ARTIFICIAL LIFE FROM THE PRINCIPLE OF HOMEOKINESIS

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Self-organization is a key phenomenon in many systems be they physical, chemical, social or economical in nature. The realisation of agents which are able of self-organizing their behavior forms a major challenge for the engineering of artificial systems. The talk demonstrates our general approach to the self-organization of robotic forms of life which has been developed and tested in various examples in recent years. The robot's "brain" consists of a controller and a self model both realized by a neural network. By minimizing the so called time loop error, both the model and the controller are adapted concomitantly from scratch. We apply this approach to different robots with complicated physical properties which are completely unknown to the "brain". Nevertheless after some time the robots develop behaviors which are both body and environment related in a completely self-organized way. The applications are demonstrated by several videos of a spherical robot, various snake like artefacts, an artificial dog and a humanoid robot. More information may be found on our video page http://robot.informatik.uni-leipzig.de/research/videos/.

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1. Introduction

The rapid technical progress in the fields of sensor, mechanotronic, and precessing technology gives rise to more and more complex robotic systems. This concerns on the one hand dedicated systems operating under some structural or functional constraints like sophisticated humanoid hand models with many degrees of freedom for specific grasping tasks. On the other hand, there is a growing tendency of developing more and more phantasy objects like snakes and other artifacts with tens of degrees of freedom. Besides of their intellectual challenge, these robotic objects may serve as tools for inspection (snakes creeping into impassable regions), exploration, and supply in unstructured and highly dynamic environments. The main problem in these fields is not so much in the technical realization but in the control of such objects under complex environmental conditions.

It is here where the principles of embodied robotics find their real playground. In fact, there is no chance of anything like classical AI realization, based on planning and a concrete world model, under these conditions. Instead, the controller has to learn to maximally exploit the physical peculiarities of the body in its interaction with the environment. So it is less an understanding but a "feeling" of the body which has to be developed by the brain. Basic to this is the general idea of embodiment, meaning that the brain, body and environment form a common dynamical system that can not be simply divided into separate operational units. Such a complex dynamical system of course is apt to nearly any kind of dynamics and there are many coarse ideas of what a convenient working regime for such a system might be. Noteworthy are notions like the edge of chaos, self-organized criticality, and the like, which however up to date are not made sufficiently operational in order to be useful for a concrete implementation in such complex robotic systems.

In particular, these approaches do not give a detailed prescription of how a complex robotic system can self-regulate into such an interesting working regime. Nature may help to give some hints. Homeostasis, one favorite (since constructive) candidate of sufficient generality has been considered in some recent papers [11], [15], see also [1]. However, the state of overall stasis can not be the best working regime for a behaving agent. Other general paradigms like autopoiesis [14], although very appealing in describing the fundamental nature of living systems, are not constructive enough so that they are difficult to operationalize.

This paper tries to elucidate further the principle of homeokinesis [10], [2], [7] which has been introduced earlier as dynamical counterpart of homeostasis. The idea on the one hand is that, in a behaving agent, body brain and environment are to be in a common kinetic regime. This of course is nothing else but the common thinking of embodied robotics on the basis of dynamical systems. However, besides of that, there is a concrete prescription, the minimization of the so called time-loop error, which tells us how to reach this regime under very general conditions.

The approach has been reported upon in a series of papers, see [3], [4] [6], and [8] for instance, which however have been devoted mainly to low-dimensional systems. This paper reports on the application to high dimensional robotic systems both in static and highly dynamic environments, it gives an improvement over the original learning rule (minimization of the time-loop error) which makes the algorithm more stable and introduces several possible applications.

The aim of the present paper is not to give a conclusive account of accomplished work. Instead we try to sketch the potentials of the homeokinesis approach and in particular to draw attention to the self-referential dynamical systems as tools for the self-organization of highly complex systems where conventional approaches fail so far.

2. The robots

Before presenting the general approach to self-organization I briefly introduce the robotic systems used in the work. We may coarsely split the system into a body in interaction with the environment and a "brain", comprising both the controller and the rudimental self-model we are using in order to estimate the sensor reactions to the motor signals.

2.1. *The body*

Our robots (constructed by Georg Martius) are simulated physically realisitc in the *lpzrobots* simulation system [13]. They consists of geometrical primitives, connected with each other by joints. Each joint is driven by a simulated servo–motor, i.e. an angular ODE motor combined with a PID controller with parameters fixed by hand. Each motor command $-1 < y_i < 1$ is the target position of the angle of joint i. The robots have proprioceptive sensors only, each sensor value x_i being the true angle of joint i. If the joints are moving freely, motor and sensor values x_i agree at each instant of time but in general there may be great differences due to physical effects like inertia and/or collisions with objects or with other limbs. The difference between true and ideal sensor values ($x_i = y_i$) is the only information the agent has about its body in interactions with the environment.

2.2. *The "brain"*

The brain of the agents consists of a controller and a self-model. The controller is realized as a simple neural network mapping at each step of time t the vector of sensor values $x_t \in \mathbf{R}^n$ to the vector of motor commands $y_t \in \mathbf{R}^n$, i.e. the net is the map $K : \mathbf{R}^n \to \mathbf{R}^n$ so that $y_t = K(x_t)$. Moreover there is a neural network $F : \mathbf{R}^n \to \mathbf{R}^n$ acting as a self-model, mapping current motor values y_t to the sensor values in the next time step, i.e. $x_{t+1} = F(y_t) + \xi_{t+1}$ where ξ is the model error. The dynamics of the sensorimotor loop is modelled by the brain as

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

where $\psi(x) = F(K(x))$. The prediction network F is learned on-line by any supervised learning algorithm with the target values given by x_{t+1}.

A true self-organization approach should be able to solve the following problem: Given an arbitrary body, connect it to our brain in a "juvenile" state and then let self-organization drive the development of the behavior of the robot. This is what we are doing in the experiments described below.

2.3. *Realizing self-organization*

As known from physics, self-organization results from the compromise between a driving force which amplifies fluctuations and a regulating force which tries to constrain the system. In our paradigm the destabilization is achieved by increasing the sensitivity of the sensor response induced by the actions taken. 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. This drives the robot towards a chaotic regime.

The counteracting force is obtained from the requirement that the consequences of the actions are still predictable. This should keep the robot in "harmony" with the physics of its body and the environment. It has been shown in earlier work, cf. [8], that these two objectives can be combined in the so called time loop error obtained from the virtual sensor values $\hat{x}_t$ defined from the requirement that $\|x_{t+1} - \psi(\hat{x}_t)\|$ is minimal. We define the time loop error

$$E = v^T v \tag{2}$$

where $v = \hat{x}_t - x_t$ and drive the parameters c of the controller network K by gradient descending E as

$$\Delta c = -\varepsilon \frac{\partial E}{\partial c} \tag{3}$$

The gradient dynamics is updated in each time step so that eqs. (1) and (3) form a combined dynamical system. An important feature of our approach is that the time scale for the gradient dynamics is of the same order than that of the behavior. In this way we have a fast synaptic dynamics which is constitutive for the behavior.

3. Experiments

The aim of the present section is to show that this general paradigm will drive artificial systems towards a creative exploration of their bodily affordances. We will consider first two of the many robots studied so far, the dog and snake like artifacts. We have chosen these objects with morphology close to biology since we want to demonstrate that behaviors may emerge which one might expect as a result of selection according to "survival of the fittest" although we do not have any fitness function as in artificial evolution. Instead these behaviors emerge as a consequence of the specific brain-body-environment interaction driven by the forces of self-organization.

3.1. *The dog*

In a typical run the controller is initialized in a "do nothing" state so that in this phase the feed back strength of the sensorimotor loop is subcritical and the robot will not muster enough strength to move its limbs. Instead it will stay in a resting position. The parameter dynamics, eq. 3, in this situation will change gradually the values of c so that after some time the feed back strength is large enough so that the dogs starts moving its legs in a more or less random fashion. After about one hour or so (real time) the ever increasing sensorimotor coordination is driving the dog to motions like jumping in many different kinds, hopping on its hind legs for quite some time, and so on, see the videos [9].

3.2. *Dog fixed in the air*

In a first series of experiments we fix the dog in the air so that the legs may move freely. In order that the "brain" may feel the embodiment we use the case of an underactuated system where the torques are so weak that large angular values can only be reached by getting the legs into a swinging motion, exploiting the inertia of the legs itself. The interesting point is that after some while (typically 20 to 50 minutes real time) the legs start swinging in different modi, the interesting point being the emerging coordination between the legs. This means that the legs swing with about the same frequency with phase relation being constant over some time. So we observe both in-phase and anti-phase correlations in the leg motions much in the way necessary for different gaits.

However, this is highly nontrivial since there is no direct information exchange between motor neurons, the only way of establishing correlations being the feed back of the motor outputs by the sensor values in the next time step which includes the physical reaction of the system to the motor outputs. This in a first step explains the origin of the correlations, since our paradigm tries to make each motor neuron sensitive to the inputs by all sensors and this can be realized best if there is some correlation between the sensor inputs.

On a more general level the coordinated swinging motion is emerging due to the fact that our parameter dynamics preserves the symmetries of the physical system so that, with a convenient initialization and isotropic sensor noise, any motions can only arise from spontaneously breaking these symmetries. In particular the dog is a physical system with time reversal symmetry so that a collective oscillation of the system seems to be the most natural mode. Moreover, due to the explorative character of the full dynamics the system is not going to establish and stabilize a specific mode. Instead modes are of a transient nature, so that we observe the playful realization of several such collective modes.

3.3. *Dog on the ground*

The main interest of course is the behavior of the dog when on the ground. In our experimental settings we often let the dog for some time fixed in the air so that the "brain" can feel the motions of the unperturbed legs. After that we let the dog fall to the ground. However, the normal setting is to start the dog directly on the ground with the "do nothing" initialization. In order to illustrate the emerging sensorimotor coordination we use an environment consisting of three concentric squares with barriers of increasing height. After its initial phase of getting into activities, the robot rather soon surmounts the innermost barrier and then lingers around for quite some time with the next barrier which has a height of about half the dogs clearance. From the video [9] one sees that the dog keeps its body low most of the time so that it has good contact with the barrier. During all that time it moves its legs repeatedly forward and backward over the barrier.

After some time the dog surmounts also this barrier completely and eventually approaches the outer barrier. It manages quite often to move its forefeet over the barrier and then after some time the hind legs, see Fig. 1.

The emerging behaviors depend much on the special anatomy. In the above experiments the dog was supported by a large weightless box on its back preventing

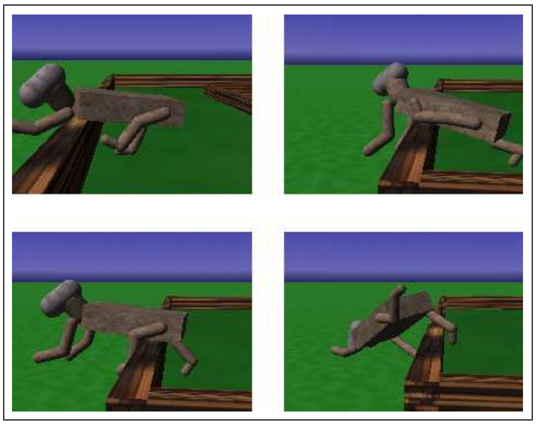

Fig. 1. The dog at the third barrier about one hour after starting in the innermost square. The dog has acquired a rather cautious behavior slowly probing different possibilities of interacting with the barrier. After some time the left hind leg is swung onto the barrier and after several minutes it climbes out completely.

it from falling over.

It should be mentioned that, according to our self-referential approach, all behaviors are contingent, meaning that the scenarios described can all happen in very different forms. In particular, the dog has no aim of surmounting any barrier so that often it returns instead of moving further ahead. The point I want to make is that the motion patterns realized by the dog may be described as activities in close dynamical contact with objects like the barrier. This leads to an increased probability for seemingly dedicated acts like surmounting the barrier.

3.4. *The hippodog*

In another artifact, the "hippodog" we have altered the above dog by giving it a spherical body. In this way we did not need the artificial backup box. Instead the spherical shape of the body is sufficient that the robot after falling over manages to get back to its "working" stance from nearly any situation. Thus one may the robot leave to itself in the same way as with its "ancestor" protected by the invisible box. In the course of time we observe similar behaviors as described with the dog above. However due to its higher mobility, the hippodog has more the tendency to reach a very active, jumpy regime. In particular, getting back to its feet is not realized by rolling over, keeping the legs stretched so that they are out of the way. Instead, the robot gets back to its feet by heavily agitating its legs catapulting itself up by ground contact with its feet, exploiting the high ground-foot friction.

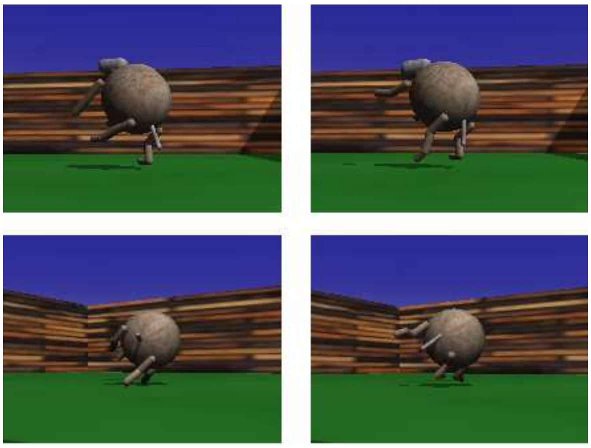

Fig. 2. The "hippodog" in full action, above when encountering a wall and below while in a curve.

3.5. *Snakes*

Snake like artifacts have also been described in [5]. These however have been of a simple construction with only a hinge joint connecting the flat segments. The experiments described here use capsules as geometric primitives connected by a universal joint releasing two degrees of freedom. Angles are constrained so that a joint can not freely rotate. When in free space, the kind of motions emerging depends very much on the friction with the ground and the torques that can be realized. The snakes display a vary wide ranging set of motions which are difficult to classify. The reason is that the physical constraints on the motion are not so stringent. The situation is different however, if the snake is in a narrow pit with diameter of about two segment lengths so that the motions are heavily constrained. Under this condition the snake displays typical modes repeatedly in a loose succession. In the videos [9] you may find the coiling mode with the snake coiling into the vessel while still rotating around its axis. In this way the snake can be active while still being in good agreement with the physical constraints given by the vessel.

The most interesting effect however is in the fact that sometimes the snake manages to escape from the vessel in a rather spectacular way, see the Fig. 3.

4. Humanoids

Most recent experiments have been carried out with a human like artifact, also simulated in the *lpzrobots* simulation system. Like the dog it consists of boxes and capsules and has human like proportions. The robot has 15 degrees of freedom, including the joint for the head and the feet. The emerging behaviors largely depend on the environmental conditions, we run the robot alone on a plane, in a cluttered environment, and together with other robots where often one observes a wrestling

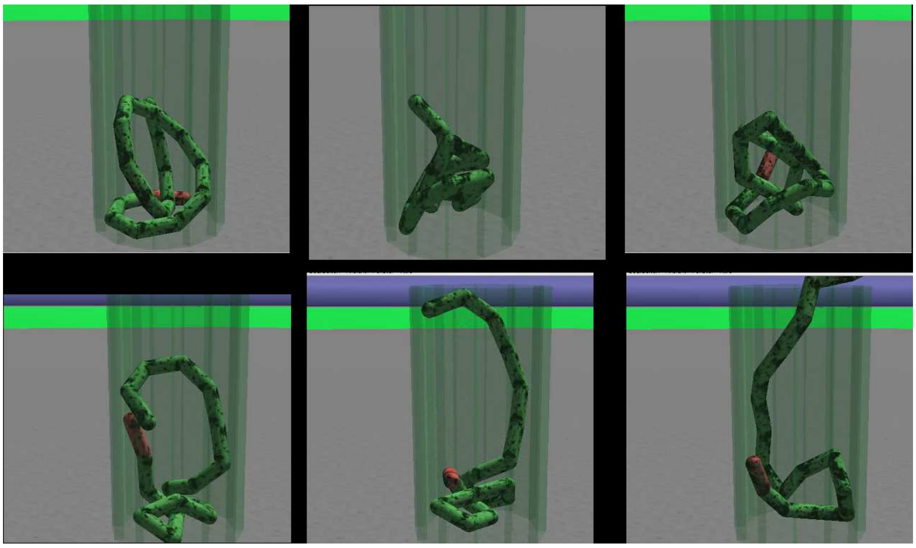

Fig. 3. How the snake may manage to get out of the narrow pit. The first picture in the sequence shows the snake in a seemingly relaxed situation. However, as the video [9] shows there are tensions building up in the body and after some time it suddenly crunches into a tight bundle of wich it decoils with very high velocity so that by the inertia effects it manages to nearly jump out of this very deep pit.

like behavior, see below.

4.1. *A step towards open ended development*

In the experiments described below, we have used an extension of our self-org controller aimed at realizing an open ended ontological development of the robot. As mentioned already, with our self-referential system behaviors are all contingent since there is no specific aim for the learning given. As a consequence, all motion patterns are transient. In order to perpetuate patterns we integrated a second controller neural network which works as a kind of satellite network (SaNN). This network is much more complicated than our self-org controller neural network (SONN), in the practical applications it is an Elman/Jordan network with one hidden layer of 40 neurons with an equal number of context neurons. The output layer of 15 neurons also has a context layer of 15 neurons. This recurrent network is able of learning many different motion patterns.

The two networks, SONN and SaNN, teach each other constantly, i. e. in each instant of time the output of the SONN is used as the target output for the learning of the SaNN and vice versa. The SONN is learning, however, preferentially as described above. In this scenario, it is hoped that the SaNN, which is capable of storing persevered motion patterns with greater probability, will manage to stabilize such patterns in the stream of transients so that the latter are recurring more often and for a longer duration. A typical example are the push up motions which are seen in tendency already without the SaNN but are, as a preliminary result, realized more often and more pronounced in later stages of the development. However, it should be mentioned that these investigations are just in the beginning.

4.2. *Robot on a flat plane*

In the most simple environmental situation the robot develops after some time behaviors which may be paralleled with floor exercises. One observes in the course of time occasionally figures like doing the splits, rolling over, jumping to its feet (seldom), push ups, and others, see the videos [9].

Fig. 4. The humanoid robot in a kind of back flip. The motion is from left to right and starts from a resting position (on the back) by a rapid swing of the left leg (not depicted).

However one of the observations we have to make is the fact that the open ended development is realized only in a certain sense. What one observes is that the repertoire of motion patterns reduces somewhat. In the earlier phases one observes a wide variety of poses and motion patterns, not only the ones mentioned but ever new and different ones which last only over a very short time or are seen only as tendencies. Later on (after 10 to 20 hours) the behaviors consist of a smaller variety of poses and patterns which last over longer times. This may be seen as a development but as already mentioned these are preliminary results.

4.3. *Strong interaction – The robot wrestling scenario*

The behavior in highly dynamic environments is one of the most challenging problems in robotics. The dynamics can be created by independent objects but it is even more interesting to consider the interaction between different robots of the same or different kind. On the video page [9] of the lpzrobots project you may find examples of very many different robots in interaction. The most interesting point in these scenarios is that the robots develop a much higher variety of behavioral modes than in the case of a static environment. We demonstrate this in particular by two humanoid robots in a narrow arena where contact between the two is nearly unavoidable. Fig. 5 displays some of the typical poses the robots are undertaking. Although without any aim of fighting each other, you observe scenes like in a real wrestling. This however is also a consequence of the general phenomenon, that our self-learning controller tries to create activity while still trying to "keep things under control". The sensitivity paradigm on the one hand makes the robot to react to collisions caused by the opponent and on the other hand control is maintained if the tactile contact is present. From the dynamical systems perspective we now have

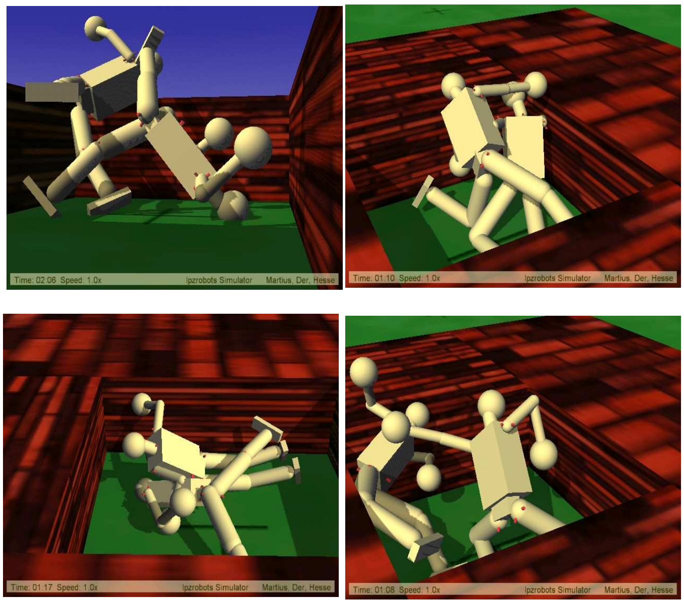

Fig. 5. Wrestling like situations in a scenario with two humaoids in a narrow arena.

two separate dynamical systems (consisting of robot + controller each) which are in heavy interaction due to the physical (spatial) constraints. Obviously one may say again that the combined dynamical system is driven by the time-loop error gradient flow towards a working regime characterized by high activity while still avoiding the strongly chaotic region.

5. The self-rescue scenario

The experiences collected over the years suggest a possible application of this self-organization system. What we have observed in many different scenarios is that the robotic objects manage to free themselves from very intricate situations. We therefore suggest to use our self-org controller as a kind of rescue system if a robot, driven by a standard controller, has maneuvered itself into a situation it can not cope with. The idea is to use in such a situation our self-org controller which will adapt after some time, usually several minutes to one hour with the robot trying ever new movements which are more or less in correspondence with the interaction of body and environment.

The guiding idea in this scenario is the robot which has been fallen into some pit or ditch or the like. The example of the snake in the vessel, see Figure 3 above, may serve as a first example. The most recent results have been done with a simulated humanoid robot in more or less hopeless situations, see the videos [9].

6. Discussion

This contribution reports, at a phenomenological level, about our approach to self-organization of behavior with self-referential dynamical systems. Far from being conclusive in a scientific sense, we have tried to illustrate some of the phenomena we have observed in many long-time experiments with this kind of systems. What we observe ever and ever again is the emergence of fundamental modes, identifiable by a high degree of activity coupled with high sensorimotor coordination. These modes may serve as behavioral primitives in more elaborate behavioral architectures, may be reinforced by task specific rewards, and eventually can form the basis for an open ended development of highly complex robotic systems which are difficult to control with conventional methods.

From a dynamical systems perspective, it is difficult to classify what exactly happens in the systems considered. Analytical work done so far has revealed in low-dimensional systems phenomena like fixed point flows and the self-tuning of limit cycles, see e.g. [12] which however do not explain satisfyingly the phenomena in the higher dimensional systems like our dogs, snakes, or the humanoid. This is no surprise. In fact, the combined system, state and learning dynamics, is a dynamical system of several hundred dimensions driven by both the physics and the gradient flow on the time loop error on comparable time scales. Speaking in neural terms we have a system with fast synaptic dynamics. We have termed such systems self-referential since the state dynamics depends on the parameters of the system which are driven by the state dynamics itself. These systems seem to have many interesting and unknown so far properties which deserve further investigation.

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