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Adaptive Behavior

Rocking Stamper and Jumping Snakes from a Dynamical Systems Approach to Artificial Life

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Dynamical systems offer intriguing possibilities as a substrate for the generation of behavior because of their rich behavioral complexity. However this complexity together with the largely covert relation between the parameters and the behavior of the agent is also the main hindrance in the goal oriented design of a behavior system. This paper presents a general approach to the self-regulation of dynamical systems so that the design problem is circumvented. We consider the controller (a neural network) as the mediator for changes in the sensor values over time and define a dynamics for the parameters of the controller by maximizing the dynamical complexity of the sensorimotor loop under the condition that the consequences of the actions taken are still predictable. This very general principle is given a concrete mathematical formulation and is implemented in an extremely robust and versatile algorithm for the parameter dynamics of the controller. We consider two different applications, a mechanical device called the rocking stamper and the ODE simulations of a “snake” with five degrees of freedom. In these and many other examples studied we observed various behavior modes of high dynamical complexity.

Keywords autonomous robots · self-organization · homeostasis · dynamical systems · learning

1 Introduction

Dynamical systems form a powerful tool for both the analysis and the realization of the behavior of autonomous robots. The increased interest in using dynamical system theory for the analysis of the robot in its environment may be dated back to the seminal paper by Randall Beer (Beer, 1995). At about the same time the book by Port and van Gelder (1995) initiated a broad interest in the role of dynamical systems for understanding life and cognition. There are numerous applications of this approach so far. In particular, the dynamical system theory has been used to understand the functionality of evolved networks for robot control (Nolfi & Floreano, 2000; Hülse & Pasemann 2002).

Apart from providing analytical tools, dynamical systems offer intriguing possibilities as a substrate for the generation of behavior. Let us consider a robot which is controlled by a neural network, say, transforming sensor values into motor commands. When using a recurrent network this transformation can be

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rather complex and reaches far beyond a simple reactive paradigm. This has been considered by several authors under varying contexts and with varying success. An elaborate behavior based design system has been developed in the context of dual dynamics. The system has a layered structure of behavioral subsystems realized by ordinary differential equations, each layer having its own time constant. Communication between the subsystems is realized by specific interaction and "bifurcation-inducing" mechanisms which have to be designed by hand (Bredenfeld, Jaeger, & Christaller, 2001). However, applications so far are scarce. Of particular interest is the dynamical system paradigm for walking machines where neural oscillators are used to generate the different gaits, see for instance Schöner, Dose, and Engels (1995), Steinhage (1997) and Hock, Schöner, and Giese (2003).

The authors quoted have mainly tried to design dynamical systems so that they realize prescribed tasks, the smooth navigation through a cluttered environment being a prominent example. The main problem with this approach, however, is in the design of the dynamical systems in view of the largely covert relation between parameters and behavior of the robot.

The main objective of our work is in fostering the self-organization of such systems under a true emergentist paradigm. Central is the aim to find mechanisms of self-regulation for the parameters so that in the rich reservoir of possible behaviors a working regime is stabilized which ensures the viability of the agent. Under this paradigm the aim is not the realization of a specific task given from outside but the emergence of organized motions.

Taking emergence at its roots means in our case the formulation of the objective for the robot on a very general not domain related level. In the present paper we develop a dynamics for the parameters of the controller which is essentially driven by the requirement that the dynamical complexity of the sensorimotor loop is to increase moderated by the requirement that the consequences of the actions taken are still predictable. It is the message of the present paper that this very general statement can be given a concrete mathematical formulation and that the emerging behaviors display a very high degree of dynamical complexity.

In concluding this introduction we will give a few remarks on related work. Our general aim has some roots in the concept of homeostasis, as introduced by Cannon (1939) and later Ashby (1954), as a general principle explaining the functionality of complex self-organizing biological systems. Homeostasis has recently received new attention in neurosciences. In particular a series of papers by Turrigiano and others, e.g. Turrigiano and Nelson (2004), have considered the role of various homeostatic mechanisms serving the purpose of counterbalancing the destabilizing effect of Hebbian learning.

There are a few attempts to introduce homeostatic mechanisms in robotics, e.g. Di Paolo (2003) and Williams (2004). However, while obviously helpful in stabilizing systems the principle of homeostasis seems of limited use for the construction of behavior systems. In fact the aim of such a system is not stasis but a common kinetic regime shared by the constituents of the system in order to produce the behavior in the world. We introduced homeokinesis (Der & Liebscher, 2002; Der, 2005a) as the dynamical pendant of homeostasis and the principle formulated in Section 2 is based on this paradigm.

The behaviors emerging from such general principles are contingent. This means that they depend strongly on the specific initial and environmental conditions and on the specific physics of the robot. In this way our work is also a contribution to the fostering and further understanding of the role of embodiment in the creation of artificial beings; see Pfeifer and Scheier (1999) for an overview. The focusing on behavior as arising from an entirely internal perspective is also an objective of the constructivistic approach (Glasersfeld, 1995) and of autopoiesis (Maturana & Varela, 1979), which underlines the internal perspective of the agent. Our contribution to these developments is to provide a concrete, mathematically grounded approach for the realization of these ideas in real robots.

2 Principles of Self-regulation

Based on the paper by Der, Hesse, and Liebscher (2005) we give here the basic principles of our approach. Basic to our approach is the dynamics of the sensor values. Let us consider a robot which produces in each instant $t = 0, 1, 2, \ldots$ of time the vector of sensor values $x_t \in R^n$. By way of example we may consider a wheel driven robot where

$$x = (v_l, v_r, IR_1, \ldots, IR_{n-2})^{\mathsf{T}} \tag{1}$$

where v_l and v_r are the wheel velocities of the left and right wheel, respectively, as measured by the wheel counters and IR_i is the value of the infrared sensor i with $0 \le IR_i \le 1$. We use closed loop control, i.e. the controller is given by a function $K : R^n \to R^m$ mapping sensor values $x \in R^n$ to motor values $y \in R^m$,

$$y = K(x)$$

with all variables being at time t. In the example we have $y = (y_1, y_2)^{\mathsf{T}}$, y_i being the control (target velocity) of wheel i. The controller may or may not depend on internal states realizing a proactive or a purely reactive behavior, respectively.

Our controller is to be adaptive, i.e. it depends on a set of parameters $C \in R^P$. In the cases considered explicitly below the controller is given by the pseudo-linear expression

$$K_i(x) = g(z_i) \tag{2}$$

where $g(z) = \tanh(z)$ and

$$z_i = \sum_j C_{ij} x_j + H_i \tag{3}$$

This seems to be overly trivial concerning the set of behaviors which are to be realized. Note however that in our case the behaviors are generated essentially also by an interplay of neuronal and synaptic dynamics which makes the system highly nontrivial.

2.1 World Model and Sensorimotor Dynamics

We assume that our robot has a minimum ability for cognition. This is realized by a world model $F : R^n \times R^m \to R^n$ mapping the actions y and old sensor values x to the new sensor values, i.e.

$$x_{t+1} = F(x_t, y_t) + \xi_t \tag{4}$$

where ξ_t is the model error. The model F can be learned by the robot using any learning algorithm of supervised learning. Let the model be a parameterized function (neural net) with parameters $a \in R^M$. The parameters a can be adapted by gradient descending the error function based on ξ. The structure of the model and the learning procedure define the passive cognitive abilities of the robot.

With these notions we may write the dynamics of the sensorimotor loop in the closed form

$$x_{t+1} = \psi(x_t) + \xi_t \tag{5}$$

where $\psi(x) = F(x, K((x))$. The function ψ can be visualized as a time series predictor for the time series of the sensor values x_t with the controller being known.

In the case considered below we have x, $y \in R^n$ and we assume that the response of the sensors is linearly related to the motor commands, i.e. we write (dropping the time index at the matrix A here and in the following)

$$x_{t+1} = Ay_t + \xi_t \tag{6}$$

where A is a matrix and ξ the modelling error, so that $\psi(x) = AK(x)$. The model can be learned by, for example, the delta rule. Again, this model seems to be over-simplified. However, model learning will be seen to be very fast so that different world situations are modeled by relearning.

2.2 The Paradigm of Controlled Sensitivity

As discussed in more detail in Der et al. (2005) the behavior is defined by formulating a parameter dynamics for the controller so that a self-regulating system is obtained. The parameter dynamics is essentially driven by two requirements: that the dynamical complexity of the sensorimotor loop is to increase; and that the consequences of the actions taken are still predictable. The dynamical complexity is directly related to the sensitivity of the sensorimotor dynamics to changes in the sensor values. We claim that one can combine the two above requirements by introducing virtual sensor values $\hat{x}_t$ defined by minimizing the objective function

$$F(\hat{x}_t) = \left\| x_{t+1} - \psi(\hat{x}_t) \right\| \tag{7}$$

with a conveniently defined norm[1]. In principle $\hat{x}_t$ must be found anew in each time step. Obviously the shift $v = \hat{x} - x$ is small if both ξ (which measures the predictability) is small and the function ψ is sensitive to its arguments. Hence the two aims of getting a robot with both highly sensitive reactions and predictability of behavior amounts to the requirement that the shift necessary to produce the new sensor values is as small as possible. Consequently we may define

$$E_t = v_t^2 \tag{8}$$

where (dropping the time index) $v^2 = v^{\mathsf{T}}v$ as our objective function for the behavior of the robot. Using gradient descent the parameter dynamics is

$$\Delta C = -\varepsilon \frac{\partial E}{\partial C}(x, C) \tag{9}$$

Note that the parameter dynamics Equation (9) is updated in each time step so that in practical applications the parameters may change on the behavioral time scale. This means that the parameter dynamics is constitutive for the behavior of the robot.

2.3 Explicit Expressions

The above equations define our approach in principle. However, in order to better understand the nature of the parameter dynamics we study it in the approximation of small v. If v is small we may use Taylor expansion to write

$$\psi(x + v) = \psi(x) + L(x)v \tag{10}$$

where L is the Jacobian matrix of the sensorimotor loop defined as

$$L_{ij} = \frac{\partial}{\partial x_j}\psi_i(x)$$

Using Equation (10) in Equation (7) we find[2]

$$v = L^{-1}(x)\xi$$

and obtaining v means now we “only” need to find the (pseudo-) inverse of the matrix L.

Introducing the positive semidefinite matrix $Q = LL^{\mathsf{T}}$ Equation (8) may now be written as

$$E = \xi^{\mathsf{T}} Q^{-1} \xi \tag{11}$$

see Der et al. (2005) for further details. We used this expression in the parameter dynamics Equation (9) in the examples given below. As explained above, in these examples we have

$$\psi_i(x) = \sum_{k=1}^{n} A_{ik} g(z_k)$$

so that

$$L_{ij}(x) = \sum_{k=1}^{n} A_{ik} g'(z_k) C_{kj} \tag{12}$$

Equation (11) involves the inverse of the matrix Q which measures the sensitivity of the sensorimotor loop towards changes in the sensor values. Therefore, minimizing E is immediately seen to increase this sensitivity. We have shown in many practical applications that in this way the robot develops an explorative behavior which, however, is moderated by the fact that E is also small if the prediction error ξ is small. Behavior may be understood as the compromise between these two opposing tendencies.

3 Example I. The Rocking Stamper

One of the interesting phenomena observed under the parameter dynamics derived from Equation (9) is the active closing of the sensorimotor loop so that the system is set into motion, see Der et al. (2005). In order to demonstrate this phenomenon we consider here a system consisting of a bowl-like object with a pole mounted on it driven by two motors in orthogonal directions, see Figure 1. The only sensors we have are two infrared sensors mounted at the two front ends of the trunk looking down and slightly sideways. Their values x_1 and x_2 depend on the distance to the ground in a highly nonlinear way. Our controller consists of two neurons with outputs y_1, y_2 controlling the angles of the pole relative to the trunk.

We use the linear world model with delta rule learning and the pseudolinear controller so that the gradient of the error $E = \xi^{\mathsf{T}} L^{-1\mathsf{T}} L^{-1} \xi$ is easily evaluated because the inversion of the matrix L can be done explicitly.

The initialization of the parameters C_{kl} can be done randomly starting with small values. However, one should check whether the sign of the determinant of L is positive, and if not reinitialize. The point here is that the error E diverges if L is singular and that the sign of the determinant defines the nature of the bifurcations taking place. If the determinant is negative, the feed-back strength in the sensorimotor loop is driven towards large negative values. Once beyond the flip bifurcation the signs of the controller outputs are inverted in each time step which is difficult to realize for the robot.

After initialization at first we have subcritical values for the feed-back strength of the sensorimotor loop

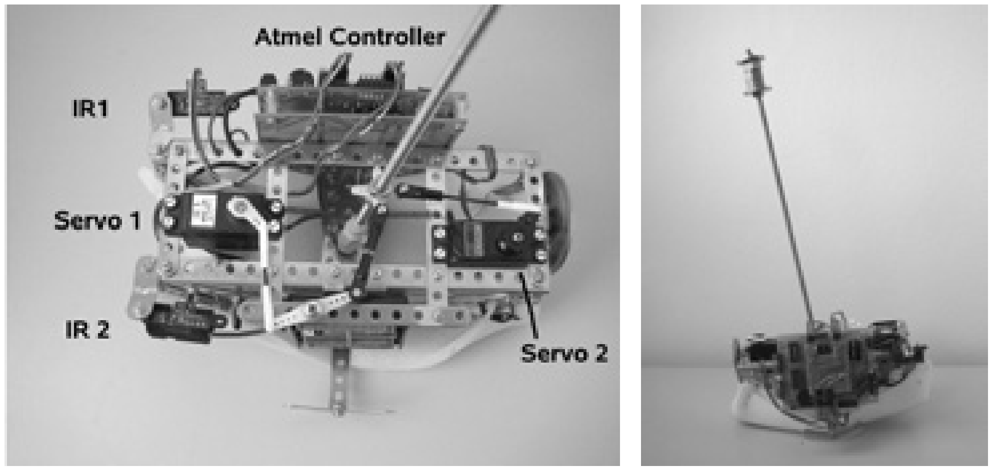

Figure 1 Pole driven stamper. Left: close view from the top; Right: pole to the front.

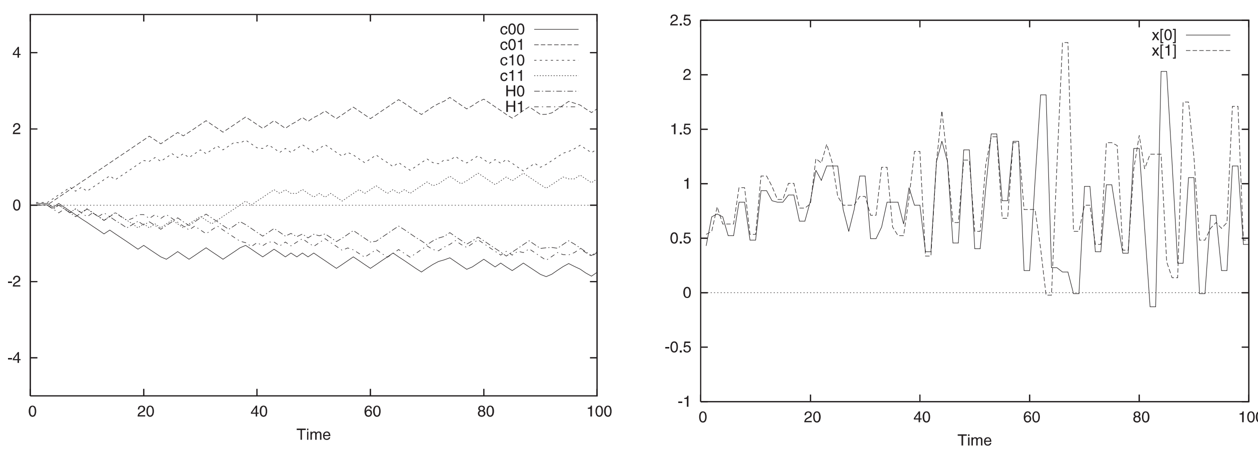

Figure 2 Behavior represented by sensor readings and controller parameters starting from low initialization. Left: sensor values from left and right infrared sensor over time. One can see clearly how the controller becomes sensitive and increases C_{kl}; The bias terms (upper two of the lower three lines) H_i are seen to be adapted so as to compensate for the positive average of the sensor values. Right: controller parameter values over time. The controller matrix is adapted to map the difference of both sensors to servo 1 (y_0) and the sum of both sensors to servo 2 (y_1).

(see Der et al., 2005 for details) so that the influence of the noise (the prediction error ξ) is damped and we observe only small fluctuations of the pole position. With increasing values of the controller parameters C and therefore increasing feed-back strength the pole movements become stronger so that after some time a bifurcation point, typically the Neimark-Sacker bifurcation (see Haschke & Steil, 2005; Pasemann, Hild, & Zahedi, 2003 for details) is reached and an (irregular) oscillatory motion sets in. In Figure 2 the behavior, reflected by the sensor readings, and the parameter adaptation is displayed over time.

The interesting point in these experiments is that despite the extremely nonlinear and nondeterministic behavior of the mechanical system the controller learns to produce a motion that probes the possibilities of its body in a more or less controlled manner. In Figure 3 the behavior in a later stage of the experiment is shown.

We observed a rocking (oscillatory) as well as a walking-like behavior, the latter being caused by a rotational mode of the pole with suitable phase shift. The emergence of these modes is a direct consequence of the sensitization paradigm. In fact, it is in these

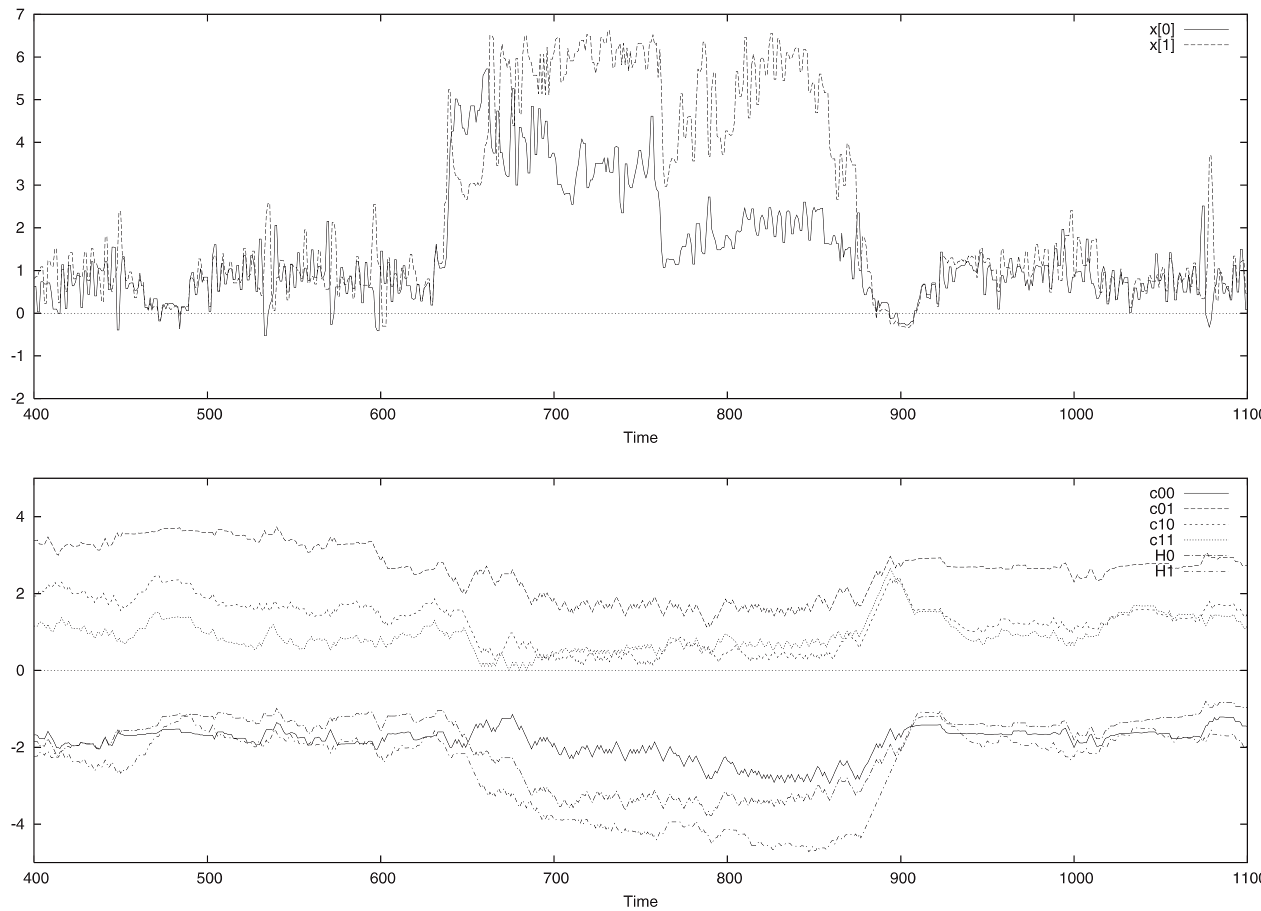

Figure 3 Environment sensitive behavior. Top: sensor values from left and right infrared sensor over time. Bottom: parameter values over time. Until time 640 we observed rocking (oscillatory) motion with a short break at time 480. Then the robot was set into a corner. The infrared sensors measure much shorter distances because they see the walls. At time 870 the robot was pulled back into free space. After each change of the environment the robot was calm for a while (low sensor fluctuation) and probed the new environment, however after a short time the robot rocked again.

modes that the controller – based on the current sensor values – can evoke the maximum change in the sensor values over the time step. Ideally this would exploit the eigenfrequency of the mechanical system, which is indeed approximately what happens.

In order to demonstrate the environment related nature of the emerging behaviors we put the performing robot into a corner where the infrared sensors measured a much shorter distance. As a result the robot became calm for a short time. Then the parameters were readapted to the new situation, so that an oscillatory behavior set in again. The same readaptation scenario occurred when moving the robot away from the corner by hand.

We see that the robot is always sensitive to its environment and adapts to new situations quickly.

4 Example II. Snakes

Systems with more degrees of freedom and of much higher complexity may be realized in ODE simulations (Smith, 2005). We consider snakes as sketched in Figure 4. In this application we use proprioceptive sensors only, so that the sensorimotor loop now has n degrees of freedom where n is the number of joints. We assume a linear world model as before.

In the general n dimensional case the inversion of the matrix L does not make sense numerically. Instead we find v directly by solving the equation $\xi = Lv$ for v by some numerical method. A rather crude approximation turns out to be appropriate.

In the following experiments we used a snake with $n = 5$ joints on a plane, see Figure 5. We initial-

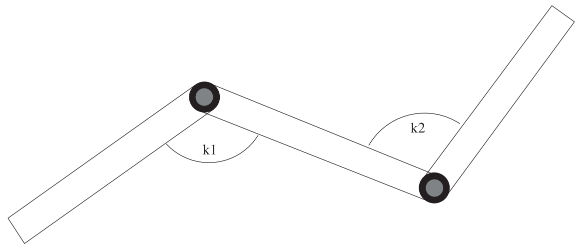

Figure 4 A snake with two joints. Sensor values sent to the controller are the angular velocities of the joints, the controller outputs being the desired angular velocities. Note that the controller has no knowledge about the angles, the masses and geometry of the arm, and other environmental observables. The only information about the world is given by collisions and friction forces.

ized the matrix A as a diagonal matrix with the A_{ii} chosen so that the response of the joints was already coarsely modeled. The matrix C was also diagonal but with very small random values for the C_{ii} so that in the beginning the joints executed fluctuating motions only. In the beginning we have n decoupled feed-back loops as a result of this diagonal initialization. As seen in Figure 6 the parameter dynamics rapidly increases the diagonal elements of C so that the feed-back strength in each of the loops increases. After some time they reach the critical values where the fixed points are destabilized and an intensive motion sets in. In this regime the nondiagonal elements are also seen to develop so that the dynamics of the joints are coupled. On the one hand this is again an effect due to the sensitization pressure which favors oscillatory modes. On the other hand the reactions of the joints to the applied forces are correlated because of collision, inertia, and friction effects. Therefore the motion of the snake is largely dependent on the environmental

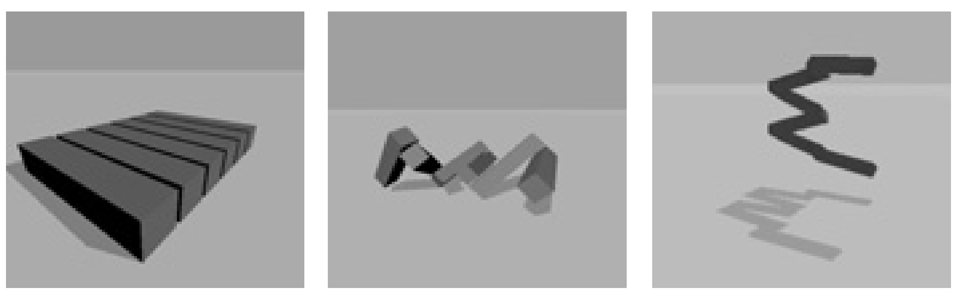

Figure 5 Screenshots of snakes on a plane. Left: in initial position; Center: crawling; Right: jumping.

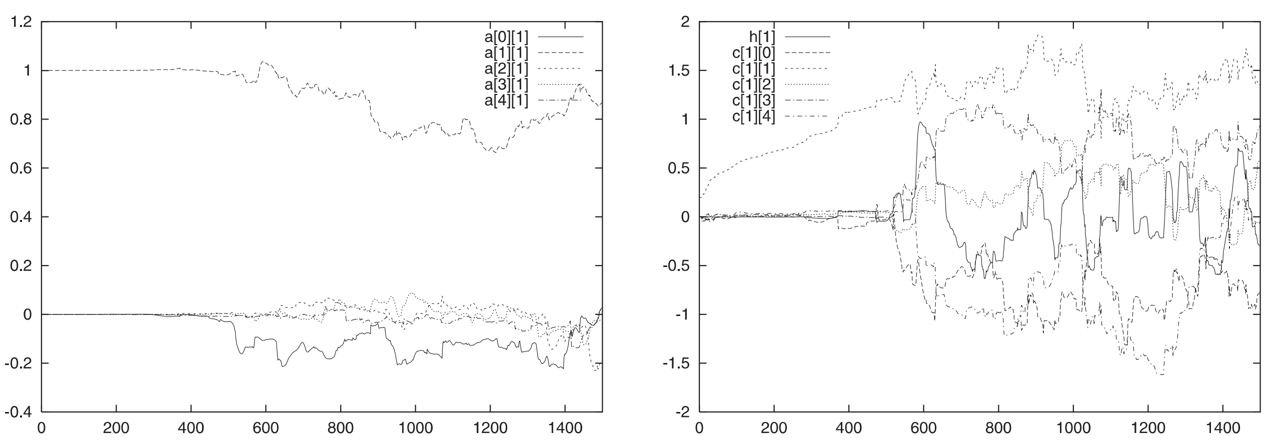

Figure 6 Development of the parameters A_{i1} and C_{1j} associated with the neuron controlling joint 1 in the initial phase of an experiment. Left: the world model matrix A is initialized as the unit matrix reflecting the independence of the joints. The learning dynamics preserves this in the initial phase. Right: the diagonal elements of the matrix C are initialized with very small random values for C_{ii}. The diagonal elements increase until the supercritical feed-back strength is reached and the system starts to move (at about time 500). The development of the nondiagonal elements reflects the integration of contributions of the other segments. However, the self coupling C_{ii} is seen to remain dominant (top line).

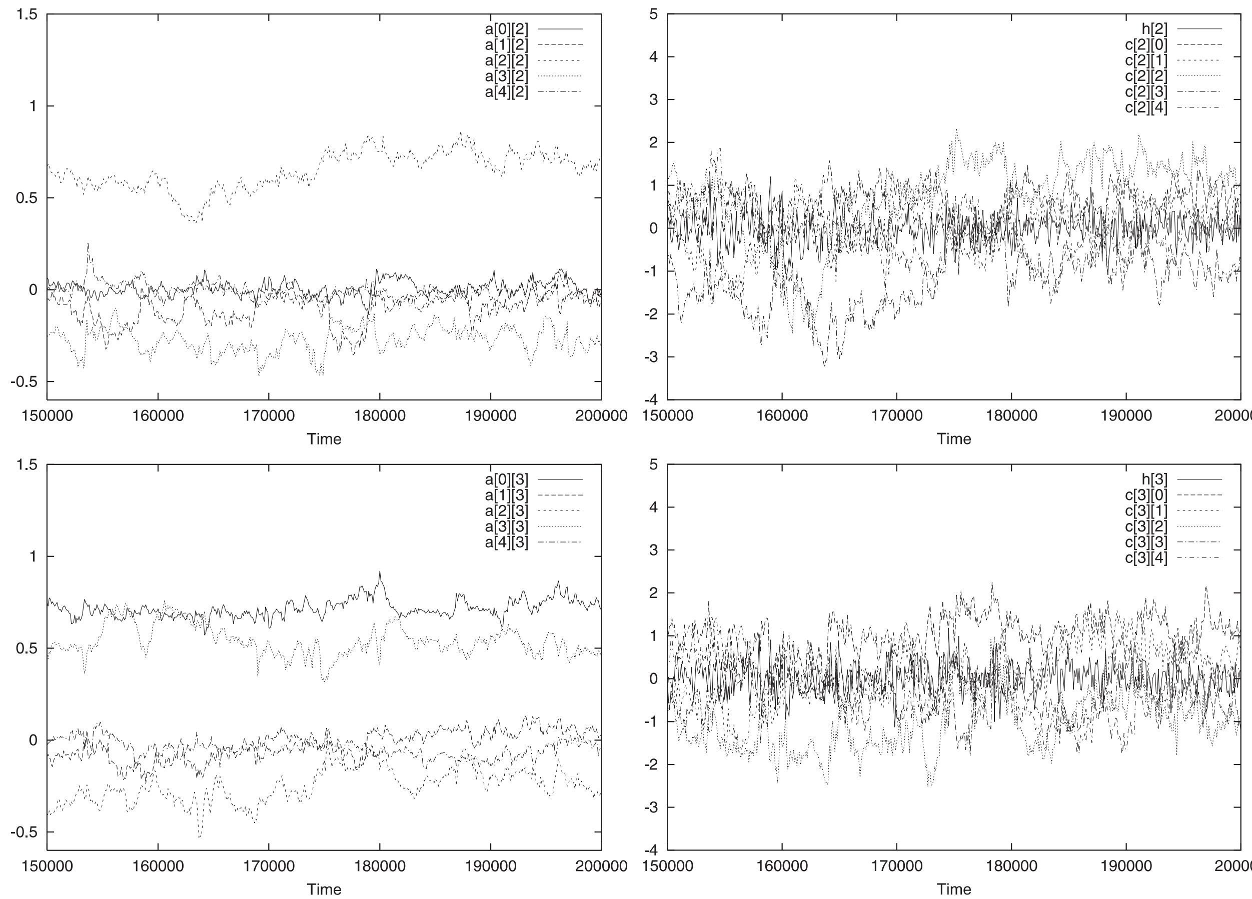

Figure 7 Controller and model parameters for joints 2 (top) and 3 (bottom) during time step 150000 to 200000 (every 100th value plotted). Left: model parameters; Right: controller parameters. In accordance with our sensitization paradigm the controller parameters are substantially changing over time but stay within a certain range, so that the neurons remain in a sensitive working regime. The model parameters A_{ij} describe the observed angular velocity at joint i as the response of the motor action applied to joint j. One would expect a diagonal matrix A, however some non-diagonal elements are non-zero, reflecting the correlations between different joints, for instance a[0][3] in the lower left diagram.

conditions and this is clearly borne out by the experiments. The coherence in the motions of the joints is reflected by the nondiagonal elements of the matrix A, see Figure 7.

The emerging dynamics is quite complex and rather difficult to analyze. However, the degree of organization of the motion can, for instance, be measured by the motion of the center of the snake projected on the plane, see Figure 8 (left). We find that in the beginning the center is more or less stationary (in a time average picture) but after some time the snake covers increasingly larger regions of space. Apart from that, the altitudes of the snake segments also provide information about the type of behavior. For analytical purposes we consider the center of the highest and lowest segment over time. The difference between both can be interpreted as a measure for the current posture. Jumping behavior is characterized by an altitude > 0.5 of the lowest segment. As shown in Figure 8 (right) the snake sits up frequently and occasionally performs jumps. Note that even on long time scales we observe qualitative changes in the parameters (Figure 7), indicating a rich behavior diversity. This is also seen directly when watching the snake over a long time (see the videos). We did this in many experiments in varying environments and also with two snakes in a cage. In all cases we observed an impressive variety of behavior.

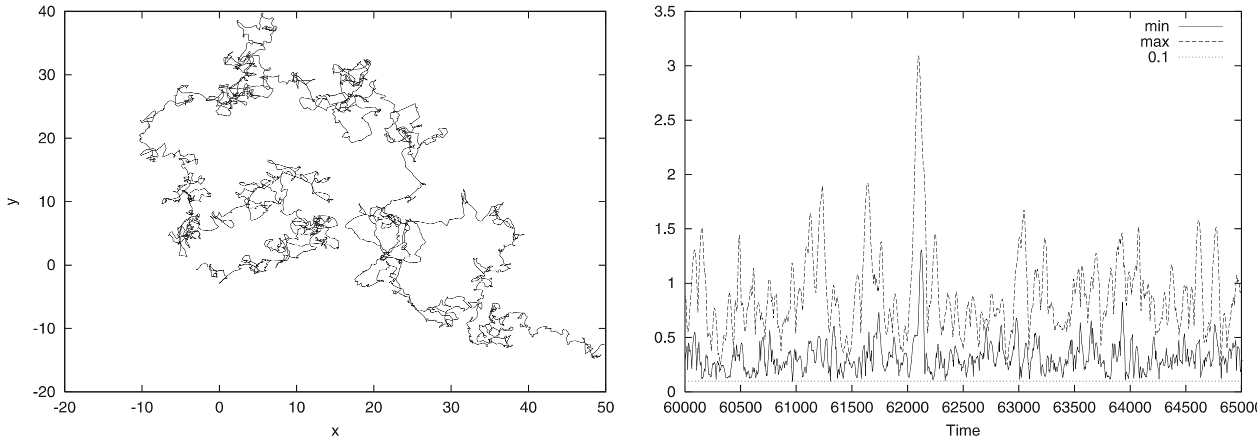

Figure 8 Motion of snake with 5 joints (6 segments with length 1) during the experiment. Left: position of the snakes center projected on the plane over 165 000 time steps with starting point at (–3,0). Right: altitudes of the centers of the highest (max) and the lowest (min) segment from time step 60000 to 65000. Segments laying completely on the ground have a altitude of 0.1 whereas standing upright they have a altitude of 0.5. One can see that the snake sits up and even jumps so that it exceeds the altitude of 0.5 with the lowest segment.

5 Discussion

We have demonstrated in this paper that in applications to completely different agents our general paradigm yields in each case an environment related active behavior. The emerging behaviors are dictated by the body of the agent. Our stamper develops rocking or even "walking" modes, sometimes covering substantial regions of space. The snake, which is mechanically completely different, is seen to develop crawling and jumping modes which may be considered as emerging behavioral organization where the snake learns to feel the possibilities of its body.

The emerging behaviors may be called environment related although they are generated by a completely domain invariant principle. For instance this is demonstrated by the stamper which when in a rocking or "walking" mode can be taken and put in a corner so that there is a completely new sensorial situation. Nevertheless, after some time it again develops its rocking behavior so that eventually it gets out of situations where it was captured. Similarly we can put one or several of our snakes into a cluttered environment (work in progress) without the snakes being caught in corners. Moreover the snakes may entangle but in all situations find a way to disentangle. First results can be found in the videos in Der (2005b).

A further interesting property of our approach is that the parameter dynamics never gets stuck in the saturation regions of the neurons and that the activity of the agents does not go down for a longer time. Although we have taken some numerical precautions this is still an amazing property of the algorithm in view of the fact that the parameter dynamics is ultimately driven by the noise (prediction error) which may change by orders of magnitude.

It is interesting to compare our results with related efforts from artificial evolution. From the point of view of dynamical complexity our snake is close to creatures of the Framstick world (Komosinski, 2000, 2005) and also to some of Karl Sims' creatures (Sims, 1994). The main difference is that the latter have been evolved for a specific behavior and the creatures can only perform correctly if situated in an appropriate environment. In contrast, the behaviors displayed by our creatures are to a very large extent contingent.

We consider our approach as a novel contribution to the realization of artificial life systems. At the present step of our development the behaviors, although related to the specific bodies and environments, are without goals. What we have achieved so far is the concomitant learning of explorative behaviors together with their forward model from scratch. This is a bootstrapping task which is solved under our paradigm in a more or less natural way invoking phenomena such as spontaneous symmetry breaking which leads to the emergence of low dimensional behavior modes in high dimensional search spaces. Our solution of this bootstrapping problem may also contribute to the so callled developmental robotics. An example close to our work is that of Kuniyoshi et al. (2003) which aims at the emergence of higher cognitive abilities from the physical dynamics of the robotic system and its sensorimotor interaction with the world. The parallel is at the level of motor learning where the authors demonstrate the need to acquire a set of explorative behaviors from scratch. This is exactly the task solved by our system. As a next step we will realize so-called behavior based reinforcement learning. Our paradigm so far creates a sequence of behavioral primitives which are to be learned by a satellite network. Under a competing expert paradigm each of the experts would be responsible for one of the emerging behaviors. As in behavior based robotics these primitives can be combined into more complex behaviors guided by reward and punishment in order to incrementally shape the system into a goal oriented behavior.

Notes

1 In general the choice of $\hat{x}$ is not unambiguous. This must be solved by additional constraints. However, in the examples considered below we can determine $\hat{x}$ by matrix inversion, which is unambiguous for nonsingular matrices. Nonsingularity is ensured through initialization and the learning rule.

2 If L is singular this is to be understood in the sense of the pseudoinverse.

Acknowledgment

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