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If it evolves it needs to learn

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ABSTRACT

We elaborate on (future) evolutionary robot systems where morphologies and controllers of real robots are evolved in the real-world. We argue that such systems must contain a *learning* component where a newborn robot refines its inherited controller to align with its body, which will inevitably be different from its parents.

CCS CONCEPTS

• **Computer systems organization → Evolutionary robotics**; • **Theory of computation → Evolutionary algorithms**.

KEYWORDS

Evolutionary robotics, online learning, Lamarckian evolution

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1 INTRODUCTION

A general definition of Evolutionary Robotics (ER) states that it "aims to apply evolutionary computation techniques to evolve the overall design or controllers, or both, for real and simulated autonomous robots" [11]. Although much of the past work in the field of Evolutionary Robotics has been limited to evolving robot controllers, more recently ER systems in which morphologies *and* controllers of robots evolve simultaneously are beginning to emerge. However, the majority of such systems follow an approach of evolving in simulation followed by construction in the real-world [9]. Researchers have even recently demonstrated that is possible to use wet materials to construct by hand a physical incarnation of an organism evolved in simulation [8], however this is even more tedious than than constructing from hardware. The 'simulate-then-construct' approach inevitably runs into the infamous reality-gap problem [5], calling for systems in which bodies and brains are evolved together in the *real-world.* With the development of 3D-printing and rapid prototyping technology, this is now becoming a viable option [1, 4, 6, 12].

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2 THREE STAGES OF A ROBOTIC LIFE

A general architecture for "evolving robots in real-time and real-space" has been suggested in [3]. A tangible implementation is captured by the notion of an EvoSphere, cf. [2],

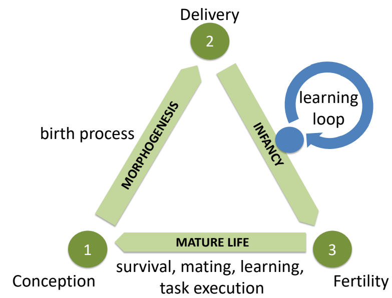

Figure 1: Generic system architecture for robot evolution conceptualized by the Triangle of Life, cf. [3].

The EvoSphere consists of three components: the Robot Fabricator, the Training Facility, and the Arena where the robots 'live and work'. The Robot Fabricator is where new robots are created (morphogenesis). The Training Facility is an environment for supervised learning during infancy, so individual robots can learn to control their –possibly unique– body to acquire basic skills (locomotion, object manipulation) and to perform complex tasks. Including an infancy stage mitigates a general problem: the potential that the brain in a newborn robot is sub-optimal for its body. This can manifest in different ways: in the worst-case, this may result in a complete mis-match (e.g. the robot has more sensors than there are inputs in the controllers), in the best-case it may simply require some tuning of the parameters of the brain. The use of indirect representations such as CPPN [10] for controllers is likely reduce this mis-match. However, evolving a completely general brain that works in every possible body is very challenging.

To acquire a brain that works well in the inherited body the learning process starts from the inherited brain and improves it until a required performance level is reached or a predefined learning budget is exhausted.[1] If a robot reaches the required performance level, it is declared a fertile adult and released into the Arena, otherwise it is removed from the system and recycled.

3 TWO LOOPS OF ADAPTATION

It is important to note that we have two loops within this evolving robot system: the main evolutionary loop that is evolving bodies

[1]Infant learning can partly take place in simulation. However, simulated learning always needs to be followed by learning / validation on the real robots to close the reality gap.

and brains and the secondary loop of the learning method. The primary/evolutionary loop is shown in green on the Triangle of Life (Figure 1). It produces robots with new bodies *and* brains, materialised by the Robot Fabricator. The secondary / learning loop is depicted by the blue circle in Figure 1. It takes place in the body of a newborn robot and produces new brains for this body via a learning algorithm. This process starts with the inherited brain and ends with what we call the learned brain.

In principle, the learning method can be of any type, including evolutionary algorithms, e.g., neuro-evolution or genetic programming. In this case we have two evolutionary loops and the terms fitness or individual will have a different meaning in each. Therefore we define the following terminology conventions for additional clarity.

Inherited body The body of a robot at birth. It is obtained by recombination of genomes that (either directly or indirectly) define the bodies of its parents. The body does not change during lifetime.

Inherited brain The brain of a robot at birth. It is obtained by recombination applied to the genomes that (either directly or indirectly) represent the brains of its parents. It forms the staring point for the infant learning process in the Training Centre.

Learned brain The brain of a robot obtained by the learning process in the Training Center. The maturity test is based on behaviour / performance produced by the learned brain.

Task performance Quantity that reflects how well a task is performed. In a system with multiple tasks there are multiple definitions of task performance. Task performance drives learning in the Training Centre. If the definition of fitness contains task-related measures, then task performance will drive evolution as well.

Fitness Quantity that determines reproduction probabilities. Drives evolution. Task performance may be part of the fitness definition.

The essential difference between task performance and fitness is that task performance is used to compare different brains in a given body thus driving the learning process in the infancy stage. In contrast, fitness is used to compare different robots when performing selection during mature life. Poor task performance implies that the given 'robot baby' fails the maturity test and is recycled. Low fitness in the Arena means that the given robot will not reproduce frequently, thus and its features will not be propagated to future generations. Obviously, system designers may choose to maintain a fitness definition that is (partly) based on task performance.

4 DARWINISM AND LAMARCKISM

All robots that make it to the mature lifetime period will have passed the learning stage. This means that they will possess a learned brain that will be different from their inherited brain. This implies a choice when this robot is about to reproduce and conceive a child.

- If the inherited brain is used by the reproduction operator, then we have a Darwinian system.
- If the learned brain is used by the reproduction operator, then we have a Lamarckian system.[2]

Observe that the fitness of the robot that determines its chances to reproduce is always based on the behavior induced by the learned brain, regardless of the above. Whether using a Lamarckian system is advisable is an open question. As of today there are not many studies of morphologically evolving robot systems with Lamarckian evolution of controllers, but the first results are encouraging [7].

[2]Note that a Lamarckian approach is impossible if an indirect representation is used for the brain but the learning acts *directly* on the brain that is produced from this.

5 CONCLUDING REMARKS

Advances in rapid prototyping technology have opened up a new avenue in Evolutionary Robotics that takes place directly in hardware, but this also implies new challenges. We note that randomized reproduction of robot bodies and brains can lead to a mis-match between the body and the brain of newborn robots. We argue that the robotic life cycle should include a specific infancy stage where (supervised) learning takes place to mitigate this problem. This increases the chances of success in the stage of maturity and it prevents reproduction of poorly performing robots and thereby it saves resources. In summary, our main thesis is that when morphologies (and not only controllers) of robots are evolvable, then the evolutionary process must be augmented with lifetime learning: If it evolves it needs to learn.

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