

# Handbook of Robotics

## Chapter 61: Evolutionary Robotics

Dario Floreano  
Laboratory of Intelligent Systems  
Swiss Federal Institute of Technology (EPFL)  
Lausanne, Switzerland

Phil Husbands  
Department of Informatics  
University of Sussex  
Falmer, United Kingdom

Stefano Nolfi  
Institute of Cognitive Technologies  
National Research Council  
Roma, Italy

August 3, 2007

# Contents

<b>61 Evolutionary Robotics</b>	<b>1</b>
61.1 Introduction . . . . .	1
61.2 First steps . . . . .	2
61.2.1 Evolution of neural controllers for walking . . . . .	3
61.3 Simulation and reality . . . . .	5
61.4 Simple controllers, complex behaviors . . . . .	7
61.5 Seeing the light . . . . .	8
61.5.1 Co-evolution of active vision and feature selection . . . . .	9
61.6 Computational neuroethology . . . . .	11
61.6.1 Emergence of place cells . . . . .	12
61.6.2 Spiking neurons . . . . .	13
61.6.3 GasNets . . . . .	15
61.7 Evolution and learning . . . . .	17
61.7.1 Learning to adapt to fast environmental variations . . . . .	17
61.7.2 Evolution of learning . . . . .	18
61.8 Competition and cooperation . . . . .	19
61.8.1 Co-evolving predator and prey robots . . . . .	19
61.8.2 Evolving cooperative behavior . . . . .	20
61.9 Evolutionary Hardware . . . . .	21
61.9.1 Evolvable hardware robot controllers . . . . .	21
61.9.2 Evolving bodies . . . . .	22
61.10 Closing remarks . . . . .	24

# Chapter 61

## Evolutionary Robotics

### 61.1 Introduction

Evolutionary Robotics is a method for the automatic creation of autonomous robots [86]. It is inspired by the Darwinian principle of selective reproduction of the fittest captured by evolutionary algorithms [54]. In Evolutionary Robotics, robots are considered as autonomous artificial organisms that develop their own control system and body configuration in close interaction with the environment without human intervention. Drawing inspiration from principles of biological self-organization, evolutionary robotics includes elements of evolutionary, neural, developmental, and morphological systems. The idea that an evolutionary process could drive the generation of control systems dates back to at least the 1950s [118] with a more explicit form appearing in the mid 1980s with the ingenious thought experiments by neuroscientist Valentino Braitenberg on neurally driven vehicles [15]. In the early 90's, the first generation of simulated artificial organisms with a genetic code describing the neural circuitry and morphology of a sensory motor system began evolving on computer screens [9, 89, 56, 29]. At that time, real robots were still complicated and expensive machines that required specialized programming techniques and skillful manipulation. Towards the end of that period, a new generation of robots started to emerge that shared important characteristics with simple biological systems: robustness, simplicity, small size, flexibility, modularity [16, 81]. Above all, those robots were designed so that they could be programmed and manipulated by people without engineering training. Those technological achievements, together with the growing influence of biological inspiration in artificial intelligence [111], coincided with the first evolutionary experiments on real robots [30, 50, 68] and the term Evolutionary Robotics was coined [20].

The major methodological steps in Evolutionary

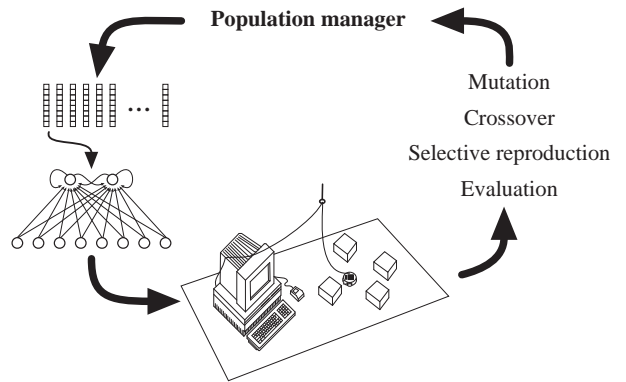


Figure 61.1: Evolutionary experiments on a single robot. Each individual of the population is decoded into a corresponding neurocontroller which reads sensory information and sends motor commands to the robot every 300 ms while its fitness is automatically evaluated and stored away for reproductive selection.

Robotics proceed as follows (Figure 61.1). An initial population of different artificial chromosomes, each encoding the control system (and possibly the morphology) of a robot, is randomly created. Each of these chromosomes is then decoded into a corresponding controller, for example a neural network, and downloaded into the processor of the robot. The robot is then let free to act (move, look around, manipulate the environment) according to a genetically specified controller while its performance for a given task is automatically evaluated. Performance evaluation is done by a fitness function that measures, for example, how fast and straight the robot moves, how frequently it collides with obstacles, etc. This procedure is repeated for all chromosomes of the population. The fittest individuals (those that have re-

ceived more fitness points) are allowed to reproduce by generating copies of their chromosomes with the addition of random modifications introduced by genetic operators (e.g., mutations and exchange of genetic material). The newly obtained population is then tested again on the same robot. This process is repeated for a number of generations until an individual is born which satisfies the fitness function set by the user. The control system of evolved robots, encoded in an artificial genome, is therefore generated by a repeated process of selective reproduction, random mutation and genetic recombination, similarly to what happens in natural evolution.

## 61.2 First steps

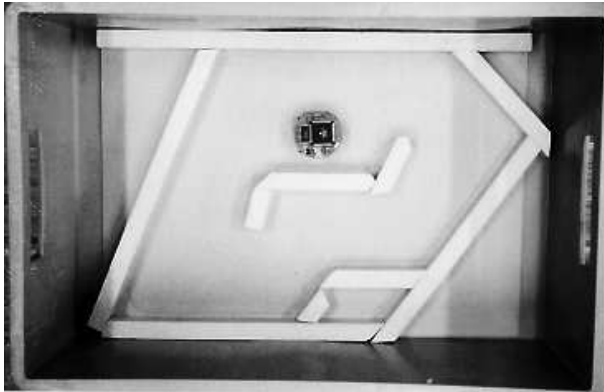


Figure 61.2: Bird's-eye view of the desktop Khepera robot in the looping maze.

In an early experiment on robot evolution without human intervention, carried out at EPFL [30], a small wheeled robot was evolved for navigation in a looping maze (Figure 61.2). The Khepera robot has a diameter of 55 mm and two wheels with controllable velocities in both directions of rotation. It also has eight infrared sensors, six on one side and two on the other side, that can function either in active mode to measure distance from obstacles or in passive mode to measure the amount of (infrared) light in the environment. The robot was connected to a desktop computer through rotating contacts that provided both power supply and data exchange through a serial port.

A simple genetic algorithm [43] was used to evolve the synaptic strengths of a neural network composed of eight sensory neurons and two motor neurons. Each sensory

unit was clamped to one of the eight active infrared sensors whose value was updated every 300 ms. Each motor unit received weighted signals from the sensory units and from the other motor unit, plus a recurrent connection with itself with a 300 ms delay. The net input of the motor units was offset by a modifiable threshold and passed through a logistic squashing function. The resulting outputs, in the range  $[0, 1]$ , were used to control the two motors so that an output of 1 generated maximum rotation speed in one direction, an output of 0 generated maximum rotation speed in the opposite direction, and an output of 0.5 did not generate any motion in the corresponding wheel. A population of 80 individuals, each coding the synaptic strengths and threshold values of the neural controllers, was initialized with all weights set to small random values centered around zero. Each individual was tested on the physical robot for 80 sensorimotor cycles (approximately 24 seconds) and evaluated at every cycle according to a fitness function with three components measured onboard the robot:

$$\Phi = V \left( 1 - \sqrt{\Delta v} \right) (1 - i) \quad (61.1)$$

where  $V$  is the average rotation speed of the two wheels,  $\Delta v$  is the absolute value of the algebraic difference between the signed speed values of the wheels (positive is one direction, negative the other) and  $i$  is the normalized activation value of the infrared sensor with the highest activity. The first component is maximized by speed, the second by straight motion, and the third by distance from objects.

During the first 100 generations, both average and best fitness values grew steadily, as shown in Figure 61.3. A fitness value of 1.0 would correspond to a robot moving straight at maximum speed in an open space and therefore was not attainable in the looping maze shown in Figure 61.2, where some of the sensors were often active and where several turns were necessary to navigate. Figure 61.4 shows the trajectory of the best individual of the last generation.

Although the fitness function did not specify in what direction the robot should navigate (given that it was perfectly circular and that the wheels could rotate in both directions), after a few generations all the best individuals moved in the direction corresponding to the side with the highest number of sensors. Individuals moving in the other direction had higher probability of colliding into corners without detecting them and thus disappeared from the population. Furthermore, the cruising speed of the best evolved robots was approximately half

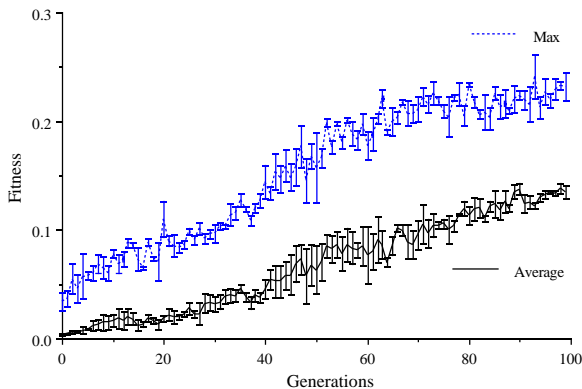


Figure 61.3: Average fitness of the population and fitness of the best individual at each generation (error bars show standard error over three runs from different initial populations).

of the maximum speed that could be technically achieved and did not increase even when the evolutionary experiment was continued up to 200 generations. Further analysis revealed that this self-limitation of the navigation speed had an adaptive function because, considering the sensory and motor refresh rate together with the response profile of the distance sensors, robots that traveled faster had a higher risk of colliding into walls before detecting them. They gradually disappeared from the population.

Despite its simplicity, this experiment shows that evolution can discover solutions that match not only the computational requirements of the task to be solved, but also the morphological and mechanical properties of the robot in relation to its physical environment.

### 61.2.1 Evolution of neural controllers for walking

Over the past fifteen years or so, there has been a growing body of work on evolving controllers for various kinds of walking robots - a non-trivial sensorimotor coordination task. Early work in this area concentrated on evolving dynamical network controllers for simple (abstract) simulated insects (often inspired by cockroach studies) which were required to walk in simple environments (e.g., [23, 10]). Earlier, Beer had introduced a neural architecture for locomotion based on studies of cockroaches [13], which is shown in Figure 61.5. The promise of this work soon led to versions of this methodology being used on

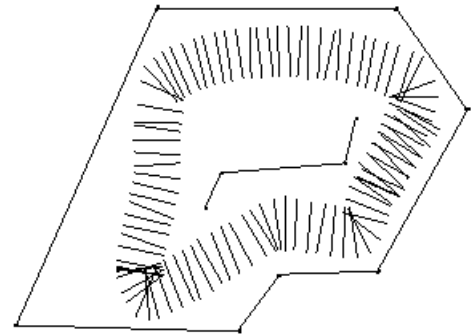


Figure 61.4: Trajectory of the robot with the best neural controller of the last generation. Segments represent the axis between the two wheels. Data was recorded and plotted every 300 ms using an external laser positioning device.

real robots. Probably the first success in this direction was by Lewis et al. [68, 69] who evolved a neural controller for a simple hexapod robot using coupled oscillators built from continuous-time, leaky-integrator, artificial neurons. All evaluations were done on the actual robot with each leg connected to its own pair of coupled neurons, leg swing being driven by one neuron and leg elevation by the other. These pairs of neurons were cross connected, in a manner similar to that used by Beer and Gallagher [10] (see Figure 61.5), to allow coordination between the legs. In order to speed up the process, they employed staged evolution where first an oscillator capable of moving a leg was evolved and then an architecture based on these oscillators was further evolved to develop walking. The robot was able to execute an efficient tripod gait on flat surfaces.

Gallagher et al. [38] described experiments where neural networks controlling locomotion in an artificial insect were evolved in simulation and then successfully downloaded onto a real hexapod robot. This machine was more complex than Lewis et al.'s, with a greater number of degrees of freedom per leg. In this approach, each leg was controlled by a fully-connected network of five continuous-time, leaky-integrator neurons, each receiving a weighted sensory input from that leg's angle sensor. Initially the architecture shown in Figure 61.5 was used, with the connection weights and neuron time constants and biases under genetic control. This produced efficient tripod gaits for walking on flat surfaces. In order to produce a wider range of gaits operating at a number

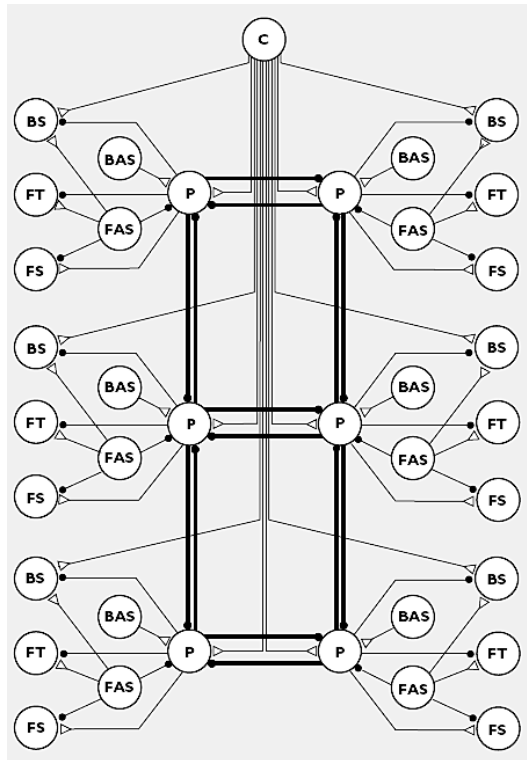


Figure 61.5: Schematic diagram of a distributed neural network for the control of locomotion as used by Beer et al. [13]. Excitatory connections are denoted by open triangles and inhibitory connections are denoted by filled circles. C, command neuron; P, pacemaker neuron; FT, foot motor neuron; FS and BS, forward swing and backward swing motor neurons; FAS and BAS, forward and backward angle sensors.

of speeds such that rougher terrain could be successfully negotiated, a different distributed architecture, more inspired by stick insect studies, was found to be more effective [11].

Galt et al. [40] used a genetic algorithm to derive the optimal gait parameters for a Robug III robot, an 8-legged, pneumatically powered walking and climbing robot. The individual genotypes represented parameters defining each leg's support period and the timing relationships between leg movements. These parameters were used as inputs to a mechanistic finite state machine pattern generating algorithm that drove the locomotion. Such algorithms, which are often used in conventional walking machines, rely on relatively simple control dynamics and do not have the same potential for the kind

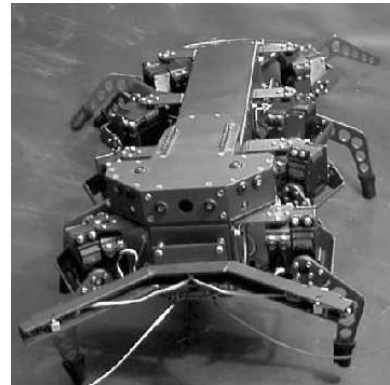


Figure 61.6: The octopod robot built by Applied AI Systems Inc.

of sophisticated multi-gait coordination that complex dynamical neural network architectures, such as those described in this section, have been shown to produce. However, controllers were successfully evolved for a wide range of environments and to cope with damage and systems failure (although an individual controller had to be tuned to each environment; they were not able to self adapt across a wide range of conditions). Gomi and Ide [44] evolved the gaits of an 8-legged robot (Figure 61.6) using genotypes made of eight similarly organized sets of genes, each gene coding for leg motion characteristics such as the amount of delay after which the leg begins to move, the direction of the leg's motion, the end positions of both vertical and horizontal swings of the leg, and the vertical and horizontal angular speed of the leg. After a few dozen generations, where evaluation was on the robot, a mixture of tetrapod and wave gaits was obtained. Using the Cellular Encoding [45] developmental approach – which genetically encodes a grammar-tree program that controls the division of cells growing into a dynamical recurrent neural network of the kind used by Beer and colleagues – Gruau [46] evolved a single-leg neural controller for the same eight-legged robot used by Gomi and Ide. This generated a smooth and fast quadrupod locomotion gait. Kodjabachian and Meyer [65] extended this work to develop more sophisticated locomotion behaviors. Jakobi [62] successfully used his minimal simulation techniques (described in Section 61.3) to evolve controllers for the same 8-legged robot as Gruau. Evolution in simulation took less than 2 hours on what would today be regarded as a very slow computer, and then transferred successfully to the real robot. Jakobi evolved modular controllers based on Beer's continuous

recurrent networks to control the robot as it engaged in walking about its environment, avoiding obstacles and seeking out goals depending on the sensory input. The robot could smoothly change gait, move backward and forward, and even turn on the spot. More recent work has used similar architectures to those explored by the researchers mentioned above, to control more mechanically sophisticated robots such as the Sony Aibo [119].

Recently there has been successful work on evolving coupled oscillator style neural controllers for the highly unstable dynamic problem of biped walking. Reil and Husbands [99] showed that accurate physics based simulations using physics-engine software could be used to develop controllers able to generate successful bipedal gaits. Reil and colleagues have now significantly developed this technology to exploits its commercial possibilities, in the animation and games industries, for the real time control of physically simulated 3D humanoid characters engaged in a variety of motor behaviors (see [www.naturalmotion.com](http://www.naturalmotion.com) for further details). Coupled neural oscillators have been evolved also to control the swimming pattern of articulated, snake-like, underwater robots using physics-based simulations [123].

Vaughan has taken related work in another direction. He has successfully applied evolutionary robotics techniques to evolve a simulation of a 3D ten-degree of freedom bipedal robot. This machine demonstrates many of the properties of human locomotion. By using passive dynamics and compliant tendons, it conserves energy while walking on a flat surface. Its speed and gait can be dynamically adjusted and it is capable of adapting to discrepancies in both its environment and its bodies' construction [121]. The parameters of the body and continuous dynamical neural network controller were under genetic control. The machine started out as a passive dynamic walker [77] on a slope, and then throughout the evolutionary process the slope was gradually lowered to a flat surface. The machine demonstrated resistance to disturbance while retaining passive dynamic features such as a passive swing leg. This machine did not have a torso, but Vaughan has also successfully applied the method to a simplified 2D machine with a torso above the hips. When pushed, this dynamically stable bipedal machine walks either forward or backwards just enough to release the pressure placed on it. It is also able to adapt to external and internal perturbations as well as variations in body size and mass [122].

McHale and Husbands [79, 78] have compared many forms of evolved neural controllers for bipedal and quadrupedal walking machines. Recurrent dynamical

continuous time networks and GasNets (described in Section 61.6.3) were shown to have advantages in most circumstances. The vast majority of the studies mentioned above were conducted for relatively benign environments. Notwithstanding this observation, we can conclude that the more complex dynamical neural network architectures, with their intricate dynamics, generally produce a wider range of gaits and generate smoother, more adaptive locomotion than the more standard use of finite state machine based systems employing parameterised rules governing the timing and coordination of individual leg movements (e.g., [66]).

### 61.3 Simulation and reality

Few of the experiments in the previous section were carried out entirely on physical robots because a) evolution may take a long time, especially if it is carried out on a single robot that incarnates the bodies of all the individuals of the evolving population; b) the physical robot can be damaged because populations always contain a certain number of poorly performing individuals (for example, colliding against walls) by effect of random mutations; c) restoring the environment to initial conditions between trails of different individuals or populations (for example, replenishing the arena with objects) may not always be feasible without human intervention; d) evolution of morphologies and evolution of robots that can grow during their lifetime is almost impossible with today's technology without some level of human intervention.

For those reasons, researchers often resort to evolution in simulation and transfer the evolved controllers to the physical robot. In the case of morphology evolution, the physical robot is manually assembled according to the evolved specifications. However, it is well known that programs that work well in simulations may not function properly in the real world because of differences in sensing, actuation and in the dynamic interactions between robot and environment [17]. This "reality gap" is even more evident in adaptive approaches, such as Evolutionary Robotics, where the control system and morphology are gradually crafted through the repeated interactions between the robot and the environment. Therefore, robots will evolve to match the specificities of the simulation, which differ from the real world. Although these issues clearly rule out any simulation based on grid worlds or pure kinematics, over the last 10 years simulation techniques have dramatically improved and resulted

in software libraries that model reasonably well dynamical properties such as friction, collision, mass, gravity, inertia, etc. [25]. These software tools allow one to simulate articulated robots of variable morphology and their environment as fast as, or faster than, real time in a desktop computer. Today, those physics-based simulations are widely used by most researchers in Evolutionary Robotics and indeed most of the work with highly articulated robots is carried out with those simulations.

Nonetheless, even physics-based simulations include small discrepancies that can accumulate over time and result in very different behavior from reality (for example, a robot may get stuck against a wall in simulation whereas it can get free in reality, or vice versa). Also, physics-based simulations cannot account for diversity of response profiles of the individual sensors, motors, and gears of a physical robot. There are at least four methods to cope with these problems and improve the quality of the transfer from simulation to reality.

A widely used method consists of adding independent noise to the values of the sensors provided by the model and to the end position of the robot computed by the simulator [63]. Some software libraries allow the introduction of noise at several levels of the simulation. That solution prevents evolution from finding solutions that rely on the specificities of the simulation model. One may also sample the actual sensor values of the real robot positioned at several angles and distances from objects of different texture. Those values are then stored in a look up table and retrieved with addition of noise according to the position of the robot in the environment [80]. This method proved to be very effective for generating controllers that transfer smoothly from simulation to reality. A drawback of the sampling method is that it does not scale up well to high-dimensional sensors (e.g., vision) or geometrically complicated objects.

Another method, also known as minimal simulations, consists in modeling only those characteristics of the robot and environment that are relevant for the emergence of desired behaviors [60]. Those characteristics, that are referred to as base-set features, should be accurately modeled in simulation. Instead, all the other characteristics, which are referred to as implementation aspects, should be randomly varied across several trials of the same individual in order to ensure that evolving individuals do not rely on implementation aspects, but rely on base-set features only. Base-set features must also be varied to some extent across trials in order to ensure some degree of robustness of the individual with respect to base-set features, but that variation should

not be so large that reliably fit controllers fail to evolve at all. This method allows very fast evolution of complex robot-environment situations, as in the example of hexapod walk described in Section 61.2.1. A drawback of minimal simulations is that it is not always easy to tell in advance which are the base-set features that are relevant for the desired behavior.

Yet another method consists in the co-evolution of the robot (control and/or morphology) and of the simulator parameters that are most likely to differ from the real world and that may affect the quality of the transfer [14]. This method consists of co-evolving two populations, one encoding the properties of the robot and one encoding the parameters of the simulator. Co-evolution happens in several passes through a two-stage process. In stage one, a randomly generated population of robots are evolved in the default simulator and the best individual is tested on the real robot while the time series of sensory values are recorded. In stage two, the population of simulators is evolved for reducing the difference between the time series recorded on the real robot and the time series obtained by testing evolved robots within the simulator. The best evolved simulator is then used for stage one where a new randomly generated population is evolved and the best individual is tested on the real robot to generate the time series for stage two of simulator evolution. This two-stage co-evolution is repeated several times until the error between simulated and real robot behavior is the smallest possible. It has been shown that approximately 20 passes of the two-stage process are sufficient to evolve a good control system that could be transferred to an articulated robot. In that case, the real robot was used to test only 20 individuals.

Finally, another method consists of genetically encoding and evolving the learning rules of the control system, rather than its parameters (e.g., connection strengths). The parameters of the decoded control system are always initialized to small random values at the beginning of an individual lifetime and must self-organize using the learning rules [120]. This method prevents evolution from finding a set of control parameters that fit the specificities of the simulation model, and encourages emergence of control systems that remain adaptive to partially unknown environments. When such an evolved individual is transferred to the real robot, it will develop online its control parameters according to the genetically evolved learning rules and taking into account the specificities of the physical world. This method is described in more detail in Section 61.7.2 on evolution of learning.



## 61.4 Simple controllers, complex behaviors

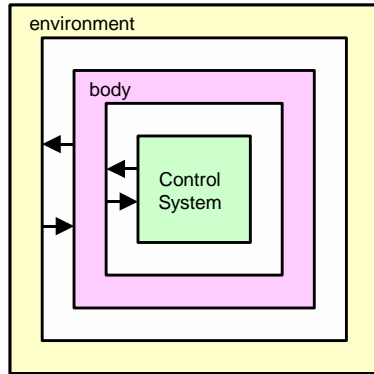


Figure 61.7: Robot behavior results from non-linear interactions, occurring at fast time rates, between the agent's control system, its body and the environment.

behavior is a dynamical process resulting from non-linear interactions (occurring at a fast time rate) between the agent's control system, its body, and the environment [75, 12]. At any time step, the environment and the agent/environment relation influence the body and the motor reaction of the agent, that in turn influences the environment and/or the agent/environmental relation (Figure 61.7). Sequences of these interactions lead to a dynamical process where the contributions of the different aspects (i.e., the robot's control system, the robot's body and the environment) cannot be separated. This implies that even a complete knowledge of the elements governing the interactions provides little insight on the behavior emerging from these interactions [36, 84].

An important advantage of Evolutionary Robotics is that it is not necessary to identify the relations between the rules governing the interactions and the resulting behavior [86, 84]. Evolutionary Robotics is an adaptation process where the free parameters of the robots that regulate the interactions, initially randomly assigned, are modified through a process of random variation and are selected and/or discarded on the basis of their effects at the behavioral level. These characteristics allow evolving robots to discover useful behavioral properties emerging from the interactions without the need to identify the relations between the rules governing the interaction and the resulting behavior. An emergent behavioral property or behavior is a form of behavior that can hardly be pre-

dicted or inferred by an external observer even when she has a complete knowledge of the interacting elements and of the rules governing those interactions. The possibility of developing robots that exploit emergent behavior, in turn, allows evolutionary methods to come up with simple solutions to problems that are complex from an observer's perspective.

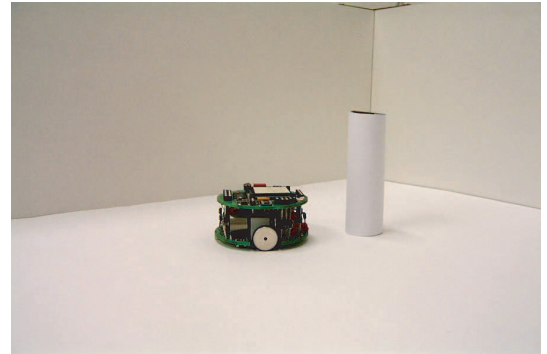


Figure 61.8: The environment and the robot. The environment consists of an arena of  $60 \times 35$  cm and contains a cylindrical objects placed in a randomly selected location.

As an example (Figure 61.8), consider the case of a Khepera robot placed in an arena surrounded by walls and containing a food object (i.e., a cylindrical object) that the robot should find and remain close to [83]. The robot is provided with eight infrared sensors and two motors controlling the two corresponding wheels. From the point of view of an external observer, solving this problem requires robots able to: (a) explore the environment until an obstacle is detected, (b) discriminate whether the obstacle detected is a wall or a cylindrical object, and (c) approach or avoid the object depending on the object type. A detailed analysis of the sensory patterns experienced by the robot indicated that the task of discriminating the two objects is far from trivial since the two classes of sensory patterns experienced by robots close to a wall and close to cylindrical objects overlap significantly. However, robots evolved for the ability to solve this task resorted to a strategy that does not require explicit discrimination of the two types of objects [83].

In all replications of the experiment, evolved robot moved away from walls, but when they encountered the food object tended to oscillate back and forth or left and right in its proximity (Figure 61.9). This solution consists in producing a behavioral attractor near the cylin-

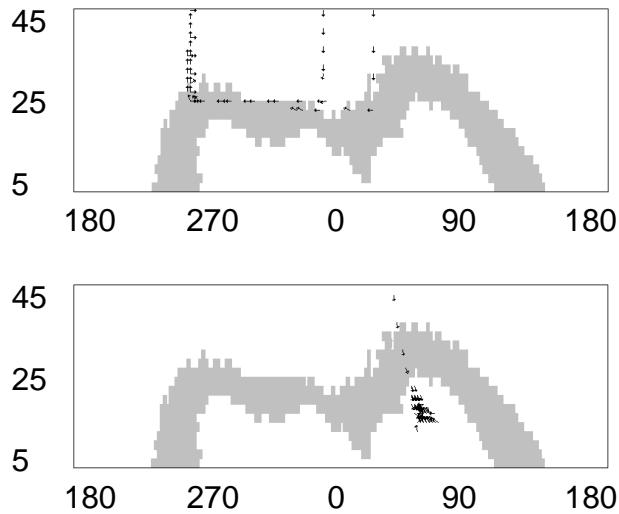


Figure 61.9: Angular trajectories of an evolved robot close to a wall (top graph) and to a cylinder (bottom graph). The picture was obtained by placing the robot at a random position in the environment, leaving it free to move for 500 cycles, and recording its relative movements with respect to the two 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.

dricular object. A behavioral attractor is a series of sensorimotor sequences that maintain the robot close to the object. In this case, the forward movement in front of the cylindrical object generates a variation of the sensory pattern experienced by the robot that, in turn, triggers a backward movement.

Therefore, evolved robots do not solve the problem by discriminating the two type of objects (cylinder and wall) and displaying an approaching or avoiding behavior, but rather exploit behaviors that emerge from the interaction between the robot's control system, robots' body, and the environment. The possibility to discover and rely on these forms of emergent behavior allows evolving robots to find computationally simple solutions to apparently complex problems. Indeed, the problem described in this section only requires a simple reactive neural controller with one layer of feedforward connections between sensors and motors.

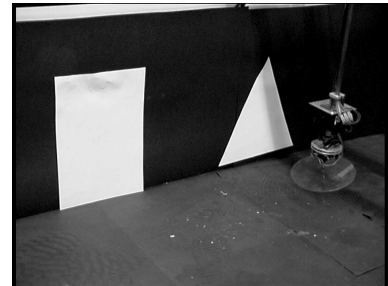


Figure 61.10: The gantry robot used in the visual discrimination task. The camera inside the top box points down at the inclined mirror which can be turned by the stepper motor beneath. The lower plastic disk is suspended from a joystick to detect collisions with obstacles.

## 61.5 Seeing the light

The experiments described so far rely mainly on relatively simple distance sensors, such as active infrared or sonar. Pioneering experiments on evolving visually guided behaviors were performed at Sussex University [49] on a specially designed gantry robot (Figure 61.10). Discrete-time dynamical recurrent neural networks and visual sampling morphologies were concurrently evolved: the brain was developed in tandem with the visual sensor [50, 57, 61]. The robot was designed to allow real-world evolution by having “off-board” power and processing so that the robot could be run for long periods while being monitored by automatic fitness evaluation functions. A CCD camera points down towards a mirror angled at 45 degrees as shown in Figure 61.10. The mirror can rotate around an axis perpendicular to the camera's image plane. The camera is suspended from the gantry allowing motion in the X, Y and Z dimensions. This effectively provides an equivalent to a wheeled robot with a forward facing camera when only the X and Y dimensions of translation are used. The additional dimension allows flying behaviors to be studied.

The apparatus was initially used in a manner similar to the real-world experiments on navigation in the looping maze with the miniature mobile robot described in Section 61.2. A population of strings encoding robot controllers and visual sensing morphologies were stored on a computer to be downloaded one at a time onto the robot. The exact position and orientation of the camera head can be accurately tracked and used in the fitness evaluations. A number of visually guided navigation be-

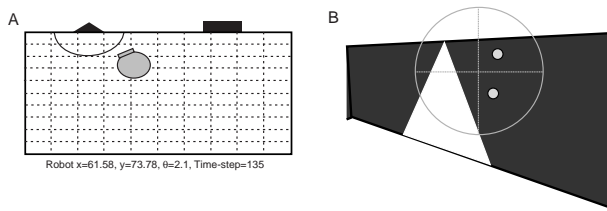


Figure 61.11: The shape discrimination task. A: the position of the robot in the arena, showing the target area in front of the triangle. B: The robot camera's field of view showing the visual patches selected by evolution for sensory input.

haviors were successfully achieved including navigating around obstacles, tracking moving targets and discriminating between different objects [57]. The evolutionary process was incremental. The ability to distinguish between two different targets was evolved on top of the single target finding behavior. The chromosome was of dynamic length so the neurocontroller was structurally further developed by evolution to achieve the new task (neurons and connections added). In the experiment illustrated in Figures 61.10 and 61.11, starting from a random position and orientation, the robot had to move to the triangle rather than the rectangle. This had to be achieved irrespective of the relative positions of the shapes and under very noisy lighting conditions. Recurrent neural network controllers were evolved in conjunction with visual sampling morphologies. Only genetically specified patches from the camera image were used (by being connected to input neurons according to the genetic specification). The rest of the image was thrown away. This resulted in extremely minimal systems using only 2 or 3 pixels of visual information, yet still able to perform the task reliably under highly variable lighting conditions [50, 57].

This was another example of staged, or incremental, evolution to obtain control systems capable of solving problems that are either too complex or may profit from an evolutionary methodology that discovers, preserves, and builds upon sub-components of the solution. For an evolutionary method that incorporate strategies to explicitly address this issue, interested readers may refer to [110]. However, staged evolution remains a poorly explored area of Evolutionary Robotics that deserves further study and a more principled approach [2] in order to achieve increasingly complex robotic systems.

### 61.5.1 Co-evolution of active vision and feature selection

Machine vision today can hardly compete with biological vision despite the enormous power of computers. One of the most remarkable –and often neglected– differences between machine vision and biological vision is that computers are often asked to process an entire image in one shot and produce an immediate answer whereas animals take time to explore the image over time searching for features and dynamically integrating information over time.

*Active vision* is the sequential and interactive process of selecting and analyzing parts of a visual scene [1, 3, 7]. *Feature selection* instead is the development of sensitivity to relevant features in the visual scene to which the system selectively responds [47, e.g.]. Each of these processes has been investigated and adopted in machine vision. However, the combination of active vision and feature selection is still largely unexplored. An intriguing hypothesis is that co-evolution of active vision and feature selection could greatly simplify the computational complexity of vision-based behavior by facilitating each other's task.

This hypothesis was investigated in a series of experiments [26] on co-evolution of active vision and feature selection for behavioral systems equipped with a primitive moving retina and a deliberately simple neural architecture (Figure 61.12). The neural architecture was composed of an artificial retina and of two sets of output units. One set of output units determined the movement and zooming factor of the retina, and the other set of units determined the behavior of the system, such as the response of a pattern recognition system, the control parameters of a robot, or the actions of a car driver. The neural network was embedded in a behavioral system and its input/output values were updated every 300 ms while its fitness was computed. Therefore, the synaptic weights of this network were responsible for both the visual features on which the system based its behavior and for the motor actions necessary to search for those features.

In a first set of experiments, the neural network was embedded in a simulated pan-tilt camera and asked it to discriminate between triangles and squares of different size that could appear at any location of a screen (Figure 61.13, left), a perceptual task similar to that explored with the gantry robot described in Section 61.5. The visual system was free to explore the image for 60 seconds while continuously telling whether the current

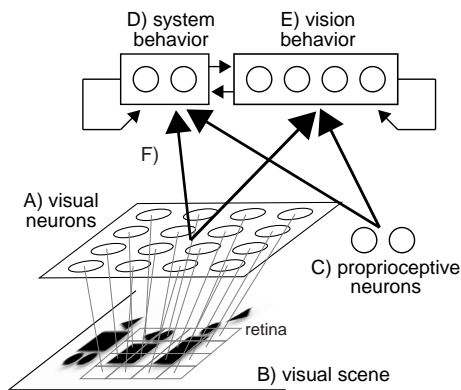


Figure 61.12: The neural architecture of the active vision system is composed of A) a grid of visual neurons with non-overlapping receptive fields whose activation is given by B) the grey level of the corresponding pixels in the image; C) a set of proprioceptive neurons that provide information about the movement of the vision system; D) a set of output neurons that determine the behavior of the system (pattern recognition, car driving, robot navigation); E) a set of output neurons that determine the behavior of the vision system; F) a set of evolvable synaptic connections. The number of neurons in each sub-system can vary according to the experimental settings.

screen showed a triangle or a square. The fitness was proportional to the amount of correct responses accumulated over the 60 seconds for several screenshots containing various instances of the two shapes. Evolved systems were capable of correctly identifying the type of shape with 100% accuracy after a few seconds despite the fact that this recognition problem is not linearly separable and that the neural network does not have hidden units, which in theory are necessary to solve non-linearly separable tasks. Indeed, the same neural network presented with the same set of images and trained with supervised learning, but without the possibility to actively explore the scene, was not capable of solving the task. The evolved active vision system developed sensitivity to vertical edges, oriented edges and corners, and used its movement to search for these features in order to tell whether the shape was a triangle or a square. These features, which are found also in the early visual system of almost all animals, are invariant to size and location.

In a second set of experiments, the neural network was embedded in a simulated car and was asked to drive over

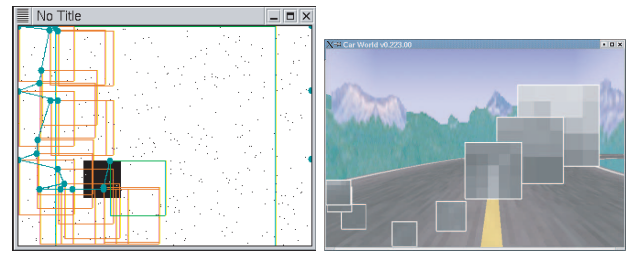


Figure 61.13: Left: An evolved individual explores the screen searching for the shape and recognizes it by the presence of a vertical edge. Right: Search for the edge of the road at the beginning of a drive over a mountain road.



Figure 61.14: A mobile robot with pan-tilt camera is asked to move within the walled arena in the office environment.

several mountain circuits (Figure 61.13, right). The simulator was a modified version of a car race video game. The neural network could move the retina across the scene seen through the windscreen at the driver's seat and control the steering, acceleration, and braking of the car. The fitness was inversely proportional to the time taken to complete the circuits without exiting the road. Evolved networks completed all circuits with time laps competitive to those of well-trained students controlling the car with a joystick. Evolved network started by searching for the edge of the road and tracked its relative position with respect to the edge of the windscreen in order to control steering and acceleration. This behavior was supported by the development of sensitivity to oriented-edges.

In a third set of experiments, the neural network was

embedded in a real mobile robot with a pan-tilt camera that was asked to navigate in a square arena with low walls located in an office (Figure 61.14). The fitness was proportional to the amount of straight motion measured over two minutes. Robots that hit the walls because they watched people or other irrelevant features of the office had lower fitness than robots that could perform long straight paths and avoid walls of the arena. Evolved robots tended to fixate the edge between the floor and the walls of the arena, and turned away from the wall when the size of its retinal projection became larger than a threshold. This combination of sensitivity to oriented edges and looming is found also in visual circuits of several insects and birds.

In a further set of experiments [33], the visual pathway of the neural network was augmented by an intermediate set of neurons whose synaptic weights could be modified by Hebbian learning [105] while the robot moved in the environment. All the other synaptic weights were genetically encoded and evolved. The results showed that lifelong development of the receptive fields improved the performance of evolved robots and allowed robust transfer of evolved neural controllers from simulated to real robots, because the receptive fields developed sensitivity to features encountered in the environment where they happen to be born (see also the section above on simulation and reality). Furthermore, the results showed that development of visual receptive fields was significantly and consistently affected by active vision as compared to the development of receptive fields passively exposed to the same set of sample images. In other words, robots evolved with active vision developed sensitivity to a smaller subset of features in the environment and actively tracked those features to maintain a stable behavior.

## 61.6 Computational neuroethology

Evolutionary Robotics is also used to investigate open questions in neuroscience and cognitive science [48] because it offers the vantage point of a behavioral system that interacts with its environment [21]. Although the results should be carefully considered when drawing analogies with biological organisms, Evolutionary Robotics can generate and test hypotheses that could be further investigated with mainstream neuroscience methods.

For example, the active vision system with Hebbian plasticity described in the previous section was used to

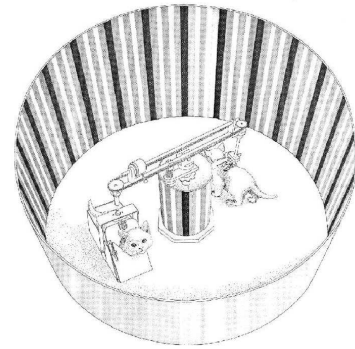


Figure 61.15: The original apparatus in [53], where the gross movements of a kitten moving almost freely were transmitted to a second kitten that was carried in a gondola. Both kittens were allowed to move their head. They received essentially the same visual stimulation because of the unvarying pattern on the walls and the center post of the apparatus. Reproduced, with permission, from [52].

answer a question raised by Held and Hein [53] in the 60's. The authors devised the apparatus shown in Figure 61.15 where the free movements of a kitten (*active kitten*) were transmitted to a second kitten that was carried in a gondola (*passive kitten*). The second kitten could move its head, but its feet did not touch the ground. Consequently, the two kitten received almost identical visual stimulation, but only one of them received that stimulation as a result of body self-movement. After a few days in that environment, only the active kitten displayed normal behavior in several visually guided tasks. The authors suggested the hypothesis that proprioceptive motor information resulting from generation of actions was necessary for the development of normal, visually-guided behavior.

The kitten experiments were replicated by cloning an evolved robot controller and randomly initializing the synaptic values of the adaptive visual pathways in both clones. One cloned robot was then left free to move in a square environment while the other cloned robot was forced to move along imposed trajectories, but was free to control its camera position, just like the passive kitten [112]. The results indicated that the visual receptive fields and behaviors of passive robots significantly differ from those of active robots. Furthermore, passive robots that were later left free to move were no longer capable of properly avoiding walls. A thorough analysis of

neural activation correlated with behavior of the robot and even transplantation of neurons across active and passive robots revealed that the poor performance was due to the fact that passive robots could not completely select the visual features they were exposed to. Consequently, passive robots developed sensitivity to features that were not functional to their normal behavior and interfered with other dominant features in the visual field. Whether this explanation hold also for living animals remains to be further investigated, but at least these experiments indicated that motor feedback is not necessary to explain the pattern of pathological behavior observed in animals and robots.

### 61.6.1 Emergence of place cells

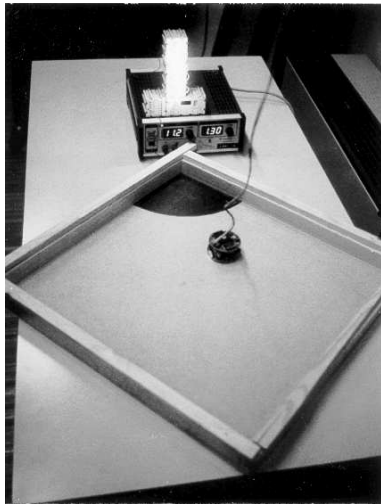


Figure 61.16: Bird's-eye view of the arena with the light tower over the recharging station and the Khepera robot.

Let us now consider the case of an animal exploring an environment and periodically returning to its nest to feed. It has been speculated that this type of situation requires the formation of spatial representations of the environment that allow the animal to find its way home [51, e.g.]. Different neural models with various degrees of complexity and biological detail have been proposed that could provide such functionality [106, 18, e.g.].

Would a robot evolved under similar survival conditions develop a spatial representation of the environment and, if so, what type of representation would that be? These questions were explored using the same Khepera robot and evolutionary methodology described in Sec-

tion 61.2 for reactive navigation in the looping maze. The environment was a square arena with a small patch on the floor in a corner where the robot could instantaneously recharge its (simulated) battery (Figure 61.16). The environment was located in a dark room with a small light tower over the “recharging station.”

The sensory system of the robot was composed of eight distance sensors, two ambient-light sensors (one on each side), one floor-color sensor, and a sensor of battery charge level. The battery lasted only 20 seconds and had a linear discharge. The evolutionary neural network included five fully-connected internal neurons between sensory and motor neurons. The same fitness function described in Section 61.2 for navigation in the looping maze was used, except for the middle term which had been used to encourage straight navigation in the looping maze. The fitness value was computed every 300 ms and accumulated over the life span of the individual. Therefore, individuals who discovered where the charger was could live longer and accumulate more fitness by exploring the environment (individuals were killed if they survived longer than 60 seconds to limit the experimentation time).

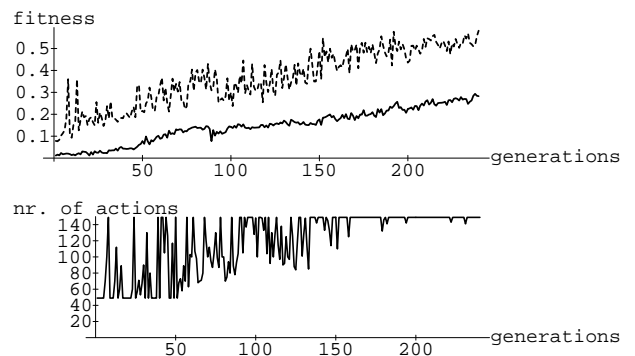


Figure 61.17: Top: Average population fitness (continuous line) and fitness of the best individual (dotted line). Bottom: Life span of best individuals measured as number of sensorimotor cycles, or actions. Individuals start with a full battery which lasts 50 actions (20 seconds), if not recharged. The maximum life span is 150 actions.

The same physical robot evolved for 10 days and nights as both the fitness and life span of individuals continued to increase (Figure 61.17). After approximately 200 generations, the robot was capable of navigating around the environment, covering long trajectories while avoiding both walls and the recharging area. When the battery

was almost discharged it initiated a straight navigation towards the recharging area and exited immediately after battery recharge to resume navigation. Best evolved individuals always entered the recharging area one or two seconds before full discharge of the battery. That implies that robots must somehow calibrate the timing and trajectory of their homing behavior depending on where they happened to be in the environment.

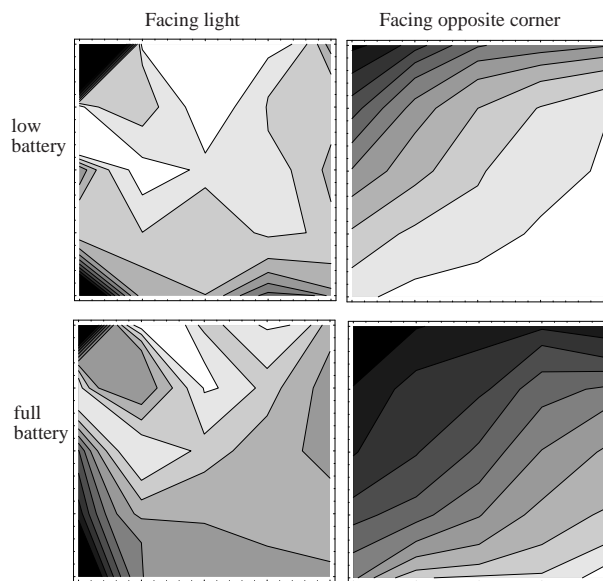


Figure 61.18: Activation levels (brightness proportional to activation) of an internal neuron plotted over the environment while the robot was positioned at various locations in each of the four conditions (facing recharging area or not, discharged battery or not). The recharging area is located at the top left corner of each map.

In order to understand how that behavior could possibly be generated, a set of neuroethological measures were performed using a laser positioning device that provided exact position and orientation of the robot every 300 ms. By correlating the robot position and behavior with the activation of the internal neurons in real time while the evolved individual freely moved in the environment, it was possible to see that some neurons specialized for reactive behaviors, such as obstacle avoidance, forward motion, and battery monitoring. Other neurons instead displayed more complex activation patterns. One of them revealed a pattern of activation levels that depended on whether the robot was oriented facing the light tower or facing the opposite direction (Figure 61.18). In the for-

mer case, the activation pattern reflected zones of the environment and paths typically followed by the robot during exploration and homing. For example, the robot trajectory towards the recharging area never crossed the two “gate walls” visible in the activation maps around the recharging station. When the robot faced the opposite direction, the same neuron displayed a gradient field orthogonally aligned with the recharging area. This gradient provides an indication of the distance from the recharging area. Interestingly, this pattern of activity is not significantly affected by the charge level of the battery.

The functioning of this neuron reminds of the classic findings on the hippocampus of the rat brain where some neurons (also known as “place cells”) selectively fire when the rat is in specific areas of the environment [88]. Also, the orientation-specific pattern of neural activation measured on the evolved robot reminds of the so-called “head-direction neurons” in the rat hippocampus, which are positioned nearby place cells, whose firing patterns depend on the rat heading direction with respect to an environmental landmark [113]. Although the analogy between brains of evolved robots and of biological organisms should not be taken too literally, these results indicate that the two organisms converge towards a functionally similar neural strategy, which may be more efficient to address this type of situation than a strategy that does not rely on representations (but only on reactive strategies such as random motion, light following, dead-reckoning).

### 61.6.2 Spiking neurons

The great majority of biological neurons communicate using self-propagating electrical pulses called *spikes*, but from an information-theoretic perspective it is not yet clear how information is encoded in the spike train. Connectionist models [104], by far the most widespread, assume that what matters is the *firing rate* of a neuron, that is, the average quantity of spikes emitted by the neuron within a relatively long time window (for example, over 100 ms). Alternatively, what matters is the average number of spikes of a small population of neurons at a give point. In these models the real-value output of an artificial neuron represents the firing rate, possibly normalized relatively to the maximum attainable value. Pulsed models [72], instead, are based on assumption that the *firing time*, that is, the precise time of emission of a single spike, may convey important information [100]. Spiking neuron models have slightly more compli-

cated dynamics of synaptic and membrane integration. Depending on one's theory of what really matters, connectionist or spiking models are used.

However, designing circuits of spiking neurons that display a desired functionality is still a challenging task. The most successful results in the field of robotics obtained so far focused on the first stages of sensory processing and on relatively simple motor control [59, 67]. Despite these implementations, there are not yet methods for developing complex spiking circuits that could display minimally-cognitive functions or learn behavioral abilities through autonomous interaction with a physical environment.

Artificial evolution represents a promising methodology to generate networks of spiking circuits with desired functionalities expressed as behavioral criteria (fitness function). Evolved networks could then be examined to detect what communication modality is used and how that correlates with observed behavior of the robot.

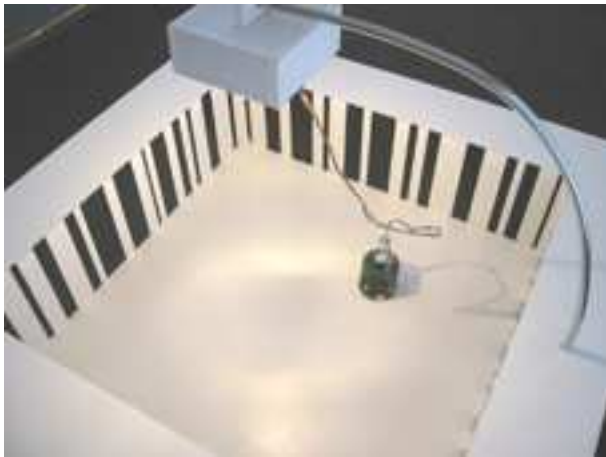


Figure 61.19: A network of spiking neurons is evolved to drive the vision-based robot in the arena. The light below the rotating contacts allows continuous evolution also overnight.

Floreano and colleagues [27] evolved a fully connected network of spiking neurons for driving a vision-based robot in an arena painted with black stripes of variable size against a white background (Figure 61.19). The Khepera robot used in these experiments was equipped with a vision turret composed of one linear array of grayscale photoreceptors spanning a visual field of 36 degrees. The output values of a bank of local contrast detection filters were converted in spikes (the strongest

the contrast, the larger the number of spikes per second) sent to ten fully connected spiking neurons implemented according to the spike response model [42]. The spike series of a subset of these neurons was translated into motor commands (more spikes per seconds corresponded to faster rotation of the wheel). The fitness function was the amount of forward translation of the robot measured over 2 minutes. Consequently robots that turned in place or hit the walls had comparatively lower fitness than robots that could move straight and turn only to avoid walls. The genome of these robots was a bit string that encoded only the sign of the neurons and the presence of synaptic connections. Existing connections were set to 1 and could not change during the lifetime of the robot.

Evolution reliably discovered very robust spiking controllers in approximately 20 generations (approx. 30 hours of evolution on the real robot). Evolved robots could avoid not only the walls, but any object positioned in front of them. Detailed analysis of the best evolved controllers revealed that neurons did not exploit time differences between spikes, which one would have expected if optic flow was used to detect distance from walls. Instead, they simply used the number of incoming spikes (firing rate) as an indication of when to turn. When the robot perceived a lot of contrast it would go straight, but when the contrast decreased below a certain threshold (indicating that it approached an object), it started to turn away. This extremely efficient and simple result seems to be in contrast with theories of optic flow detection in insects and may be worth considering it as an alternative hypothesis for vision-based behavior.

Spiking neural networks turned out to be more evolvable than connectionist models (at least for this task). One possible explanation is that spiking neurons have sub-threshold dynamics that, to some extent, can be affected by mutations without immediately affecting the output of the network.

The robust results and compact genetic encoding encouraged the authors to use an even simpler model of spiking neuron so that the entire neural network could be mapped in less than 50 bytes of memory. The evolutionary algorithm was also reduced to a few lines of code and the entire system was implemented within a PIC microcontroller without need of any external computer for data storage. The system was used for a sugar-cube robot (Figure 61.20) that autonomously and reliably developed the ability to navigate around a maze in less than an hour [28]. Interestingly, evolved spiking controllers developed a pattern of connections where spiking neurons received



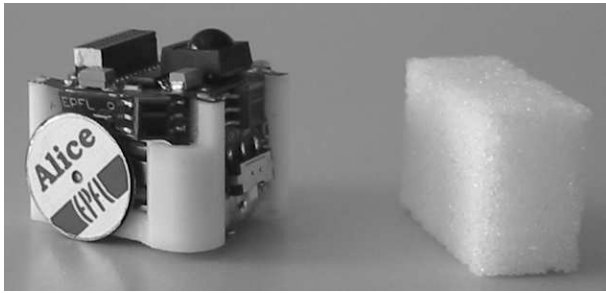


Figure 61.20: The Alice sugar-cube robot equipped with the evolutionary spiking neural network implemented within its PIC microcontroller.

connections from a small patch of neighboring sensors, but not from other sensors, and were connected only to neighboring spiking neurons. This pattern of connectivity is observed also in biological systems and encourages specialization of neurons to sensory features.

### 61.6.3 GasNets

This section describes another style of artificial neural network strongly inspired by those parts of contemporary neuroscience that emphasize the complex electrochemical nature of real nervous systems. In particular, they make use of an analogue of *volume signaling*, whereby neurotransmitters freely diffuse into a relatively large volume around a nerve cell, potentially affecting many other neurons [39, 126]. This exotic form of neural signaling does not sit easily with classical pictures of brain mechanisms and is forcing a radical re-think of existing theory [22, 41, 93, 55]. The class of artificial neural networks developed to explore artificial volume signaling are known as GasNets [58]. These are essentially standard neural networks augmented by a chemical signaling system comprising a diffusing *virtual* gas which can modulate the response of other neurons. A number of GasNet variants, inspired by different aspects of real nervous systems, have been explored in an evolutionary robotics context as artificial nervous systems for mobile autonomous robots. They have been shown to be significantly more evolvable, in terms of speed to a good solution, than other forms of neural networks for a variety of robot tasks and behaviors [58, 79, 108, 95]. They are being investigated as potentially useful engineering tools and as a way of gaining helpful insights into biological systems [93, 94, 96].

By analogy with biological neuronal networks, Gas-

Nets incorporate two distinct signaling mechanisms, one ‘electrical’ and one ‘chemical’. The underlying ‘electrical’ network is a discrete time step, recurrent neural network with a variable number of nodes. These nodes are connected by either excitatory or inhibitory links.

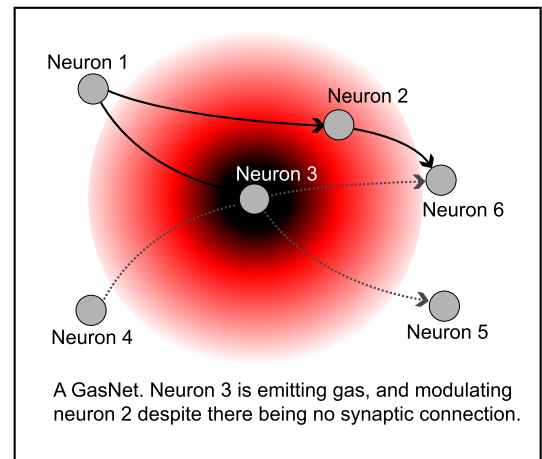


Figure 61.21: A basic GasNet showing positive (solid) and negative (dashed) “electrical” connections and a diffusing virtual gas creating a “chemical” gradient.

In addition to this underlying network in which positive and negative “signals” flow between units, an abstract process loosely analogous to the diffusion of gaseous modulators is at play. Some units can emit virtual “gases” which diffuse and are capable of modulating the behavior of other units by changing the profile of their output functions. The networks occupy a 2D space; the diffusion processes mean that the relative positioning of nodes is crucial to the functioning of the network. Spatially, the gas concentration varies as an inverse exponential of the distance from the emitting node with a spread governed by a parameter,  $r$ , with the concentration set to zero for all distances greater than  $r$ . The total concentration of gas at a node is determined by summing the contributions from all other emitting nodes.

For mathematical convenience, in the original GasNet there are two “gases”, one whose modulatory effect is to increase the transfer function gain parameter and one whose effect is to decrease it. Thus the gas does not alter the electrical activity in the network directly but rather acts by continuously changing the mapping between input and output for individual nodes, either directly or by stimulating the production of further virtual gas. The general form of the diffusion is based on the properties

of a (real) single source neuron as modeled in detail by Philippides et al. [93, 94]. The modulation chosen is motivated by what is known of NO modulatory effects at synapses [8]. For full details see [58].

Various extensions of the basic GasNet have been produced. Two in particular are strongly inspired by contemporary neuroscience. The *plexus model* is directly inspired by a type of signaling seen in the mammalian cerebral cortex in which the NO signal is generated by the combined action of many fine NO producing fibers, giving a targeted ‘cloud’ which is distant from the neurons from which the fiber plexus emanates [96]. In the plexus GasNet, which models this form of signaling at an abstract level, the spatial distribution of gas concentration has been modified to be uniform over the area of affect. The center of this gas diffusion cloud is under genetic control and can be distant from the controlling node (which, by analogy, is the source of the ‘plexus’) [95]. All other details of the models are identical to the original GasNet model, as described earlier. The *receptor GasNet* incorporates an aspect of biological neuronal networks that has no analog in the vast majority of ANNs: the role of receptor molecules. Although neuroscience is a long way from a full understanding of receptor mechanisms, a number of powerful systems level ideas we can abstracted.

Details of the receptor variant are similar to the basic GasNet except there is now *only one* virtual gas and each node in the network can have one of three discrete quantities (zero, medium, maximum) of a number of possible receptors. The modulation the diffusing neurotransmitter affects at a neuron depends on which receptors are present. The strength of a modulation at node is proportional to the product of the gas concentration at the node and the relevant receptor quantity. In the original GasNet, any node that was in the path of a diffusing transmitter would be modulated in a fixed way. The receptor model allows site specific modulations, including no modulation (no receptors) and multiple modulations at a single site (see [95] for further details).

Although most of the GasNet variants described in this section have been successfully used in a number of robotic tasks, their evolvability and other properties were thoroughly compared on a version of the (gantry) robot visual discrimination task described in Section 61.5. All aspects of the networks were under genetic control: the number of nodes, the connectivity and, in the case of the GasNets, all parameters governing volume signaling (including the position of the nodes and whether or not they were ‘virtual gas’ emitters). The visual sampling

morphology was also under evolutionary control. The original basic GasNet was found to be significantly more evolvable than a variety of other styles of connectionist neural networks as well as a GasNet with the volume signaling disabled. Successful GasNet controllers for this task tended to be rather minimal, in terms of numbers of nodes and connections, while possessing complex dynamics [58]. Later experiments comparing the basic GasNet with the plexus and receptor variants showed the latter two to be considerably more evolvable than the former, with the receptor GasNet being particularly successful [95].

The GasNet experiments mentioned above demonstrated that the intricate network dynamics made possible by the artificial volume signaling mechanisms can be readily harnessed to generate adaptive behaviors in autonomous agents. They also throw up such question as why GasNets are more evolvable than many other forms of ANN and why there is a difference in evolvability between GasNet variants. Investigations of this question indicate that the interaction between the two GasNet signaling mechanisms, ‘electrical’ and ‘chemical’, plays a crucial role [95, 108]. Evolutionary theory led to the hypothesis that systems involving distinct yet coupled processes are highly evolvable when the coupling is flexible (i.e., it is relatively easy for evolution to change the degree of coupling in the system) with a bias towards a loose coupling; this allows the possibility of “tuning” one process against the other without destructive interference [95, 108, 109]. This may also be the case for sub-threshold dynamics of spiking neural networks, which, although not yet compared to GasNets, were shown to be more evolvable than connectionist networks. Measurements of the degree of coupling in the GasNets variants versus speed of evolution supported this view [95]; the receptor GasNet, for which the evolutionary search process has the most direct control over the degree of coupling between the signaling processes, and which has a bias towards a loose coupling, was by far the most evolvable [95]. These and ongoing investigations indicate that explicitly dealing with the electrochemical nature of nervous systems is likely to be an increasingly fruitful area of research, both for evolutionary robotics and for neuroscience, that will likely force us to broaden our notions of what behavior generating mechanisms might look like.

## 61.7 Evolution and learning

Evolution and learning (or phylogenetic and ontogenetic adaptation) are two forms of biological adaptation that differ in space and time. Evolution is a process of selective reproduction and substitution based on the existence of a population of individuals displaying variability at the genetic level. Learning, instead, is a set of modifications taking place within each single individual during its own life time. Evolution and learning operate on different time scales. Evolution is a form of adaptation capable of capturing relatively slow environmental changes that might encompass several generations (e.g., the perceptual characteristics of food sources for a given species). Learning, instead, allows an individual to adapt to environmental modifications that are unpredictable at the generational level. Learning might include a variety of mechanisms that produce adaptive changes in an individual during its lifetime, such as physical development, neural maturation, variation of the connectivity between neurons, and synaptic plasticity. Finally, whereas evolution operates on the genotype, learning affects only the phenotype and phenotypic modifications cannot directly modify the genotype.

Researchers have combined evolutionary techniques and learning techniques (supervised or unsupervised learning algorithm such as reinforcement learning or Hebbian learning, for a review see [85]). These studies have been conducted with two different purposes: (a) identifying the potential advantage of combining these two methods from the point of view and of developing robust and effective robots; (b) understanding the role of the interaction between learning and evolution in nature.

Within an evolutionary perspective, learning has several different adaptive functions. First, it might allow individuals to adapt to changes that occur too quickly to be tracked by evolution [87]. Secondly, learning might allow robots to use information extracted during their interaction with environment to develop adaptive characters ontogenetically without necessarily discovering these characters through genetic variations and without encoding these characters in their genome. To understand the importance of this aspect, we should consider that evolutionary adaptation is based on an explicit but concise indication of how well an individual robot coped with its environment — the fitness value of a robot. Ontogenetic adaptation, on the contrary, is based on extremely rich information — the state of the sensors while the robot interacts with its environment. This huge amount of information encode very indirectly how well an indi-

vidual is doing in different phases of its lifetime or how it should modify its behavior to increase its fitness. However, evolving robots that have acquired a predisposition to exploit this information to produce adaptive changes during their lifetime might be able to develop adaptive characteristics on the fly thus leading to the possibility to produce “complex” phenotypes on the basis of parsimonious genotype. Finally, learning can help and guide evolution. Although physical changes of the phenotype, such as strengthening of synapses during learning, cannot be written back into the genotype, Baldwin [6] and Waddington [124] suggested that learning might indeed affect the evolutionary course in subtle but effective ways. Baldwin’s argument was that learning accelerates evolution because sub-optimal individuals can reproduce by acquiring during life necessary features for survival. However, variation occurring during successive generation might lead to the discovery of genetic traits that lead to the establishment of the same characteristics that were previously acquired thorough lifetime learning. This latter aspect of Baldwin’s effect, namely indirect genetic assimilation of learned traits, has been later supported by scientific evidence and defined by Waddington [124] as a canalization effect.

Learning however, also has costs such as (1) a delay in the ability to acquire fitness (due to the need to develop fit behavior ontogenetically), and (2) an increase unreliability due to the fact that the possibility to develop certain abilities ontogenetically is subjected to partially unpredictable characteristics of the robot/environment interaction [76]. In the next two sub-section we describe two experiments that show some of the potential advantages of combining evolution and learning.

### 61.7.1 Learning to adapt to fast environmental variations

Consider the case of a Khepera robot that should explore an arena surrounded by black or white walls to reach a target placed in a randomly selected location [87]. Evolving robots are provided with eight sensory neurons that encode the state of the four corresponding infrared sensors and two motor neurons that control the desired speed of the two wheels. Since the color of the walls change every generation and since the color significantly affects the intensity of the response of the infrared sensors, evolving robots should develop an ability to “infer” whether they are currently located in an environment with white or black walls and learn to modify their behavior during lifetime. That is, robots should avoid walls

only when the infrared sensors are almost fully activated in the case of arenas with white walls, while they should avoid walls even when the infrared sensors are slightly activated in the case of arenas with black walls.

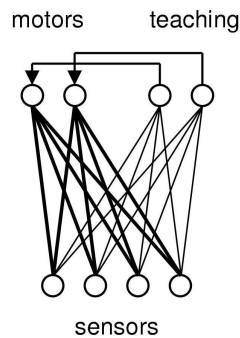


Figure 61.22: Self-teaching network. The output of the two teaching neurons is used as teaching value of two motor neurons. The weights that connect the sensory neurons to the teaching neurons do not vary during robots' lifetime while the weights that connect the sensory neurons to the motor neurons are modified with an error-correction algorithm.

Robots were provided with a neural controller (Figure 61.22) including four sensory neurons that encoded the state of four corresponding infrared sensors; two motors neurons that encoded the desired speed of the two wheels; and two teaching neurons that encoded the teaching values used to modify the connection weights from the sensory neurons to the motor neurons during robots' lifetime. This special architecture allows evolving robots to transform the sensory states experienced by the robots during their lifetime into teaching signals that might potentially lead to adaptive variations during lifetime. Analysis of evolved robots revealed that they developed two different behaviors that are adapted to the particular arena where they happen to be "born" (surrounded by white or black walls). Evolving robots did not inherit an ability to behave effectively, but rather a predisposition to learn to behave. This predisposition to learn involves several aspects such as a tendency to experience useful learning experiences, a tendency to acquire useful adaptive characters through learning, and a tendency to channel variations toward different directions in different environmental conditions [87].

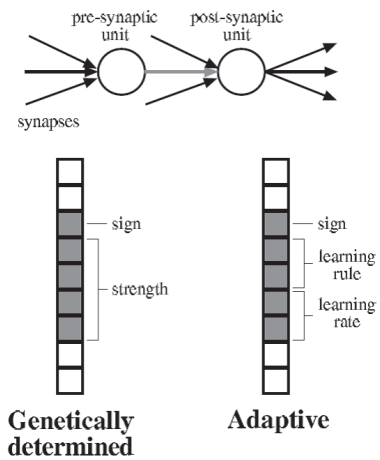


Figure 61.23: Two methods for genetically encoding a synaptic connection. Genetically determined synapses cannot change during lifetime of the robot. Adaptive synapses instead are randomly initialized and can change during lifetime of the robot according to the learning rules and rates specified in the genome.

### 61.7.2 Evolution of learning

In the previous example, the evolutionary neural network learned using a standard learning rule that was applied to all synaptic connections. Floreano and collaborators [31] explored the possibility of genetically encoding and evolving the learning rules associated to the different synaptic connections of a neural network embedded in a real robot. The main motivation of that line of work was to evolve robots capable of adapting to a partially unknown environment, rather than robots adapted to the environment(s) seen during evolution. In order to prevent evolutionary tuning of the neural network to the specificities of the evolutionary environment (which would limit transfer to different environments or transfer from simulation to reality), the synaptic weight values were not genetically encoded. Instead, each synaptic connection in the network was described by three genes that defined its sign, its learning rule, and its learning rate (Figure 61.23). Every time a genome was decoded into a neural network and downloaded onto the robot, the synaptic strengths were initialized to small random values and could change according to the genetically specified rules and rates while the robot interacted with the environment. Variations of this methodology included a more compact genetic encoding where the learning properties were associated to a neuron, instead

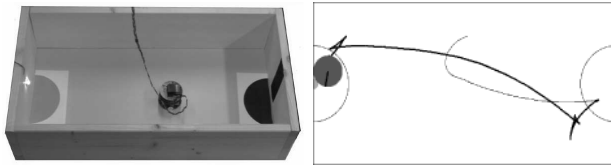


Figure 61.24: Left: A mobile robot Khepera equipped with a vision module can gain fitness points by staying on the gray area only when the light is on. The light is normally off, but it can be switched on if the robot passes over the black area positioned on the other side of the arena. The robot can detect ambient light and wall color, but not the color of the floor. Right: Behavior of an individual evolved in simulation with genetic encoding of learning rules.

of a synapse. All synapses afferent to a neuron used its genetically specified rules and rates. Genes could encode four types of Hebbian learning that were modeled upon neurophysiological data and were complementary to each other [34].

Experimental results in a non-trivial, multi-task environment (Figure 61.24) indicated that this methodology has a number of significant advantages with respect to the evolution of synaptic strengths without learning [120]. Robots evolved faster and obtained better fitness values. Furthermore, evolved behaviors were qualitatively different, notably in that they did not exploit minimal solutions tuned to the environment (such as turning only on one side, or turning in circles tuned to the dimensions of the evolutionary arena). Most important, these robots displayed remarkable adaptive properties after evolution. Best evolved individuals 1) transferred perfectly from simulated to physical robots, 2) accomplished the task when the light and reflection properties of the environment were modified, 3) accomplished the task when key landmarks and target areas of the environment were displaced, and 4) transferred well across morphologically different robotic platforms. In other words, these robots were selected for their ability to solve a partially unknown problem by adapting on the fly, rather than for being a solution to the problem seen during evolution.

In further experiments where the genetic code for each synapse of the network included one gene whose value caused its remaining genes to be interpreted as connection strengths or learning rules and rates, 80% of the synapses “made the choice” of using learning, reinforcing

the fact that this genetic strategy has a comparatively stronger adaptive power [34]. This methodology could also be used to evolve the morphology of neural controllers where synapses are created at runtime and therefore their strengths cannot be genetically specified [35]. Recently, the adaptive properties of this type of adaptive genetic encoding were confirmed also in the context of evolutionary spiking neurons for robot control [24].

## 61.8 Competition and cooperation

In the previous sections, we have limited our analysis to individual behaviors, i.e., to the evolution of robots placed in an environment that does not include other robots. The evolutionary method, however, can also be applied to develop collective behaviors in which evolving robots are placed in environment that also contain other individual robots and are selected for the ability to display competitive or cooperative behavior.

In this section we briefly review two examples involving competitive and cooperative behaviors. As we see, the evolution of collective behavior is particularly interesting from the point of view of synthesizing progressively more complex behaviors and from the point of view of developing solutions that are robust with respect to environmental variations.

### 61.8.1 Co-evolving predator and prey robots

Competitive co-evolution, for example the co-evolution of two populations of predator and prey robots that are evolved for the ability to catch prey and to escape predators respectively, has two characteristics that are particularly interesting from an evolutionary robotics perspective. The first aspect is that the competition between populations with different interests might spontaneously lead to a sort of incremental evolutionary process where evolving individuals are faced with progressively more complex challenges (although this is not necessarily the case). Indeed, in initial generations the task of the two populations is relatively simple because opponents have simple and poorly developed abilities on average. After few generation, however, the abilities of the two populations increase and, consequently, the challenges for each population become more difficult. The second aspect consists in the fact that the environment varies across generations because it includes other coevolving individ-

uals. This implies that coevolving individuals should be able to adapt to ever changing environments and to develop behaviors that are robust with respect to environmental variations.

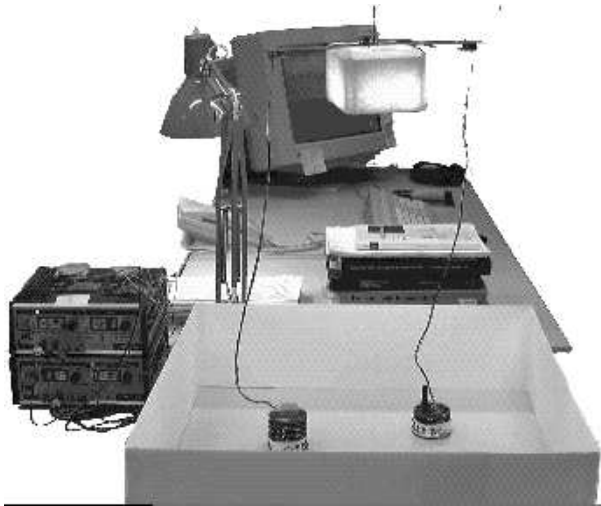


Figure 61.25: Experimental setup. The predator and prey robot (from left to right) are placed in an arena surrounded by walls and are allowed to interact for several trials starting at different randomly generated orientations. Predators are selected on the basis of the percentage of trials in which they are able to catch (i.e., to touch) the prey, and prey on the basis of the percentage of trials in which they were able to escape (i.e., to not be touched by) predators. Predator has a vision system, whereas the prey has only short-range distance sensors, but can go twice as fast as the predator. Collision between the robots is detected by a conductive belt at the base of the robots.

The potential advantages of competitive co-evolution for evolutionary robotics have been demonstrated by a set of experiments conducted by Floreano and Nolfi [32, 85] where two populations of robots were evolved for the ability to catch prey and escape predators, respectively (Figure 61.25).

The results indicated that both predator and prey robots tended to vary their behavior throughout generations without converging on a stable strategy. The behavior displayed by individuals at each generation tended to be tightly adapted to the counter-strategy exhibited by the opponent of the same generation. This evolutionary dynamic however does not really lead to long-lasting progress because, after an initial evolutionary

phase, the co-evolutionary process led to a limit cycle dynamic where the same small set of behavioral strategies recycled over and over again along generations (see [85]). This limit cycle dynamic can be explained by considering that prey robots tended to vary their behavior so to disorient predators as soon as predator become effective against the current behavioral strategies exhibited by prey robots.

However, in experiments [32] where robots were allowed to change their behavior on the fly on the basis of unsupervised Hebbian learning rules showed that the evolutionary phase where coevolving robots were able to produce real progress was significantly longer, and evolved predators displayed an ability to effectively cope with prey exhibiting different behavioral strategies by adapting their behavior on the fly to the prey's behavior. Prey instead tended to display behavior that changed in unpredictable ways.

Further experiments showed that competitive co-evolution can solve problem that the evolution of a single population cannot. Nolfi and Floreano [85] demonstrated that the attempt to evolve predators robot for the ability to catch a fixed pre-evolved prey produced lower performance with respect to control experiments where predators and prey were co-evolved at the same time.

### 61.8.2 Evolving cooperative behavior

Cooperative behavior refers to the situation where a group of robots sharing the same environment coordinate and help each other to solve a problem that cannot be solved by a single robot [19]. Although the synthesis of cooperative robots through evolutionary methods is a rather recent enterprise, obtained results are very promising. When it comes to evolving a population of robots for cooperative behaviors, it is necessary to decide the genetic relation among members of a team and the method for selective reproduction. Robots in a team can be genetically homogeneous (clones) or heterogeneous (they differ from each other). Furthermore, the fitness can be computed at the level of the team (in which case, the entire team of robots is reproduced) or at the level of the individual (in which case, only individuals of the team are selected for reproduction). The combination two variables, genetic relatedness and level of selection, generate at least four different conditions, with a variety of mixed conditions in between. It has been experimentally shown that the choice of homogeneous teams with team-level selection is the most efficient for generating

robots that display altruistic cooperation where individual robots are willing to pay a cost for the benefit of the entire team [90, 125].

Recent research showed that teams of evolved robots can: (a) develop robust and effective behavior [4, 5, 98], (b) display an ability to differentiate their behavior so to better cooperate [4, 98]; (c) develop communication capabilities and a shared communication system [97, 73].

Here we briefly review one of these experiments where Swarm-bots [82], i.e., teams of autonomous robots capable of dynamically assembling by physically connecting together, were evolved for displaying coordinated motion, navigation on rough terrains, collective negotiation of obstacles and holes, and dynamical shape re-organization in order to go through narrow passages.

Each s-bot consisted of a main platform (chassis) and turret that could actively rotate with respect to each other (see Figure 61.26). The chassis included tracks with teathed wheels for navigation on both rough and flat terrain, and four infrared sensors pointing to the ground. The turret included a gripper, a loudspeaker, 16 infrared sensors, three microphones and a traction sensor placed between the turret and the chassis to detect the direction and the intensity of the traction force that the turret exerts on the chassis. Each s-bot was provided with a simple neural controller where sensory neurons were directly connected to the motors neurons that controlled the desired speed of the tracks and whether or not a sound signal was produced. The team of s-bots forming a swarm-bot was homogeneous and evolved with team-level selection.

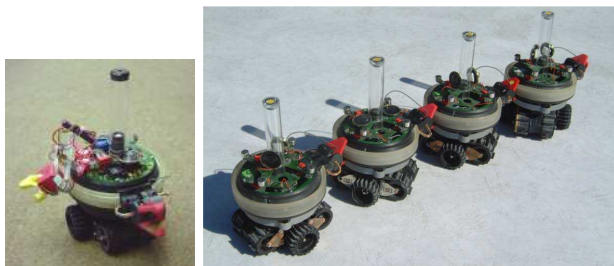


Figure 61.26: An s-bot and a simulated swarm-bot consisting of four s-bots assembled in chain formation.

Swarm-bots of four s-bots assembled in chain formation (Figure 61.26) were evolved for the ability to move coordinately on a flat terrain. Evolved neural controllers were also capable of producing coordinated movements when the swarm-bot was augmented by additional s-bots

and re-organized in different shapes. Swarm-bots also dynamically rearranged their shape so to effectively negotiate narrow passages and were capable of moving on rough terrains by negotiating situations that could not be handled by a single robot. Such robots also collectively avoided obstacles and coordinated to transport heavy objects [4, 5, 117].

## 61.9 Evolutionary Hardware

The work described so far was mainly conducted on robots that did not change shape during evolution, with the exception of self-assembling robots where several individuals can connect to become a super-organism of variable shape. In recent years, technology advancements allowed researchers to explore evolution of electronic circuits and morphologies. In this section, we briefly summarize some foundational work in this direction.

### 61.9.1 Evolvable hardware robot controllers

In most of the work discussed so far some form of genetically specified neural network, implemented in software, has been at the center of the robot control system. Work on a related approach of evolving control systems directly onto hardware dates back to Thompson's work in the mid 1990s [114]. In contrast to hardware controllers that are designed or programmed to follow a well defined sequence of instructions, evolved hardware controllers are directly configured by evolution and then allowed to behave in real time according to semiconductor physics. By removing standard electronics design constraints, the physics can be exploited to produce highly non-standard and often very efficient and minimal systems [116].

Thompson [114] used artificial evolution to design an on-board hardware controller for a two-wheeled autonomous mobile robot engaged in simple wall-avoidance behavior in an empty arena. Starting from a random orientation, and position near the wall, the robot had to move to the center of the arena and stay there using limited sensory input (Figure 61.27). The D.C. motors driving the wheels were not allowed to run in reverse and the robot's only sensors were a pair of time-of-flight sonars rigidly mounted on the robot, pointing left and right.

Thompson's approach made use of a so-called DSM (Dynamic State Machine) – a kind of generalized ROM

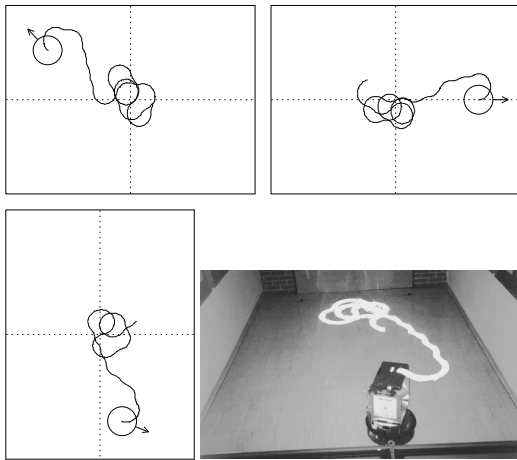


Figure 61.27: Wall avoidance behavior of a robot with an evolved hardware controller in virtual reality and (bottom right) the real world.

implementation of a finite-state machine where the usual constraint of strict synchronisation of input signals and state transitions are relaxed (in fact put under evolutionary control). The system had access to a global clock whose frequency was also under genetic control. Thus evolution determined whether each signal was synchronised to the clock or allowed to flow asynchronously. This allowed the evolving DSM to be tightly coupled to the dynamics of interaction between the robot and environment and for evolution to explore a wide range of systems dynamics. The process took place within the robot in a kind of “virtual reality” in the sense that the real evolving hardware controlled the real motors, but the wheels were just spinning in the air. The movements that the robot would have actually performed if the wheels had been actually supporting it were then simulated and the sonar echo signals that the robot was expected to receive were supplied in real time to the hardware DSM. Excellent performances were attained after 35 generations, with good transfer from the virtual environment to the real world (Figure 61.27).

Shortly after this research was performed, particular types of Field Programmable Gate Arrays (FPGAs) which were appropriate for evolutionary applications became available. FPGAs are reconfigurable systems allowing the construction of circuits built from basic logic elements. Thompson exploited their properties to demonstrate evolution directly in the chip. By again relaxing standard constraints, such as synchronising all elements with a central clock, he was able to develop very

novel forms of functional circuits, including a controller for a Khepera robot using infrared sensors to avoid obstacle [115, 116].

Following Thompson’s pioneering work, Keymeulen evolved a robot control system using a Boolean function approach implemented on gate-level evolvable hardware [64]. This system acted as a navigation system for a mobile robot capable of locating and reaching a coloured ball while avoiding obstacles. The robot was equipped with infrared sensors and a vision system giving the direction and distance to the target. A programmable logic device (PLD) was used to implement a Boolean function in its disjunctive form. This work demonstrated that such gate level evolvable hardware was able to take advantage of the correlations in the input states and to exhibit useful generalization abilities, thus allowing the evolution of robust behavior in simulation followed by a good transfer into the real world.

In a rather different approach, Ritter et al. used an FPGA implementation of an on-board evolutionary algorithm to develop a controller for a hexapod robot [101]. Floreano and collaborators devised a multi-cellular reconfigurable circuit capable of evolution, self-repair, and adaptation [102] and used it as a substrate for evolving spiking controllers of a wheeled robot [103]. Although evolved hardware controllers are not widely used in evolutionary robotics, they still hold out the promise of some very useful properties, such as robustness to faults, which make them interesting for extreme condition applications such as space robotics.

### 61.9.2 Evolving bodies

In the work described so far there has been an overwhelming tendency to evolve control system for pre-existing robots: the brain is constrained to fit a particular body and set of sensors. Of course in nature the nervous system evolved simultaneously with the rest of the organism. As a result, the nervous system is highly integrated with the sensory apparatus and the rest of the body: the whole operates in a harmonious and balanced way - there are no distinct boundaries between control system, sensors and body. From the start, work at Sussex University incorporated the evolution of sensor properties, including positions, but other aspects of the physical robot were fixed [20]. Although the limitations of not being able to genetically control body morphology were acknowledged at this stage, there were severe technical difficulties in overcoming them, so this issue was somewhat sidelined.



Karl Sims started to unlock the possibilities in his highly imaginative work on evolving simulated 3D “creatures” in an environment with realistic physics [107]. In this work, the creatures co-evolved under a competitive scenario in which they were required to try and gain control of a resource (a cube) placed in the center of an arena. Both the morphology of the creatures and the neural system controlling their actuators were under evolutionary control. Their bodies were built from rigid 3D primitives with the overall morphology being determined by a developmental process encoded as a directed graph. Various kinds of genetically determined joints were allowed between body parts. A variety of sensors could be specified for a specific body part. The simulated world included realistic modeling of gravity, frictions, collisions and other dynamics such that behaviors were restricted to be physically plausible. Many different styles of locomotion evolved along with a variety of interesting, and often entertaining, strategies to capture the resource. These included pushing the opponent away and covering up the cube.

With the later developments of sophisticated physics engines for modeling a variety of physical bodies, Sims’ work inspired a rash of evolved virtual creatures, including realistic humanoid figures capable of a variety of behaviors [99].

In what might be regarded as a step towards evolving robot bodies, Funes and Pollack explored the use of evolutionary algorithms in the design of physical structures taking account of stresses and torques [37]. They experimented with evolving structures assembled from elementary components (Lego bricks). Evolution took place in simulation and the designs were verified in the real world. Stable 3D brick structures such as tables, cranes, bridges and scaffolds were evolved within the restrictions of maximum stress torques at each joint between brick pairs. Each brick is modeled as exerting an external load with a lever arm from its center of mass to the supporting joint, resulting in a network of masses and forces representing the structure. A genetic programming approach was taken using tree structures to represent the 3D LEGO structures. A mutation operator acted on individual brick parameters while sub-tree cross-over allowed more radical changes to the structure. As well as fitness functions designed to encourage particular types of structures, an additional low-level fitness factor favoring the fewest bricks successfully weeded out many of the redundant bricks that inevitably arose. Lego proved to be a predictable building tool with modes of breakage and linkage that could be relatively easily modeled.

While this work was successful, producing very strong designs, it focused on static structures, so was limited in terms of its relevance to functional robotic body parts. However, it did demonstrate a viable approach to evolving physical structures.

While various researchers advocated the use of fully evolvable hardware to develop not only a robot’s control circuits, but also its body plan, which might include the types, numbers and positions of the sensors, the body size, the wheel radius, actuator properties and so on (e.g., [71]), this was still largely confined to theoretical discussion until Lipson and Pollack’s work on the Golem project [70], which was a significant step on from the earlier Lego work [37].

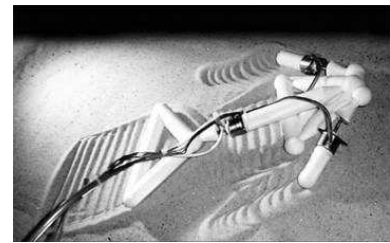


Figure 61.28: A locomoting “creature” evolved by Lipson and Pollack in research which achieved an autonomous design and fabrication process.

Lipson and Pollack, working at Brandeis University, pushed the idea of fully evolvable robot hardware about as far as is reasonably technologically feasible at present. In an important piece of research, directly inspired by Sims’ earlier simulation work, autonomous “creatures” were evolved in simulation out of basic building blocks (neurons, plastic bars, actuators) [70]. The bars could connect together to form arbitrary truss structures with the possibility of both rigid and articulated sub-structures. Neurons could be connected to each other and to bars whose length they would then control via a linear actuator. Machines defined in this way were required to move as far as possible in a limited time. The fittest individuals were then fabricated robotically using rapid manufacturing technology (plastic extrusion 3-D printing) to produce results such as that shown in Figure 61.28). They thus achieved autonomy of design and construction using evolution in a ‘limited universe’ physical simulation coupled to automatic fabrication. The fitness function employed was simply the euclidean distance moved by the center of mass of a machine over a fixed small number of cycles of its neural controller.

A number of different mutation operators acted in concert: small changes to bar or neuron properties, additions and deletions of bars or neurons, changes to connections between neurons and bars, and creation of new vertices. The highly unconventional designs thus realised performed as well in reality as in simulation. The success of this work points the way to new possibilities in developing energy efficient fault tolerant machines.

Pfeifer and colleagues at Zurich University have explored issues central to the key motivation for fully evolvable robot hardware: the balanced interplay between body morphology, neural processing and generation of adaptive behavior [91, 92]. Work from this group has involved a number of approaches, including evolutionary robotics. One focus is on studying how to exploit the dynamic interaction between the embodied agent and the environment. Pfeifer uses the term 'morphological computation' to draw attention to the fact that some of the control of behavior can be performed by the dynamic interaction derived from morphological properties (e.g., the passive forward swing of the leg in walking, the spring-like properties of muscles). By taking morphological computation into account, it is very likely that more robust, energy efficient robots can be developed. Pfeifer has developed a set of design principles for intelligent systems that take into account this balance between environment, morphology and behavior [91].

## 61.10 Closing remarks

Evolutionary Robotics is a young and integrated approach to robot development without human intervention where machines change and adapt by capitalizing on the interactions with their environment. Despite initial skepticism by mainstream and applied robotics practitioners and even by pioneers of this approach [74], over the years the field has been constantly growing with new methods and approaches for evolving more complex, efficient, and sometimes surprising robotic systems. In some areas, such as morphology and self-assembly, Evolutionary Robotics is still the most widely used and powerful approach.

Evolutionary Robotics is not only a method for automatic robot development inspired by biology, but also a tool for investigating open questions in biology concerning evolutionary, developmental, and brain dynamics. Its richness and fecundity make us believe that this approach will further grow and progress towards the creation of a new species of machines capable of self-

evolution.

## Acknowledgments

We thank the anonymous reviewers and Michael Arbib for constructive suggestions and Mototaka Suzuki for further corrections and editorial help. Dario Floreano was supported by the Swiss National Science Foundation.

# Bibliography

- [1] J. Aloimonos, I. Weiss, and A. Bandopadhyay. Active vision. *International Journal of Computer Vision*, 1(4):333–356, 1987.
- [2] M. A. Arbib. Self-reproducing automata – some implications for theoretical biology. In C. H. Waddington, editor, *Towards a Theoretical Biology*, volume 2, pages 204–226. Edinburgh University Press, 1969.
- [3] R. Bajcsy. Active perception. *Proceedings of the IEEE*, 76:996–1005, 1988.
- [4] G. Baldassarre, S. Nolfi, and D. Parisi. Evolving mobile robots able to display collective behavior. *Artificial Life*, 9:255–267, 2003.
- [5] G. Baldassarre, D. Parisi, and S. Nolfi. Coordination and behavior integration in cooperating simulated robots. In S. Schaal, A. Ijspeert, A. Billard, S. Vijayakumar, J. Hallam, and J.-A. Meyer, editors, *From Animals to Animats 8: Proceedings of the VIII International Conference on Simulation of Adaptive Behavior*, pages 385–394. Cambridge, MA, 2003. MIT Press.
- [6] J. M. Baldwin. A new factor in evolution. *American Naturalist*, 30:441–451, 1896.
- [7] D. H. Ballard. Animate vision. *Artificial Intelligence*, 48(1):57–86, 1991.
- [8] D. Barañano, C. Ferris, and S. Snyder. A typical neural messenger. *Trends in Neurosciences*, 24(2):99–106, 2001.
- [9] R. D. Beer. *Intelligence as Adaptive Behavior: An Experiment in Computational Neuroethology*. Academic Press, San Diego, CA, 1990.
- [10] R. D. Beer and J. C. Gallagher. Evolving dynamical neural networks for adaptive behavior. *Adaptive behavior*, 1:94–110, 1992.
- [11] R. D. Beer, R. D. Quinn, H. J. Chiel, and R. E. Ritzmann. Biologically inspired approaches to robotics. *Communications of the ACM*, 40:31–38, 1997.
- [12] R. D. Beer. A dynamical systems perspective on agent-environment interaction. *Artificial Intelligence*, 72:173–215, 1995.
- [13] R. D. Beer, H. J. Chiel, and L. S. Sterling. Heterogeneous neural networks for adaptive behavior in dynamic environments. In D. Touretzky, editor, *Neural Information Processing Systems 1*, pages 577–585. Morgan Kaufman, 1989.
- [14] J. Bongard and H. Lipson. Nonlinear system identification using coevolution of models and tests. *IEEE Transactions on Evolutionary Computation*, 9(4):361–384, 2005.
- [15] V. Braitenberg. *Vehicles. Experiments in Synthetic Psychology*. MIT Press, Cambridge, MA, 1984.
- [16] R. A. Brooks. Intelligence without representation. *Artificial Intelligence*, 47:139–59, 1991.
- [17] R. A. Brooks. Artificial life and real robots. In F. J. Varela and P. Bourguine, editors, *Toward a Practice of Autonomous Systems: Proceedings of the First European Conference on Artificial Life*, pages 3–10. MIT Press, Cambridge, MA, 1992.
- [18] N. Burgess, J. G. Donnett, K. J. Jeffery, and J. O’Keefe. Robotic and neuronal simulation of the hippocampus and rat navigation. *Philosophical Transactions of the Royal Society*, B-352:1535–1543, 1997.
- [19] Y. U. Cao, A. S. Fukunaga, and A. Kahng. Cooperative mobile robotics: Antecedents and directions. *Autonomous Robots*, 4:7–27, 1997.
- [20] D. Cliff, I. Harvey, and P. Husbands. Explorations in evolutionary robotics. *Adaptive Behavior*, 2:73–110, 1993.

- [21] D. T. Cliff. Computational neuroethology: a provisional manifesto. In J.-A. Meyer and S. W. Wilson, editors, *From Animals to Animats: Proceedings of the First International Conference on Simulation of Adaptive Behavior*, pages 29–39. MIT Press-Bradford Books, Cambridge, MA, 1991.
- [22] T. M. Dawson and S. N. Snyder. Gases as biological messengers: Nitric oxide and carbon monoxide in the brain. *Journal of Neuroscience*, 14(9):5147–5159, 1994.
- [23] H. de Garis. Genetic programming: Evolution of time dependent neural network modules which teach a pair of stick legs to walk. In *Proceedings of the 9th European Conference on Artificial Intelligence*, pages 204–206. Stockholm, 1990.
- [24] E. Di Paolo. Evolving spike-timing-dependent plasticity for single-trial learning in robots. *Philosophical Transactions of the Royal Society of London, Series A*, 361:2299–2319, 2003.
- [25] R. Featherstone and D. Orin. Robot dynamics: Equations and algorithms. In *Proceedings of the IEEE International Conference on Robotics and Automation*, pages 826–834. IEEE Press, 2000.
- [26] D. Floreano, T. Kato, D. Marocco, and E. Sauser. Coevolution of active vision and feature selection. *Biological Cybernetics*, 90(3):218–228, 2004.
- [27] D. Floreano and C. Mattiussi. Evolution of Spiking Neural Controllers for Autonomous Vision-Based Robots. In T. Gomi, editor, *Evolutionary Robotics. From Intelligent Robotics to Artificial Life*, pages 38–61. Springer Verlag, Tokyo, 2001.
- [28] D. Floreano, Y. Epars, J.-C. Zufferey, and C. Mattiussi. Evolution of spiking neural circuits in autonomous mobile robots. *International Journal of Intelligent Systems*, 21(9): 1005–1024, 2006.
- [29] D. Floreano, O. Miglino, and D. Parisi. Emergent complex behaviors in ecosystems of neural networks. In E. Caianiello, editor, *Parallel Architectures and Neural Networks*. World Scientific Press, Singapore, 1991.
- [30] D. Floreano and F. Mondada. Automatic creation of an autonomous agent: Genetic evolution of a neural-network driven robot. In D. Cliff, P. Husbands, J.-A. Meyer, and S. W. Wilson, editors, *From Animals to Animats III: Proceedings of the Third International Conference on Simulation of Adaptive Behavior*, pages 402–410. MIT Press-Bradford Books, Cambridge, MA, 1994.
- [31] D. Floreano and F. Mondada. Evolution of plastic neurocontrollers for situated agents. In P. Maes, M. Matarić, J.-A. Meyer, J. Pollack, H. Roitblat, and S. Wilson, editors, *From Animals to Animats IV: Proceedings of the Fourth International Conference on Simulation of Adaptive Behavior*, pages 402–410. MIT Press-Bradford Books, Cambridge, MA, 1996.
- [32] D. Floreano and S. Nolfi. Adaptive behavior in competing co-evolving species. In P. Husbands and I. Harvey, editors, *Proceedings of the 4th European Conference on Artificial Life*, pages 378–387. Cambridge, MA, 1997. MIT Press.
- [33] D. Floreano, M. Suzuki, and C. Mattiussi. Active vision and receptive field development in evolutionary robots. *Evolutionary Computation*, 13(4):527–544, 2005.
- [34] D. Floreano and J. Urzelai. Evolutionary robots with online self-organization and behavioral fitness. *Neural Networks*, 13:431–443, 2000.
- [35] D. Floreano and J. Urzelai. Neural morphogenesis, synaptic plasticity, and evolution. *Theory in Biosciences*, 120(3-4):225–240, 2001.
- [36] P. Funes, B. Orme, and E. Bonabeau. Evolving emergent group behaviors for simple humans agents. In J. Dittrich and T. Kim, editors, *Proceedings of the Seventh European Conference on Artificial Life*, pages 76–89. Berlin: Springer Verlag, 2003.
- [37] P. Funes and J. Pollack. Evolutionary body building: adaptive physical designs for robots. *Artificial Life*, 4(4):337–357, 1998.
- [38] J. Gallagher, R. Beer, M. Espenschiel, and R. Quinn. Application of evolved locomotion controllers to a hexapod robot. *Robotics and Autonomous Systems*, 19(1):95–103, 1996.
- [39] J. A. Gally, P. R. Montague, G. N. Reeke, and G. M. Edelman. The NO hypothesis: Possible effects of a short-lived, rapidly diffusible signal in the development and function of the nervous system. *Proceedings of the National Academy of Sciences USA*, 87:3547–3551, 1990.

- [40] S. Galt, B. L. Luk, and A. A. Collie. Evolution of smooth and efficient walking motions for an 8-legged robot. In *Proceedings of the 6th European Workshop on Learning Robots*. Brighton, UK, 1997.
- [41] J. Garthwaite and C. L. Boulton. Nitric oxide signaling in the central nervous system. *Annual Review of Physiology*, 57:683–706, 1995.
- [42] W. Gerstner, J. L. van Hemmen, and J. D. Cowan. What matters in neuronal locking? *Neural Computation*, 8:1653–1676, 1996.
- [43] D. E. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Addison-Wesley, Redwood City, CA, 1989.
- [44] T. Gomi and K. Ide. Emergence of gaits of a legged robot by collaboration through evolution. In *IEEE World Congress on Computational Intelligence*. IEEE Press, New York, 1998.
- [45] F. Gruau. Automatic definition of modular neural networks. *Adaptive Behavior*, 3(2):151–183, 1995.
- [46] F. Gruau and K. Quatramaran. Cellular encoding for interactive evolutionary robotics. In P. Husbands and I. Harvey, editors, *Proceeding 4th European Conference on Artificial Life*, pages 368–377. MIT Press, 1997.
- [47] P. J. Hancock, R. J. Baddeley, and L. S. Smith. The principal components of natural images. *Network*, 3:61–70, 1992.
- [48] I. Harvey, E. A. Di Paolo, R. Wood, M. Quinn, and E. Tuci. Evolutionary robotics: A new scientific tool for studying cognition. *Artificial Life*, 11(1-2):79–98, 2005.
- [49] I. Harvey, P. Husbands, D. T. Cliff, A. Thompson, and N. Jakobi. Evolutionary robotics: The Sussex approach. *Robotics and Autonomous Systems*, 20:205–224, 1997.
- [50] I. Harvey, P. Husbands, and D. T. Cliff. Seeing the light: Artificial evolution, real vision. In D. T. Cliff, P. Husbands, J.-A. Meyer, and S. Wilson, editors, *From Animals to Animats 3: Proceedings of the Third International Conference on Simulation of Adaptive behavior, SAB94*, pages 392–401. MIT Press, Cambridge, Massachusetts, 1994.
- [51] S. Healy, editor. *Spatial Representations in Animals*. Oxford University Press, Oxford, UK, 1998.
- [52] R. Held. Plasticity in sensory-motor systems. *Scientific American*, 213(5):84–94, Nov 1965.
- [53] R. Held and A. Hein. Movement-produced stimulation in the development of visually guided behavior. *Journal of Comparative and Physiological Psychology*, 56(5):872–876, 1963.
- [54] J. H. Holland. *Adaptation in Natural and Artificial Systems*. The University of Michigan Press, Ann Arbor, 1975.
- [55] C. Hölscher. Nitric oxide, the enigmatic neuronal messenger: Its role in synaptic plasticity. *Trends in Neurosciences*, 20:298–303, 1997.
- [56] P. Husbands and I. Harvey. Evolution versus design: Controlling autonomous robots. In *Integrating Perception, Planning and Action, Proceedings of 3rd IEEE Annual Conference on Artificial Intelligence, Simulation and Planning*, pages 139–146. IEEE Press, 1992.
- [57] P. Husbands, I. Harvey, D. Cliff, and G. Miller. Artificial evolution: A new path for AI? *Brain and Cognition*, 34:130–159, 1997.
- [58] P. Husbands, T. Smith, N. Jakobi, and M. O’Shea. Better living through chemistry: Evolving GasNets for robot control. *Connection Science*, 10(4):185–210, 1998.
- [59] G. Indiveri and P. Verschure. Autonomous vehicle guidance using analog VLSI neuromorphic sensors. In W. Gerstner, A. Germond, M. Hasler, and J.-D. Nicoud, editors, *Proceedings of the 7th International Conference on Neural Networks*, pages 811–816, Berlin, 1997. Springer Verlag.
- [60] N. Jakobi. Half-baked, ad-hoc and noisy: Minimal simulations for evolutionary robotics. In P. Husbands and I. Harvey, editors, *Proceedings of the 4th European Conference on Artificial Life*, pages 348–357, Cambridge, MA, 1997. MIT Press.
- [61] N. Jakobi. Evolutionary robotics and the radical envelope of noise hypothesis. *Adaptive behavior*, 6:325–368, 1998.
- [62] N. Jakobi. Running across the reality gap: Octopod locomotion evolved in a minimal simulation. In P. Husbands and J.-A. Meyer, editors, *Evolutionary Robotics: First European Workshop, EvoRobot98*, pages 39–58. Springer, 1998.

- [63] N. Jakobi, P. Husbands, and I. Harvey. Noise and the reality gap: The use of simulation in evolutionary robotics. In F. Moran, A. Moreno, J. J. Merelo, and P. Chacon, editors, *Advances in Artificial Life: Proceedings of the 3rd European Conference on Artificial Life*, pages 704–720. Springer-Verlag, Lecture Notes in Artificial Intelligence 929, 1995.
- [64] D. Keymeulen, M. Durantez, M. Konaka, Y. Kuniyoshi, and T. Higuchi. An evolutionary robot navigation system using a gate-level evolvable hardware. In T. Higuchi, editor, *Proceedings of the 1st International Conference on Evolvable Systems: From Biology to Hardware, LNCS vol. 1259*, pages 195–209. Springer, 1996.
- [65] J. Kodjabachian and J.-A. Meyer. Evolution and development of neural networks controlling locomotion, gradient following and obstacle avoidance in artificial insects. *IEEE Transactions on Neural Networks*, 9:796–812, 1998.
- [66] J. F. Laszlo, M. van de Panne, and E. Fiume. Limit cycle control and its application to the animation of balancing and walking. In *Proceedings of SIGGRAPH'96, vol. 30*, pages 155–162. ACM, 1996.
- [67] M. A. Lewis, R. Etienne-Cummings, A. H. Cohen, and M. Hartmann. Toward biomorphic control using custom aVLSI CPG chips. In *Proceedings of IEEE International Conference on Robotics and Automation*, pages 494–500. IEEE Press, 2000.
- [68] M. A. Lewis, A. H. Fagg, and A. Solidum. Genetic programming approach to the construction of a neural network for a walking robot. In *Proceedings of IEEE International Conference on Robotics and Automation*, pages 2618–2623. IEEE Press, 1992.
- [69] M. A. Lewis, A. H. Fagg, and G. Bekey. Genetic algorithms for gait synthesis in a hexapod robot. In Y. Zheng, editor, *Recent Trends in Mobile Robots*, pages 317–331. World Scientific, New Jersey, 1994.
- [70] H. Lipson and J. Pollack. Automatic design and manufacture of robotic lifeforms. *Nature*, 406:974–978, 2000.
- [71] H. H. Lund, J. Hallam, and W. P. Lee. Evolving robot morphology. In *Proceedings of IEEE Fourth International Conference on Evolutionary Computation*, pages 197–202. IEEE Press, 1997.
- [72] W. Maas and C. M. Bishop, editors. *Pulsed Neural Networks*. MIT Press, Cambridge, MA, 1999.
- [73] D. Marocco and S. Nolfi. Self-organization of communication in evolving robots. In L. Rocha, L. Yeager, M. Bedau, D. Floreano, R. Goldstone, and A. Vespignani, editors, *Proceeding of the Tenth International Conference on Artificial Life*, pages 178–184. Cambridge, MA, 2006. MIT Press.
- [74] M. Matarić and D. Cliff. Challenges in evolving controllers for physical robots. *Robotics and Autonomous Systems*, 19(1):67–83, 1996.
- [75] H. R. Maturana and F. J. Varela. *Autopoiesis and Cognition: The Realization of the Living*. Dordrecht: Reidel, 1980.
- [76] G. Mayley. Landscapes, learning costs, and genetic assimilation. *Evolutionary Computation*, 4:213–234, 1997.
- [77] T. McGeer. Passive walking with knees. In *Proceedings of the IEEE Conference on Robotics and Automation, vol.2*, pages 1640–1645. IEEE Press, 1990.
- [78] G. McHale and P. Husbands. GasNets and other evolvable neural networks applied to bipedal locomotion. In S. Schaal, editor, *From Animals to Animats 8: Proceedings of the 8th International Conference on Simulation of Adaptive behavior, SAB'2004*, pages 163–172. MIT Press, 2004.
- [79] G. McHale and P. Husbands. Quadrupedal locomotion: Gasnets, CTRNNs and hybrid CTRNN/PNNs compared. In J. Pollack, M. Bedau, P. Husbands, T. Ikegami, and R. Watson, editors, *Proceedings of the 9th International Conference on the Simulation and Synthesis of Living Systems (Alife IX)*, pages 106–112. MIT Press, 2004.
- [80] O. Miglino, H. H. Lund, and S. Nolfi. Evolving mobile robots in simulated and real environments. *Artificial Life*, 2:417–434, 1996.
- [81] F. Mondada, E. Franzi, and P. Ienne. Mobile robot miniaturization: A tool for investigation in control algorithms. In T. Yoshikawa and F. Miyazaki, editors, *Proceedings of the Third International Symposium on Experimental Robotics*, pages 501–513. Tokyo, 1993. Springer Verlag.

- [82] F. Mondada, G. Pettinaro, A. Guignard, I. Kwee, D. Floreano, J.-L. Deneubourg, S. Nolfi, L.M. Gambardella, and M. Dorigo. Swarm-bot: A new distributed robotic concept. *Autonomous Robots*, 17:193–221, 2004.
- [83] S. Nolfi. Power and limits of reactive agents. *Neurocomputing*, 42:119–145, 2002.
- [84] S. Nolfi. Behaviour as a complex adaptive system: On the role of self-organization in the development of individual and collective behavior. *ComplexUs*, 2006.
- [85] S. Nolfi and D. Floreano. Learning and evolution. *Autonomous Robots*, 7:89–113, 1999.
- [86] S. Nolfi and D. Floreano. *Evolutionary Robotics: The Biology, Intelligence, and Technology of Self-Organizing Machines*. Cambridge, MA: MIT Press/Bradford Books, 2000.
- [87] S. Nolfi and D. Parisi. Learning to adapt to changing environments in evolving neural networks. *Adaptive behavior*, 1:75–98, 1997.
- [88] J. O’Keefe and L. Nadel. *The Hippocampus as a Cognitive Map*. Clarendon Press, Oxford, 1978.
- [89] D. Parisi, F. Cecconi, and S. Nolfi. Econets: Neural networks that learn in an environment. *Network*, 1:149–168, 1990.
- [90] A. Perez-Urbe, D. Floreano, and L. Keller. Effects of group composition and level of selection in the evolution of cooperation in artificial ants. In *Proceedings of the 7th European Conference on Artificial Life (ECAL’2003)*, pages 128–137, Berlin, 2003. Springer Verlag.
- [91] R. Pfeifer, F. Iida, and J. Bongard. New robotics: Design principles for intelligent systems. *Artificial Life*, 11(1-2):99–120, 2005.
- [92] R. Pfeifer and C. Scheier. *Understanding Intelligence*. MIT Press, Cambridge, MA, 1999.
- [93] A. O. Philippides, P. Husbands, and M. O’Shea. Four-dimensional neuronal signaling by nitric oxide: A computational analysis. *Journal of Neuroscience*, 20(3):1199–1207, 2000.
- [94] A. O. Philippides, P. Husbands, T. Smith, and M. O’Shea. Structure based models of NO diffusion in the nervous system. In J. Feng, editor, *Computational Neuroscience: a Comprehensive Approach*, pages 97–130. Chapman and Hall/CRC Press, 2003.
- [95] A. O. Philippides, P. Husbands, T. Smith, and M. O’Shea. Flexible couplings: Diffusing neuromodulators and adaptive robotics. *Artificial Life*, 11(1-2):139–160, 2005.
- [96] A. O. Philippides, S. R. Ott, P. Husbands, T. Lovick, and M. O’Shea. Modeling co-operative volume signaling in a plexus of nitric oxide synthase-expressing neurons. *Journal of Neuroscience*, 25(28):6520–6532, 2005.
- [97] M. Quinn. Evolving communication without dedicated communication channels. In J. Kelemen and P. Sosik, editors, *Proceedings of the Sixth European Conference on Artificial Life*, pages 357–366. Berlin: Springer Verlag, 2001.
- [98] M. Quinn, L. Smith, G. Mayley, and P. Husbands. Evolving controllers for a homogeneous system of physical robots: Structured cooperation with minimal sensors. *Philosophical Transactions of the Royal Society of London, Series A: Mathematical, Physical and Engineering Sciences*, 361:2321–2344, 2003.
- [99] T. Reil and P. Husbands. Evolution of central pattern generators for bipedal walking in real-time physics environments. *IEEE Transactions on Evolutionary Computation*, 6(2):10–21, 2002.
- [100] F. Rieke, D. Warland, R. van Steveninck, and W. Bialek. *Spikes:: Exploring the neural code*. MIT Press, Cambridge, MA, 1997.
- [101] G. Ritter, J.-M. Puiatti, and E. Sanchez. Leonardo and discipulus simplex: An autonomous, evolvable six-legged walking robot. In J. Rolim, editor, *Parallel and Distributed Processing, LNCS vol 1586*, pages 688–696. Springer, 1999.
- [102] D. Roggen, D. Floreano, and C. Mattiussi. A morphogenetic evolutionary system: Phylogenesis of the POETIC circuit. In A. M. Tyrrell, P. C. Haddow, and J. Torresen, editors, *Proceedings of the Fifth International Conference on Evolvable Systems*, pages 83–99, Heidelberg, 2003. Springer Verlag.

- [103] D. Roggen, S. Hofmann, Y. Thoma, and D. Floreano. Hardware spiking neural network with runtime reconfigurable connectivity in an autonomous robot. In J. Lohn, R. Zebulum, J. Steincamp, D. Keymeulen, A. Stoica, and M. I. Ferguson, editors, *NASA/DoD Conference on Evolvable Hardware*, pages 189–198, IEEE Press, 2003. Los Alamitos, CA.
- [104] D. E. Rumelhart, J. McClelland, and PDP Group. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition: Foundations*. MIT Press-Bradford Books, Cambridge, MA, 1986.
- [105] T. D. Sanger. Optimal unsupervised learning in a single-layer feedforward neural network. *Neural Networks*, 2:459–473, 1989.
- [106] N. A. Schmajuk and H. T. Blair. Place learning and the dynamics of spatial navigation: A neural network approach. *Adaptive Behaviour*, 1:353–385, 1993.
- [107] K. Sims. Evolving 3D morphology and behavior by competition. In R. A. Brooks and P. Maes, editors, *Proceedings of Artificial Life IV*, pages 28–39. MIT Press, 1994.
- [108] T. M. C. Smith, P. Husbands, and M. O’Shea. Local evolvability, neutrality, and search difficulty in evolutionary robotics. *Biosystems*, 69:223–243, 2003.
- [109] T. M. C. Smith, P. Husbands, A. Philippides, and M. O’Shea. Neuronal plasticity and temporal adaptivity: Gasnet robot control networks. *Adaptive Behaviour*, 10(3/4):161–184, 2002.
- [110] K. O. Stanley and R. Miikkulainen. Evolving neural networks through augmenting topologies. *Evolutionary Computation*, 10(2):99–127, 2002.
- [111] L. Steels, editor. *The Biology and Technology of Intelligent Autonomous Agents*. Springer-Verlag – NATO ASI Series, Berlin, 1995.
- [112] M. Suzuki, D. Floreano, and E. A. Di Paolo. The contribution of active body movement to visual development in evolutionary robots. *Neural Networks*, 18(5/6):656–665, 2005.
- [113] J. S. Taube, R. U. Muller, and J. B. Jr. Ranck. Head-direction cells recorded from the postsubiculum in freely moving rats. I. Description and quantitative analysis. *Journal of Neuroscience*, 10:420–435, 1990.
- [114] A. Thompson. Evolving electronic robot controllers that exploit hardware resources. In F. Moran, A. Moreno, J. J. Merelo, and P. Chacon, editors, *Advances in Artificial Life: Proceedings of the 3rd European Conference on Artificial Life*, pages 640–656. Springer-Verlag, Lecture Notes in Artificial Intelligence 929, 1995.
- [115] A. Thompson. Artificial evolution in the physical world. In T. Gomi, editor, *Evolutionary Robotics. From Intelligent Robots to Artificial Life (ER’97)*, pages 101–125. AAI Books, 1997.
- [116] A. Thompson. *Hardware Evolution: Automatic Design of Electronic Circuits in Reconfigurable Hardware by Artificial Evolution*. Distinguished Dissertation Series. Springer, Berlin, 1998.
- [117] V. Trianni, S. Nolfi, and M. Dorigo. Cooperative hole-avoidance in a swarm-bot. *Robotics and Autonomous Systems*, 54:97–103, 2006.
- [118] A. M. Turing. Computing machinery and intelligence. *Mind*, LIX 236:433–460, 1950.
- [119] R. Tllez, C. Angulo, and D. Pardo. Evolving the walking behavior of a 12 DOF quadruped using a distributed neural architecture. In *Proceedings of the 2nd International Workshop on Biologically Inspired Approaches to Advanced Information Technology (Bio-ADIT’2006)*, LNCS vol. 3853, pages 5–19. Springer, 2006.
- [120] J. Urzelay and D. Floreano. Evolution of adaptive synapses: Robots with fast adaptive behavior in new environments. *Evolutionary Computation*, 9:495–524, 2001.
- [121] E. Vaughan, E. A. Di Paolo, and I. Harvey. The evolution of control and adaptation in a 3D powered passive dynamic walker. In J. Pollack, M. Bédau, P. Husbands, T. Ikegami, and R. Watson, editors, *Proceedings of the Ninth International Conference on the Simulation and Synthesis of Living Systems, Artificial Life IX*, pages 139–145. MIT Press, 2004.



- [122] E. Vaughan, E. A. Di Paolo, and I. Harvey. The tango of a load balancing biped. In M. Armada and P. Gonzalez De Santos, editors, *Proceedings of the Seventh International Conference on Climbing and Walking Robots (CLAWAR)*. Springer, 2004.
- [123] B. von Haller, A. J. Ijspeert, and D. Floreano. Co-evolution of structures and controllers for Neobot underwater modular robots. In M. S. Capcarrere, A. A. Freitas, P. J. Bentley, C. G. Johnson, and J. Timmis, editors, *8th European Conference on Artificial Life (ECAL'2005)*, pages 189–199, Berlin, 2005. Springer Verlag.
- [124] C. H. Waddington. Canalization of development and the inheritance of acquired characters. *Nature*, 150:563–565, 1942.
- [125] M. Waibel, D. Floreano, S. Magnenat, and L. Keller. Division of labour and colony efficiency in social insects: effects of interactions between genetic architecture, colony kin structure and rate of perturbations. *Proceedings of the Royal Society B*, 273:1815–23, 2006.
- [126] J. Wood and J. Garthwaite. Models of the diffusional spread of nitric oxide: Implications for neural nitric oxide signaling and its pharmacological properties. *Neuropharmacology*, 33:1235–1244, 1994.