evolvability of an evolutionary system. Moreover, the encoding of the modular robot can also influence its evolvability and thereby the speed of acquiring decent robot behaviors [16]. Being able to change the available connections places on an evolved modular robot when the modular robot has already been subjected to evolution might also be advantageous for the current implemented method. In this case, incrementally evolving modular morphologies with different module types could enhance performance. Furthermore, to improve the transferability of the evolved robots we can do some additional evolutionary runs on the real robot [21] or have a feedback loop from the evolved robots to the simulation as discussed in [22].

VI. CONCLUSION

We showed how the availability of connection faces on robot modules influenced the evolvability of modular robots. Specifically, we proposed an approach that is useful to compare different types of modules, not only based on how many configurations can be generated but also taking into account their performance when they are assembled. Results showed that by using a specific type of module morphology drastically improved the acquisition of locomotion in modular robots, which has been confirmed in the transferred robots. When designing a modular robot for a specified task it might thus be advantageous to limit the amount of connection faces when using evolutionary algorithms. Limiting the amount of connection faces can in turn be helpful to acquire robotic behaviors where computational time needs to be limited. This approach can help improve the efficiency of acquiring robotic morphologies by shaping the configurational space of the modular robot.

ACKNOWLEDGMENT

This research was in part funded by the CHINA SCHOLARSHIP COUNCIL, fund number: 201506430032. The Simulated evolutionary runs were supported by the DeIC National HPC Centre, SDU. Thanks to Luxi Zhao for her aid in typesetting.

REFERENCES

[1] Stoy, K., Brandt, D., & Christensen, D. J. (2010). Self-reconfigurable robots: an introduction.

[2] Pfeifer, R., & Bongard, J. (2006). How the body shapes the way we think: a new view of intelligence. MIT press.

[3] Stoy, K., & Brandt, D. (2013, November). Efficient enumeration of modular robot configurations and shapes. In Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on (pp. 4296-4301). IEEE.

[4] Colegrave N, Collins S (May 2008). "Experimental evolution: experimental evolution and evolvability". Heredity. 100 (5): 464–70.

[5] Nolfi, Stefano, and Dario Floreano. Evolutionary robotics: The biology, intelligence, and technology of self-organizing machines. MIT press, 2000.

[6] Sims, K. (1994, July). Evolving virtual creatures. In Proceedings of the 21st annual conference on Computer graphics and interactive techniques (pp. 15-22). ACM.

[7] Komosinski, M. (2003). The Framsticks system: versatile simulator of 3D agents and their evolution. Kybernetes, 32(1/2), 156-173.

[8] Mazzapioda, M., Cangelosi, A., & Nolfi, S. (2009, May). Evolving morphology and control: a distributed approach. In Evolutionary Computation, 2009. CEC'09. IEEE Congress on (pp. 2217-2224). IEEE.

[9] Chaumont, N., Egli, R., & Adami, C. (2007). Evolving virtual creatures and catapults. Artificial life, 13(2), 139-157.

[10] Pollack, J. B., & Lipson, H. (2000). The GOLEM project: Evolving hardware bodies and brains. In Evolvable Hardware, 2000. Proceedings. The Second NASA/DoD Workshop on (pp. 37-42). IEEE.

[11] Marbach, D., & Ijspeert, A. J. (2004). Co-evolution of configuration and control for homogenous modular robots. In Proceedings of the eighth conference on intelligent autonomous systems (IAS8) (No. BIOROB-CONF-2004-004, pp. 712-719). IOS Press.

[12] Lund, H. H. (2003). Co-evolving control and morphology with LEGO robots. In Morpho-functional machines: the new species (pp. 59-79). Springer Japan.

[13] Faíña, A., Bellas, F., López-Peña, F., & Duro, R. J. (2013). EDHMoR: Evolutionary designer of heterogeneous modular robots. Engineering Applications of Artificial Intelligence, 26(10), 2408-2423.

[14] Rodrigo Moreno, Ceyue Liu, Andres Faina, Henry Hernandez, and Jonatan Gomez. 2017. The EMeRGE modular robot, an open platform for quick testing of evolved robot morphologies. In Proceedings of GECCO '17 Companion,,Berlin, Germany, July 15-19, 2017, 3 pages. DOI: http://dx.doi.org/10.1145/3067695.3075616

[15] Freese, M., Singh, S., Ozaki, F., & Matsuhira, N. (2010, November). Virtual robot experimentation platform v-rep: A versatile 3d robot simulator. In International Conference on Simulation, Modeling, and Programming for Autonomous Robots (pp. 51-62). Springer Berlin Heidelberg.

[16] Veenstra F, Faina A, Risi S, Stoy K, 2017, Evolution and Morphogenesis of Simulated Modular Robots: A Comparison Between a Direct and Generative Encoding, Evostar 2017, In press.

[17] Stanley, K. O., Bryant, B. D., & Miikkulainen, R. (2003, December). Evolving adaptive neural networks with and without adaptive synapses. In Evolutionary Computation, 2003. CEC'03. The 2003 Congress on (Vol. 4, pp. 2557-2564). IEEE.

[18] Lehman, J., & Stanley, K. O. (2011). Novelty search and the problem with objectives. In Genetic Programming Theory and Practice IX (pp. 37-56). Springer New York.

[19] Hornby, G. S. (2006, July). ALPS: the age-layered population structure for reducing the problem of premature convergence. In Proceedings of the 8th annual conference on Genetic and evolutionary computation (pp. 815-822). ACM.

[20] Hornby, G. S. (2009). The age-layered population structure(ALPS) evolutionary algorithm.

[21] Nolfi, S. (1997). Evolving non-trivial behaviors on real robots: A garbage collecting robot. Robotics and Autonomous Systems, 22(3-4), 187-198.

[22] Koos, S., Mouret, J. B., & Doncieux, S. (2013). The transferability approach: Crossing the reality gap in evolutionary robotics. IEEE Transactions on Evolutionary Computation, 17(1), 122-145.