Dynamical Neural Schmitt Trigger for Robot Control *

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Abstract

Structure and function of a small but effective neural network controlling the behavior of an autonomous miniatur robot is analyzed. The controller was developed with the help of an evolutionary algorithm, and it uses recurrent connectivity structure allowing non-trivial dynamical effects. The interplay of three different hysteresis elements leading to a skilled behavior of the robot in challenging environments is explicitly discussed.

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1 Introduction

A modular neuro-dynamics approach to behavior control of autonomous systems starts with the basic assumption that the particular abilities of these systems are based on non-trivial internal dynamical features which are provided by neural systems with recurrent connectivity structure. As has been argued elsewhere [2], there are of course many difficult problems with such an approach. These are, for instance, related to questions like what type of dynamics and what type of recurrent structure to use for the generation of a successful behavior.

To tackle these difficulties we use an evolutionary algorithm, called ENS^3 (evolution of neural systems by stochastic synthesis), for the structural development of neural networks, which optimizes parameters with respect to a given fitness function at the same time. This evolutionary algorithm was successfully applied to benchmark control tasks [7] and to robot control tasks [8]. After having generated several examples of effective neuro-controllers, we analyze the dynamics of the resulting neural networks, the relation to the underlying connectivity structure, the relevance of specific dynamical properties for the resulting behavior or control strategy and look for differences in their performance, like differences in robustness, for example. In addition, kind of lesion techniques are used and parameters values can be varied by hand to study details of a structure-function relationship.

In this paper we want to report a simple mechanism, called a *dynamical neural Schmitt Trigger*. The context in which this mechanism became active is the following: We evolved neuro-controllers for Khepera robots [3] which should be able to move continuously (exploration behavior) in a given environment cluttered with obstacles (obstacle avoidance) [9], [4]. The robot could use eight proximity (infrared) sensors, 6 in front and 2 in the rear, and they where driven by two motors. There were many evolved networks solving the task, larger ones using 3 or more internal neurons, but also a few with no internal neurons at all. Noteworthy is the fact that most of the effective controllers used recurrent connections for their two output neurons (compare [8]). There are some situations in this setting, which usual robot controllers have difficulties to handle. These are situations where the robot drives into sharp corners or runs into dead ends. Then the robots usually just come to a rest (Braitenberg-like controllers [1]) or they start to oscillate left-right-left. We observed some robots which in these situations quickly turned around at large angles and then moved out of such an “unpleasant situation”.

When analyzing the corresponding networks, we realized that their output units were connected and that one or both output neurons had positive self-connections. To be sure that the underlying dynamical feature is exactly that of a hysteresis phenomenon, observed for instance for single neurons with super-critical positive self-connection [5], we reduced the number of controller inputs to only two, and used the ENS^3 algorithm to generate appropriate networks for this more demanding setup.

2 Evolving a Neuro-controller

In the following experiment the mean value of the three left proximity sensors, respectively, the three right proximity sensors was calculated and used as inputs $Inp1$ and $Inp2$ for the neuro-controller. The two proximity sensors at the rear were not used. The initial neural structure for this experiment has only two input and two output neurons. The input neurons are simply buffers and the output neurons 3 and 4 are of additive type with sigmoidal transfer function *tanh*, so that the motors can turn forward and backward. Bias terms are set to zero. The fitness function used for the evaluation of the controllers says: For a given time T go straight ahead as long and as fast as possible. This is coded in terms of the two network output signals $Out3$, $Out4$ as follows:

$$F := \sum_{t=1}^{T} (M_0(t) + M_1(t))(2 - |Out4(t) - Out3(t)|), \tag{1}$$

with $0 < M_0,\ M_1 < 1$ defined by $M_0 := max\{0, Out3\}$, $M_1 := max\{0, Out4\}$. There is also a stopping condition: If the robot collides before T time steps the evaluation of the network stops and the value of the current performance is taken as the maximum performance of the individual.

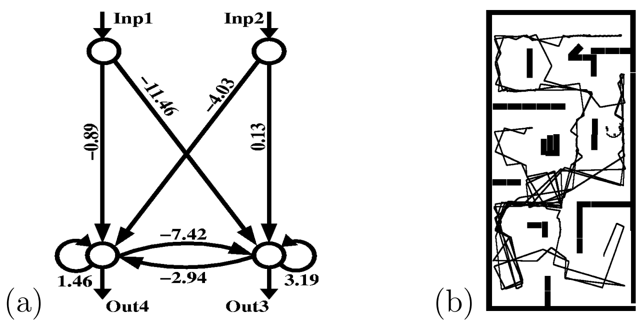

Figure 1: *(a) A small evolved neurocontroller with only two input neurons. (b) Typical paths of a simulated robot controlled by this network.*

Figure 1(a) shows one of the resulting networks which generates a very successful robot behavior. Both output neurons of this controller have positive self-connections, $w_{33} = 3.19$ and $w_{44} = 1.46$, respectively. Furthermore, one can find inhibitory connections $w_{34} = -7.42$ and $w_{43} = -2.94$ between the two output neurons establishing a feedback loop. In figure 1(b) a typical path of the simulated robot is plotted. It shows both, obstacle avoidance and exploration behavior. The behavior of the physical robot controlled by this network is comparable to that of the simulated one. Especially it is observed that the robots leave sharp corners as well as dead ends as it is indicated, for instance, in the upper right corner of the environment in figure 1(b).

For the considered small network with only two inputs it is easy to relate explicite input configurations with typical situations during the interaction of the robot with its environment. Furthermore, it is possible to simulate and visualize the whole dynamics of this network and to relate special dynamics to the observable behavior of the robot. Thus, we will be able to precisely explain how the recurrent network structure creates this well skilled robot behavior. With this aim in view, we summarize what will be called

3 A Dynamical Neural Schmitt Trigger Module

The *dynamical neural Schmitt Trigger module* consist of a single additive neuron with sigmoidal transfer function *tanh* and excitatory self-connection w_s, as shown in figure 2. Let θ denote a fixed internal bias or a stationary input to this neuron. For given parameter values of θ and w_s the fixed point equation for its discrete-time dynamics reads

$$x^* = \theta + w_s \tanh(x^*) \ , \quad x^* \in \mathbf{R}. \tag{2}$$

The stability condition for a fixed point x^* is given by $w_s \tanh'(x) < 1$; i.e.,

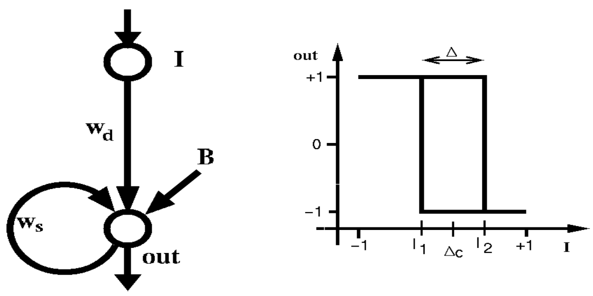

Figure 2: *Basic setup for a dynamical Schmitt trigger module with a buffered input I, weigth w_d, excitatory self-connection w_s, and a modulating input B.*

we are looking for bifurcation points in (θ, w_s)-parameter space, for which the condition

$$w_s \tanh'(x) = 1 \tag{3}$$

is satisfied; i.e., parameter values for which a fixed point gets unstable. For this equation to hold, the self-connection must be strong enough, i.e. $w_s > 1$, since $0 < \tanh'(x) < 1$. Furthermore $\tanh'$ is symmetric, i.e. there will exist two fixed points $x^*_{1,2}$, with $x^*_1 = -x^*_2$ satisfying condition (3). Thus, there will be two critical θ-values

$$\theta^*_{1,2} = \pm x^* \mp w_s \tanh(x^*)\,,$$

and for the corresponding *hysteresis interval* Δ^* with center at $\Delta^*_c = 0$, we get $\Delta^* = |\,\theta^*_1 - \theta^*_2\,| = 2\,|\,\theta^*_1\,|$.

Using the identities $\tanh'(x) = (1 - \tanh^2(x))$ and $\tanh^{-1} = \frac{1}{2}\ln\frac{1+y}{1-y}$ for fixed self-connections w_s the critical θ-values $\theta^*_{1,2}$ are calculated by solving equation (3) for x. For Δ^* we obtain

$$\Delta^* = \left|\,\ln\left[\frac{1+\alpha}{1-\alpha}\right] - 2 \cdot w_s \cdot \alpha\,\right|\,, \quad \alpha := \sqrt{1 - \frac{1}{w_s}}\,, \quad w_s > 1\,. \tag{4}$$

If we now feed this neuron by an external input I with weighted connection w_d then in this input space we will observe the characteristic jumps at values $I_{1,2} = \frac{\theta_{1,2}}{w_d}$. That is in input space the hysteresis interval with center at zero has length $\Delta = \frac{\Delta^*}{w_d}$. If, in addition, we have a "slowly" varying input B modulating the neuron, then the center Δ_c of the hysteresis interval Δ for the "fast" input signal I is shifted dynamically by B, i.e. $\Delta_c = -\frac{B}{w_d}$, and jumps will occur at

$$I_{1,2} = \frac{\theta_{1,2} - B}{w_d}\,, \quad w_d \neq 0\,, \quad B \in \mathbf{R}\,. \tag{5}$$

4 Network Dynamics and Robot Behavior

Both output neurons of the considered network (figure 1(a)) have "supercritical" self-connections. Therefore two hysteresis effects should cooperate during the control actions. But, in addition, there is a third hysteresis phenomenon involved which is associated to the 2-loop (w_{34}, w_{43}) between the output neurons. Such purely inhibitory 2-loops are known to have parameter domains where two stable fixed points co-exist with a period-2 attractor [6]. A complete overview about the dynamical properties of the output configuration is given in figure 3 where one can find four different domains in the ($Inp1$, $Inp2$)-space. For input values in domain 1 (white) there exists

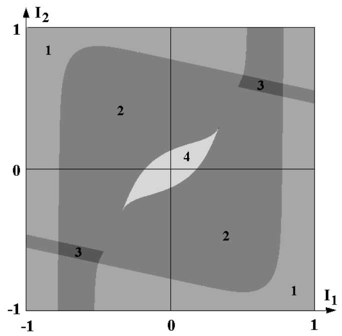

Figure 3: *Dynamical properties of the controller output configuration (compare text).*

only one fixed point attractor, in domain 2 (light grey) there are two fixed point attractors, in domain 3 (dark grey) there are three of them, and in the eye shaped domain 4 we have two fixed point attractors co-existing with a period-2 orbit.

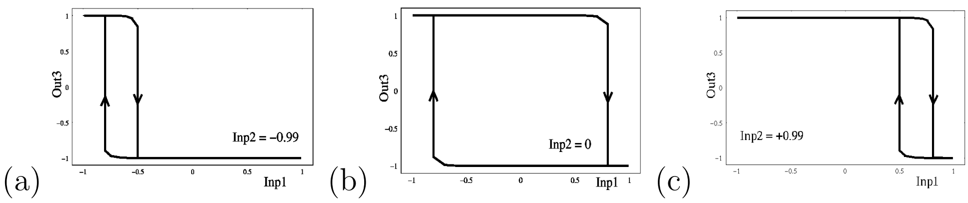

Figure 4: *Hysteresis domain of $Inp1$ for output neuron $Out3$ of the network (fig. 1(a)) with $Inp2$ fixed.*

To relate this picture to the behavior of the controlled robot one may have a look at the corresponding hysteresis diagrams plotted in figure 4. These diagrams for the output $Out3$ of neuron 3 are related to typical situations of an obstacle avoidance task. For instance figure 4(a) represents a turn to the right if there is an obstacle on the left (right input $Inp2$ is low: no obstacle).

The hysteresis interval of figure 4(c) represents a situation for which both input values reach their maximum. This will only rarely occur in experiments, because for this input configuration (narrow impasses or sharp corners) the robot will always turn away. In contrast to the “a” and “c” pictures the hysteresis interval of figure 4(b) is much larger. As can be seen from figure 3 this interval $-0.6 < Inp1 < 0.6$ exists for input values $-0.6 < Inp2 < 0.6$. These input constellations are related to deadlock situations, because sharp corners or impasses usually leads to sensor values in this domain. The oscillatory mode, also existing for ($Inp1$, $Inp2$)-values around the origin, will be never observed because inputs usually will sweep over this domain staying in the fixed point mode.

That the well skilled behavior of the robot is really the result of the interplay between all three hysteresis effects can be seen in various experiments. The behavior of the robot looses much of its performance if any of the underlying structures is destroyed. For instance, if the self-connection w_{44} of neuron 4 is deleted the robot leaves dead ends always by a turn to the right. For $w_{33} = 0$ it always leaves it by turning to the left. If both self-connections are deleted it can not leave deadlock situations. If self-connections are fixed but the 2-loop (w_{34}, w_{43}) is deleted then the robot gets stuck in critical situations.

5 Conclusion

Evolution and analysis of a minimal recurrent neuro-controller, enabeling a Khepera robot to avoid obstacles and to leave deadlock situations, led us to derive a generic function-structure relationship. The basis for the observed well skilled robot behavior was found to be the hysteresis effects associated to specific recurrences of the controller. Although the discussed task is a simple one, it was used here to demonstrate the behavioral relevance of non-trivial dynamical phenomena provided by recurrent neural networks. The theoretical results, summarized by the term *dynamical neural Schmitt trigger*, provide a guideline for the implementation of efficient control modules also for other robot platforms. This is of relevance because obstacle avoidance is one of the most basic behaviors mobile robots should acquire.

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