The Importance of Viewing Cognition as the Result of Emergent Processes Occurring at Different Time Scales

S. Nolfi[1], G. Baldassarre[1], and D. Marocco[2 1]

[1]Institute of Cognitive Science and Technologies
National Research Council (CNR) - Viale Marx, 15, 00137, Roma, Italy

[2] University of Calabria, "Centro Interdipartimentale della Comunicazione"
87036 Arcavacata di Rende, Cosenza, Italy

E-mail: nolfi,baldassarre,dmarocco@ip.rm.cnr.it

Abstract. In this paper we will show how robots that are able to exploit behavior that emerge from fine-grained interaction with the physical and social environment can solve complex problems in simple and effective ways. By exploiting the interaction with the environment robots are also able to produce dynamical behaviors involving phases that extend over time scales that are significant larger than the time scale at which interactions with the environment occur. Moreover, we will show how problems that require robots able to detect regularities occurring at different time scales might require control systems that are able to process sensory-motor information at different time scales and to detect amount of changes in amount of time.

1 Introduction

A new research paradigm, that has been called *Embodied Cognitive Science* [1-4], has recently challenged the traditional view according to which intelligence is an abstract process that can be studied without taking into consideration the physical aspects of natural systems. In this new paradigm, researchers tend to stress (1) situatedness, i.e., the importance of studying systems that are situated in an environment [2-3], (2) embodiment, i.e., the importance of study systems that have bodies, receive input from their sensors and produce motor actions as output [2-3], and (3) emergence, i.e. the importance of viewing behavior and intelligence as the emergent result of fine-grained interactions between the control system of an agent including its constituents parts, the body structure, and the environment. An important consequence of this view is that the agent and the environment constitutes a single system, i.e. the two aspects are so intimately connected that a description of each of them in isolation does not make much sense [1, 5].

By reviewing the results of a set of evolutionary experiments in which robots are free to develop their skills in close interaction with the environment [6] we will show that in many cases robots can solve complex problems in simple and effective ways by exploiting behaviors that emerge from fine-grained interactions. Moreover, we will show that in order to detect regularities occurring at different time scales, robots might need control systems able to work at different time rates.

2 Exploiting the interaction with the environment

The behavior of embodied and situated organisms is an emergent result of the dynamical interaction between the nervous system, the body, and the external environment [5, 7]. This simple consideration has several important consequences that are far from being fully understood. One important aspect, for instance, is the fact that motor actions partially determine the sensory pattern that organisms receive from the environment. By coordinating sensory and motor processes organisms can select favorable sensory patterns and thus enhance their ability to achieve their adaptive goals.

Examples of processes falling within this category have been identified in natural organisms. Dill *et al.* demonstrated that since the fruit fly *drosophila* cannot always recognize a pattern appearing at different locations in the retina, the insect solves this problem of shift invariance by moving so to bring the pattern to the same retinal location where it has been presented during the storage process [8]. Franceschini demonstrated that flies use motion to visually identify the depth of perceived obstacles [9]. Moreover, there is evidence that environmental feedback obtained through motor actions plays a crucial role in normal development [10, 11].

In artificial system, however, aside a few notable exceptions [12-15], the possibility to design systems that exploit sensory-motor coordination is still largely unexplored. This can be explained by considering that, as we said above, behavior is the emergent result of the interactions between the individual and the environment. Given that in dynamical systems there is a complex and indirect relation between the rules that determine the interactions and the emergent result of those interactions, it is very difficult to identify how the interactions between the organism and the external environments contribute to the resulting behavior. As a consequence, designing systems that exploit sensory-motor coordination is rather difficult (for an attempt to identify new design principles that might help to achieve this goal, see [4]).

From this point of view evolutionary experiments where robots autonomously develop their skills in close interaction with the environment represent an ideal framework for studying sensory-motor coordination. Indeed, in most of the experiment conducted with artificial evolution one can observe the emergence of behavior exploiting sensory-motor coordination to solve difficult tasks.

As an example consider the case of a robot with an artificial finger that has to discriminate objects with different shapes on the basis of simple tactile information [16]. The finger consists of 3-segments with 6 degrees of freedom (DOF) and extremely coarse touch sensors (see Figure 1, left).

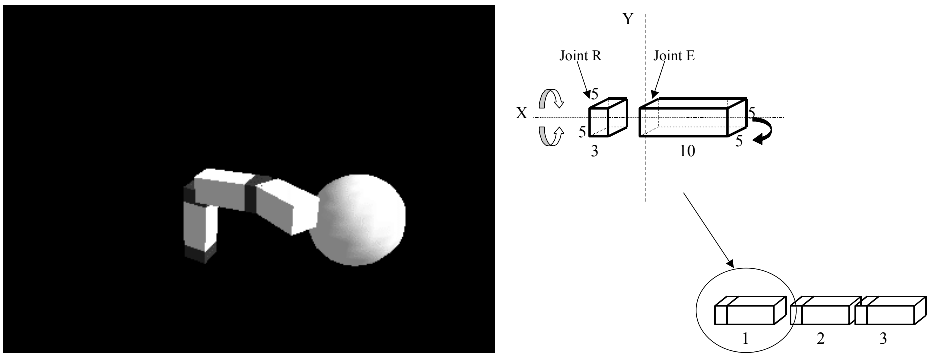

Figure 1. Left: The artificial finger and a spherical object. Right: A schematic representation of the finger.

To reduce the time necessary to test individual behaviors and model the real physical dynamics as accurately as possible we used the rigid body dynamics simulation SDK of Vortex^{TM} (see http://www.cm-labs.com/products/vortex/). This software allowed to build our robotic finger by means of several bodies connected between joints and to run simulations faster than real time.

The artificial finger consists in a basic structure of two bodies and two joints replicated for three times (see Figure 1). This two bodies are connected by means of a joint (i.e. the *Joint E* in the Figure) that allows only one DOF on axis *Y* , while the shorter body is connected at the floor, or at the longer body, by means of a joint (i.e. the *Joint R*) that provides one DOF on axis *X*. In practice, the *Joint E* allows to elevate and lower the connected segments and the *Joint R* allows to rotate them in both direction. *Joint E and Joint R* are free to moves only in a range between [0 and $\pi/2$] and [$-\pi/2$, $+\pi/2$], respectively. Each actuator is provided with a corresponding motor that can apply a maximum force of 50. Therefore, to reach every position in the environment the control system has to appropriately control several joints and to deal with the constraints due to gravity.

The sensory system consists of three simple contact sensors placed on each longer body that detects when these bodies collides with an other body and six proprioceptive sensors that provide the current position of each joint.

Each individual of the population was tested for 36 epochs, each epoch consisting of 150 lifecycles. At the beginning of each epoch the finger is fully extended and a spherical or a cubic object is placed in a random selected position in front of the finger (the position of the object is randomly selected between the following intervals: 20.0 >= X <= 30.0; 7.5 >= Y <= 17.5; -10.0 >= Z <= 10.0). The object is a sphere (15 units in diameter) during even epochs and a cube (15 units in side) during odd epochs so that each individual has to discriminate the same number of spherical and cubic objects during its "lifetime".

The controller of each individual consists of a neural networks with 10 sensory neurons directly connected to 7 motor neurons and 2 internal neurons receiving connections from the sensory neurons and from themselves and projecting connections to the motor neurons. The first 9 sensory neurons encode the angular position (normalized between 0.0 and 1.0) of the 6 DOF of the joints and the state of the three contact sensors located in the three corresponding segments of the finger. The last sensory neuron is a copy of the last motor neuron that encode the current classification produced by the individual (see below). The first 6 motor neurons control the actuators of the 6 corresponding joints. The output of the neurons is normalized between [0, $+\pi/2$] and [$-\pi/2$, $+\pi/2$] in the case of elevation or rotational joints respectively and is used to encode the desired position of the corresponding joint. The motor is activated so to apply a force (up to 50) proportional to the difference between the current and the desired position of the joint. The seventh motor neuron encodes the classification of the object produced by the individual (value below or above 0.5 are interpreted as classifications corresponding to a cubic or spherical object respectively). The classification is correct if at the end of the epoch (i.e. after 150 cycles) the activation of the last motor units is below 0.5 and the object is a cube or is above 0.5 and the object is a sphere.

By running 10 replications of the experiment and by evolving individuals for 50 generations we observed that in many of the replications evolved individuals display a good ability to discriminate the two objects and, in some cases, they produce close to optimal performance.

By analyzing the obtained behaviors one can clearly see that in all experiments evolved individuals select a well defined behavior that assures that perceived sensory states corresponding to different objects can be easily discriminated and allows robust and effective categorizations. Figure 2 shows how a typical evolved individual behave with a spherical and a cubic object (left and right side of the Figure respectively). As can be seen, first the finger bends on the left side and move to the right so to start to feel the object with the touch sensor of the third segment. Then the finger moves so to follow the curvilinear surface of the sphere or so to keep touching one of the angle of the cubic object.

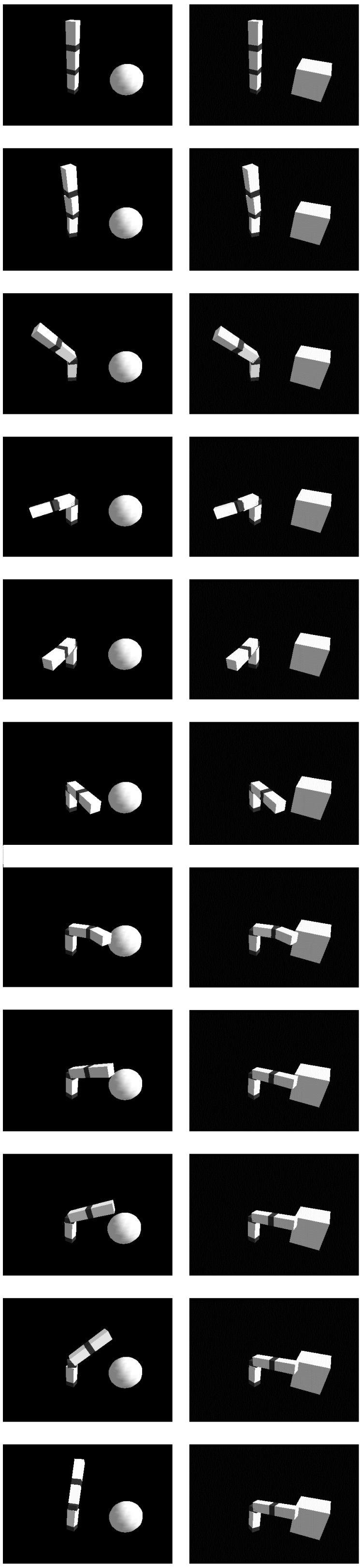

Figure 2. Behavior of a typical evolved individual during an epoch (150 cycles) in which the object consists of a sphere (left pictures) and of a cube (right pictures). For reason of space, the pictures show the position of the finger each 15 cycles.

The fact that such behavior significantly simplifies the discrimination of the two objects can be explained by considering that the finger ends in very different conditions in the case of a sphere or of a cubic object. In particular, after a certain amount of time in which the finger is negotiating with the object, it ends almost fully extended in the case of spherical object and almost fully bended in the case of a cubic object. This implies that, given such a behavior, the state of the proprioceptive sensors after a certain amount of time can be used as a direct and straightforward indication of the category of the object. The fact that such behavior allows evolved individuals to produce robust and effective classifications can be explained by considering that the final classification is not the result of a single decision but is the end result of an interaction between the agent and the object that last several lifecycles during which the agent keeps following the surface of the object so to ascertain it is curvilinear or not. Indeed, evolved individuals that display shorter negotiation periods with spherical objects also produce worse classification performance (result not shown).

The fact that, at the end of the epoch, the internal units tend to have the same activation states in the two cases [16] shows that the classification is not accomplished on the basis of internal information extracted during the interaction between the finger and the object but rather on the basis of the final position of finger itself that, as claimed above, directly provide a clear indication of the category of the object with which the agent has previously interacted.

Other similar evolutionary experiments revealed several other ways in which evolved robots can exploit sensory-motor coordination [14], such as to: (a) increase the frequency of sensory states to which they can react more effectively and reduce the frequency of sensory states to which they react less effectively [17]; (b) select sensory states in which groups of sensory patterns requiring different motor answers do not strongly overlap [18]; (c) increase the perceived differences between different objects [19, 20]; (d) select useful learning experiences [19]; (d) exploit behavioral attractors resulting from the interaction between the robot and the environment [14].

2 Exploiting social interactions

In the previous section we discussed how individual robots might exploit behaviors emerging from the interaction between the robot and the environment. The ability to exploit fine-grained interaction between the robot and the environment allow individual robots to solve non-trivial problem in rather simple and effective ways.

In this section we will discuss how a group of robots that are placed in the same environment might exploit the interaction between themselves. Also in this case, we will see that: (a) by exploiting interactions, groups of robots might solve complex problems in rather simple and effective ways, and (b) artificial evolution is an ideal framework for synthesizing robots able to exploit emergent behavior, i.e. behavior that emerge from a large number of interactions among constituent parts.

Consider the case of four assembled robots forming a linear structure (see Figure 3) that are asked to move as straight and as fast as possible [21]. Given that the orientation of each individual robot might vary, robots should first negotiate a common direction and then move along such a direction in a coordinated fashion. This is one of the control problem we are facing within a research project founded by CEC in which we are trying to develop a Swarm-bots [22-24], i.e. group of individual robots (called s-bots) that are able to self-assemble into different physical structures and to cooperate in order to solve problems that cannot be solved by a single s-bot.

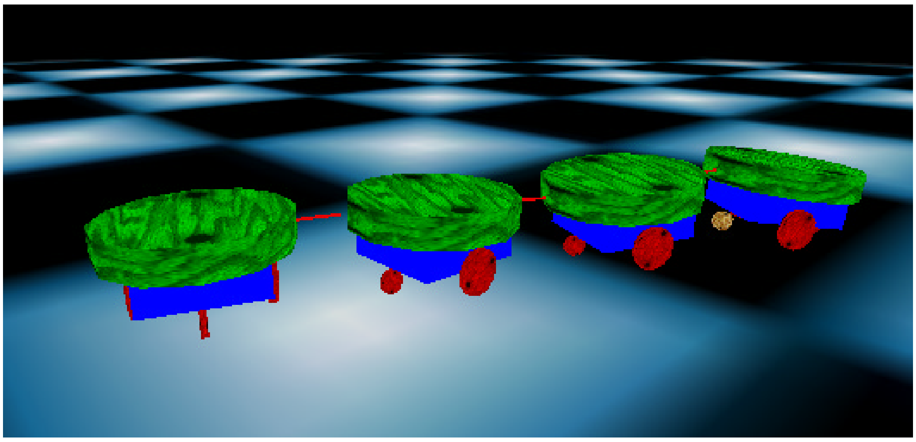

Figure 3. A swarm-bot composed of four aggregated s-bots forming a linear structure.

Experiments have been conducted in simulation by developing a software based on the rigid body dynamics simulator SDK of Vortex^{TM} [24]. Each s-bot (Figure 4, left) consists of a rectangular chassis provided with two motorised and two passive wheels and of a cylindrical turret that is connected to the chassis through a "hinge joint" and can rotate freely around the vertical axis with respect to the chassis. Each s-bot has also a physical link through which it can be attached to another robot along the perimeter of its turret. The link consists of another "hinge joint" that has a rotation axis parallel to the horizontal plane and perpendicular to the line formed by the four robots (i.e. it is rigid with respect to the horizontal plane).

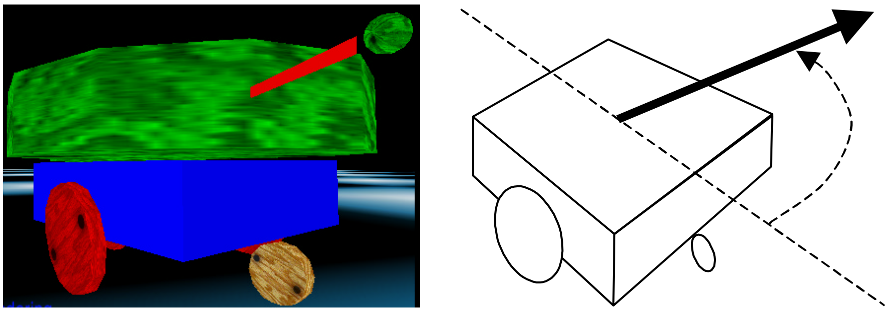

Figure 4. Left: A single s-bot. The upper and the lower part of the body represent the turret and the chassis, respectively. The larger and the smaller wheel represent the motorized and passive wheels, respectively. The line represents the link through which an s-bot is attached to another s-bot. **Right**: The traction force detected by the sensors of the s-bot. The dashed line indicates the frontal direction of the s-bot. The full arrow indicates the traction that the turret exerts on the chassis. The dashed arrow indicates the angle between the traction force and the frontal direction of the chassis.

The two motorised joints controlling the two corresponding motorized wheels are controlled by setting the desired angular speed of the joint and the maximum torque that the motor can generate.

Each s-bot is provided with a sensor placed at the junction between the chassis and the turret that returns the direction (i.e. the angle with respect to the chassis' orientation) and intensity of the force of traction that the turret exerts on the chassis (Figure 4, right). Henceforth this force will be called "traction" for simplicity. A traction force might be due both to the movements of other connected s-bots and/or to the movement of the s-bot itself.

Notice that the turrets of the s-bots, by physically integrating the different forces that are applied to the robot by its own chassis and by the other s-bots, directly provide an indication of the average direction toward which the group is trying to move as a whole. More precisely, it measures the mismatch between the direction where the whole group is trying to move and the orientation of the robot's chassis. The intensity of the traction is a measure of the dimension of this mismatch. From the point of view of each s-bot, this type of information is obviously particularly relevant to change the direction of its own chassis to follow the rest of the group or to push the group to move toward a different desired direction.

The initial population consists of 100 randomly generated genotype strings that encode the connection weights of 100 corresponding neural controllers. Each controller is made up of a neural network with 4 sensory neurons that encode the state of the traction sensor and that are directly connected with 2 motor neurons that control the two corresponding wheels. The four sensory neurons encode the intensity of the traction from four different orientations with respect to the chassis (front, back, left and right). The intensity of the traction is normalized in the range [0.0, 1.0] on the basis of the maximum value observed in an experiment in which s-bots moved randomly, and linearly scaled with the difference with respect to the orientation of the sensors so that, for example, a maximum traction from the front side produces an activation of 1.0 only of the front sensor while a maximum traction from the front-left side results in an activation value of 0.5 of both the front and left sensors. The activation state of the motor units is normalized between [-10.0, 10.0] and is used to set the desired speed of the two corresponding wheels. Each connection weight is represented in the genotype with 8 bits that are transformed in a number in the interval [–10, +10]. Therefore, the total length of the genotype is 10 (8 connection weights and two biases) * 8 = 80 bits. A single-pool-single-genotype selection schema [25-26] was used, i.e. we evolved a single population of genotypes each of which encoded the connection weights of a team of identical neural controllers.

Each genotype is translated into 4 identical neural controllers corresponding to a group of 4 assembled s-bots forming a linear structure. The group is allowed to "live" for 5 "epochs" (each epoch consists of 150 cycles). During each cycle, for each s-bot: (1) the activation state of the sensors is set according to the procedure described above; (2) the activation state of the two motor neurons is computed according to the standard logistic function; (3) the desired speed of the two wheels is set according the activation states of the motor units. At the beginning of each epoch the chassis of the four s-bots are placed in randomly selected orientations. However, to assure a fair comparisons between the performance displayed by different teams, all teams of the same generation started with the same 5 randomly selected orientations in the 5 corresponding epochs. The orientation of the tracks of each individual s-bot is randomly set at the beginning of each epoch. The best 20 genotypes of each generation were allowed to reproduce by generating 5 copies of their genotype with 3% of their bits replaced with a new randomly selected value. The evolutionary process lasted 100 generations.

To force the assembled swarm-bot to move as fast and as straight as possible, we devised a fitness function that compute the Euclidean distance between the barycentre of the team at the beginning and at the end of each epoch.

The analysis of the evolved individuals showed that s-bots are able to coordinate and to move consistently toward a unique direction. S-bots start to pull in different directions, orient their chassis in the direction where the majority of the other s-bots are pulling, and finally move straight toward the direction that emerged by the negotiation between them by compensating successive mismatch in direction that arise while they are moving. By analyzing how evolved s-bots solve this problem we observed that evolved individuals adopt a simple strategy that can be described by distinguishing three main cases:

1) When the chassis of the s-bots are oriented toward the same direction, the intensity of the traction is null and the s-bots move straight.

2) when the intensity of the traction is low, the chassis of the s-bots are oriented toward similar but different directions. In this case s-bots tend to turn toward the average direction in which the whole group is moving (i.e. they tend to turn left when the traction comes from the left side and right when the traction comes from the right side).

3) when the intensity of the traction is high and the traction comes from the frontal direction, the chassis of the s-bots might be oriented in rather different directions. For instance three s-bots might be oriented toward north and one s-bot might be oriented toward south. In this case the s-bots tend to suddenly change their direction. The fact that the s-bots that have the higher mismatch with respect to the rest of the group, on the average, feel a stronger traction than the others, assure that the whole team finally reaches an unique direction. In particular, in the example described above, the s-bot facing south will change its direction more quickly than the other three robots facing north. Notice that in the case in which three s-bots are facing and trying to move toward north, for example, and the remaining s-bot is facing and trying to move toward south, all s-bots would feel a traction toward south with respect to their respective orientation. The only difference between the four s-bots would be that the individual oriented toward south would feel a stronger traction force than the other individuals.

Interestingly this simple strategy generalize to linear structures formed by more or less individuals but also to s-bots assembled so to form completely different shapes (see Figure 5). Indeed, we observed that s-bots display an ability to negotiate a single direction and then to produce a coordinated movement independently from the size and the shape of the team. Moreover, we observed that swarm-bots composed of s-bots adopting this simple strategy are also able to collectively avoid obstacles on the basis of the traction forces originating from collisions with obstacles. Also in this case, swarm-bots display a form of the collective obstacle avoidance behavior independently from the number of s-bots involved and of the shape resulting from how they are assembled.

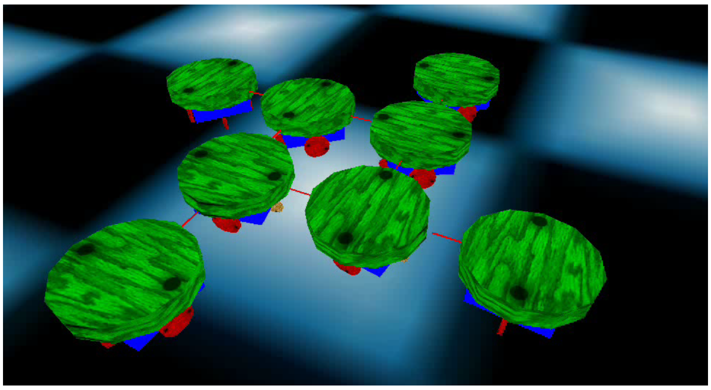

Figure 5. An example of how the simple strategy evolved on a linear structure formed by four s-bots generalize on a larger number of s-bots assembled so to form a different shape.

This results show, once more, how rather complex problems might be solved by exploiting behaviors that emerge from a large number of fine-grained interactions that, in this case, consists of social interactions, i.e. interactions between a number of robots situated in the same environment.

Finally, as in the case of the experiments described in the previous section, these results show how artificial evolution, is an effective framework for synthesizing robots able to exploit emergent behaviors (i.e. behaviors that emerge from the interaction between the robot and the environment or between an individual robot and other robots situated in the same environment).

3. Behaviors involving dynamical processes occurring at different time scales

The evolved robots described in the previous two sections are example of systems that works at a single time scale. Indeed, the control system of the artificial finger and of s-bots are updated every 100ms and the state of the motors is determined only on the basis of the current state of the sensors (in the case of the experiments described in section 2, the neural controllers also include internal neurons with recurrent connections. However similar behaviors were observed by using neural controllers in which the current motor action was only based on the current sensory pattern, see [16]). Despite these robots are simple reactive systems that do not have any internal dynamics and work at a rather fast time scale, they are able to display dynamical behaviors involving different phases that might last several seconds (i.e. that might involve processes occurring at rather different time scale). The artificial finger described in Section 1, for example, first physically interacts with the current object for few seconds and then reach two different final positions (close to the object in the case of a cube or far from the object in the case of a sphere) that are the emergent results of the previous dynamical interaction between the finger and the object. Similarly, in the case of the s-bots described in the previous section, they first negotiate a common direction and then move consistently toward such a direction that is the emergent results of the previous negotiation between the group of assembled robots. This can be explained by considering that the behavior is not only the result of the control system of the robot but also of the dynamical interaction between the robot and the physical and/or social environment.

This however, does not implies that all type of problems might be solved by simple systems that do not have any internal dynamics and produce dynamical behavior only by exploiting the interaction with the environment. As we will see in the next example, in fact, problems that require to detect regularities occurring at different time scales might require robot provided with control systems that are also able to process sensory-motor information at different time scales and to detect amount of changes in amount of time.

Consider the case of a mobile robot that should be able to travel along a loopy corridor (see Figure 6, left) and to self-localize by identifying its current location in the environment [27].

The robot used in the experiments described here is Khepera [28] a miniature mobile robot with a diameter of 55 mm and a weight of 70 g. It is supported by two lateral wheels that can rotate in both directions and two rigid pivots in the front and in the back. By spinning the wheels in opposite directions at the same speed, the robot can rotate without lateral displacement. The sensory system employs eight infrared sensors that are able to detect obstacles up to about four cm. Experiments were conducted in simulation by using an extended version of Evorobot [29]. To simulate the robot and the environment as accurately as possible, a sampling procedure was used to compute the activation state of the infrared sensors [6].

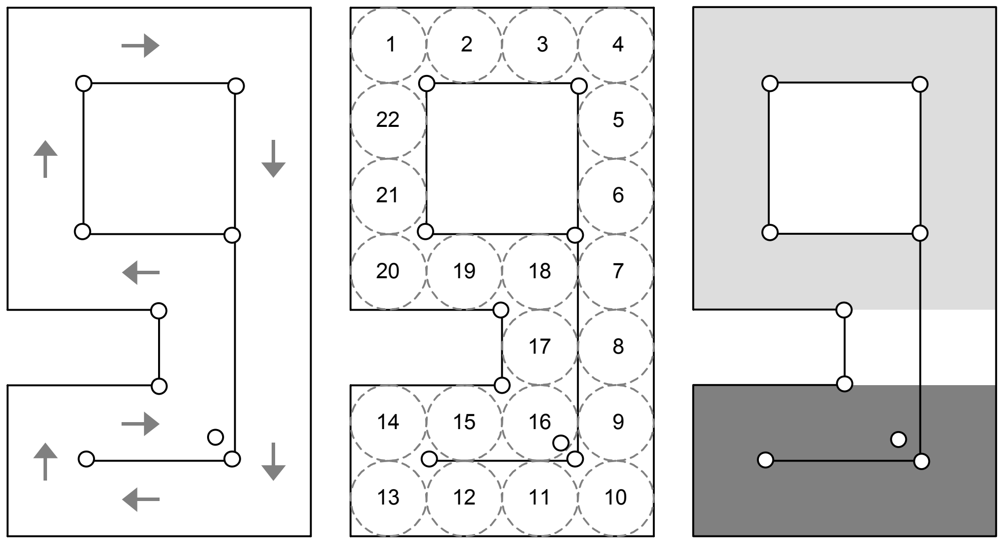

Figure 6. Left: The environment consists of a loopy corridor of 40x70 cm. Lines represent walls, circles represent cylindrical objects, and arrows represent the starting positions and orientations in which the robot is placed at the beginning of each trial. **Center:** The environment is divided into 22 idealized regions placed along the corridor clockwise. **Right:** The environment is also ideally divided into two rooms that are indicated in the Figure with light and dark gray colours.

The controller of each individual consists of a neural network with nine sensory neurons directly connected to three motor neurons and five internal self-recurrent neurons receiving connections from the sensory neurons and sending connections to the motor neurons (see Figure 7). The first three sensory neurons encode the state of the three corresponding motor neurons at the previous time step, the other six sensory neurons encode the six frontal infrared sensors (normalized between [0.0, 1.0]). The first two motor neurons encode the desired speed of the two corresponding wheels and the last motor neuron encodes the robot's self-localization output (see below). During the evolutionary process the architecture is kept fixed.

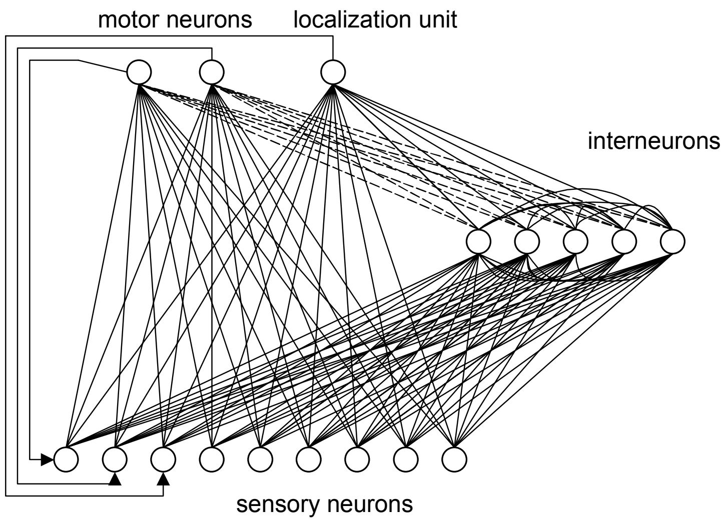

Figure 7. The architecture of the neural controller.

The initial population consists of 100 randomly generated genotypes. Each individual of the population is allowed to leave for eight epochs consisting of 2500 lifecycles each (each lifecycle lasts 100ms). At the beginning of each epoch the robot is initially placed in the eight corresponding positions and orientations indicated with the arrows in the left of Figure 6. Orientations are chosen to follow the clockwise direction of the corridor, however, a randomly selected angle in the range [-10, + 10] is in each trial added to the initial orientation of the robot. The 20 fittest individuals of each generation are allowed to reproduce by generating five copies of their genotype with 2% of their bits replaced with a new randomly selected value. The process is repeated for 500 generations.

The fitness function has two components that reward, respectively, the ability to travel clockwise along the corridor and the ability to indicate the current position of the robot in the environment. The first component is calculated by virtually dividing the environment in 22 adjacent regions (see Figure 6, center) and by computing the number of times a robot moves from one region to the next during its lifetime. The second component is calculated by virtually dividing the environment in two rooms, a dark and a light gray room, and by computing the percentage of times in which the robot correctly self-localizes in the two rooms (i.e. the fractions of lifecycles in which, while the robot is situated in the dark gray room, the activation of the robot's self-localization unit is lower than 0.5, and the fraction of lifecycles in which, while the robot is situated in the light gray room, the activation of the robot's self-localization unit was higher than 0.5).

By running a set of control experiments in which individuals were provided with reactive controllers without internal neurons or with internal neurons updated according to the standard logistic function we observed that evolved individuals were unable to solve the self-localization problem (result not shown). An ability to self-localize only emerges by providing evolving individuals with internal neurons that (a) vary their activity at different rates to detect regularities at different time scales in the sensory-motor flow, and (b) use thresholded activation functions to detect events extending over time (see [27] for more details). As we will see, in fact, these neurons, are suited to extract regularities at different time scales and to detect regularities that extend over a given amount of time.

To explain why these type of neurons are necessary to solve the self-localization problem we can analyze the activation state of internal neurons in successful evolved individuals. As shown in Figure 8, that displays the behavior and the neural activity of one evolved individual, the internal neuron i1 is turned off when the robot negotiates corners (see the locations indicated with the letter **A** on the left side of the Figure) and increases its output while the robot travels along a straight corridor. Thanks to a recurrent positive connection, however, the neuron is turned off on corners only if its activation level is below a given threshold or when the robot negotiates the narrow passage indicated with the letter **C**. The final result is that this neuron is always below a given threshold in the light gray room due to the reset of its activity occurring in C and in A corners and is always over that threshold in the dark gray room. Notice that internal neurons i1 is used to capture sensory-motor regularities that extend over rather long time scales (ranging from few to several seconds). Indeed, in order to display self-localization this robot is able to detect regularities such us corners or narrow passages (that extend over a period of few hundreds of milliseconds) and regularities such as corridors of different length (that extend from few to several seconds).

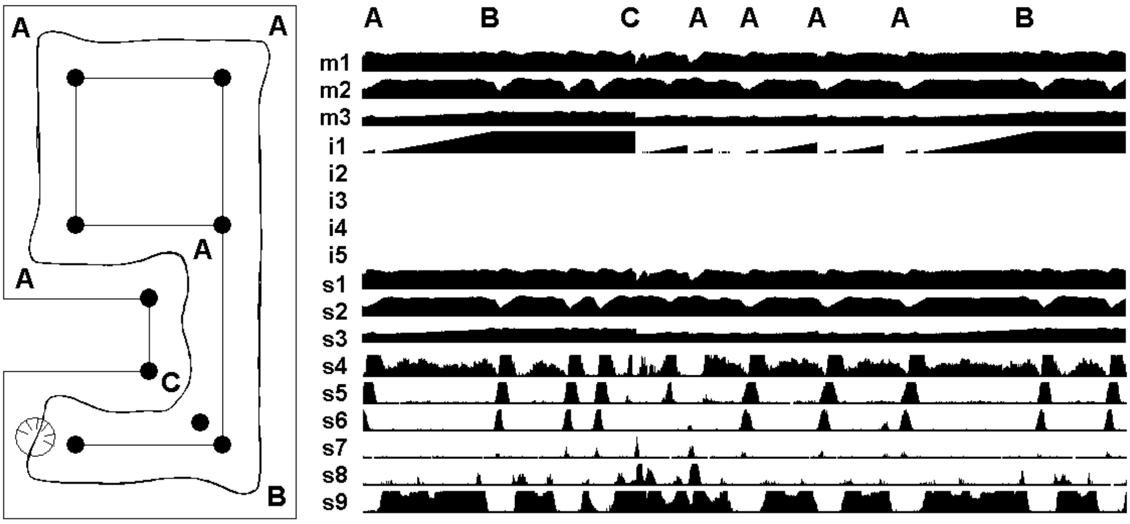

Figure 8. The architecture of the neural controller. Neural outputs of a successful evolved robot travelling in the environment. **Left**: The environment and the robot trajectory during a few laps of the corridor. A and C indicate the approximate positions of the robot when the output of the first internal unit is reset to 0. B indicates the position of the robot when the first internal unit reaches its maximum activation level. **Right**: The output value of motor (m1-m3), internal (i1-i5), and sensory (s1-s9) neurons while the robot is travelling along the corridor (the output value is represented by the height with respect to the baseline).

The results described in this section demonstrate that robots provided with control systems that are suited to deal with amount of changes in amount of time can solve hard problems that require to integrate sensory-motor information over time at different time scales. Indeed, the self-localization problem described in the previous sections could only be solved by using artificial neurons in which: (1) the output changes at different rate according to genetically encoded parameters, and (2) the output is reset when the net input goes below a genetically encoded threshold (corresponding to the bias of the neuron). The former aspect seems to be crucial for detecting regularities occurring at different time scales. The analysis of the evolved individuals indeed shows that regularities occurring at short time scales (such us sensory-motor states experienced while the robot negotiates a corner) were detected by neurons with fast changing rates while regularities occurring at longer time scales (such as sensory-motor states experienced while the robot was traveling along a long corridor) were detected by neurons with slow changing rates. The latter aspect seems to be crucial to detect events that last a given amount of time such as the fact that the activation state of the infrared sensors remain constant for a given amount of time in a corridor of a given length. In agents that are situated in a realistic environment, sensory and internal neurons provide information that extends over time and that does not have any meaning when isolated from time duration.

From this point of view one might observe that robots able to solve a given problem by processing sensory-motor information at a single time scale are a limit case in which regularities necessary to achieve the goal are visible at a single time scale which, at least roughly, corresponds to the time scale used to update the neurons of the agent.

4. Discussion

In this paper we showed how robots that are able to exploit behavior that emerge from fine-grained interaction with the physical and social environment can solve complex problems in simple and effective ways. By exploiting the interaction with the environment robots are also able to produce dynamical behaviors involving phases that might extend over time scales that are significant larger than the time scale at which interactions with the environment occur.

Moreover, we showed how problems that require to detect regularities occurring at rather different time scales might require robot provided with control systems that are also able to process sensory-motor information at different time scales and to detect amount of changes in amount of time. Dealing with the real world necessarily implies to deal with events that extend over a wide range of time scales. Regularities of this sort can only be detected by considering amount of changes in amount of time [30] and by choosing the appropriate time scale. As reported by Keijzer [31], the picture-book *Powers of Ten* of Philip and Phylis Morrison is a clear example of the relation between the scale chosen and the regularities that can be detected (in the context of space instead of time). The book is a visual journey consisting of 42 images, ranging from the entire known universe to three quarks with a proton, where each image portrays a part of the previous one magnified by a power of ten. Galaxies, planets, lakes, DNA, atoms can obviously only be detected at the appropriate space scales. Similarly, in the experiments reported in the previous section different type of regularities (e.g. corners and long corridors) extend over different time scales (ranging from a few hundreds of milliseconds to several seconds) and can only be detected by neural processes integrating information at different time scales.

Acknowledgment

Part of the research described in this paper has been supported by the SWARM-BOT project founded by the Future and Emerging Technologies program (IST-FET) of the European Community under grant IST-2000-31010. The information provided is the sole responsibility of the authors and does not reflect the Community's opinion. The Community is not responsible for any use that may be made of data appearing in this publication. The Swiss participants of the project has been supported under grant 01.0012 by the Swiss Government.

References

[1] Varela F.J., Rosch E., and Thompson E. (1991). *The Embodied Mind: Cognitive Science and Human Experience*. Cambridge, MA: MIT Press/Bradford Books.

[2] Brooks R.A. (1991) Intelligence without reason. In J. Mylopoulos & R. Reiter (Eds.), *Proceedings of 12th International Joint Conference on Artificial Intelligence*. San Mateo, CA: Morgan Kaufmann.

[3] Clark A. (1997) *Being There: Putting Brain, Body and World Together Again.* Cambridge, MA: MIT Press.

[4] Pfeifer R. and Scheier C. (1999) *Understanding Intelligence*. Cambridge, MA: MIT Press.

[5] Beer R.D. (1995). A dynamical systems perspective on agent-environment interaction. *Artificial Intelligence,* 72:173-215.

[6] Nolfi S. and Floreano D. (2000). *Evolutionary Robotics*. Cambridge, MA: MIT Press.

[7] Ashby W.R. (1952) *Design for a Brain*. London: Chapman and Hall.

[8] Dill M. *et al*. (1993) Visual pattern recognition in Drosophila involves retinotopic matching *Nature* 365, 751-753.

[9] Franceschini N. (1997) Combined optical, neuroanatomical, electrophysiological and behavioral studies on signal processing in the fly compound eye. In C. Taddei-Ferretti (Ed.), *Biocybernetics of Vision: Integrative Mechanisms and Cognitive Processes*. London: World Scientific

[10] Thelen E. and Smith L.B. (1994) *A Dynamics Systems Approach to the Development of Cognition and Action*. Cambridge, MA: MIT Press.
[11] Chiel H.J. and Beer R.D. (1997) The brain has a body: Adaptive behavior emerges from interactions of nervous system, body and environment *Trends in Neurosciences* 20, 553-557.
[12] Braitenberg V. (1984) *Vehicles*. Cambridge, MA: MIT Press.
[13] Scheier C. and Pfeifer R. (1995) Classification as sensorimotor coordination: A case study on autonomous agents. In F. Moran, A. Moreno, J.J. Merelo and P. Chacon (Eds.), *Advances in Artificial Life: Proceedings of the Third European Conference on Artificial Life*. Berlin: Springer Verlag.
[14] Nolfi S. (2002). Power and Limits of Reactive Agents. *Neurocomputing*, 42:119-145.
[15] Bajcsy R. (1988) Active perception *Proceedings of the IEEE* (76) 8, 996-1005.
[16] Nolfi S. Marocco D. (2002). Active perception: A sensorimotor account of object categorization. In *From Animals to Animats 7.* In B. Hallam, D. Floreano, J. Hallam, G. Hayes, J-A. Meyer (eds.) *Proceedings of the VII International Conference on Simulation of Adaptive Behavior*. Cambridge, MA: MIT Press.
[17] Nolfi S. and Parisi D. (1993) Self-selection of input stimuli for improving performance. In G. A. Bekey (Ed.), *Neural Networks and Robotics.* Kluwer Academic Publisher.
[18] Scheier C. *et al*. (1998) Embedded neural networks: exploiting constraints *Neural Networks* 11, 1551-1596
[19] Nolfi, S. and Parisi, D. (1997) Learning to adapt to changing environments in evolving neural networks *Adaptive Behavior* 5, 99-105.
[20] Slocum, A.C. *et al*. (2000) Further experiments in the evolution of minimally cognitive behavior: From perceiving affordances to selective attention. In J. Meyer, A. Berthoz, D. Floreano, H. Roitblat and S. Wilson (Eds.), *From Animals to Animats 6: Proceedings of the Sixth International Conference on Simulation of Adaptive Behavior*. Cambridge, MA: MIT Press
[21] Baldassarre G., Nolfi S. and Parisi D. (2002). Evolving groups of assembled robots able to display coordinated movements. *Technical Report*. Roma, Italia: Institute of Cognitive Science and Technology, CNR.
[22] Mondada F., Guignard A., Colot A., Floreano D., Deneubourg J.-L., Gambardella L.M., Nolfi S. and Dorigo M. (2002) *Technical Report*, LSA2 - I2S - STI, Lausanne, Switzerland: Swiss Federal Institute of Technology,
[23] Mondada F., Pettinaro G.C., Kwee I., Guignard A., Gambardella L.M., Floreano D., Nolfi S., Deneubourg J.-L. and Dorigo M. (2002). SWARM-BOT: A Swarm of Autonomous Mobile Robots with Self-Assembling Capabilities**.** In C. K. Hemelrijk and E. Bonabeau, editors, *Proceedings of the International Workshop on Self-Organisation and Evolution of Social Behaviour*, Monte Verità, Ascona, Switzerland: University of Zurich.
[24] Pettinaro G.C., Kwee I., Gambardella L.M., Mondada F., Floreano D., Nolfi S., Deneubourg J.-L. and Dorigo M. (2002). SWARM Robotics: A Different Approach to Service Robotics In *Proceedings of the 33rd International Symposium on Robotics*, Stockholm, Sweden: International Federation of Robotics.
[25] Baldassarre G., Nolfi S. & Parisi D. (2002). Evolving mobile robots able to display collective behaviours. In C.K. Hemelrijk (ed.) *Proceedings of the International Workshop on Self-Organisation and Evolution of Social Behaviour*. Zurich, Switzerland: Swiss Federal Institute of Technology.
[26] Quinn, M., Smith, L., Mayley, G. and Husband P. (in press). Evolving teamwork and role allocation with real robots. In *Proceedings of the 8th International Conference on The Simulation and Synthesis of Living Systems (Artificial Life VIII)*.
[27] Nolfi S. (in press). Evolving robots able to self-localize in the environment: The importance of viewing cognition as the result of processes occurring at different time scales. *Connection Science*.
[28] Mondada R., Franzi E. & Ienne P. (1993). Mobile robot miniaturization: A tool for investigation in control algorithms. In T.Y. Yoshikawa & F. Miyazaki (Eds.), *Proceedings of the Third International Symposium on Experimental Robots*. Berlin, Springer-Verlag.
[29] Nolfi S. (2000). Evorobot 1.1 User Manual. *Technical Report*. Roma, Italy: Institute of Psychology, CNR. (available at http://gral.ip.rm.cnr.it/evorobot/simulator.html)
[30] Van Gelder T. and Port R.F. (1995). It's about time: an overview of the dynamical approach to cognition. In R.F. Port and T van Gelder (eds.) *Minds as motion: exploration in the dynamics of cognition*. Cambridge, MA: MIT Press
[31] Keijzer F. (2001). *Representation and behavior*. Cambridge, MA: MIT Press.