Let it roll – Emerging Sensorimotor Coordination in a Spherical Robot

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Abstract

Self-organization and the phenomenon of emergence play an essential role in living systems and form a challenge to artificial life systems. This is not only because systems become more life like but also since self-organization may help in reducing the design efforts in creating complex behavior systems. The present paper exemplifies a general approach to the self-organization of behavior which has been developed and tested in various examples in recent years. We apply this approach to a spherical robot driven by shifting internal masses. The complex physics of this robotic object is completely unknown to the controller. Nevertheless after a short time the robot develops systematic rolling movements covering large distances with high velocity. In a hilly landscape it is capable of maneuvering out of the wells and in landscapes with a fixed rotational geometry the robot more or less adapts its movements to this geometry – the controller so to say develops a kind of feeling for its environment although there are no sensors for measuring the positions or the velocity of the robot. We argue that this behavior is a result of the spontaneous symmetry breaking effects which are responsible for the emergence of behavior in our approach.

Introduction

Self-organization and emergent functionality are the main phenomena which make living beings so different from machines (robots) built on rule based paradigms. This is one of the reasons why many researchers in robotics and artificial life are using neural networks, dynamical systems and artificial evolution in order to create complex behavior systems with live like properties. Beside of mimicking living beings, self-organization is also an interesting phenomenon since it may help in reducing the design efforts in creating complex behavior systems.

The spontaneous creation of patterns in time, space or space-time in complex many-component systems is a well known phenomenon in physics with a well developed theoretical background. Moreover as shown in synergetics, the physical principles are effective in quite different systems of biology, economy and the like. In robotics these results are becoming fruitful currently in swarm robotics which may be considered as a complex many body system, cf. (Kim, 2004), (Lerman et al., 2004), (Lerman and Galstyan, 2004). Self-organization is also an objective in the embodied intelligence approach, cf. (Pfeifer and Scheier, 1999) and in the dynamical systems theory as applied to robotics, cf. (Tani and Ito, 2003), (Tschacher and Dauwalder, 2003) to name just a few.

The encouraging results obtained already in different fields cry for a general approach to the self-organization of behavior. We understand by a general approach that there is a completely domain invariant objective function which produces seemingly domain related behaviors. The present paper exemplifies a general approach to the self-organization of behavior which has been developed and tested in various examples in recent years which tries to meet this challenge, cf. (Der, 2001), (Der and Liebscher, 2002), (Der et al., 2004), (Der et al., 2005a), and (Der et al., 2005b). The objective function is derived from the following principle: The ideal behavior of the robot is qualified by (i) a maximum sensitivity to current sensor values. This induces a self-amplification of changes in the sensor values and thus is the source of activity; and by (ii) a maximum predictability of future sensor values. This keeps the behavior in "harmony" with the physics of the body and the environment. The difference between the current and the ideal behavior is used as the objective function which by gradient descent yields the synaptic dynamics of the controller neural network. The explicit form of both the objective function and the synaptic dynamics is given below.

We apply this approach to a spherical robot driven by shifting internal masses. Like in previous applications the example demonstrates and further elucidates the emergence of environment related behavior – the robot does what it seemingly is meant to do – out of our domain invariant general paradigm of self-organization. The paper is organized as follows. We give in the next section the general theory as applied to the spherical robot and in the following section we present experiments corresponding to different sensor equipments. In the first set of experiments the sensor values are given by the projections of its internal axes on the z-axis of the world coordinate system whereas in second set of experiments we have infrared sensors so that the robot can take its environment into account. We will see that the in the latter case we obtain emerging locomotion modes specific to structured environments. Some conclusions may be found in the closing section.

Self-organizing dynamical systems

Based on the papers (Der et al., 2005a), (Der et al., 2005b) we give here the basic principles of our approach. We start from the information the robot gets by way of its sensor values. In the presented experiments we use a spherical robot driven by moving internal masses situated on three orthogonal axes, see Fig. 1. In each instant $t = 0, 1, 2, \ldots$ of time the robot produces a vector of sensor values $x_t \in R^3$. The sensor values are the projections of the axes vectors on the z-axis of the world coordinate system.

The motor values $y_t \in R^3$ give the target positions of the internal masses on the corresponding axes.

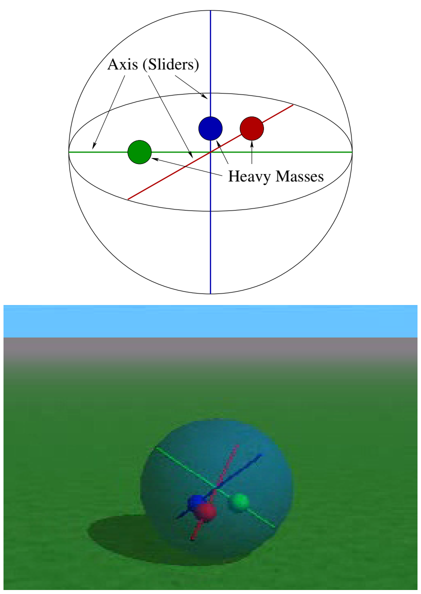

Figure 1: Simulated spherical robots used in the experiment. Top: Sketch of a sphere. Inside each sphere there are three orthogonal axes equipped with sliders. To each slider a heavy mass is attached which can be shifted along the axis. There is no collision or interaction of the masses at the intersection point of the axes. Bottom: Picture of a sphere on the ground.

The controller is given by a function $K : R^n \to R^m$ mapping sensor values $x \in R^n$ to motor values $y \in R^m$

$$y = K(x)$$

all variables being at time t.

Our controller is to be adaptive, i.e. it depends on a set of parameters $c \in R^C$. In the cases considered explicitly below the controller is realized by a one layer neural network defined by the pseudolinear expression

$$K_i(x) = g(z_i) \tag{1}$$

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

$$z_i = \sum_j c_{ij} x_j + H_i \tag{2}$$

This seems to be overly trivial concerning the set of behaviors which are observed in the experiments. Note, however, that in our case the behaviors are generated essentially also by an interplay of neuronal and synaptic dynamics (see Eq. 11) which makes the system highly nontrivial.

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 of the robot on the new sensor values, i.e.

$$x_{t+1} = F(x_t, y_t) + \xi_t \tag{3}$$

where ξ_t is the model error. The model F can be learned by the robot using any learning algorithm of supervised learning.

In the case considered below we have $x, y \in R^n$ and we assume that the response of the sensor is linearly related to the motor command, i.e. we write

$$x_{t+1} = Ay_t + B + \xi_t \tag{4}$$

where A is a $n \times m$ matrix, B a column vector, and ξ the modeling error. The model is learned by gradient descent as

$$\begin{aligned} \Delta A &= \varepsilon_M \, \xi y^T \\ \Delta B &= \varepsilon_M \, \xi \end{aligned} \tag{5}$$

both ξ and y taken at time t. Again, this expression seems to be oversimplified. However model learning will be seen to be very fast so that the model parameters change rapidly in time so that different world situations are modeled by relearning. Moreover the model only is to represent the coarse response of the world to the actions y of the robot, behavior being organized such that this reaction is more or less predictable. Hence the world model mainly is to give a qualitative measure of these response properties.

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

$$x_{t+1} = \psi(x_t) + \xi_t \tag{6}$$

where in our specific case

$$\psi(x) = AK(x)$$

Realizing self-organization

As well known from physics, self-organization results from the compromise between a driving force which amplifies fluctuations and a regulating force which tries to restabilize order in the system. In our paradigm the destabilization is achieved by increasing the sensitivity of the sensoric response induced by the actions given by the controller. Since the controls (motor values) are based on the current sensor values, increasing the sensitivity in this sense means amplifying small changes in sensor values over time which drives the robot towards a chaotic regime.

The counteracting incentive is obtained from the requirement that the consequences of the actions taken are still predictable. More details may be found in (Der and Liebscher, 2002), (Der et al., 2005a), (Der et al., 2005b). It is one of the results of our work that these general statements about the behavior of the robot can be formulated into an objective function so that the parameter dynamics can be obtained by gradient descent. As derived earlier, the difference between the ideal and the true behavior of the robot can be measured by

$$E = \xi^T Q^{-1} \xi \tag{7}$$

where ξ is the model error as introduced above, the positive semidefinite matrix $Q = LL^T$ and $L = \partial\psi/\partial x$ is the Jacobi matrix of the sensorimotor dynamics which in the specific case reads

$$L_{ij}(x) = \sum_{k=1}^{n} A_{ik} g'(z_k) c_{kj} \tag{8}$$

all quantities depending on time t. Using gradient descent the parameter dynamics is

$$\Delta c_t = -\varepsilon \frac{\partial E_t}{\partial c_t}(x_t, c_t) \tag{9}$$

explicit expressions for the parameter dynamics being given below, cf. Eq. 11. Note that the parameter dynamics Eq. 9 is updated in each time step so that the parameters in practical applications may change on the behavioral time scale if the update rate ε is chosen conveniently. This means that the parameter dynamics is constitutive for the behavior of the robot.

The explicit expression Eq. 7 displays rather obviously the essence of our approach. The matrix Q measures the sensitivity of the sensorimotor loop towards changes in the sensor values. Minimizing E is thus immediately seen to increase this sensitivity since E contains the inverse of Q. 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 which is the case for smooth environment related behaviors. The emerging behaviors may be understood as the compromise between these two opposing tendencies.

Explicit parameter dynamics

The parameter dynamics is given by the gradient descent on the error function E, cf. Eq. 7 of the controller as given in general form by Eq. 9. The parameter dynamics may be obtained for any concrete realization of the controller in a straightforward way. In the special case of L as given by Eq. 8 the dependence on c enters both directly and via z in an indirect way. Using $z = cx + H$ so that

$$\frac{\partial}{\partial c_{ik}} z_j = \delta_{ij} x_k \tag{10}$$

and using that for $g(z) = \tanh(z)$ we have $g''(z) = -2gg'$ the explicit formulae are (omitting the time indices everywhere)

$$\begin{aligned} \varepsilon^{-1} \Delta c_{ij} &= \zeta_i v_j - 2\zeta_i \rho_i y_i x_j \\ \varepsilon^{-1} \Delta H_i &= -2\zeta_i \rho_i y_i \end{aligned} \tag{11}$$

where[1] $v = L^{-1}\xi$, $\zeta_i = g_i' \mu_i$, $\mu = A^T Q^{-1} \xi$, and $\rho = cv$. The inversion of the matrix Q is done by standard techniques and has proven in many applications to be feasible and not time critical in applications with up to 20 degrees of freedom.

We may interprete the first term $\zeta_i v_j$ in Eq. 11 as a general driving term which is seen to increase the sensitivity of the sensorimotor loop. The second term contains the nonlinearity effects due to Eq. 10 and essentially keeps the neurons out of the saturation regime where they are not sensitive to the inputs. It may be interpreted as an (anti-) Hebbian learning term with strength given by $2\zeta_i\rho_i$. The H dynamics is driven exclusively by this term.

Note that the parameter ε is chosen such that the parameters change at about the same time scale as the behavior. The interplay between synaptic and state dynamics of the controller induces a high dynamical complexity of the sensorimotor loop. The ensuing robot behaviors thus are of a much larger complexity than the pseudolinear expression with fixed parameters might ever realize.

Experiments

The simulated spherical robot used in the present paper, see Fig. 1, was originally inspired by Julius Popp (Popp, 2004). We used the ODE tool (open dynamic engine (Smith, 2005)) for the computer simulation experiments. The sphere is driven by moving internal masses situated on three orthogonal axes by servo motors. The motor values are the target positions of each of the masses on its axis. Motor values of 1 and -1 correspond to the outer positions on the axis, while a zero value corresponds to the center position at the intersection point of the axes. Collisions of these masses especially at the intersection point are ignored in the simulations. In the first example considered below three proprioceptive sensor are used. The sensor values are the projections of the axes

[1] A convinient regularization procedure is to be used if L is singular.

vectors of the sphere on the z-axis of the world coordinate system. Other sensors will be introduced later.

Both sensor and motor values are related to the motions of the sphere in a very complicated manner. The task of the controller is to close the sensorimotor loop so that a rolling motion of the robot is achieved. This would be usually done by constructing the controller conveniently. In our case the rolling motion will be seen to emerge from our general principle given above.

Emergence of a rolling mode

In the experiments the spherical robot is put into different environments ranging from a free plane up to complex landscapes with many spherical robots in them. We initialize the complete system in a "do nothing" and "know nothing" setting, meaning that the parameters of both the controller and the world model are initialized with very small random values so that the feed-back strength, given by the eigenvalues of the response matrix $R = CA$, of the sensorimotor loop is very low. The only motion emerging in this subcritical situation is being caused by the sensor noise which makes also the controls y fluctuate around zero so that the sphere executes weak random movements.

With y close to zero the update of the parameters is dominated by the driving term in Eq. 11 with the effect that the feed-back strength is increasing. Once the critical level is exceeded fluctuations are beginning to be amplified and the symmetry of the system is spontaneously broken which affords the emergence of new modes of behavior.

In a first experiment we put the robot onto a horizontal surface without any obstacles. In this free space situation the most simple mode seems to be a stable rolling behavior, which may be realized by rotating around one axis of the object coordinate system with the mass on this axis being used for steering. This mode is realized repeatedly. Due to the explorative character of the paradigm the steering mass shifts so that a slightly curvy trajectory is created. This mode is being left when the trajectory is getting too curvy. The alternative rolling mode is realized by all three mass points shifting on an equal footing, see the free space video (Der et al., 2005c) and the trajectories in the Figure 2. Occasionally we also observe jumping behavior obtained by a sudden synchronous motion of the masses in the vertical direction. These modes are the manifestation of a tight sensorimotor coordination which is realized by our parameter dynamics.

Feeling the geometry of the environment

Sensorimotor coordination is seen from considering in particular the spheres when rotating in our landscape consisting of one or several basins. In a first experiment we consider one sphere in a basin with a rotational symmetry, see Fig. 3. The sphere is put to the bottom of the basin and initialized in the "do nothing and know nothing" setting. Initially one observes a fluctuating motion. After some time a rolling

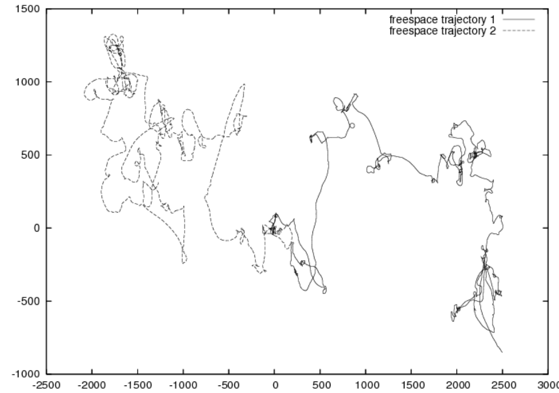

Figure 2: Two independent trajectories each of a 200 minute run of the spherical robot in free space observed from above. The axes are the coordinates in the $x-y$ plane. Please note that the robot has a diameter of 1. One can see passages of straight rolling as well as curvy behavior.

motion emerges just as in free space. However, the trajectory now is essentially determined by the geometry of the basin. In the beginning of the large scale motions the trajectory crosses the bottom of the basin but after some time a circular trajectory is repeatedly realized. In this case the robot essentially keeps at a constant height where the terrain might be quite steep. This however is not an effect of the centrifugal forces because the velocity of the robot is not high enough.

Instead this trajectory is generated by a complicated regime of shifting the internal masses of the robot. This motion has to be brought about by the controller which however sees only the projections of the object coordinate system to the z axis of the world coordinate system. The mode "rotation around one axis" as described above is not well suited for this task because it would require that the position of the steering mass which depends on the radius of the circle is to be inferred from the very small projection of the steering axis on the z axis of the world coordinate system. As seen in the sphere robot videos (Der et al., 2005c) the system finds another mode for realizing a circular trajectory where all three axes are involved in the creation of the motion of the sphere.

At this point one may ask how the controller is able to learn this behavior. We speculate this to be a consequence of the symmetry breaking mechanisms underlying the emergence of the large-scale motions. The point is that the parameter dynamics is generated by gradient descending the function E which is defined entirely by the dynamics of the sensorimotor loop. Hence the symmetries present in the sensorimotor dynamics are conserved also in the full system comprising the parameter dynamics. Our sensitization paradigm destabilizes the sensorimotor dynamics so that every large scale motion is a result of a spontaneous symmetry breaking. These symmetry breakings tend to be economical, i.e. symmetries are broken in the least possible way. A circular trajectory in a rotational symmetric basin seems to be a convenient realization of this paradigm since we have a large-scale motion while keeping as much of the full symmetry of the system as possible.

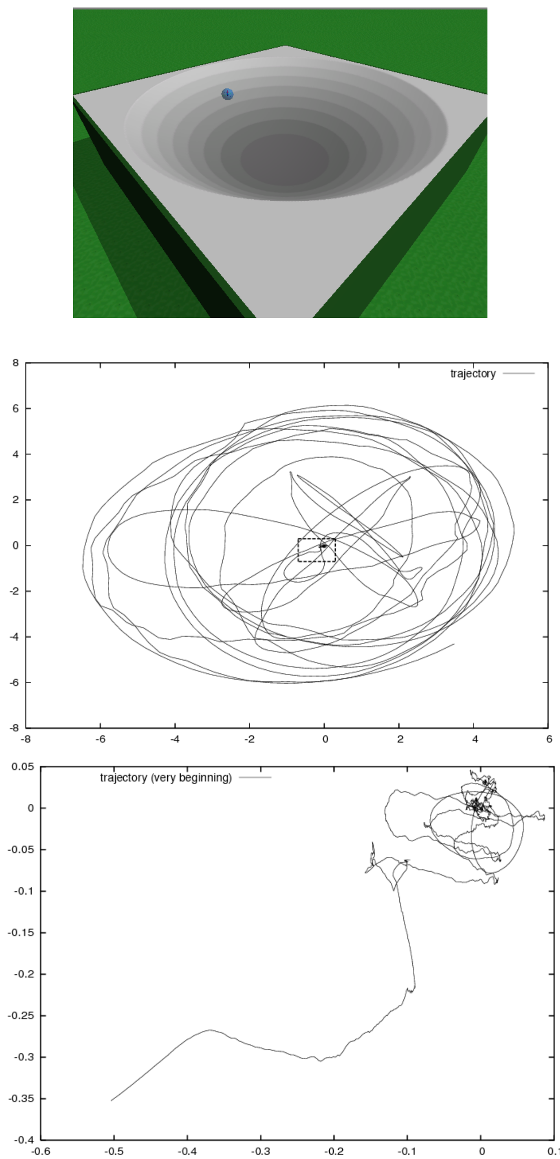

Figure 3: Spherical robot in a basin. Top: Picture of the environment with the robot. Middle: Trajectory in $x-y$ plane (first 4 min). Bottom: Zoomed trajectory in $x-y$ plane at the very beginning (first 45 sec), corresponding to the dotted rectangle in diagram above. The diameter of the robot is 1. At the beginning one can see random movements, which are driven by noise. Later the symmetry in the system is broken and the sphere starts explore its environment.

Feeling the environment with external sensors

Up to now we have used the orientation of the internal axes as sensor values. We are now going to discuss experiments with infrared sensors. We installed in the ODE realization one infrared sensor in each point of intersection of the axes with the surface of the sphere with the direction along the axis and range of about two diameters of the sphere. The 6 sensors obtained in this way are fed directly to the controller. The sensor characteristic was chosen nonlinear as $x = s^{\alpha}$, where s is the primary sensor value and $\alpha = 1.5$. The effect is that the sensor characteristic is a smoother function of the angular position of the robot.

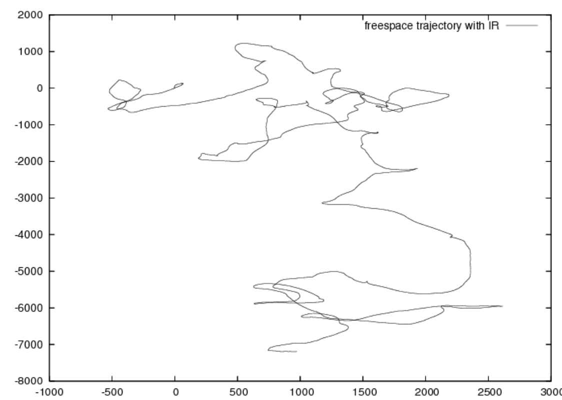

Figure 4: Trajectory of the spherical robot with infrared sensors in free space. The axis are coordinates in the $x-y$ plane (diameter of sphere is 1). One can see long passages of straight rolling as well as curvy behavior.

The interplay between the sensor values and the rotation of the sphere is largely different from the angular sensors. Nevertheless our controller again generates nice rolling modes. In free space there is no substantial difference between the two sensor cases, only that the sphere is rolling more straight ahead, see the trajectories given in Fig. 4. However a qualitative difference is observed if we put our spherical robot into an environment. For that we put the robot into a circular corridor with a diameter of 20 and a width of 2 sphere diameters. What happens is that the robot follows the corridor. However, if the robot is rolling straight on it will collide with the walls quite often, which effects the rotation axis substantially. In order to go around the environment smoothly the robot needs to steer in a circular manner. In figure 5 one can see the difference between the z-axis sensor and the infrared sensor cases. The result is distinguishing and shows that the robot with infrared sensors is performing much better in this environment. By observing the robot we have encountered a mode where the sphere is balancing carefully at the wall so that the rotation around one axis is preserved, cf. Fig. 6. This is much better possible with infrared sensors than with axis sensors, because the walls can actually be sensed. There is also a video (Der et al., 2005c) which shows this behavior, however the corridor is a bit wider there to allow easier video recording.

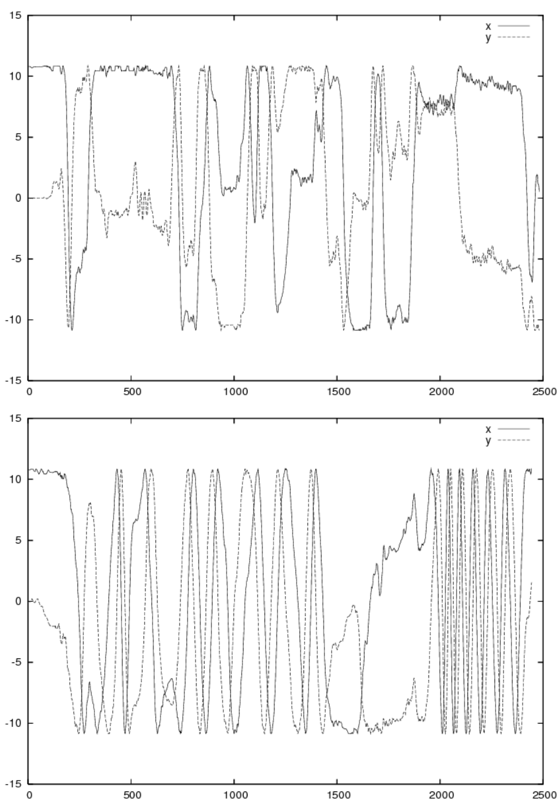

Figure 5: Plot of the x and y coordinate of the spherical robot in a circular corridor over time. The time scale is in steps of $\frac{1}{2}$ seconds, i.e. a total length of about 20 min. Top: With z-axis sensors. Bottom: With infrared sensors. At the sine-like shape of the lower plot one can clearly see that after some initial time the robot with infrared sensors is passing several rounds in a row in a smooth manner. The robot with z-axis sensor as described above is much less successful.

Discussion and outlook

We have applied in the present paper our general paradigm of self-organization to a spherical robot driven by shifting internal masses. Our approach is seen to generate the sensorimotor coordination necessary for the large-scale behavioral modes in a self-organized way. In particular the robot in the corridor has to realize a high degree of sensorimotor

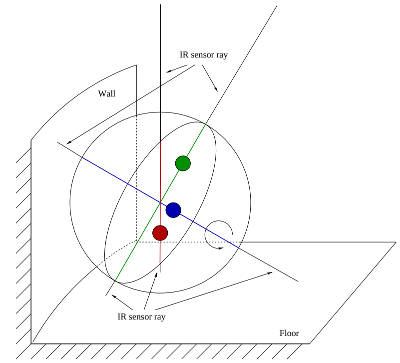

Figure 6: Illustration of the rolling mode of the spherical robot with infrared sensors at curved wall.

coordination in order to follow the corridor. The interesting point here is again that this specific property emerges from the general principle without any external guidance. This is a direct result of our paradigm. In fact the prediction of future sensor values is better realizable if the robot more or less follows the corridor instead of zigzagging as it does without the infrared sensors. As argued in the text these behaviors are truly emerging, i.e. they are a result of spontaneously breaking the symmetries of the system.

An important consequence is also derived for the interplay between the world model and the controller. The system does not have any information on the structure and dynamics of the body so that the world model has to learn this from scratch. This involves the so called cognitive bootstrapping problem meaning that on the one hand the controls are to be such that the world model is provided with the necessary informations. On the other hand these actions require a certain knowledge of the reactions of the body – information is acquired best by informed actions. The concerted manner by which both the controller and the world model evolve during the emergence of the behavioral modes seems to be a good example of this process.

We consider our approach as a novel contribution to the self-organization of complex robotic systems. At the present step of our development the behaviors although related to the specific bodies and environments are without goal. As a next step we will realize a so called behavior based reinforcement learning. When watching the behaving system one often observes behavioral sequences which might be helpful in reaching a specific goal. The idea is to endorse these with reinforcements in order to incrementally shape the system into a goal oriented behavior.

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