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RoboGen: Robot Generation through Artificial Evolution

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Extended Abstract

Science instructors from a wide range of disciplines agree that hands-on laboratory components of courses are pedagogically necessary (Freedman, 1997). However, certain shortcomings of current laboratory exercises have been pointed out by several authors (Mataric, 2004; Hofstein and Lunetta, 2004). The overarching theme of these analyses is that hands-on components of courses tend to be formulaic, closed-ended, and at times outdated. To address these issues, we envision a novel platform that is not only a didactic tool but is also an experimental testbed for users to play with different ideas in evolutionary robotics (Nolfi and Floreano, 2000), neural networks, physical simulation, 3D printing, mechanical assembly, and embedded processing.

Here, we introduce RoboGen™: an open-source software and hardware platform designed for the joint evolution of robot morphologies and controllers a la Sims (1994); Lipson and Pollack (2000); Bongard and Pfeifer (2003). RoboGen has been designed specifically to allow evolved robots to be easily manufactured via widely available desktop 3D-printers[1], and the use of simple, open-source, low-cost, off-the-shelf electronic components. RoboGen features an evolution engine complete with a physics simulator, as well as utilities both for generating design files of body components for 3D printing, and for compiling neural-network controllers to run on an Arduino microcontroller board[2].

In this paper, we describe the RoboGen platform, and provide some metrics to assess the success of using it as the hands-on component of a masters-level bio-inspired artificial intelligence course.

Software Suite

The RoboGen software suite is comprised of two main components: an evolution engine that generates and reproduces robots, and a simulator that renders the evolutionary environment and assesses the fitness of the evolved solutions. Users may go from serial fitness evaluations (using a single simulator) to massive parallelism distributed across a network depending on their computational resources.

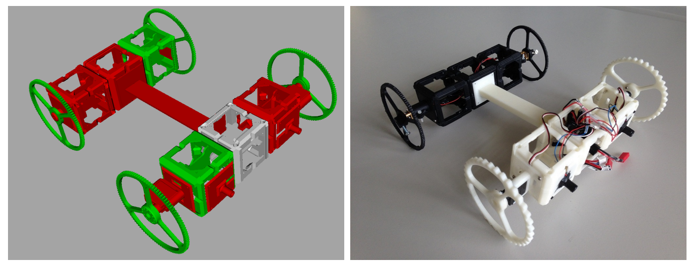

Figure 1: Sample robot evolved with RoboGen: simulation (left) and reality (right).

Robot bodies Robots evolved with RoboGen (see Fig. 1) are composed of predefined and parameterized modules, and are represented as genetic programming trees (Koza, 1992). The modular building blocks that make up the body representations include passive and active structural elements as well as sensing components. A full list of components, and their detailed specifications may be found on the RoboGen website `http://www.robogen.org`.

Robot brains The "brains" of the RoboGen robots are fully-connected, recurrent artificial neural networks. The robots can sense their environment through touch sensors, light sensors and a six degree-of-freedom inertial measurement unit (IMU). The number of sensors and actuators used in robots increase the complexity of the simulations, but their use may be necessary to evolve robots that are truly adapted to diverse tasks and environments.

In the classroom environment, we provide several scenarios for the students to explore the utility of various parameters and components of the software suite. Specifically, we aim to promote an understanding of how the tasks and environments affect the evolved morphologies (Auerbach and Bongard, 2014), and how allowed simulation complexity changes the adaptedness of the robots generated through the evolutionary process.

[1] Such as the MakerBot Replicator 2x: `http://store.makerbot.com/replicator2x`

[2] `http://www.arduino.cc`

The complexity of simulations achievable with this software is entirely dependent on the user: beginners can familiarize themselves with new concepts in a more controlled way by evolving only the neural network controllers, whereas advanced users can work on the evolution engine to customize the evolutionary algorithm or simulator or even introduce new morphological building blocks. This open-endedness is a major advantage of the platform and addresses the current concerns regarding science laboratory education (Mataric, 2004). Additionally, our software is also the first educational platform that provides the users with the ability to manufacture their own evolved robots. By allowing users to get completely immersed in the artificial evolution process, we hope to encourage users to think about real-life applicability of their simulations. Finally, we aim to foster collaborations among groups of students with different expertise by having them design evolutionary scenarios, carry out experiments, and test their evolved designs in hardware.

Teaching Assessment

Discerning whether RoboGen is indeed an effective tool for teaching evolutionary robotics requires an analytical approach. For this reason, we devised a measuring tool to get a sense of how well the students in our class meet the desired learning outcomes. In our teaching assessment we focus on a set of measurable learning outcomes that were defined based on the "Content, Skills and Values (CSV)" classification of learning outcomes (Carleton University, 2014). A brief questionnaire was prepared to be administered twice during the course: once after the first in-depth introduction to the RoboGen project (but before the students begin working on the project), and once at the end of the project. The purpose of this scheduling is to determine the improvement in the technical skills targeted in this course.

The evaluation questions fall under one of the aforementioned CSV categories, and are answered on a Likert scale from 1 to 5, with 5 being the strongest positive response (Likert, 1932). The first questionnaire saw 67% participation (53 students).

The psychosocial and environmental factors that influence learning will be measured through a separate questionnaire administered at the end of the course, determining both the students' perception of the classroom environment for learning and their "ideal" environment. This questionnaire is an adapted version of the Science Laboratory Environment Inventory tailored to suit the teaching environment of the course given at EPFL (Fraser et al., 1995).

Conclusions

Overall, we envision RoboGen as not only an effective platform for evolving the morphologies and controllers of manufacturable robots, but also a valuable educational tool. It is a system that should be attractive to researchers, hobbyists, educators and students alike. Going forward we hope to develop a worldwide community around RoboGen. Users will be able to discuss their experiences, share ideas, and contribute to the growth of the project by introducing new morphological building blocks, evolutionary scenarios, and educational exercises.

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