ADAPT
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Artificial Development Approach to Presence Technologies

Deliverable Item 3.2
Hardware and software in place to run experiments on changing morphologies

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Short Description: We have investigated the deep and important question of how the physical or body dynamics and the control or neural dynamics can be coupled in optimal ways. By simulating development in a robot, we examined if developmental progressions in the robot's sensory-motor and neural systems can speed up the learning process. This might be indeed the case as shown by the results presented in this report.
New developments in the robotic setup where the intrinsic physical properties of the materials used for sensors and actuators will play an important role are also outlined.

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1 Introduction

There is a trivial meaning of embodiment namely that "intelligence requires a body". In this sense, anyone using robots for his or her research is doing embodied artificial intelligence. It is also obvious that if we are dealing with a physical agent, we have to take into account gravity, friction, torques, inertia, energy dissipation, etc. However, there is a non-trivial meaning, namely that there is a tight interplay between the physical and the information theoretic aspects of an agent. A short note on terminology is in place, here. We talked about information theoretic implications of embodiment. What we mean is the effect of morphology on neural processing, or better, the interplay between the two. The important point is that the implications are not only of a purely physical nature.

All the design principles described in Pfeifer and Scheier (1999) and Pfeifer et al. (2004), directly or indirectly refer to this issue, but some focus on this interplay, i.e. the principle of sensory-motor coordination where through the embodied interaction with the environment sensory-motor patterns are induced, the principle of cheap design where the proper embodiment leads to simpler and more robust control, the redundancy principle which states that proper choice and positioning of sensors leads to robust behavior, and the principle of ecological balance that explicitly capitalizes on the relation between morphology, materials, and neural control.

In previous work we have investigated in detail the effect of changing sensor morphology on neural processing (e.g. Lichtensteiger and Eggenberger (1999); Maris and te Boekhorst (1996); Pfeifer (2000a,b); Pfeifer and Scheier (1999)).

In an other set of studies we have focused on the motor system (e.g., Iida and Pfeifer (2004), Iida (2003)) were it is shown that by exploiting the dynamics of the agent, often control can be significantly simplified while maintaining a certain level of behavioral diversity.

We have applied artificial evolution to evolve learning mechanisms that can control the performance of a robot interacting with the environment and tested its robustness by changing the robot's task as well as its sensory and motor systems while its neural controller was kept untouched (Eggenberger Hotz et al. (2002); Gómez and Eggenberger Hotz (2004a,b)).

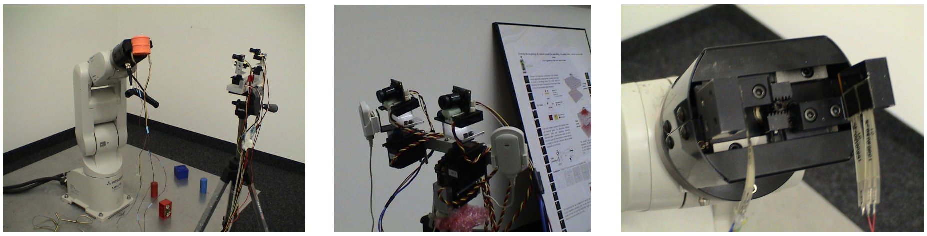
Here, we report our efforts in order to extend the principle of ecological balance to developmental time, and attempt to comply to it by simultaneously increasing the sensor resolution, the precision of the motors, as well as the size of the neural structure. Such concurrent changes are thought to simplify learning processes by maintaining an adequate balance between the complexity of the three sub-systems.

2 Exploiting morphological constraints and adapting to morphological changes during development

We propose a method to "simulate" development in an embodied artifact at the levels of sensory, motor, and neural systems. We use a high-resolution sensory system and a high-precision motor system with a large number of mechanical degrees of freedom, but we start out by simulating, in software, lower resolution sensors (i.e, by blurring the camera image and using only a few pressure sensors) and an increased "controllability" (i.e., by freezing most degrees of freedom). Over time, we gradually increase the resolution of the sensors (i.e., by sharping the camera image and using a larger number of pressure sensors) and the precision of the motors by successively freeing these "degrees of freedom" (i.e. by starting to use the "frozen" joints) and added neuronal units to the neural control architecture to cope with more sensory input and with more degrees of freedom of the motor system.

2.1 Current experimental setup

Our experimental setup consisted of an industrial robot manipulator with six degrees of freedom (DOF), a color stereo active vision system, and a set of tactile sensors placed on the robot's gripper as can be seen in Figure 1.



(a) (b) (c)

Figure 1: Experimental setup. (a) A six degrees of freedom robot arm, (b) robot's head with 6 degrees of freedom composed of a stereo color active vision system (pan-tilt for each camera plus two additional degrees of freedom for the neck) and sound detection, and (c) a set of tactile (force sensing resistors type) sensors placed on the robot's gripper.

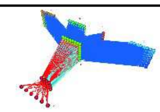
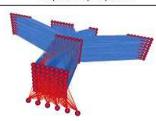
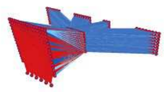
Sensory system		Motor system	Neural system
Vision	Touch		
	1 pressure sensor	J0	 286 neuronal units 13,920 synapses
	2 pressure sensors	J0, J2	 342 neuronal units 17,792 synapses
	4 pressure sensors	J0, J1, J2	 542 neuronal units 31,744 synapses

Figure 2: Configuration of the sensory, motor and neural components of the robot through the developmental approach. From top to bottom: DS-1 ("immature state"), DS-2 ("intermediate state") and DS-3 ("mature state").

2.2 Developmental schedule

Figure 2 presents a summary of the configuration of the robot as well as the number of neuronal units in each neuronal area at each developmental stage. Through this simulated development (from DS-1 ("immature state of the robot") to DS-3 ("mature state of the robot")) the initial setup with reduced visual capabilities, low number of degrees of freedom, a few pressure sensors and a neural control architecture with a reduced number of neuronal units, was converted into an experimental setup with good vision, larger number of degrees of freedom, larger number of pressure sensors and a neural control architecture with a sufficient number of neuronal units.

3 Experiments

3.1 Task specification

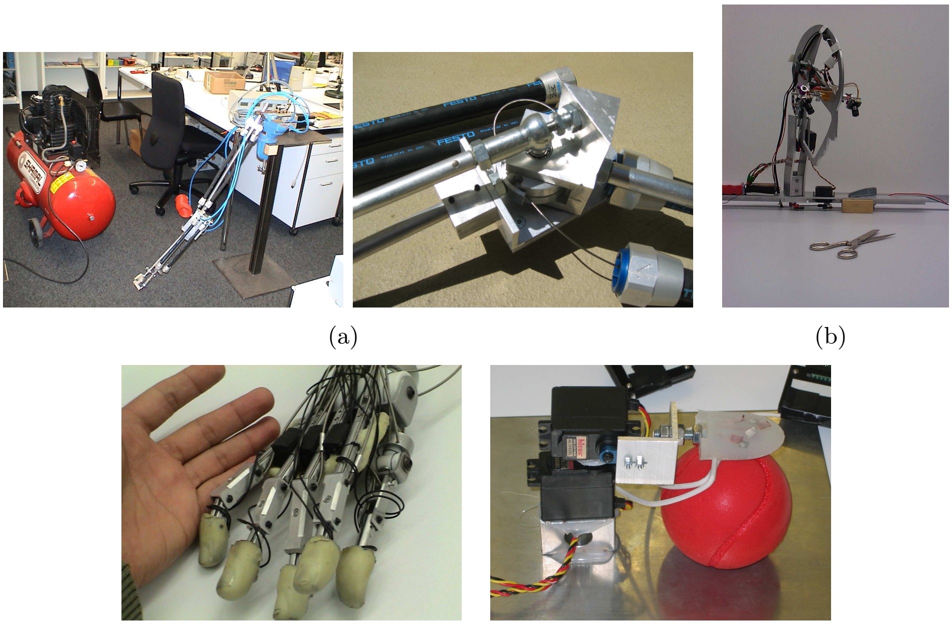
The task of the robot was to learn how to bring a colored object from the periphery of the visual field to the center of it through movements of its robotic arm. At the outset of each experimental run, the active vision system was initialized to look at the center of the visual scene (x_c, y_c), and the position of its motors were kept steady throughout the operation. The robot arm was placed at a random position in the periphery of the robot's visual field and a colored object was put in its gripper. Once the object was detected by the pressure sensors the robot started to learn how to move the arm in order to bring the object from the periphery of the visual field (x_0, y_0) to the center of it (x_c, y_c). For more details see Gómez and Eggenberger Hotz (2004a,b).

3.2 Results

A total of 15 experiments were performed with two types of robotic agents: one subjected to developmental changes (i.e., DS-1, then DS-2 and finally DS-3), and one fully developed since the onset (control setup). The results clearly show that the robotic agents that followed a developmental path took considerably less time to learn to perform the task. These robotic agents started with the configuration of the developmental stage number 1 and learned to solve the task during the learning cycle 483 ± 70 (where $\pm$ indicates the standard deviation), then they were converted to robotic agents with a configuration as described by the developmental stage number 2 which subsequently learned to solve the task around the learning cycle 1671 ± 102 and finally they become to be in the developmental stage number 3 (with the same configuration than the control setup) and solve the task around the learning cycle 4150 ± 149 (this is a cumulative value).
The control setup agents with full resolution camera images, four pressure sensor, three DOF (i.e., $J0$, $J1$ and $J2$), and a neural network with 542 neuronal units (randomly initialized synaptic connections) learned to solve the task around the learning cycle 7480 ± 105.
In other words, a reduction of about 44.5 percent in the number of learning cycles needed to solve the task can be observed in the case of robotic agents that followed a developmental approach when compared to the control setup agents. For more details see Gómez et al. (2004).

4 Future work

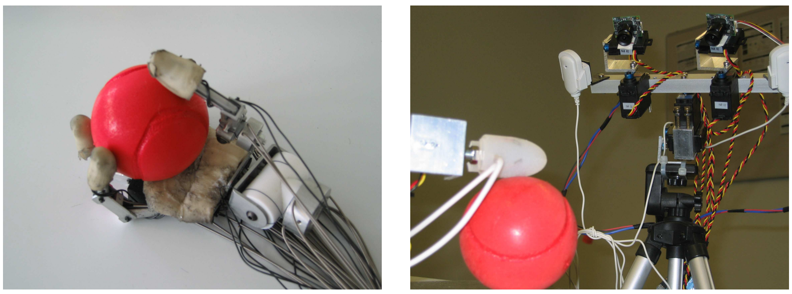
In order to simulate a later state in the robot's development, and continue testing the interplay between morphology, materials, and control, we have been working in a new experimental setup that can be seen in Figure 3.



(a) (b) (c) (d)

Figure 3: New experimental setup. (a) pneumatic robot arm, (b) robot's head, (c) new robot hand, and (d) anthropomorphic soft finger tip with 25 sensors inside mounted on a 2 degrees of freedom finger.

4.1 New experimental setup



(a) (b)

Figure 4: New set of experiments. (a) anthropomorphic hand enclosing an object, (b) visually guided exploratory experiments.

We have started building a new robot arm with artificial muscles (see Figure 3a), the important point here is that we are not simply replacing one type of actuator, an electrical motor, by a different one. This would not be very interesting. The point is that the new type of actuator - i.e. a pneumatic one - has intrinsic physical properties such as elasticity and damping, that can be exploited by the neural control. We will get for free passive compliance: if an arm, for example, encounters resistance it will yield elastically rather than pushing harder. In the case of the pneumatic actuators this is due to the elastic properties of the rubber tubes. This arm will have proprioceptive feedback from the joints regarding position and torque.

The new robot's head has a stereo color active vision system with 4 degrees of freedom (pan-tilt for each camera) and a neck with two additional degrees of freedom(see Figure 3b).

The new robotic hand has 11 degrees of freedom, 8 tactile (force sensing resistors type) sensors and will provide the robot with more capabilities for manipulating objects (see Figure 3c and Figure 4a).
We have established a program of cooperation with professor Koh Hosoda, from the Department of Adaptive Machine Systems, at Osaka University. He and his team have manufactured soft artificial fingers that they made available for our research. The fingers have two layers made of different kinds of silicon rubber imitating the human finger, a cutis layer and an epidermis one. The rubber used for the epidermis is harder than the one used for the cutis. Inside the finger are embedded strain gauges that deliver an analog signal of the strain that results on the finger's surface as a result of pressure and touch. The embedded strain gauges are randomly distributed inside the finger (Tada et al. (2003)). We are going to perform visually guided exploratory experiments, where the soft-finger tip (see Figure 3d and Figure 4b) is moved over different objects that are made of different materials with different tactile characteristics. We expect to enhance the tactile capabilities of the robot as well as to be able to optimize the location of the strain gauges inside the finger.

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