An Evolved Learning Mechanism for Teaching a Robot to Foveate

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Abstract

We showed in a previous work that an artificial evolutionary system whose task was to track a light source was able not only to evolve and grow a neural network, but was also able to evolve learning mechanisms. The evolved neural network was then transferred to a robotic system consistent of a camera mounted on the gripper of a robot arm with results comparable to the ones achieved by the simulation (Eggenberger et al.[1]). In this paper we continued testing the evolved controller in the real-world increasing the sensory-motor capabilities and the robot's task as follows: (a) The visual system was enhanced to detect color and movement in the environment and a proprioceptive system was added to have feedback of the arm movements. (b) The number of degrees of freedom (DOF) of the robot was increased from two to three. (c) The position of the cameras was fixed and the same underlying principles were used to teach the robot arm in front of the cameras to move a colored object from an initial location at the periphery of the visual field to the center of it. The arm could solve the task not only for two DOF, but also for three DOF.

1 Introduction

In evolutionary robotics the standard approach is to take a particular robot and use a genetic algorithm to evolve a control architecture for a particular task. Changes in the sensory-motor capabilities of the robot or in its task imply that a new control architecture must be evolved. Most of these approaches use direct genotype-to-phenotype encodings, where each synaptic weight is represented by a genetic parameter. As such an encoding scheme scales quadratically with network size, considerable effort has been put into the development of indirect encoding schemes, where the genome is a developmental program specifying processes which in their turn grow the neural structures and fine-tune the synaptic weights according to the tasks specified by the designer. Here, a more biological approach is propose to evolve large neural networks, which are able to grow and learn; in this method the genetic information no longer directly encodes for specific properties (in this case a neural network), but controls developmental processes generating the functioning structures. This will be explained in the following section. In section 3 the robustness of the learning mechanism is tested, the neural structure and its connections to the robot are described, then the experiments and results are shown in section 4 and we conclude with a discussion in the last section.

2 Evolutionary methods and developmental processes

To be able to explore both, growth and learning, the concept of selective recognition between entities, we call it "ligand-receptor interactions" played a crucially important role (Eggenberger[2]). This concept allows (a) a neuron to recognize more or less specifically another partner neuron, (b) an axon to follow cues in the environment and (c) a neuromodulator to diffuse in the environment and influence specific synapses to change their weights. In this way learning rules can be evolved and have not to be pre-specified by the designer of the system.

2.1 Growth mechanisms

By varying axonal receptor types different influences can be easily explored by the evolutionary strategy (ES) and growth patterns resulting in topological maps between interneurons and the sensory input emerged. Figure 1 illustrates the mechanisms by which the gene activities of the cells will determine the types of receptors expressed on their axons and finally determine if a source of signaling molecules has an attracting or repelling influence. Similar ligand-receptor interactions will control which cells will stick together or which will build up synapses or which neuromodulator will change the synaptic weight. By varying the expression of different ligand-receptor interactions the ES can easily explore different connectivity patterns with a small load of genetic information.

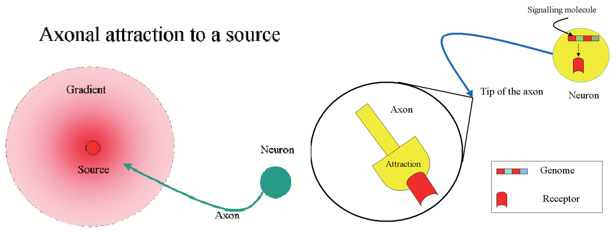

Figure 1: Overview of the most important biological mechanisms used in the proposed artificial evolutionary system.

To illustrate the proposed evolutionary approach a retinal structure was evolved, the task of the system was to evolve a neural network that could move the eye in such a way that an incoming peripheral sensory stimulus falls in the center of the "eye". The fitness function depended on the number of cells, on the movements, and on the precision of the movements measured by the deviation of the position of a stimulus from the center of the eye after peripheral stimulation. More details about how this controller was evolved and transferred to the robot can be found in the following references: Eggenberger[3] and Eggenberger et al.[1]. Figure 2 gives a schematic overview of the neural network at different stages of evolution.

2.2 Learning mechanisms

The exploration of learning mechanisms is based on the expression of artificial receptors on the synapses

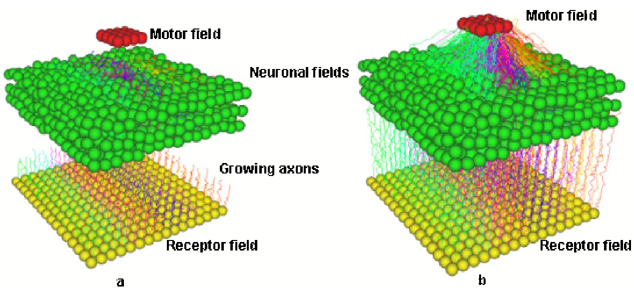

Figure 2: Schematic overview of the growing neural network. (a) Growing neural network. (b) The final neural network controlling a foveating retina.

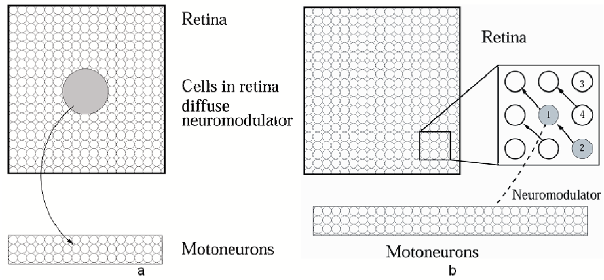

Figure 3: Two different evolved foveating systems.

and the interactions with signaling molecules.(In Ishiguro et al.[4], this concept was also explored by us to simulate the evolution of a biped robot). In general the change of the weights depends on the activity of different ligand-receptor complexes. By varying the place and time of these interactions, the ES is able to explore learning mechanisms without the need of the designer to declare a set of learning rules (e.g., Hebbian, Anti-Hebbian), because such rules can be evolved. The following example gives a solution of how a Hebbian learning rule could be evolved: Neurons can link the emission of a signaling molecule to their neural activity. Depending on their specific differentiation, the cells produce and emit signaling molecules, the synaptic weight changes if ligands emitted from other cells have a strong enough impact on the synapse. Let us suppose that a neuron emits a substance and the emitted transmitter has an affinity to one of two receptors on a particular synapse and a second neuron emits a substance for a second receptor on that synapse, then the weight will be increased in an AND fashion, a Hebbian learning rule is found. The AES evolved two neuromodulatory systems able to teach the robot about the success of its exploratory movements. The first mechanism localized in the center of the retina cells able to emit neuromodulators when they where activated. This had the effect that the system could learn to move the camera correctly (see figure 3 a). The second mechanism was more sophisticated and efficient: the neuromodulator was emitted if at any given position the movement of the robot brought the light source closer to the center (see figure 3b). This evolved mechanism is quite similar to a value system (Edelman[5], Friston et al.[6] and Sporns et al.[7]). In contrast to their hand-designed methods, where the value system is located in other brain parts, our evolved value system is located directly in the network performing the task.

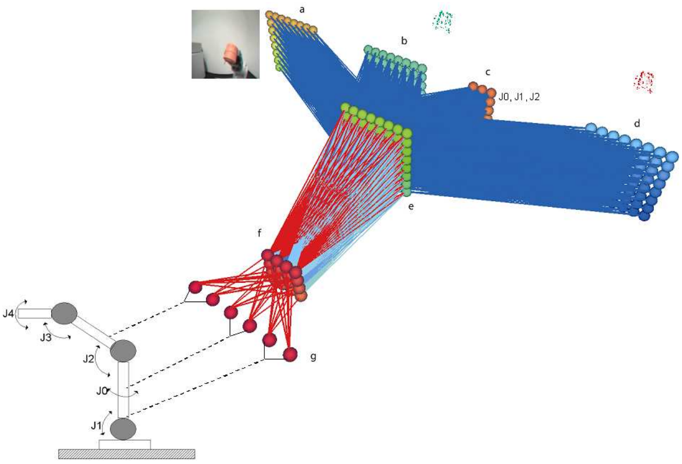

Figure 4: Neural structure and its connections to the robot arm. Neuronal areas: (a) RedColorField. (b) RedMovementToRightField. (c) ProprioceptiveField. (d) RedMovementToLeftField. (e) NeuronalField. (f) MotorField. (g) MotorActivites.

3 Testing the robustness of the learning mechanism

There is an intimate linkage between the neural controller, the sensory-motor system and the task-environment. Therefore to test the robustness of the learning mechanism we increased the sensory-motor capabilities of the robot as well as its task-environment.

3.1 Increasing the complexity of the robot's task

At the beginning of each experiment the active vision system was initialized looking at the center of the visual scene and the position of its motors were held still. The robot arm was placed at a random position at the periphery of the robot's visual field and a colored object was put on its gripper. The robot's task was then to learn how to move the arm in order to bring the object from the periphery of the visual field to the center of it.

3.2 Increasing the neural structure

In figure 4 a somewhat geometric looking overview of the evolved neural net is given, because the paths of the axons searching for their targets are omitted. The neural network was enhanced to couple with more sensory input and with more degrees of freedom of the motor system.

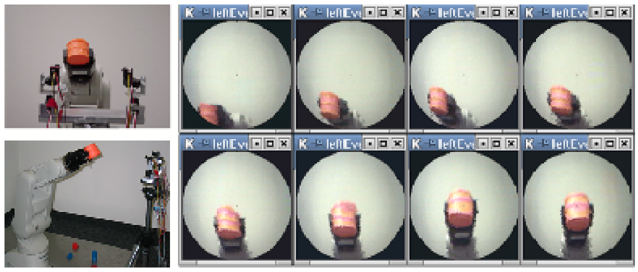

Figure 5: Robotic setup performing an experiment moving an object from the bottom-left corner of its visual field to the center of it.

3.3 Increasing the sensory-motor capabilities of the robot

In the previous work the sensory input consisted of the intensity channel (i.e., $I = (r + g + b) / 3$) and two degrees of freedom were used. In these set of experiments we augmented the sensory-motor capabilities to use visual and proprioceptive feedback as follows: (a) A "broadly" color-tuned channel was created for red: $R = r - (g + b) / 2$. This channel yields maximal response for the fully-saturated red color, and zero response for black and white inputs. The negative values were set to zero. Each pixel was then mapped directly to neuronal units of area *redColorField* (see figure 4a) which activity was calculated as:

$$S_i = \begin{cases} 1.0 & : \; if \;\; R_i > \theta_1 \\ 0.0 & : \; otherwise \end{cases} \tag{1}$$

Where S_i is the activity of the i-th neuron on area *RedColorField*; R_i is the value of the red color-tuned channel for the pixel i-th; and θ_1 is a threshold value. (b) Motion detectors were created to detect movements of red objects in the environment. These motion detectors are based in the well-known elementary motion detector (EMD) of the spatio-temporal correlation type (Marr[8]). Motion detectors reacting to red objects moving to the right side of the image were mapped directly to neuronal units of the area *RedMovementToRightField* (see figure 4b) and the motion detectors reacting to red objects moving to the left side of the image were mapped directly to neuronal units of the area *RedMovementToLeftField* (see figure 4d). The activities of the neurons in these areas were calculated as:

$$S_i = \begin{cases} 1.0 & : \; if \;\; |EMDOutput_i| > \theta_2 \\ 0.0 & : \; otherwise \end{cases} \tag{2}$$

Where S_i is the activity of the i-th neuron; $EMDOutput_i$ is the output of the motion detector

at position i-th; and θ_2 is a threshold value.
(c) Sensors to encode the position of the joints: J0 ("shoulder"), J1 ("shoulder") and J2("elbow") of the arm were also created. See figure 4c.

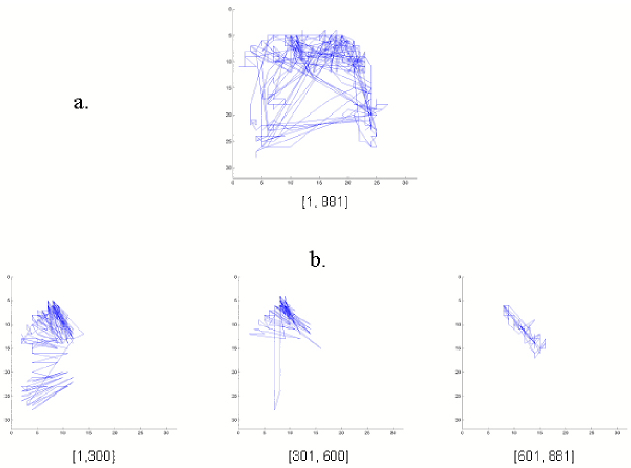

Figure 6: Position of the center of the object in the visual field during the experiments. (a) Random exploration. (b) Sensory-motor coordinated experiment.

4 Experiments and results

Our experiments were performed using the experimental setup showed in figure 5. In order to compare the effects of the learning mechanism different sets of experiments were performed. The result of a non-sensory motor coordinated experiment can be seen in figure 6a, in this experiment the learning mechanism was not activated and therefore the robot arm made only random movements without being able to solve the task. In contrast when the learning mechanism was activated, the robot was engaged in a sensory motor coordinated loop, as can be seen in the figure 6b. In this experiment the robot was able to solve the task bringing the object to the target position several times in a stabilized trajectory.

5 Discussion

With the above results we could show that the evolved learning mechanism can be transferred to a robot arm and that the task could be learned by the robot and that the eyes can teach the robot arm to bring an object to the center of the visual field. These results point to a new direction of how to overcome the reality gap: the goal should be to evolve learning mechanisms (not fixed neural networks) that can control the performance of a robot interacting with the real-world.

Acknowledgments

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