Self-Exploration of Autonomous Robots Using Attractor-Based Behavior Control and ABC-Learning

MANFRED HILD and MATTHIAS KUBISCH

Neurorobotics Research Laboratory, Humboldt-Universität zu Berlin, Germany

Abstract. An autonomous robot which is equipped with sensorimotor loops and situated within a specific environment can be regarded as a dynamical system. By using Attractor-Based Behavior Control (ABC), the attractors of this dynamical system correspond to energy-efficient behavioral body postures, and the attractor-connecting heteroclinic orbits can be utilized to generate stable motion trajectories. We introduce ABC-Learning and demonstrate how it enables an autonomous robot to self-explore its behavioral capabilities from scratch and without any given body model.

Keywords. developmental robotics, self-exploration, sensorimotor control

1. Introduction

Infants who explore the motion of their own body and, later in development, peculiarities of their environment are always very fascinating to watch. Although research on the foundations of learning has made tremendous progress within the last decades, scenarios like the aforementioned have hardly been seen with autonomous robots. In the paper at hand, we propose a framework which may help to tackle this challenge on the ground of nonlinear dynamical systems, following the well-known pattern of [1], but taking the perspective of perceptual control theory [2] and a modern model of adaptive systems that respects Ashby's approach [3]. This immediately leads to the study of sensorimotor manifolds. Only for the most simple systems can they be described analytically. Sensorimotor manifolds of real robots mostly need to be extracted numerically [4].

If a robot is supposed to actively self-explore its behavioral manifolds some kind of heuristic or motivational system is needed. Many different approaches have been proposed, e.g., using sensorimotor loops which are driven close to bifurcation [5], using intrinsic motivations [6], or using extensions of self-organizing maps [7]. All those mechanisms generate manifold-representing structures which in fact are behavioral memories. Since they grow rapidly they have to be transformed into more abstract and compressed representations. Promising approaches, e.g., are based on quadrics [8], or more general on manifold retractions using the theory of lie-groups [9]. Surely, blind data compression is a dead end to autonomous learning – semantic information has to be extracted concurrently and sensorimotor loops continuously have to be adapted during this process, even under varying environmental context [10].

Regarding the control of autonomous robots, biologically inspired approaches may be most attractive to achieve 'natural' behaviors [11]. One also has to guarantee smooth motion behavior and therefore the adaptive compensation of the actuators' nonlinearities has to be taken care of. Partial results exist for the compensation of backlash [12] and friction [13], but approaches which are fully integrated into a 'whole systems' framework for self-exploration are still to be investigated. Recent results [14] may be used, but existing theoretical findings [15] may also be adopted and tested on real robots. The presented framework in this paper builds upon existing work in the fields of motion control [16], neural dynamical systems [17], and adaptive systems [18]. We advance current results which address the improvement of dynamic behaviors [19], the extraction of sensorimotor manifolds [20], and use of heuristics for the exploration of the self and its environment [21].

The rest of the paper is organized as follows. We first define dynamical systems and recap the general terminology using a minimalist, abstract example. Then, we will introduce a promising new sensorimotor control paradigm, the so-called *Attractor-Based Behavior Control (ABC)*, which is able to generate robust behavioral sequences. This will be demonstrated by results of an experiment with a real robot leg. After that, we propose a learning heuristic called *ABC-Learning* which is able to systematically extract behavioral manifolds. Again, a real robot example is given. Finally, we discuss the implications of the presented new framework and give an outlook over future research.

2. Autonomous Robots as Dynamical Systems

A dynamical system S describes the evolution of a *state* $\boldsymbol{x}(t) \in \mathbb{R}^n$ over time t. Generally, the state is just a point in n-dimensional space, and the set of all possible states of S is a manifold $M \subset \mathbb{R}^n$ called the *phase space*. Time is continuous if physical systems are considered, but since we will deal with robots that use sampled sensorimotor values we restrict ourselves to discrete-time systems, i.e., $t \in \mathbb{N}$.

2.1. An Abstract Example

Consider the minimalist system of two fully recurrently connected neurons defined as follows:

$$\boldsymbol{x}(t+1) = F(\boldsymbol{x}(t)), \qquad F(\boldsymbol{x}) = \tanh\left(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b}_p\right), \tag{1}$$

where t is the discrete time step, $\boldsymbol{x}$ the output of both neurons, i.e. the system state,

$$\boldsymbol{W} = \begin{pmatrix} 1.06 & 0.02 \\ -0.01 & 1.05 \end{pmatrix} \tag{2}$$

is the weight matrix, and

$$\boldsymbol{b}_p = \begin{pmatrix} p \\ 0 \end{pmatrix} \tag{3}$$

a parameterized bias term. Since the hyperbolic tangent is bounded by $(-1, +1)$, it is possible to draw the phase space within a two-dimensional square, as can be seen in
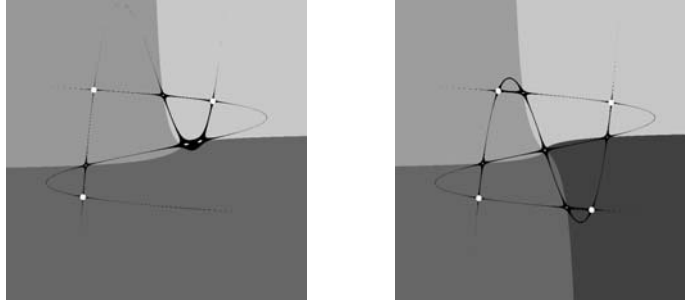
Figure 1. Phase space of a parameterized, fully recurrent neural network of Eq. (1). The left picture shows the phase space for $p = -0.01$, and the right picture for $p = 0$. Different gray areas denote different basins, each of which exhibits a stable fixed point (big white dots). Unstable fixed points exist on the boundaries between basins (small white spots). The black curves denote nullclines which connect stable and unstable fixed points.

Figure 1 for the parameter values $p = -0.01$ and $p = 0$. When analyzing a dynamical system, one is interested in the long-term behavior of $\boldsymbol{x}(t)$ for $t \to \infty$. Starting with a specific state $\boldsymbol{x}(0) = \boldsymbol{x}_0$ at time $t = 0$, the transients will fade away after some time, and the system finally settles down into an F-invariant subset $A \subset M$ of the phase space, i.e. $F(A) = A$.

2.2. Fixed Points, Attractors, Basins, and Bifurcations

The F-invariant subset $A \subset M$ of the phase space towards which a dynamical system evolves over time is called *attractor*. That is, points that get close enough to the attractor remain close even if slightly disturbed. The set of all system states which end up in the same attractor A is called the *basin* B_A of A. As can be seen in Figure 1, our system exhibits three basins for $p = -0.01$. In each basin there is a fixed point attractor. Geometrically, an attractor can be a point, a curve, a manifold, or even a complicated fractal set, but for the rest of the paper fixed points are of special interest.

Only stable fixed points are attractors. Unstable fixed points exist on the boundaries between adjacent basins, the so-called *separatrices*. Those fixed points are hyperbolic in the sense that the system state is attracted to them along the separatrices, but repelled from them in the direction of the stable fixed points. A family of *nullclines* connects stable and unstable fixed points. Traveling along nullclines is advantageous since always only one dimension needs to be controlled actively.

If the parameter p is varied slowly from -0.01 to 0, then the separatrices and attractors are continuously moving. At some value $p = p_0$ one attractor suddenly disappears completely. This is called a *bifurcation* and p_0 a *bifurcation point*. If a system has more than one parameter, then the set of all bifurcation points can be a complex manifold in parameter space.

2.3. Robots Situated in an Environment

We now transfer the presented concepts to embodied robots which are equipped with sensorimotor loops and situated within a specific environment. The dynamical system under investigation not only consists of the robot's actuated body, but also the internal states of the control loops as well as the interaction of the robot with the environment
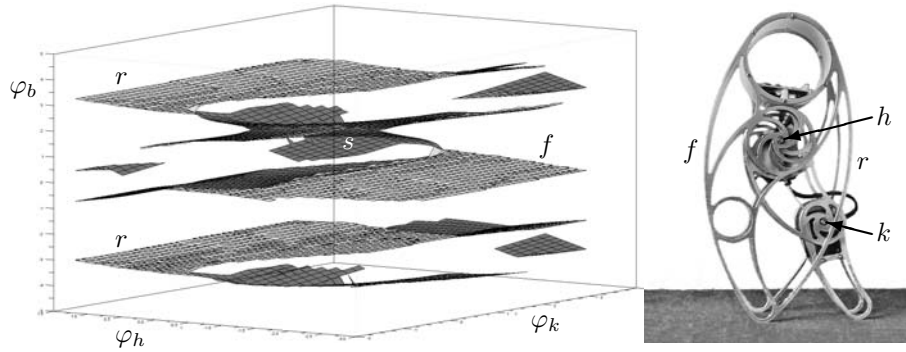
Figure 2. The autonomous robot SEMNI is 30cm tall and exhibits two degrees of freedom, namely the rotatory joints at the hip (h) and at the knee (k). The angles between body and hip (φ_h), hip and knee (φ_k), and the robot's main body axis and the ground (φ_b) define a two-dimensional manifold $M \subset \mathbb{R}^3$ under the constraint that the robot rests on the ground. The part of M marked with (s) corresponds to postures where the robot is standing upright, as shown. Lying on the front (f) and lying on the rear (r) are identified likewise.

have to be taken into account. Figure 2 shows the autonomous robot SEMNI. If the robot rests on the ground and the internal control loops keep the joint angles constant, then the state vector $\boldsymbol{x} := (\varphi_h, \varphi_k, \varphi_b)$ settles into an attractor, namely a stable fixed point. The set of all fixed point attractors carves a two-dimensional manifold M out of the three-dimensional phase space. As long as the robot moves slowly, i.e. $d\boldsymbol{x}/dt \approx 0$, we can say which postures can be reached, and where bifurcations take place, i.e. $\boldsymbol{x}$ falls off the manifold M and reenters M at another point. In that case the robot falls down and is exposed to physical impacts. Figure 3 shows a diagonal cut through M in more detail. Dashed lines indicate where bifurcations take place. As can be seen, posture i cannot be reached by only using slow moves, since the robot will end up at posture e instead.
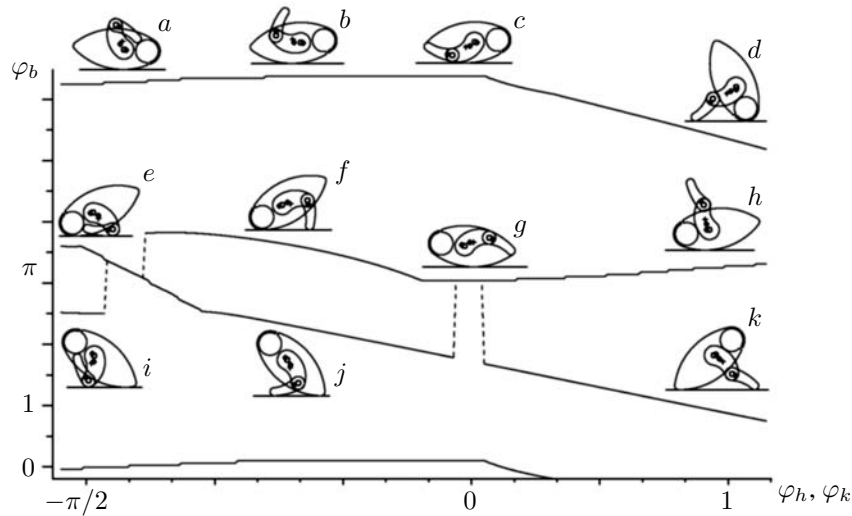

Figure 3. Diagonal cut ($\varphi_h = \varphi_k$) through the manifold M of Figure 2. For each body configuration two or three different orientations coexist relative to the ground. Some postures (d, j, k) need significant holding torques, whereas others (a, e, h, i) cost no energy. All angles are in radiant. They are all zero at posture c.

3. Attractor-Based Behavior Control (ABC)

Having dealt with robot postures, we will now study controlled behaviors and introduce a sensorimotor loop which enables us to actively stabilize unstable fixed points, even if they are drifting over time. This allows us to travel along the nullclines of behavioral manifolds, so we let the robot's body physics do the work whenever possible, only using energy when necessary. We call this approach *Attractor-Based Behavior Control* (ABC).

3.1. Energy Efficiency and the Principle of Contraction and Release

One of the most essential mechanisms of living organisms is the principle of contraction and release. From the locomotion of a jellyfish to the respiration of humans – everything relies on contraction-pulsations and in-between phases of release. Talking about dynamical systems, the contraction corresponds to quick passages from one fixed point to another. After each transient motion, the system is kept in the next fixed point, either fully released, or in a stabilizing mode, but always using only little energy.

3.2. One Cognitive Sensorimotor Loop (CSL) per Joint

The main idea of the well-known center manifold theorem is that the dynamics of a system can be governed by the evolution of a few critical dimensions, while the system follows along the other dimensions in a passive fashion. Regarding autonomous robots, this enables us to use one sensorimotor loop per actuated joint, and to run those either in contraction or release mode. Referring to the left diagram of Figure 4, the contraction mode would drive the system uphill to P_3 or P_4, whereas the release mode would let the system fall back onto one of the other points, depending on the system's starting state.

Even the most simple sensorimotor loop can possess cognitive abilities. A well-proven control structure is the one shown in Figure 4, to which we from now on refer to as *Cognitive Sensorimotor Loop* (CSL). It just uses the joint angle φ as input, and outputs the actuator's driving voltage u. Actually, not even the absolute angle is needed. As the left half of the CSL, comprising the input paths $(-g_i, g_i)$ and the unit delay (z^{-1}), forms a differentiator with input gain g_i, it is sufficient to fed a velocity signal into the CSL and remove the lower pathway (g_i). As a consequence, there is no need for calibrated,
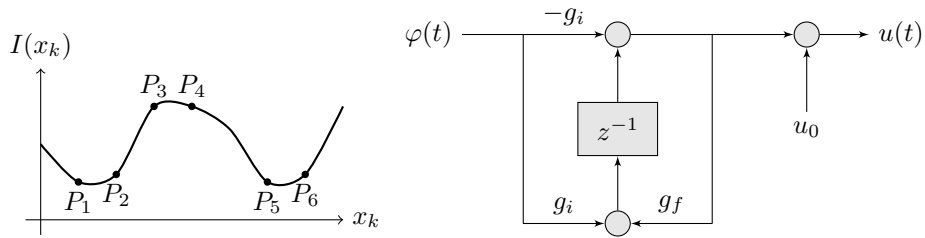

Figure 4. Considering the center manifold theorem enables us to explore the behavioral manifold by always varying one dimension only. The left picture shows the general situation along an arbitrary component x_k of the phase space. The uncontrolled system evolves according to $\Delta x_k = -dI/dx_k$. It does not cost much energy to stay at the points $P_1 \ldots P_6$. Using the principle of contraction and release always leads to the next such point. The picture to the right shows a Cognitive Sensorimotor Loop (CSL) which enables the required control paradigm as a function of the three-dimensional parameter vector (g_i, g_f, u_0).

absolute sensor values when using CSLs. The right half of the CSL can either function as leaky integrator, ideal integrator, or integrator with additional feedback, depending on the parameter g_f. Finally, u_0 is a biasing motor signal which can be used to induce a static body tension. If input and output values are standardized, so that $\varphi, u \in [-1, 1]$, then the parameter vector lies within the range $(g_i, g_f, u_0) \in [0, 2] \times [0, 2] \times [-1, 1]$. In the following section we will see in which way the CSL can be considered cognitive.

3.3. How a Single Leg Stands Up Using Attractor-Based Behavior Control

To demonstrate the power of ABC, we conducted an experiment with a single leg from the modular humanoid robot MYON, as shown in Figure 5. The leg possesses three actuated degrees of freedom, namely the rotary joints at the hip, knee, and ankle. Each joint was equipped with its own local CSL. We used the same parameter vector $(g_i, g_f, u_0) = \boldsymbol{v}_c$ for all three CSLs, where $\boldsymbol{v}_c := (0.9, 1.1, 0.0)$. This is a contracting CSL, the behavior of which has been described abstractly in the previous section. On the robot leg a complex behavioral sequence emerges, as shown in Figure 5. First, only ankle, knee, and the mass touch the ground, so the hip experiences load and starts to contract (1-2). This lifts the knee from the ground, so the knee also starts to contract (3). At some point the leg tilts over onto toe and heel, so that the mass is in the air (4). This makes the knee joint turn its rotational direction, it now works against the earth's gravitation (5). The other joints are equally well balancing out the forces, so the leg ends up in a fully upright position (6-7) and defies external disturbances of any kind.
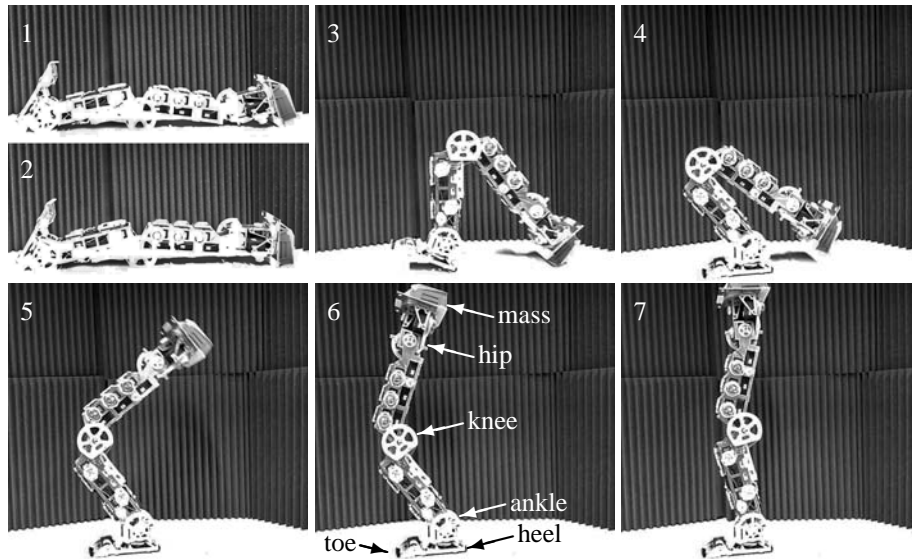

Figure 5. This single leg of the robot MYON is able to stand up using the proposed ABC paradigm. Each of the three joints is locally controlled by a contracting CSL ($\boldsymbol{v}_c$). No sensory data is needed other than the three joint velocities – actually not even absolute joint angles are necessary, so sensor calibration is obsolete for ABC-driven robots. Furthermore, no communication takes place between the joints. The complex stand up behavior solely emerges due to the interaction between the CSLs, the leg's mechanical properties, the ground, and the earth's gravitational force. Once stood up, the leg stays in an upright position even if the ground is tilted, external forces are applied, or the mass distribution on top of the leg is altered.

4. Exploring Sensorimotor Manifolds Using ABC-Learning

The stand-up motion of a single robot leg is a complex behavioral sequence. At different time points some joints start moving, slow down again, or even turn their rotational direction. Distinct motional episodes take place, and to the naive observer this looks like action sequences which are intentionally selected. For most existing robots this may indeed be the case. But here quite the contrary is true: the underlying ABC mechanism has *no* such concepts as, e.g., *action* or *action selection*. We will now go one step further and see where we get by actively switching between contraction and release modes.

4.1. Boredom and Pain: Recognizing Unpleasant States

We first have to decide, when and why to switch the CSL mode. There are three conditions which immediately come to mind. First, if the robot reaches a steady state, where nothing more happens than slight motions, it should try to explore something new. This can be recognized easily by checking the internal states of all CSLs are almost zero for some time. Second, if the robot touches itself while in contraction mode, then some CSLs will increase their output signal beyond all limits. This is harmful for the robot, since the motors will heat up quickly and burn out, if no countermeasure is initiated. Fortunately, this stall situation can also be detected easily by checking if at least one of the CSLs grows out of bounds. If current measurements are available as sensory inputs, then monitoring them would make an even more appropriate stall detector. Third, as already shown in Figure 3, there exist bifurcations where the robot falls off the manifold – no help whatever cautious motion the robot will make. There is no immediate remedy to this situation, because there will always be a physical impact to the robot's body in first place. Surely, fully fledged ABC-Learning includes the memorization of such events in order to prevent the same situation next time, but here, we will only deal with the first two situations. If one of the conditions is fulfilled, then a trigger signal will be activated.

4.2. Switching the CSLs Between Contraction and Release Modes

As already explained, we can explore a sensorimotor manifold by just changing the mode of one CSL after the other. So, we restrict ourselves to a single dimension and assume that the system rests in a stabilized fixed point using a CSL in contraction mode. Referring to Figure 4, let us say that we are somewhere between P_3 and P_4. Now, there are two possible directions to go, in order to reach the next stable fixed point, namely towards P_2 or P_5. An analogous situation arises when we are, e.g., between P_1 and P_2. So, it would be ambiguous if we only had two CSL modes, a contraction and a release mode. We somehow have to actively break the symmetry, or random forces from the environment will take over control. The most simple arrangement to do so, is to use two slightly oppositely biased release modes instead of one. For the experiment that we will describe subsequently, we used the following CSL modes (which are fully defined by their parameter vectors): $\boldsymbol{v}_r^+ := (0.0, 0.0, 0.1)$, $\boldsymbol{v}_r^- := (0.0, 0.0, -0.1)$, and $\boldsymbol{v}_c := (0.9, 1.1, 0.0)$, as defined before. For a given set of CSL modes (here: $\{\boldsymbol{v}_r^+, \boldsymbol{v}_r^-, \boldsymbol{v}_c\}$), we are now able to define a finite state machine which directs the mode switching of the CSLs dependent on a given direction, as shown on the left hand side of Figure 6. Each time a trigger signal is activated, we randomly choose one of the CSLs and a random direction ($+$ or $-$), and
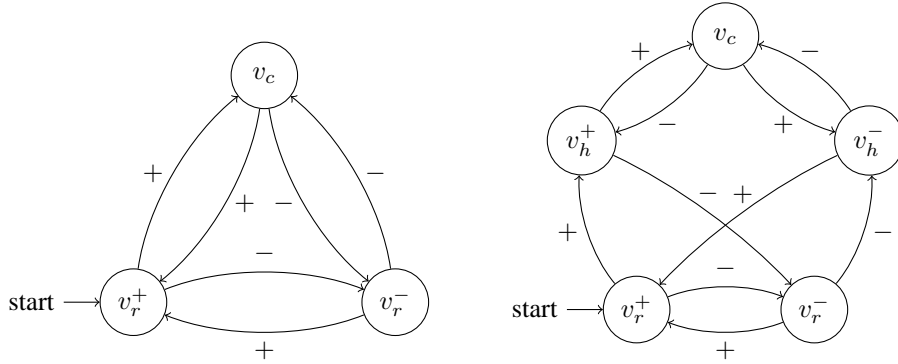
Figure 6. Two finite state machines used for ABC-Learning. Due to the nature of the nullclines, there are only two possible directions ($+$ and $-$) per motor dimension to leave a current fixed point. For a given set of CSL modes, the state machine defines in which order they have to be switched to continue traveling into the same direction. The left state machine is the most minimal. Each state will lead the system into a fixed point. The right state machine is an expanded version of the left one, where two additional states with maximal energy consumption (v_h^+ and v_h^-) are included. Those always lie in-between a stable and an unstable fixed point.

update the parameter vector of the chosen CSL according to the finite state machine. There are by far wiser mechanisms in ABC-Learning than just using random decisions, but we will not go into more detail here, since random decisions are already sufficient to fully explore the sensorimotor manifold of a simple robot in short time.

4.3. Self-Exploration of a Robot's Sensorimotor Manifold

Being equipped with the ground truth of the robot SEMNI's sensorimotor manifold, as shown in Figures 2 and 3, we tested ABC-Learning on the real robot, using the aforementioned CSLs, the minimalist set of three CSL modes $\{v_r^+, v_r^-, v_c\}$, the corresponding finite state machine (see left hand side of Figure 6), the recognition mechanism for resting states and stall situations, and a random decision heuristic. ABC-Learning started from scratch with the robot placed on the ground in posture c, i.e. lying on its front (see Figure 3). The results after a ten minute run are shown in Figure 7. Over 90% of all possible low-energy postures (30 out of 33) have been found by ABC-Learning. This is insofar impressive as the algorithm is computationally simple and not even optimized regarding the decision heuristic. Note, that there are no parameters that need to be fine-tuned. The exact values of the CSL mode vectors are not critical – the same values can be used for a lightweight robot of 30cm height and for a 125cm tall humanoid robot alike. In addition to the found postures, the algorithm also builds up a directed graph of optimal (in the sense of energy efficient) motion behaviors to get from one posture to another. We finally bring to mind that, as long as the current basin of attraction is not forcibly left, all postures and motion behaviors are invariant with respect to ground friction, mechanical wear-out, environmental disturbances, and the like.

5. Discussion and Outlook

To sum up, we have presented a novel framework for the self-exploration of a robot's sensorimotor manifold, called ABC-Learning, which consists of several components. The
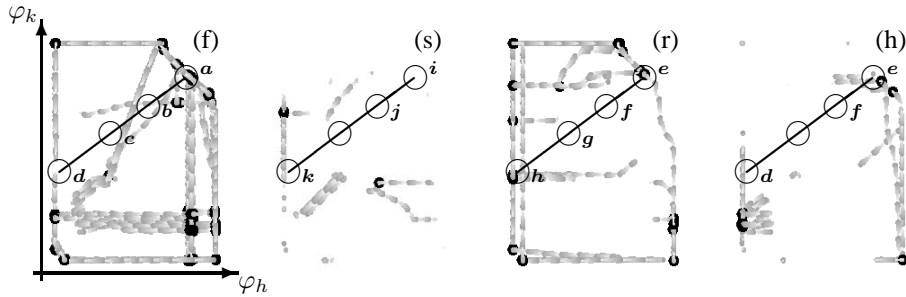
Figure 7. Results of the ABC-Learning experiment with the robot SEMNI. Black dots denote postures, while gray traces show the transient motions in-between. Postures and traces lie within the two-dimensional manifold M shown in Figure 2. Since M is embedded in $\mathbb{R}^3$, it has been cut into four sets along the third dimension φ_b, which corresponds to the robot's orientation relative to the ground. (f), (s), (r), and (h) denote orientations where the robot is lying on its front, standing upright, lying on its back, being in a handstand-like position, respectively. The four letters correspond to those in Figure 2. The diagonal cut through M which is shown in Figure 3 is indicated as black line here. The labeled circles identify the same body configurations and postures as in Figure 3. As can be seen, all of the energy efficient postures (a, e, h) have been found by ABC-Learning. We used each one CSL for hip and knee joint, and the minimal state machine of Figure 6. Posture i could not be found because it is unreachable, as has already been pointed out. The shown part of M has been explored from scratch during the first ten minutes and already includes almost all existing postures.

essential part is what we defined as Attractor-Based Behavior Control, namely using local sensorimotor control loops which exhibit the cognitive ability to indirectly detect environmental forces and to either follow them or work against them. These so-called CSLs come computationally at no cost, do not need absolute or even calibrated sensory input data, and are set to different operational modes by means of a three-dimensional parameter vector, the value of which is uncritical. We presented experimental evidence for the robust and efficient operation of stand-alone CSLs and the whole framework on different robot platforms. The quality of ABC-Learning was benchmarked against ground truth data. The basic ABC-Learning framework already exhibits advantages like the inherent robustness against all kind of mechanical wear-outs and environmental disturbances, the ability to start from scratch without prior parameter fine-tuning, and the sparse and highly semantic coding of postures and motion behaviors. Interestingly, people immediately name the postures found by ABC-Learning with verbs like *lying, sitting, standing, kneeing, holding up*, which seems plausible if we realize that, e.g., the verb *sitting* represents all variations of sitting, be it on a chair with the feet on the ground, or on a table with dangling feet, but always the defining property being that hip and neck are held upright (contraction mode), whereas knees and ankles are free to move (release mode). The validity of this analogy becomes even more obvious, if we place the standing robot leg controlled by CSLs beside a person and start to tilt the ground.

Future work will focus on robots with more joints. We believe that the *curse of dimensionality* can be *tamed* using ABC-Learning, since the number of possible motion behaviors only grows linearly with the number of joints! In parallel, we will investigate additional CSLs which allow for increasingly dynamic motions.

Acknowledgements

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