Evolutionary On-Line Self-Organization of Autonomous Robots

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Abstract

We review recent experiments in evolutionary robotics carried out in dynamic environments and across different robotic platforms. We then introduce a new evolutionary approach where robots are evolved for their ability to adapt online. Several experiments show that this new approach is much faster, more powerful, and scalable than the traditional approach.

1 Evolutionary Robotics

Autonomous robots are largely replacing computers as a metaphor for investigating natural and artificial intelligent systems because they interact with a real environment through sensors and actuators in a closed feedback loop, are subject to the laws of physics, operate in real-time, and are required to cope with partially unknown and unpredictable situations. Artificial evolution is a selectionist procedure that discovers suitable controllers by exploiting the interactions between the robot and its environment rather than following a model-based adaptation scheme [1]. The approach is characterized by online evolution carried out on physical robots without human intervention and simple fitness functions in order to emphasize environmental interactions (figure 1).

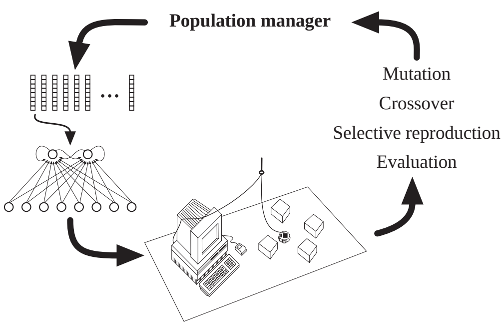

Figure 1: A single physical robot is connected to a host computer through a serial cable with rotating contacts. The serial cable provides power to the robot and data communication. The population of chromosomes, genetic operators, and decoding takes place on the host computer, but the decoded control system runs on the onboard processor. The fitness is computed onboard without external measuring devices.

Figure 2: An evolved 4 legged robot. The control system of the robot, its body size, and length of legs have been evolved in realistic 3D simulations. The physical robot in the picture has been partially built according to the evolved genetic specifications. The evolved control system is transferred from the simulated to the physical robot. Such evolved robot can walk and avoid obstacles. The robot is approximately 20 cm long and weights less than 1 kg without batteries. Leg control is given by low consumption HC11 microcontrollers.

Evolved sensory motor controllers adapt their navigation strategies to the physical characteristics of the environment and of the robot hardware. The methodology has been applied to several types of robots, with wheels and legs (figure 2). When placed in more complex environments, robots can evolve neural mechanisms that build internal representations of space and time in relationship to internally-defined goals [2].

When co-evolved with a competing robot (figure 3), the reciprocal bootstrapping of the competing controllers drives the ecosystem to increased levels of com-

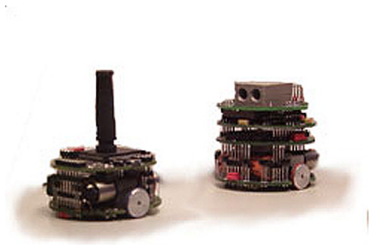

Figure 3: Prey and predator robots co-evolved in competition with each other. The predator on the right has a vision system; its fitness is inversely proportional to the *time* it takes to hit the prey. The prey can be seen thanks to its characteristic black protuberance and does not have vision, but it can detect if something is nearby with infrared sensors and can go at double speed than the predator. The fitness of the prey is proportional to the time it manages to survive without being hit by the predator. The "artificial brains" of the two robots are artificial neural networks.

plexity and eventually to behavioral cycles displaying rapid alternation of non-trivial pursuit-evasion strategies [3].

The most important concept is that the fitness function should leave space for free interaction between the robot and its environment; in other words, the fitness function should not be very detailed. This allows the robot to explore several different ways of solving a problem making evolution easier, faster, and often surprising for an external observer.

2 Evolution of Adaptive Robots

Traditionally, artificial evolution operates on parameters of the controllers, such as synaptic connections and architectures, that are maintained fixed during operation of the controller. This approach does not capture the adaptive plasticity that characterizes biological nervous systems. One way to re-adapt to new conditions, such as a new robot platform (figure 4), is to incrementally continue evolution in the new conditions, but this often takes long time [4].

I suggest to exploit artificial evolution for discovering adaptive controllers that can continuously modify their synaptic parameters in relation to environmental inputs according to evolved adaptive rules. In other words, the genetic string encodes only the parameters of Hebbian plasticity that drive synaptic modification, but *not* the synaptic strengths. Every time an individual is born, its synaptic values are *randomly initialized*

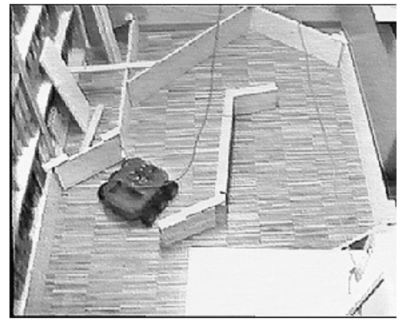

Figure 4: Incremental evolution across platforms. Initially a neural control system has been evolved using a miniature mobile robot Khepera. After 100 generations, the last population has been transferred on the much larger and more powerful Koala robot shown in the figure and evolution has been resumed. The population takes 20 generations to readapt to the new sensors, motors, and geometry of the larger robot.

	Bits for one synapse				
Condition	1	2	3	4	5
1	sign	strength			
2	sign	Hebb rule		rate	

Table 1: Genetic encoding of synaptic parameters. 1: Traditional approach; 2: Evolution of adaptive synapses.

(always, from generation 1 to the final generation) and are let free to adapt using the evoved Hebbian rules while the robot moves in the environment.

In this new approach artificial evolution selects individuals that can adapt continuously and online starting always from random initial weights. This does not allow evolution to impress on the synaptic weights a strategy that fits a particular environment (which would not generalize to environmental changes), but rather forces evolution to discover individuals capable of solving a problem by adapting online to the actual environmental characteristics.

Table 1 shows the difference of synapse encoding between the traditional approach (row 1) and our new approach (row 2). In both approaches, the first bit of each synapse encode its sign (excitatory or inhibitory). In the traditional approach, the remaining four bits encode the synaptic strength as a value in the range $[0, 1]$. No changes take place during the life of the individuals. In the second case instead, two bits encode four Hebbian rules and the remaining two bits the learning rate (0.0, 0.337, 0.667, and 1.0). The four Hebb rules are: "pure Hebb" whereby the synaptic strength can only increase when both presynaptic and postsynaptic units are active, "presynaptic" whereby the synapse changes only when the presynaptic unit is active (strengthened when the postsynaptic unit is active, and weakened when the postsynaptic unit is inactive), "postsynaptic" whereby the synapse changes only when the postsynaptic unit is active (strengthened when the presynaptic unit is active, and weakened when the presynaptic unit is inactive), and "covariance" whereby the synapse is strengthened if the difference between pre- and post-synaptic activations is smaller than a threshold (half the activation level, that is 0.5) and is weakened if the difference is larger than such threshold. After decoding a genotype into the corresponding controller, each synapse was randomly initialised to a value in the range $[0, 1]$ and modified at each time step according to the corresponding hebbian rule and learning rate.

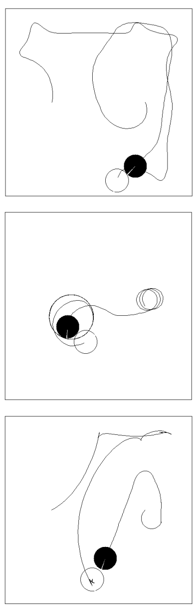

Figure 5: Three examples of co-evolved predator (filled disk) and prey (empty disk). The genes of the two robots encode adaptive characteristics of the synapses. Prey robots always attempt to modify weight in random fashion to generate unpredictable behaviors. Instead predator robots evolve combinations of Hebbian rules that almost always succeed at hitting the prey by quickly modifying their behaviors online.

Evolved adaptive controllers are capable of quickly generating stable behaviors from randomly initialized synaptic strengths. Although the synapses keep changing in relation to presynaptic and postsynaptic activations, the controller is dynamically stable. The ability of rapid online adaptation proves useful in dynamic environments. For example, co-evolved predator robots with adaptive controllers are better at catching prey robots because they can rapidly switch between different behavioral strategies depending on the prey behavior [5].

Figure 6: A robot equipped with a vision module can gain fitness points only when it is sitting on the light (grey zone on the left) *when the light is on.* Initially the light is off, but the robot can switch it on by going over the black area on the right. No fitness points are given for the light switching behavior.

Evolution of adaptive controllers can develop solutions for complex problems that the traditional approach can hardly manage. Consider for example the robot in figure 6 equipped with a vision module, proximity sensors, and light sensors. This robot can gain fitness points only when it sits on the grey area on the left *when the light is on.* At the beginning of its life the light is off but it can be switched on if the robot goes to the right area on the right of the arena. Therefore, in order to receive fitness points this robot must evolve the ability to find the light switching area, go there, and once the light goes on rapidly move on the fitness area and remain there for the rest of its life. [1] Our adaptive approach can solve generate very quickly neural controllers that solve this problem in a very reliable and efficient manner, whereas the tradiotnal approach takes almost twice as many generations and the result is a much less efficient (because it is equivalent to a fixed navigation pattern largely independent of the sensory information).

Since in the new adaptive approach synaptic weights adapt online, the genetic encoding can be made more more compact by specifying only the adaptive properties of entire neurons. Very recent results indicate that this amounts to faster evolution and generates more robust controllers [6]. It is thus a promising step toward artificial evolution of developmental rules

[1] Note that the robot cannot see the patches on the floor and therefore must look at the patterns on the walls and at the light.

for neural morphologies. From an engineering perspective, evolution of adaptive controllers provides a method for generating systems capable of rapid self-configuration and increased robustness.

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