Towards the Evolution of Things

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Evolutionary Computing has received major exposure this year. Nature, the top dog of scientific journals, devoted a full-length review article to this field [1]. Evolutionary algorithms have been around for about three decades, without obtaining such high profile coverage, so what changed?

In our view the new interest is based on a possible new role for artificial evolutionary systems. Traditionally, artificial evolution equated to evolutionary problem solving, that is, using evolutionary algorithms as heuristic methods for solving optimization, design, and modelling tasks [2]. We strongly believe that such systems will always be important, and that research in this area will continue to flourish. However, increased interest has been sparked not just by high-profile success stories, but also by interesting developments in other directions. First of all, there is a wider interest in, and debate around AI-in-general, prompted by fears and by some well publicised advances in areas such as deep learning [3]. Perhaps more critically for our field, developments over the last couple of years boosted a latent opportunity of employing artificial evolution far beyond using it as an optimizer. The punchiest way to explain this potential is through the following four statements.

- Evolution can produce intelligence.
- Artificial evolution can produce artificial intelligence.
- The physical form of an agent plays a significant role in its "intelligence".
- New fabrication technologies are transforming how we can create objects.

The first statement is proven by our own intelligence that is a result of evolution on Earth. The second one, then, is a reasonable expectation, a plausible working hypothesis if you wish - and has been around for more than fifty years.
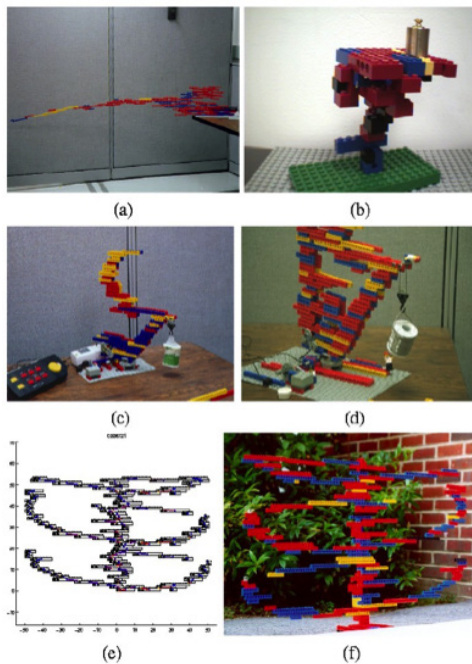

Figure 1. 1998: 2D and 3D LOGO objects evolved in simulation and built in real world afterwards [6]. These constructions are not actuated and have no controllers.
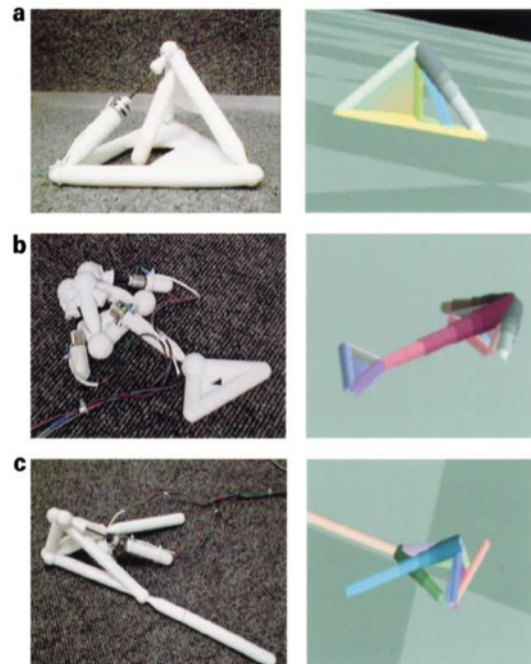

Figure 2. 2000: The GOLEM project [7] co-evolved robot bodies and controllers in simulation and fabricated the evolved robot afterwards. The robots did not have sensors.
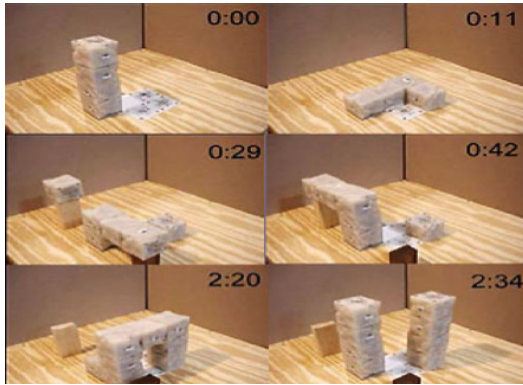
Figure 3. 2005: A physical system based on Molecubes, demonstrated non-adaptive robots able to construct a replica of themselves [8].
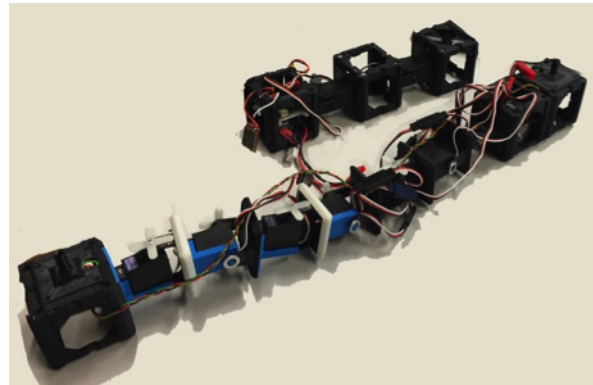

Figure 4. 2014: Robots with Arduino controllers, fixed parts and 3D-printed components that can be evolved in simulation and built afterwards.[9]

The third statement reflects much more recent thinking [4], but raises the question of how we design both bodies and controllers. Designing these separately is a complex task, that becomes even more so when coupled. In the fourth lies part of the answer: if we can now rapidly and automatically fabricate new parts, and assemble things, then we can apply evolutionary algorithms to both design tasks, and so achieve new levels of artificial intelligence.

The quest for artificial intelligence started with a narrow focus on the Mind. The bold dream in the 20th century was to create thinking machines. This was reflected by the Grand Challenge of creating a computer program that can beat the world champion of chess. As we all know, this was successfully accomplished before the end of the century. Acknowledging that intelligence is a characteristic of behaviour which arises from the interactions of mind, body and environment the focus on thinking machines is widening and the bold dream of the 21st century is to create acting machines, commonly known as robots. Judging by the furore generated by an advert purporting to show a robot competing with a world-class table-tennis player [4] , the corresponding Grand Challenge of embodied intelligence to create a robot that can play against a human at sport. Beyond that we have the greater challenges of coordinated action: a team of robots that can beat the world champions of football.

This brings us back to the working hypothesis above that identifies evolution as a potential approach to achieving intelligent behavior in entities with a mind and a body, i.e., in robots. The field of evolutionary robotics [11, 12], aims to evolve the controllers, the morphologies, or both, for real and simulated autonomous robots [13]. Considering the complexity of interactions between environment, morphology and controller, evolution may be not just one approach, but the approach to designing intelligent robots for a range of circumstances.

However, forced by technical constraints the usual modus operandi in evolutionary robotics is quite limited: evolve robot controllers in simulation and transfer the outcome to real hardware afterwards. Thus, even though the final goal is to obtain physical robots with evolved intelligence, the evolutionary process is still digital, which leads to the notorious reality gap problem [14].

The exciting new opportunity is to have physically embedded evolutionary processes on real --not simulated-- robots. Figures 1-6 demonstrate progress that has been made to date with self-assembly and the creation of physical artefacts - and the work still to be done. One option is to evolve controllers on-the-fly in a population of real robots (with fixed morphologies). This has been demonstrated in a handful of studies, for instance [15]. Another one is to evolve robot morphologies in real hardware by manually constructing each individual of the next generation. The only example we know of is the work of **John Long** described in [16,17]. The ultimate goal is of course a system
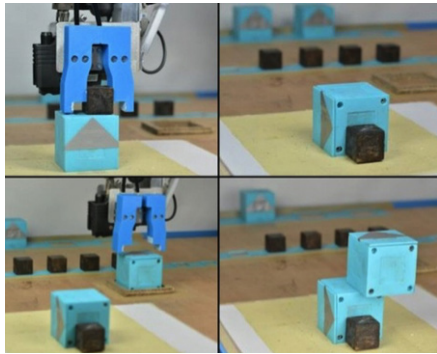
Figure 5. 2015: Quasi hands-free construction of genetically encoded modular robot bodies [10]. Consecutive generations were constructed and evaluated in real hardware The robots had no sensors and were driven by an external PC rather than an onboard controller.
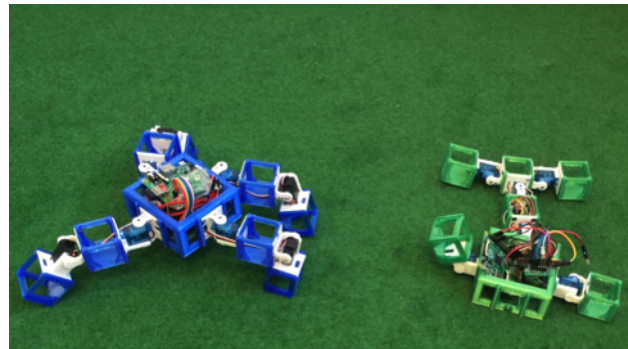

Figure 6. 2016: Robots are constructed in real hardware, undergo online learning, and can meet and mate in real life [18]. Offspring specified by the recombined genome is hand constructed from fixed components and 3D-printed blocks. Design is based on RoboGen [9].

where robots can reproduce themselves and evolve in real space and real time. To date this may seem far fetched, but advances in 3D printing and automated assembly are quickly bringing a robotic EvoSphere within reach [18]. Moreover, increases in the computing power we can put on-board robots, and in our understanding of surrogate modelling, and of how to avoid the reality gap [19] might make it feasible for each robot to add evolution to the life-time learning as a way of improving its controller - so it may not be necessary for evolution of morphologies and controllers to proceed in lock-step. The Evolution of Things may be closer than it seems.

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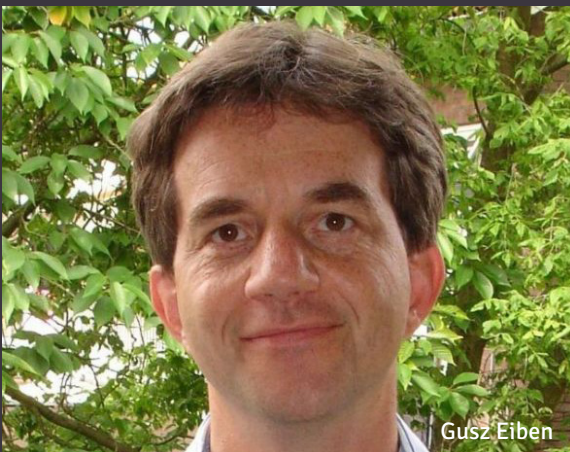
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Gusz Eiben is professor of Artificial Intelligence at the Vrije Universiteit Amsterdam. He is one of the European early birds of Evolutionary Computing, his first paper dates back to 1989. Since then he has published over 200 research papers, and he co-authored the first comprehensive book on evolutionary computing (Introduction to Evolutionary Computing, Springer, 2003, 2007, 2015). He has been actively pursuing research related to evolutionary operators, constraint handling, parameter calibration, and most recently evolutionary robotics.

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Jim Smith is Professor in Interactive Artificial Intelligence (AI) at the University of the West of England, Bristol, UK. He has been researching and publishing on aspects of Evolutionary Computation since 1994. A major research interest has been evolutionary systems that "learn how to learn" - whether through self-adaptation of genetic search operators, or via adaptive individual and social learning with Memetic Algorithms. A closely related parallel interest is harnessing evolutionary and other learning paradigms simultaneously to produce more effective and efficient Interactive AI.