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Evolved Neurodynamics for Robot Control

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Abstract. Small recurrent neural network with two and three neurons are able to control autonomous robots showing obstacle avoidance and photo-tropic behaviors. They have been generated by evolutionary processes, and they demonstrate, how dynamical properties can be used for an effective behavior control. Presented examples also show how sensor fusion can be obtained by evolution. Additional techniques are used to excavate the relevant neural processing mechanisms underlying specific behavior features.

1 Introduction

Robot intelligence is often associated with the concept of autonomous systems which have to decide and act without central control, external technical guidances, or human assistance. Especially autonomous mobile robots are nowadays conceived of as robots that can operate in complex, dynamically changing environments. Following an A-Life approach to evolutionary robotics [3] these systems have to learn to navigate, act, and survive in a sometimes unpredictable world. Control mechanisms of robots, showing a goal-directed behavior, will be modelled after their biological counterparts as neural networks of general recurrent connectivity. As already demonstrated by Braitenbergs gedanken experiments [1], the apparent complexity of robot behavior is not primarily caused by the complexity of their neural control structures but reflects mainly the complexity of the environment in which they are acting; i.e., very simple mechanisms may lead to interesting life-like behavior.

Our main interest here is to learn about recurrent neural structures with non-trivial dynamical behavior which are able to control the behavior of autonomous physical robots in an effective way. Because in general the dynamics of recurrent neural networks is difficult to analyse and to predict, an evolution algorithm is used to develop neural structures and at the same time to optimize their parameters like the synaptic weights. As first basic behaviors "exploration" of a given terrain and "light tropism" are evolved for a miniature Khepera robot. Combining evolution with "lesion" experiments guided by an appropriate hypothesis, one was able to identify an effective neurocontroller for

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obstacle avoidance of very simple type called the *minimal recurrent controller* (MRC) [2]. Having understood that hysteresis is the underlying mechanism for the excellent behavior control, in this paper we start with a corresponding "hand shaped" controller, which is even more simple. To demonstrate one of our strategies for sensor fusion, the so called *restricted module expansion* technique [4] is used to evolve a controller which, besides exploration and obstacle avoidance behavior inherited from the "hand shaped" controller, also generates positive photo-tropism. Again a kind of minimal recurrent neural network is presented as one of the interesting solutions to the problem. Different from a corresponding controller introduced in [4], which was evolved from scratch with a different fitness function, this controller is even less complex and uses less sensor inputs, demonstrating that mean values from suitable groups of sensors are sufficient for a reasonable control.

2 MRC: A Controller for Obstacle Avoidance

The applied evolutionary algorithm [4] was originally designed to study the appearance of complex dynamics and the corresponding structure-function relationship in recurrent neural networks which act as embodied cognitive systems in a sensorimotor loop. The goal is to find analyzable examples of such systems which can be related to specific behavioral properties of the robot. That is, one of the distinguishing features of the evolutionary algorithm is its simultaneous acquisition of network topology and parameter optimization.

The following experiments use standard additive neurons with sigmoidal transfer functions $\sigma = tanh$ for output and internal units. The discrete-time activity dynamics of a controller reads

$$a_i(t+1) = \sum_{j=1}^{k} w_{ij} \cdot \sigma(a_j(t)) \ , \quad i = 1, \ldots, k \ ,$$

where k denotes the number of units. Input units are only used as buffers.

Evolution of neural control is done with the 2-dim Khepera simulator. The control can be switched any time from the simulator to the physical robot. The final solution than can be downloaded onto the robot. Additional techniques allow analysis of electrode-like signals from the neurons of the evolved network while the robot is active, as well as "lesion experiments" to identify functional subsystems of the controller.

Preceeding experiments [2] showed that effective obstacle avoidance is due to hysteresis effects of neural control. To extricate exactly this mechanism we try to be structurally as parsimonious as possible: for the following experiments all six front proximity sensors are used, but the controller has only two inputs I_1, I_2 and no internal neurons. One input I_1 corresponds to the mean value of the three left proximity sensors, the second input I_2 to that of the three right proximity sensors. They satisfy $-1 < I_1, I_2 < 1$, with increasing values by decreasing distance to an obstacle. The two proximity sensors at the rear of

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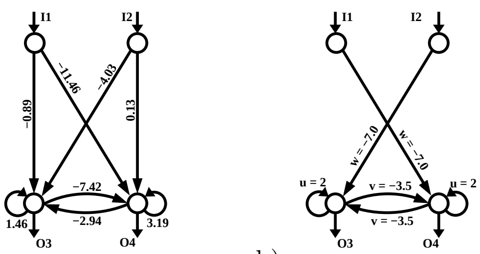
the robot are not used. Therefore initial neural structure for this experiment has only two input and two output neurons. The input neurons 1, 2, are linear buffers and the two output neurons, 3, 4, driving the left and right motor, are of additive type with sigmoidal transfer function *tanh*. The corresponding outputs are denoted by O_3 and O_4, turning the motors forward and backward. Bias terms are set to zero. The fitness function F_{oa} used for the evaluation of the controllers is given by

$$F_{oa} := \sum_{t=1}^{T} \kappa_1 \left(O_3(t) + O_4(t)\right) + \kappa_2 \left(|O_3(t) - O_4(t)|\right), \tag{1}$$

where κ_1, κ_2 denote appropriate constants. This fitness function rewards forward turns of wheels and punishes backward turns and curving. It simply states: For a given time T go straight ahead as long and as fast as possible.

Since the probability for inserting an internal neuron was set to zero, only connections are added or deleted and their weights are changed stochastically. There is also a stopping condition: If the robot collides before T time steps the evaluation of the network stops.



a) b)

Figure 1: a) Evolved MRC with two input neurons. b) The principal structure of an MRC.

Resulting networks, generating a very successful robot behavior, all had a connectivity like the one shown in figure 1a. They were called *minimal recurrent controllers* (MRC). The output neurons of a MRC have super-critical positive self-connections, $w_{33},\ w_{44} > 1$, turning these motor neurons into hysteresis elements. Furthermore, there is a recurrent inhibition between the output neurons; i.e., $w_{34},\ w_{43} < 0$ which generates a third hysteresis domain. A physical Khepera robot endowed with such an MRC shows both, obstacle avoidance and exploration behavior. The behavior of physical Khepera robots, controlled by this network, is comparable to that of the simulated one. Especially, the robots are enabled to leave sharp corners as well as deadends.

In [2] it was analyzed that the efficient behavior of the robots originates from the interplay of the three different hysteresis effects. Small hysteresis, related to left or right turning angles at obstacles, are provided by the super-critical excitatory self-connections of the motor neurons; i.e., $w_{33},\ w_{44} > 1$. A broader

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hysteresis interval, necessary to leave sharp corners or deadlock situations, is generated by the even super-critical 2-loop; i.e. $w_{34} \cdot w_{43} > 1$. Having identified this output configuration as the essential structural component for effective robot behavior, it can be shown that optimal controllers for obstacle avoidance and exploration behavior are of structural type depicted in figure 1b. They can be described as Braitenberg controllers [1] with additional hysteresis domains. One can use also symmetrical connectivity with u, v, $w > 0$ and a relation roughly given by $u \approx 4u$, $v \approx 2u$, and $u > 1$.

3 Photo-tropism

Using a MRC for obstacle avoidance, the Khepera robot now should be endowed with a light seeking behavior; i.e., the Khepera should look for a light source, turn to it, and stay in front of it. This behavior may be given the interpretation: Look for food and eat as much as you can. Starting with the MRC the robot will always move forward as fast as possible. Therefore the controller has to be modified in such way that the robot comes to a halt in front of a light source. To be able to detect a light source in its environment, the robot controller is endowed with additional four inputs $L_1, \ldots, L_4$. They represent the mean values of the two left, the two front, the two right, and the two rear light sensors of the Khepera robot. Values $0 < L_1, \ldots, L_4 < 1$ are increasing while the robot approaches a light source.

To evolve a convenient controller, we use the so called *restricted module expansion technique* [4]. This means the new controller will "grow" upon the MRC. The first generation starts with the MRC as controller but now with the additional four light sensor inputs. The structure and the weight values of the MRC with its two proximity sensor inputs are fixed, but additional neurons and connection may appear during the evolutionary process.

The fitness function F_{ls} for the light seeking task simply adds the input signals coming from the two light sensors at the front:

$$F_{ls} := \sum_{t=1}^{T} L_2(t) \ , \tag{2}$$

An average number of 50 individuals per generation is chosen, and an incremental evolution process is applied. This means for the first 10 generations there are several light sources distributed in an environment with only a few obstacles. Then gradually the number of light sources is reduced and the number of obstacles increased. The initial position for all robots in one generation is the same. It changes randomly only from generation to generation. Finally, after around 300 generations there are individuals which solve the task sufficiently well.

One of these solutions is shown in figure 2a. It uses only one additional internal neuron $H1$ with a super-critical inhibitory self-connection and takes all four inputs from the light sensors and the two inputs from the proximity sensors.

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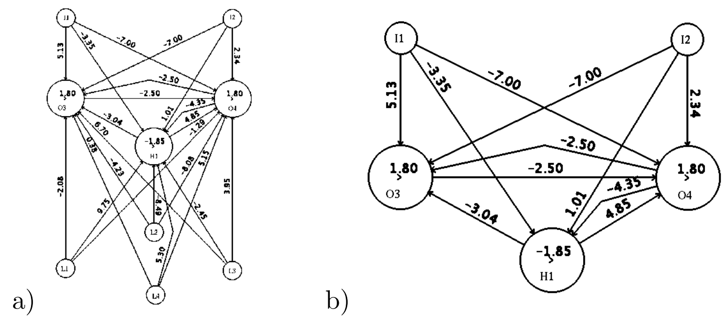

Figure 2: An evolved neural controller generating exploratory behavior with photo-tropism: a.) the full network, b) detail without light sensor inputs.

Furthermore, it has an odd recurrent loop with one of the motor neurons $O4$ and inhibits the other motor neuron $O3$. Figure 2b displays the same network without connections from the light sensor inputs for better visibility. A 2-neuron configuration like $(H1, O4)$ was named a *chaotic 2-module* in [5] because it allows all kinds of complex dynamics like oscillations and chaos.

Of course these dynamical properties should be reflected in the behavior of the robot. First, the behavior of the simulated robot appeared to be quite successfull as can be read from the following figures. Figure 3a demonstrates the basic search behavior of the robot: it moves along large circles avoiding walls and obstacles. The next two figures show positive photo-tropism of the robot: If no obstacles are present, the robot finally gets attracted by the light source and moves slowly around it in a roughly constant distance (figure 3b). Figure 3c demonstrates that the robot is able to find the light source even if it is at the end of a corridor, and it stays in front of the light source, because it can not move aside in this situation. What can not be seen from these pictures is the fact that the robot stays near the light source by oscillating forward and backward. Second, the behavior of the physical Khepera robot was studied in a dark room with a small light bulb, the intensity of which was adjustable. The robot showed roughly the same behavior as its simulated counterpart, although the sensitivity and the noise of the physical light sensors are quite different from those of simulated ones. The oscillations of the robot near a light source are of course not really desirable.

Analysis of the central 2-neuron module $(H1, O4)$ as well as "electrode data" taken from hidden neuron $H1$ while the robot is active revealed that the controller is really working in the complex dynamics domain. One reason for this evolutionary solution is, that the fixed MRC allows the robot only to move at almost maximal speed. So stopping before a light source is only possible by an exact ballance of input signals (which is impossible because of the sensor noise), or by the kind of oscillation observed for this solution.

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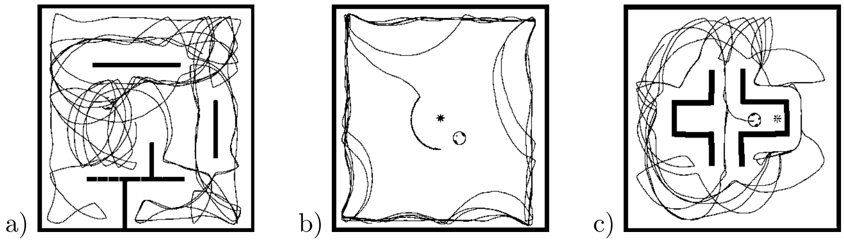

Figure 3: The simulated robot: Its obstacle avoidance and photo-tropic behavior in different environments.

4 Conclusions

Although the considered behavior tasks are simple and standard for autonomous mobile robots the presented results demonstrate, that evolved neural networks with non-trivial dynamical features can control the behavior of autonomous robots efficiently. Additional techniques like "lesion" of subsystems and "electrode data" may help to understand basic mechanisms of neural signal processing. Then, with this knowledge, located structures with specific functionality can be "manually" designed for specific control tasks. Finally one should remark, that incremental evolution allows to develop robust controllers, in the sense that they run comparably good on different robot platforms (compare http://www.ais.fraunhofer.de/INDY/MO_ME/BBR/BBR.html).

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