Self-organization of robotic forms of life

Ralf Der
University of Leipzig – Institute of Computer Science
Germany

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Abstract

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 this task which has been developed and tested in various examples in recent years. The robot's "brain" consists of a controller and a world model both realized by a neural network. Our general paradigm of minimizing the so called time loop error is used in order to learn both the model and the controller 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 wheeled robots, a "rocking stamper", a spherical robot, various snake like artefacts, and an artificial dog. More information on our video page http://robot.informatik.uni-leipzig.de/research/videos/.

1 Introduction

Artificial life in the sense of "life as it could be" (Langton) offers a number of intriguing possibilities for different fields of science as mirrored by the different directions the AL research has taken in the two decades of its existence. In particular, it allows to see life in a different and even broader view as the one given by biology itself. The latter is dictated by the fighting for ressources, the ulitmate goal of life being to survive in a competing ecology. As a consequence nature has taken the way of building on solutions once found effective, and to further optimize those, instead of having the freedom to just play around and try ever new possibilities.

The study of robotic systems can shed some light into the roots of life which range deeper than the pure necessity of survival. Stripping life from the necessities of survival will seek the key features of artificial creatures in autonomy, curiosity, creativity and an inherent drive for exploring the body and the world. There are several approaches able to meeting these challenges. In particular we note the attempts of guiding autonomous learning by internal reinforcement signals [11] and to task independent learning [7, 9], [5]. The problem is that these and other approaches work best with discrete state-action spaces of not too many dimensions.

Robots on the other hand are physical systems with potentially infinitely many degrees of freedom. We believe that the forces of self-organization as we know it from physical and biological systems may provide an artificial being with the intrinsic drive for development. We developed such an approach and demonstrated it to work in real time and continuous space with embodied robots of up to 25 active degrees of freedom. Applications with both real [1] and simulated robots have shown many interesting and unexpected behaviours ranging from coiling, hurling and jumping modes in snake like artifacts, over stable rolling modes of spherical robots [3] to dogs climbing over walls and the like, see our video page http://robot.informatik.uni-leipzig.de/research/videos/. What we observe in these experiments are behaviours with high sensorimotor coordination, emerging in a "playful" exploration of the bodily affordances. Our approach is closely related to the thinking of embodied Artificial Intelligence [8] which sees brain and body of the behaving agent together with the environment as a common dynamical system which can not be simply divided into its parts.

Potential applications are expected among others in the field of developmental robotics, see [12], [4], in the early sensorimotor stage, cf. [2].

2 The robots

Our approach can be applied to a great variety of robots. In the present paper we consider an artificial dog and discuss the behaviors emerging from our general self-organization paradigm presented in Sec. 2.3 below.

2.1 The body

Our robots are simulated in the *lpzrobots* simulation tool [6]. The dog, constructed by Georg Martius, consists of geometrical primitives, connected with each other by joints. Each joint is driven by a servo–motor developed. Each motor command $-1 < y_i < 1$ is the target position of the angle of joint i. The dog has proprioceptive sensors only each 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 collissions 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 interactions with the environment.

Figure 1: The dog when facing a wall sometimes starts attacking it.

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 with one hidden layer 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 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

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

where $\psi(x) = F(K(x))$. 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.

2.3 Realizing self-organization

As known from physics, self-organisation 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 destabilisation is achieved by increasing the sensitivity of the sensoric 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. [?], 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

$$E = v^T v \tag{1}$$

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

$$\Delta c = -\varepsilon \frac{\partial E}{\partial c} \tag{2}$$

An important feature of our approach is the time scale for the gradient dynamics which is of the same order than that of the behavior. In this way we have a fast synaptic dynamics which is consitutive for the behavior.

3 Experiments

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. 2, 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 diffferent kinds, hopping on its hind legs for quite some time, and so on, see the videos.

In order to illsutrate 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 lingeres around for quite some time with the next barrier with a height of about half the dogs clearance. From the video one sees that it keeps its body low so that it has most of the time 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 soon to move its forefoots over the barrier and then after some time the hind legs, see Fig. 2.

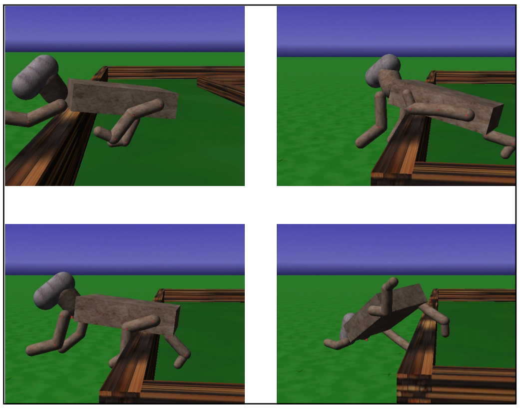

Figure 2: The dog at the third barrier about one hour after starting in the innermost square. The dog has acquired a rather cautious behavior slowly probing different possibilities of interacting with the barrier. After some time the left hind leg is swung onto the barrier and after several minutes it climes out completely.

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 it from falling over. 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 invisibel 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 particluar, getting back to its feet is not realised by rolling over, keeping the legs streched so that they are our 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.

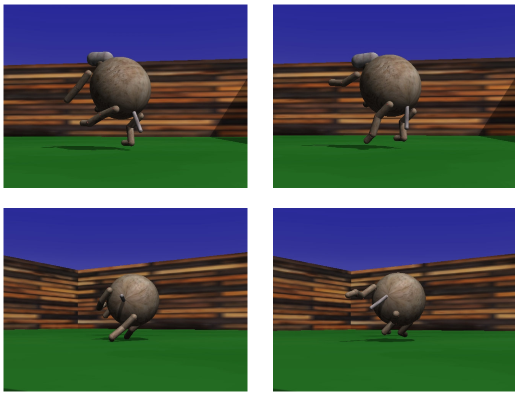

Figure 3: The "hippodog" in full action, above when encountering a wall and below while in a curve.

4 Discussion

We have applied in the present paper a general paradigm of self-organization to a dog and hippodog robot. The approach is seen to generate the sensorimotor coordination necessary for large-scale behavioral modes in a self-organized way. In particular when surmounting the barrier, the dog has to realize a high degree of sensorimotor coordination. An important consequence is also derived for the interplay between the world model and the controller. The "brain" 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 aquired 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-orgnization 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, for instance when climbing over the barrier, 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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