

Synthesis of Autonomous Robots Through Evolution

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Summary

Evolutionary robotics is the attempt to develop robots through a self-organized process based on artificial evolution. This approach stresses the importance of the study of systems that: (1) have a body and are situated in a physical environment, and (2) autonomously develop their own skills in close interaction with the environment. In this article we will briefly illustrate the method and the main idea, we will review the most significant contribution in this area and finally, we will discuss some of the contributions that this research area is making to the foundational debate in cognitive science.

Introduction

The basic idea behind evolutionary robotics [1, 2], i.e. the attempts to synthesize robots through evolutionary techniques [3-5], goes as follows. An initial population of different artificial chromosomes, each encoding the control system (and sometimes the morphology) of a robot, are randomly created and put in the environment. Each robot is then let free to act (move, look around, manipulate) according to a genetically specified controller while its performance on various tasks is automatically evaluated. The fittest robots are allowed to reproduce by generating copies of their genotypes with the addition of changes introduced by some genetic operators (e.g., mutations, crossover, duplication). This process is repeated for a number of generations until an individual is born which satisfies the performance criterion (fitness function) set by the experimenter. Robots might also change during lifetime and therefore might adapt to their environment both phylogenetically and ontogenetically.

This approach stresses the importance of studying systems that, just like natural organisms, (1) have a body and are situated in a physical environment [6-10], and (2) autonomously develop their own skills in close interaction with the environment. Systems of this sort are difficult to design from the perspective of an external observer. However, they can be obtained either by carefully mimicking natural organisms (as long as a detailed description of their organization is available, see for example [11]) or by resorting to an automatic process such as artificial evolution that allows them to self-organize autonomously.

In this paper we will briefly illustrate three research topics in which experimental studies conducted with this approach are producing significant contributions, namely the synthesis and study of robots that: (1) exploit the opportunities that arise from the possibility to interact with an

external environment; (2) consist of a control system and a body morphology that are tightly coupled (3) display an ability to adapt to varying environmental conditions. Finally we will briefly discuss some of the contributions that this research area is making to the foundational debate in cognitive science.

Exploiting the interaction with the environment

The behavior of embodied and situated organisms is an emergent result of the dynamical interaction between the nervous system, the body, and the external environment [12, 13]. This simple consideration has several important consequences that are far from being fully understood. One important aspect, for instance, is the fact that motor actions partially determine the sensory pattern that organisms receive from the environment. By coordinating sensory and motor processes organisms can select favorable sensory patterns and thus enhance their ability to achieve their adaptive goals.

Examples of processes falling within this category have been identified in natural organisms. Dill *et al.* demonstrated that since the fruit fly *drosophila* cannot always recognize a pattern appearing at different locations in the retina, the insect solves this problem of shift invariance by moving so to bring the pattern to the same retinal location where it has been presented during the storage process [14]. Franceschini demonstrated that flies use motion to visually identify the depth of perceived obstacles [11]. Moreover, there is evidence that environmental feedback obtained through motor actions plays a crucial role in normal development [15, 16].

Instead, in artificial system, aside a few notable exceptions [17-19], the possibility to design systems that exploit sensory-motor coordination is still largely unexplored. This can be explained by considering that, as we said above, behavior is the emergent result of the interactions between the individual and the environment. Given that in dynamical systems (for an introduction to dynamical systems and to dynamical approaches to the study of behavior see [13]) there is a complex and indirect relation between the rules that determine the interactions and the emergent result of those interactions, it is very difficult to identify how the interactions between the organism and the external environments contribute to the resulting behavior. As a consequence, designing systems that exploit sensory-motor coordination is rather difficult (for an attempt to identify new design principles that might help to achieve this goal, see [10]).

From this point of view evolutionary experiments where robots autonomously develop their skills in close interaction with the environment represent an ideal framework for studying sensory-motor coordination. Indeed, in most of the experiment conducted with artificial evolution one can observe the emergence of behavior exploiting sensory-motor coordination to solve difficult tasks. The analysis of evolved robots and the identification of how they exploit the interaction with the environment is often very difficult and requires significant effort, but is generally much simpler than the analysis of natural organisms because the former are much more simple and can be manipulated much more freely than the latter. In addition, such analysis may allow the identification of new explanatory hypotheses that may produce new models of natural behavior.

By carefully analyzing the result of a simple evolutionary experiment, Nolfi [20, 21] showed that evolved individuals exploit behavioral attractors resulting from the interaction between the robot and the environment in order to discriminate between different objects. In this experiment the miniature mobile Khepera robot [22] was asked to locate and remain close to a target object. The robot (Figure 1) was equipped with 6 infrared proximity sensors in the front side and two wheels that could rotate in both directions at different speeds. The environment consisted of an arena of 60×35 cm surrounded by walls and contained a cylindrical object with a diameter of 2.3 cm located at a random position.

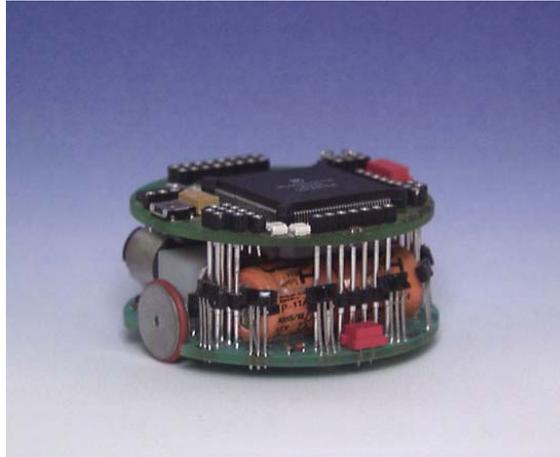


Figure 1. The miniature mobile Khepera robot has a diameter of 6 cm. It is equipped with two wheels and 8 active infrared sensors (6 on the front and 2 on the back) that can measure distance from objects or the amount of ambient light.

The control system of the robot was a neural network with six sensory neurons encoding the activation of the six frontal infrared sensors and two output neurons encoding the speeds of the two wheels (for a detailed description of the experiment parameters see [20, 21]). By evolving the weights of the neural controllers, the author observed that after few generations evolved individuals were able to find a solution to the problem. The evolved robots were capable of discriminating between walls and cylinders.

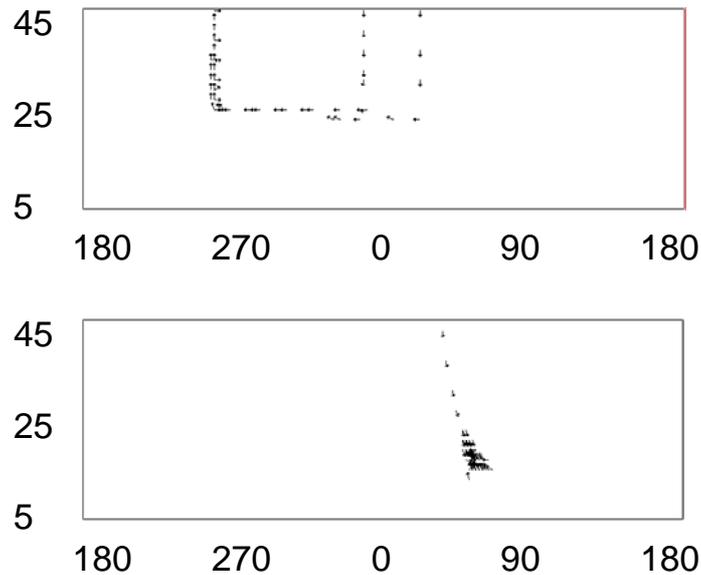


Figure 2. Angular trajectories of a typical evolved individual close to a wall (top graph) and to a cylinder (bottom graph). The picture was obtained by placing the individual at a random position in the environment, leaving it free to move for 500 sensory-motor cycles, and recording displacements at positions relative to the two types of objects for distances smaller than 45 mm. For sake of clarity, arrows are used to indicate the relative direction but not the amplitude of movements. When the individual reaches a distance of about 20mm from an object, it avoids walls but approaches cylinders until it reaches the attractor area located at a distance of about 15 mm and an angle of about 60 degrees. The resulting trajectories converge to the center of the area allowing the individual to keep more or less the same position relative to the cylinder.

Further analysis of the problem and of the evolved solutions [20, 21] revealed that: (a) the problem of discriminating between sensory patterns belonging to walls and cylinders is far from trivial given that the sensory patterns corresponding to the two different objects were very similar, and (b) the discrimination behavior resulted from a large number of sensory-motor interactions with

the environment. In particular, evolved individuals acted so to produce behavioral attractors (i.e. back and forth and left and right movements that, overall, keep the robot in the same relative position) close to cylinders, but not close to walls (Figure 2). This experiment showed that artificial evolution can synthesize solutions that are much more simple than those that can be obtained through explicit design [20, 21].

Further experiments revealed several other ways in which evolved robots can exploit sensory-motor coordination, such as to: (a) increase the frequency of sensory states to which they can react more effectively and reduce the frequency of sensory states to which they react less effectively [23]; (b) select sensory states in which groups of sensory patterns requiring different motor answers do not strongly overlap [24], see also the box on "Exploiting sensory-motor coordination to turn hard problems into simpler ones"; (c) increase the perceived differences between different objects [25, 26]; (d) select useful learning experiences [25].

Exploiting sensory-motor coordination to turn hard problems into simpler ones

In a recent paper Clark and Thornton [27] introduced the term *type-2* problems to denote hard tasks in which the problem of mapping input patterns into suitable output patterns is complicated by the fact that the regularities which can allow such a mapping, are marginal or hidden in the sensory patterns (regularities are features of the input patterns that can be used to discriminate between classes of patterns requiring different answers). On the basis of this consideration they distinguished *type-2* problems (i.e., hard problems) from *type-1* problems (i.e., easy problems) in which regularities are directly available in the sensory patterns.

Type-2 problems, which require complex input-output mappings, may be reduced to type-1 (tractable) problems by recoding input patterns so to enhance useful regularities [27]. This can be obtained in two ways. One possibility is to recode input patterns internally. Elman [28], for example, showed how complex tasks that cannot be solved by training a feed-forward neural network with back-propagation for the entire task, can be solved if the network is first trained on a simpler subtask and then on the entire task. The first learning phase affects how the sensory patterns are recoded at the level of the internal neural layer [28]. This recoding enhances the regularities of the sensory patterns and thus turns the process of learning the entire task from a type-2 to a type-1 problem [27].

Another possibility is to exploit sensory-motor coordination. Embodied and situated robots can transform type-2 problems into type-1 problems by actively structuring their own input. Scheier *et al.* [24] evolved a Khepera robot to approach large, and avoid small, cylindrical objects located in an arena surrounded by walls. Analysis of evolved robots showed that selected behaviors allowed the robot to experience sensory patterns easy to discriminate (such that the two groups of sensory patterns corresponding to the two objects were well separated in the input space). To understand this point, we should consider that individuals that act differently may experience different sensory states and therefore may face simpler or harder discrimination problems. The analysis of different individuals showed that while individuals of the first generation were facing a type-2 discrimination problem, after about 40 generations individuals were facing a simple type-1 discrimination problem where the two groups of experienced sensory states were nicely separated in the input space. In other words, evolved robots can exploit sensory-motor coordination to simplify the task of discriminating between objects.

Co-evolution of body and brain

The fact that behavior results from the interaction between the control system, the robot body, and the external environment implies that not only the control system, but also the morphology of the robot body (i.e. the shape, the position of sensors and motors, and the characteristics of the materials) can affect the resulting behavior. This means that the control system and the morphology of the body are intimately related.

The existence of an extensive matching between the control system and the morphology of the body in natural organisms is hardly surprising given that they co-evolve and co-develop during the life of an organism [16]. The close match between these two systems in natural organisms is probably one of the key reasons for the extraordinary achievements of natural evolution. The tight interaction between the control system and the body morphology complicates the study of adaptive behavior in natural organisms because it is not always possible to assign credit to individual aspects of observed behaviors since they are effective only when coupled with a given morphology [16].

Some examples of effective coupling between body and brains have been identified in natural organisms. In crickets, for example, the morphology of the body filters and amplifies specific auditory inputs. This allows crickets to easily identify a specific calling song [29-30]. Extra-tympanic structures play a crucial role also in the hearing of vertebrates [16]. The morphology of the body plays important functional roles also on the effect of neural outputs. For instance, "Muscle acts as a low pass filter of motor neural outputs, that is, it filters out the high frequency components of the neural outputs..... In addition, the mechanical advantage of a muscle and the response of the whole body to the contraction of any particular muscle are a complex function of the geometric relationships and positions of other muscles and joints, and the prior history of activation of that muscle" (Chiel and Beer [16], p. 553).

Evolutionary robotics experiments where both the control system and the morphology of the robot are encoded in the genotype and co-evolved can shed light on the complex interplay between body and brains in natural organisms and may lead to the development of new and more effective artifacts.

Although rather few and preliminary experiments have been conducted in this area up to now, this topic is receiving increased attention [31]. Cliff *et al.* [1] and Harvey *et al.* [32] co-evolved the control system and the sensory morphology of a mobile robot. The genotype consisted of two parts encoding the control system (i.e. the connection weights and the architecture of a neural controller) and the visual morphology (i.e. number, size, and position of visual receptive fields), respectively. The authors reported that co-evolution of the two systems allowed evolved robots to rely on very simple strategies, such as comparing the correlated activities of only two visual receptors located at strategic positions on the retinal surface. Lichtensteiger and Eggenberger [33] evolved the morphology of a compound eye of a robot asked to move on a straight trajectory and observed that evolved individuals displayed higher density of photoreceptors in the front.

Lund *et al.* [34] co-evolved in simulation the control system and some characteristics of the body of Khepera-like robots that were selected for their ability to navigate while avoiding obstacles. The morphological features that were allowed to change were the diameter of the body, the distance between the two wheels, and the wheel radius. The authors analyzed the distribution of evolved robots in the morphological space and observed interesting correlations between evolved morphological characteristics (such as an almost linear relationship between body size and wheel distance), and between morphology and environmental properties (robots evolved in environments with several obstacles were smaller).

Jordan Pollack and his research team have explored the possibility of evolving the morphology of physical robots. In preliminary work, they evolved the shape of functional objects such as bridges and moving cranes in simulation and later built the evolved structures out of Lego™ bricks [35]. More recently, they evolved the control system (sigmoid neurons) and morphology of robots composed of linear actuators, bars, and joints [36]. Some evolved individuals were automatically built out of thermoplastic material with a 3D printer. The printer takes as input the genetic description of the robot morphology and its temperature-controlled head lays down thermoplastic material layer by layer with holes for motors and joints, which are snapped in later on. The authors demonstrated this technology in the case of robots evolved for straight navigation where the fitness function was the distance covered by the robot (see Figure 3). These robots displayed various forms of locomotion, including crawling and forms of walking, both in simulation and in reality.

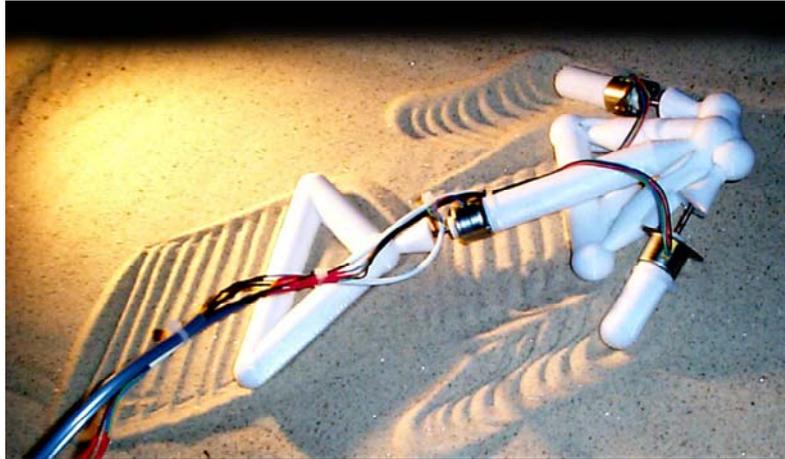


Figure 3. An evolved morphology. The control system consists of a neural network driving the central actuator in perfect anti-phase with the two synchronized lateral limbs so that while the upper two limbs push, the central body is retracted, and vice-versa. Figure courtesy of Hod Lipson and Jordan Pollack. Reprinted with permission.

Evolution of plastic individuals

In the experiments described in the previous sections, evolving individuals change phylogenetically but not ontogenetically (i.e. they do not change during lifetime). Over the last few years, there has been an increasing interest in evolving plastic individuals (i.e. individuals that are also capable of adapting during lifetime). These studies have been conducted for two different purposes: (a) looking at the advantages, in terms of performance, obtained by combining these two adaptive techniques; (b) understanding the role of the interaction between two adaptive processes that resort to different mechanisms and occur at different time scales. The general picture emerging from this body of research is that lifetime adaptation has several functions within an evolutionary perspective [37]:

- 1) It complements evolution by allowing individuals to adapt to environmental changes that take place during the lifetime of the individual or within few generations and therefore cannot be tracked by evolution [25, 38, 39]. In addition, plastic individuals can adapt to sensory, motor, and environmental change that take place after the evolutionary process [40].
- 2) It can help and guide evolution by channelling the evolutionary process towards promising directions [31-43] and it can significantly speed up the synthesis of viable individuals [40, 44].
- 3) It might produce more effective behaviors and facilitate the ability to scale up to problems that involve a larger search space [40].

More generally these researches show that the interaction between evolution and lifetime adaptation deeply alters both processes. Evolution in interaction with learning displays dynamics that differ significantly from those observed when evolution operates alone. While in non-plastic individuals the inherited characters are directly selected for their ability to produce successful behaviors, in the case of individuals that learn, the inherited characters are selected for their ability to incorporate a predisposition to learn. Similarly, learning within an evolutionary perspective has rather different characteristics from learning studied in isolation, as in "traditional" connectionist research.

To better illustrate this point, consider the experiment performed by Urzelai and Floreano [40] where a Khepera robot provided with a linear array of visual receptors has to perform a sequential task that consists of switching a light on and then moving towards the light bulb (Figure 4).

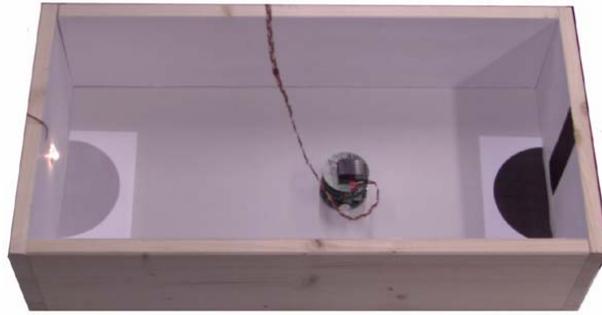


Figure 4. A mobile robot Khepera equipped with a vision module can gain fitness points by staying on the gray area under the light bulb *only* when the light is on. The light is normally off, but it can be switched on if the robot passes over the black area positioned on the other side of the arena. The robot can detect ambient light and wall color, but not the color of the floor.

The robot was controlled by a fully-recurrent neural network composed of 12 neurons. 10 sensory neurons received input from 4 proximity sensors, 3 ambient light sensors, and 3 areas of the camera, respectively; 2 motor neurons controlled the speeds of the two wheels. The genotype of the evolving individuals consisted of 12 blocks, each encoding the properties of all the incoming synapses of the corresponding neuron. These properties consisted in the sign of the synapses, the adaptation rule (one of four possible Hebb learning rules), and the learning rate. The synaptic strengths were not encoded in the genotype, as in the case of the experiments described in the previous sections, but were always initialized to small random values at the beginning of the lifetime of the individual. As soon as the robot begins to move and sensory signals flow through the network, synaptic strengths can change according to the genetically encoded properties and activations of the pre-synaptic and post-synaptic neurons. The precise balance between weighted signals necessary to drive the motor neurons in a coordinated fashion had to be learned during lifetime according to genetically specified learning rules.

The analysis of the evolved individuals and the comparison with a control experiment in which the synaptic strengths were directly encoded in the genotype and individuals were not allowed to adapt during lifetime showed that plastic outperformed non-plastic individuals. Moreover plastic individuals showed a better ability to adapt to varied environmental conditions or to a different body structure (achieved by transferring the evolved individual in a larger and geometrically different robot) than non-plastic individuals.

Node Encoding / Adaptive Synapses

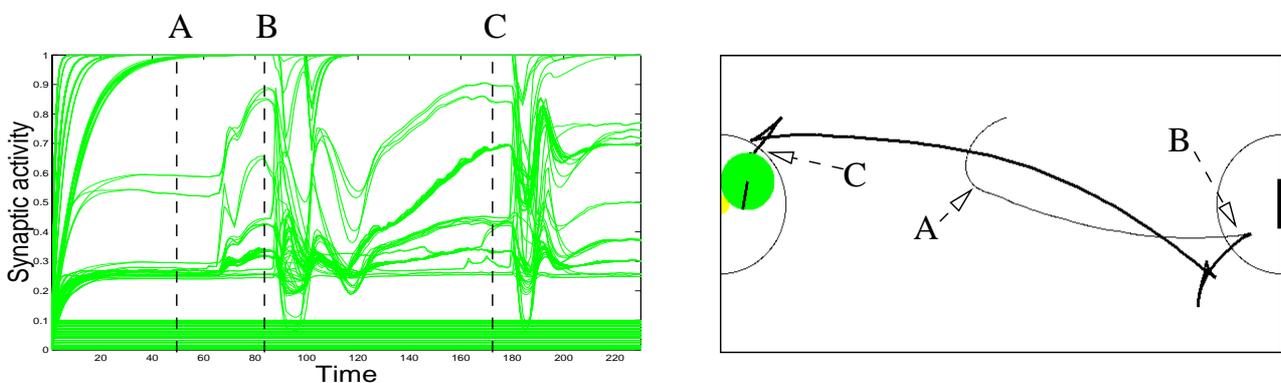


Figure 5. Relation between synaptic activity and behavior of an adaptive individual. **Left:** Synaptic activity recorded during the trajectory of the robot. Each line corresponds to the instantaneous strength of a synapse measured every 100

ms. Ticks on the time scale represent the measurements. **Right:** Trajectory of the robot. Points A, B, and C correspond to attraction by the black stripe, switching on of light, and arrival to the fitness area, respectively.

The analysis of the synaptic activity of the evolved controllers while the robot moved in the environment showed that several synapses kept changing during the whole duration of the behavioral sequence (Figure 5). This pattern of change was characterized by three major events where most synapses transitioned into new states. These events are labelled as A, B, and C in Figure 4 and correspond to three clearly different behavioral stages. Event A marks the point when most changing synapses reach a temporarily stable state from their initial random values and the robot displays a smooth trajectory towards the black stripe corresponding to the light switch. Event B is in between the end of a minor transition and the beginning of a major transition, and corresponds to the point when the robot switches the light on. Finally, event C marks the end of another period of relatively-long change and the beginning of another major temporary transition, and corresponds to the moment when the robot enters for the first time the fitness area (since the robot does not receive information from the floor sensor, it “knows” that it is on the fitness area by using the pattern of light detected by its sensors). These data suggest that synaptic change corresponds to the acquisition of and switching between different sub-behaviors.

This series of tests indicates that evolved adaptive controllers can develop and/or modify online new behaviors according to the actual environmental conditions. These behaviors are not learned in the classic meaning of the term because they are not necessarily retained forever. For example, the ability to visually locate the black stripe on the wall and move towards it is acquired at a certain stage and disappears once it is no longer necessary. Instead, the attraction towards the light develops early on, even before experiencing the light bulb switched on (notice that light sensors are always activated to some extent by normal ambient light), and is retained also after having reached the fitness area. The graph of synaptic activity shows that after each event there is a major temporary change in all synapses. This always corresponds to the situations when the robot is close to the walls and (re-)develops online the ability to move away from them.

Conclusion

An organism is an embodied system that lives and acts in an environment. Unfortunately, in cognitive science this obvious statement is often overlooked even by biologically inspired approaches, such as connectionism, where cognition is considered as a structure that develops in an abstract environment. It is implicitly assumed that we will know the intrinsic nature of cognition when the laws that govern the dynamics of our brain have been discovered. However, an organism is not only a collection of neurons; it is also immersed in a physical environment and, using its own sensory-motor apparatus, actively selects information from the environment. If we want to understand intelligent life and cognition, it is important to investigate how organisms autonomously interact with their environments, i.e. how they behave.

The tendency of underestimating the role of behavior can be partially explained by considering the difficulty of analyzing and designing behavioral systems. Behavior emerges from the interaction between the control system, the body, and the external environment and cannot be analytically described by trying to identify components with rather independent functions. A promising direction consists of describing the control system, the body, and the environment as a coupled dynamical system [13] where each element affects the others and where the dynamics produced by an element in isolation tend to be significantly different from the dynamics produced by the whole system.

Artificial evolution is an ideal framework to synthesize and study systems whose behaviors emerge from the interaction between the control system, the body, and the environment. In these experiments, as in the case of natural evolution, the control system and the body structure co-evolve in interaction with the environment and selective reproduction is based on the emerging behavior.

Another research topic that can be successfully tackled with this methodology is the study of lifetime adaptation from an evolutionary perspective. As we illustrated in the previous section, artificial evolution generates individuals that exploit the interaction between the phylo-genetic and ontogenetic processes occurring at different time scales. Also in this case, one observes that once the two processes are left free to interact between themselves and with other elements (e.g. the environment) they deeply affect each other in order to improve the adaptive behavior of the evolving individuals.

The analysis of the solutions that emerge from these experiments may help us to understand how the interactions between such different entities are exploited in natural organisms and how to develop artifacts with the robustness, adaptability and flexibility of natural organisms.

The contribution of this body of research to the understanding of natural systems is twofold. On the one hand experiments conducted by evolving robots in specific environmental conditions can help us to understand how natural organisms solve similar problems in the similar environmental conditions. Obviously, the results obtained by analyzing evolved robots do not necessarily have a direct relevance for explaining how natural organism produce similar behavior. However, they can be used to develop new models of adaptive behavior and cognition that, through experimental analysis, may prove better than previous existing explanations.

On the other hand evolutionary robotics experiments may allow us to understand general principles that regulate natural systems. Examples include a better understanding of the role of sensory-motor coordination [19, 21, 24]; of the importance of pre-adaptation and of the ability to adapt on the fly to the current environmental conditions [39, 40, 44, 45]; of the advantages that arise from the interaction between evolution and lifetime adaptation [25, 37].

Evolutionary Robotics has also a number of drawbacks. From an engineering perspective, the most serious problem is the amount of time needed to conduct an evolutionary process on physical robots. From a scientific perspective, the most important challenge is the identification of methods of encoding information into the genotype that are suitable to produce incremental and open-ended evolutionary processes. The extent to which these researches will impact our understanding of natural organisms and our ability to develop artifacts with the robustness, adaptability and flexibility of natural organisms will ultimately depend on the extent to which we will be able to tackle these challenges.

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