USING CO-EXISTING ATTRACTORS OF A SENSORIMOTOR LOOP FOR THE MOTION CONTROL OF A HUMANOID ROBOT

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Abstract: The implementation of a biped robot gait is a challenging task within the field of mobile robotics. Particularly, when the robot is subject to unknown disturbance in constantly changing terrain, a stable and robust gait is crucial. Regarding the machine together with the controller as an integrated system, the Dynamical Systems Approach yields a new perspective on legged robots. So called Limit Cycle Walkers have shown their inherent stability against moderate disturbances of different kinds because gaits can be constructed as attractors of the dynamical system. Here, we will show how co-existing attractors in neural sensorimotor loops can be used for the construction of robot gaits and for easy switching among behaviours. The results are demonstrated using a humanoid robot with neural control and it is shown that walking and standing upright can be implemented as co-existing attractors of the same pure sensorimotor loop.

1 INTRODUCTION

Legged robots should be able to walk around robustly in different types of terrain. Also, it is desirable that switching between various behaviours, like standing upright, walking forward or walking in different directions, takes place smoothly and reliably. Oscillations have been discovered in countless biological systems and almost all gaits comprise repetitive patterns.

As (Hein, 2007; Hein et al., 2007) have shown, different gaits for bipedal robots can be found by artificial evolution using a central neural oscillator. The robot's actuators were driven using weighted and phase-shifted variants of a single fundamental sine wave but the resulting gaits were not inherently stable because they lacked sensory feedback.

Limit cycle walkers (Solomon et al., 2010; Collins, 2005) have shown their benefits in terms of gait stability and simplifying the control strategy when used in a tightly closed sensorimotor loop. So, a gait has been successfully expressed as an attractor of the overall system which underlines the potential of the dynamical systems approach.

In the paper at hand we describe a sensorimotor loop as the basis for humanoid robot walking and show how to use the inherent properties of its attractors to switch the robot's behaviours from standing to walking and vice versa. The rest of the paper is organised as follows: In the next section, we briefly recap the terminology of discrete dynamical systems, especially discrete time recurrent neural networks and discuss switching between co-existing attractors. Section 3 describes the implementation of a neural controller for humanoid robot walking with the use of the proposed co-existing attractors of the sensorimotor loop. We demonstrate that behaviours like standing upright and walking can co-exist within the same pure sensorimotor loop and that it is easy to switch between them. Finally, we give an outlook on our future research.

2 NEURAL DYNAMICS

Dynamical systems theory (Guckenheimer and Holmes, 1983; Thompson and Stewart, 1986) has become an important tool for roboticists and turned out to be beneficial for the construction and understanding of recurrent neural networks (Hild et al., 2007), sensorimotor control loops (Martius et al., 2008) and the physical system—the robot itself. To briefly recap the terminology, consider the neural network with the update rule

$$\mathbf{x}(t+1) = \tanh\left(\mathbf{W}\mathbf{x}(t) + \mathbf{b} + \mathbf{u}(t)\right), \qquad (1)$$

where $\mathbf{x}(t) \in M$ is the *state* of the dynamical system at discrete time $t \in \mathbb{N}$. The manifold M of all possible states is called the *state space* or *phase space* and is $M = (-1, +1)^N \subset \mathbb{R}^N$ for N neurons due to the hyperbolic tangent transfer function. A *trajectory* is an ordered set of successive states, and is called a *p-orbit* if it has a definite periodicity p. The weight matrix $\mathbf{W}$ and bias vector $\mathbf{b}$ constitute the *configuration* of the system. Optionally, a control input $\mathbf{u}(t)$ is used to externally manipulate the system.

A set towards which the system evolves over time is called an *attractor*, which can be a point, curve or manifold in phase space. Attractors can *co-exist* within the same system and, depending on initial conditions, the system evolves in either way. The set of initial conditions leading to the same attractor is the *basin* of that attractor, whereas borders between adjacent basins are called *separatrices*.

2.1 Co-Existing Attractors in Discrete Time Recurrent Neural Networks

Discrete time recurrent neural networks can exhibit a variety of functionality—even if the number of neurons is small. Consider the network's configuration

$$\mathbf{W} = \begin{pmatrix} 1.282 & -0.4 \\ 0.1 & 0.865 \end{pmatrix} \quad \mathbf{b} = \begin{pmatrix} 0.04 \\ 0.02 \end{pmatrix} \qquad (2)$$

with only two neurons and, for now, $\mathbf{u}(t) = 0$. The corresponding phase space is depicted in Figure 1. This dynamical system has two co-existing attractors, namely a stable fixed point and a quasiperiodic orbit, and in between the separatrix. The system's outputs are bounded by $[-1, +1]$.

Usually we would expect an unstable fixed point inside the quasiperiodic orbit, a so-called *repellor*. But in this configuration we can identify another complete basin inside and therefore we find another, so-called *co-existing attractor*. This attractor is a stable fixed point with the vector field having a curl in that point. The expected unstable regime has become a separatrix, here in form of a closed unstable orbit.

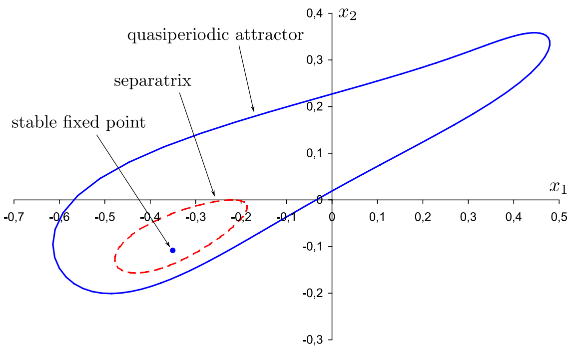

Figure 1: Phase space of the neural network with co-existing attractors. A basin with a stable fixed point is being enveloped by another basin with a quasiperiodic orbit.

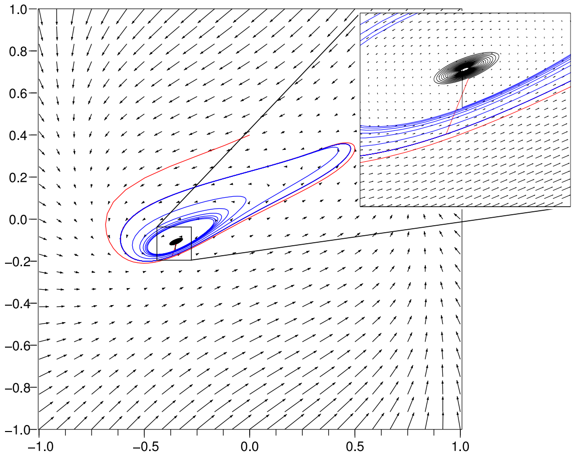

Figure 2: Switching between co-existing attractors with short and small control inputs, cf. also Figure 3.

Please note, if we would invert the system by interchanging inputs and outputs, the time is *flowing backwards* and attractors become unstable. In turn, formerly unstable areas become attractors. So, the separatrix becomes a stable orbit and the area outside the former quasiperiodic orbit diverges beyond all bounds. This is due to the poles of the inverse hyperbolic tangent.

2.2 Switching Co-Existing Attractors

Switching between co-existing attractors can be realised by introducing a controller $\mathbf{u}(t) = \mathrm{K}(\mathbf{x}(t))$ which usually depends on the current state and provides the control input $\mathbf{u}(t)$. Switching from the stable fixed point to the quasiperiodic orbit takes place when the control input is powerful enough to *hop over* the separatrix as depicted in Figure 2.

Here, the direction of the control input is of lower importance since the orbit envelops the fixed point. Switching to the basin of the fixed point mainly depends on the phase of the oscillation. So the controller needs an exact timing and pulse shape for a suitable jump.

Actually, the system together with the controller form a new dynamical system of higher dimension than the initial one. But, since we are considering short and small control inputs, we omit additional dimensions for convenience.

Switching between attractors is of major interest since different behaviours can be expressed as co-existing attractors (Hild and Kubisch, 2011). In other words, to blend over from one behaviour to another,

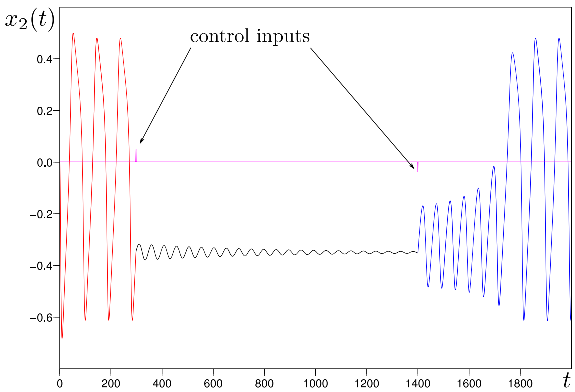

Figure 3: Switching between co-existing attractors: output of x_2. Small control inputs $\mathbf{u}(t_1) = (0, 0.05)$ and $\mathbf{u}(t_2) = (0, -0.04)$ are exerted to the system, each with a length of only one time step.

we simply have to switch attractors. The next section describes how behaviours like walking and standing upright can be formulated as attractors of the robot's sensorimotor system and how switching between them both can take place.

3 A PURE SENSORIMOTOR GAIT

The type of gait that is to be shaped, highly depends on the robot's morphology, i. e. actuators, elasticities, sensors and so on. For a better understanding of the complex interplay, one has to bring to mind which parts are mandatory to shape an attractor. A generic walking pattern can therefore be separated into parts resulting in the following sequence:

First, the weight has to be shifted within the frontal plane to one side using the hip and ankle roll motors. This lifts the hip and enables sagittal leg motion. The ankle and hip pitch motors of the stance leg can now push the body forward so that the swing leg has enough distance to the ground and can freely move forward. After the swing leg has touched the ground steadily, the weight is shifted back to the other side. The necessary weight shift is achieved by an oscillatory lateral movement of the full body. Walking forward can then be realised by superposing sagittal leg movements with the same frequency using left and right, hip and ankle roll motors.

3.1 Structure of the Sensorimotor Loop

An upright standing humanoid robot can approximately be regarded as an inverted pendulum with a single contact point to the ground. To stabilise the upright posture the controller has to exert enough torque to swing back the robot in case of disturbance. To initiate the walking motion, the controller has to shift the weight smoothly. This is realised by direct sensory feedback forming a closed sensorimotor loop.

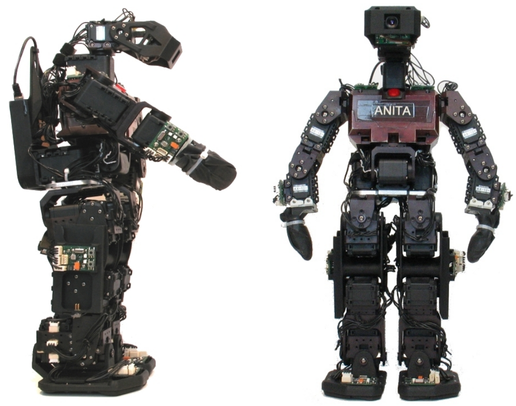

Figure 4: The A-Series humanoid robot used for walking experiments. Among others, two acceleration sensors are mounted on top of the robot's shoulders.

The A-Series humanoid robot (Hild, 2007; Werner, 2008) as depicted in Figure 4 possesses sixteen 2D acceleration sensors which are distributed all over the body. Two of them are mounted on top of the robot's shoulders and their sensory values are added together to measure the lateral and sagittal acceleration of the robot's torso. The lateral sensory information is weighted and fed back to the left and right, hip and ankle roll motors (cf. Figure 5).

Robot and neural control together constitute a dynamical system holding co-existing attractors such as lying on back or belly. Even when the motors are not actively driven, due to stiction and activated motor brakes, standing upright is also an attractor, however with a very small basin. Imprecisely speaking, this is a blurred fixed point, i. e. a densely packed set of fixed points. So, the stated postures are all sta-

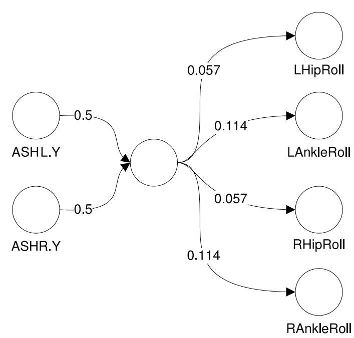

Figure 5: First attempt of a sensorimotor loop for robot walking. Lateral acceleration data are directly fed back to the actuators.

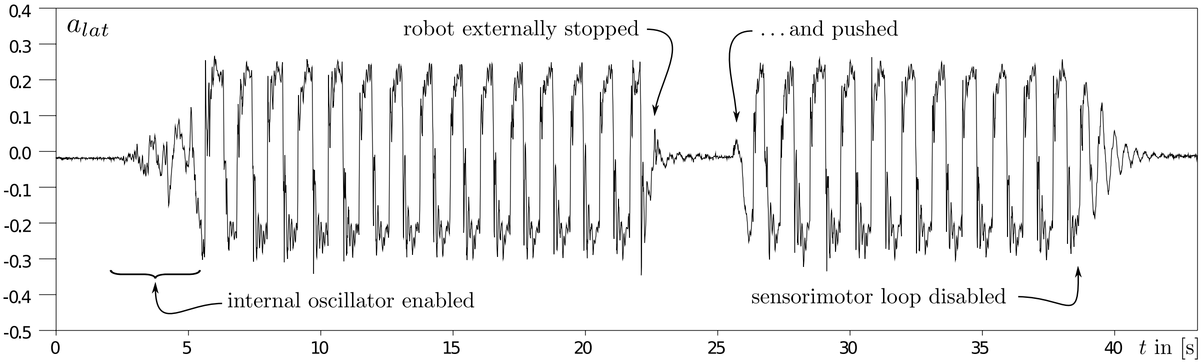

Figure 6: Lateral acceleration data of an about 40 second trial. At the beginning, the internal oscillator initiates the lateral body movement. After approximately 22 seconds the motion is manually stopped and again reinitialised by the experimenter. Finally, the controller internally disables the sensorimotor loop causing the robot to stop.

ble fixed points of the system. When driving a lateral oscillation the dynamical system now possesses a quasiperiodic orbit or *limit cycle*. A small impulse within the frontal plane, e. g. a gentle push, makes the robot leave the fixed point *standing* and start swinging. In turn, if the robot is being externally held by the experimenter, the system falls back into the basin of the standing posture's fixed point. Figure 6 depicts the data from lateral acceleration sensors during a 40 second trial with several starts and stops of the oscillation. Figure 9 on the next page shows successive snapshots of an A-Series humanoid robot, performing lateral oscillation.

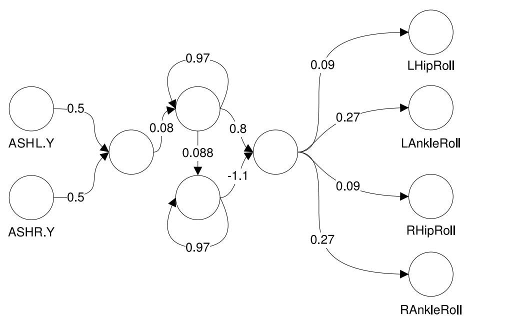

Figure 7: Sensorimotor loop with low-pass filtering and phase correction. Filtering is implemented as neural analogues of recursive filters.

3.2 Widening the Basin of Attraction

For now, the simplicity of our first attempt to build this sensorimotor loop has a drawback: The outputs of the acceleration sensors usually contain a variety of different high frequencies due to non-linearities in the motion of the physical system and sensor noise. Most essentially, when the feet are touching or are lifted from the ground, these events produce perceptible impulses yielding salient peaks in the acceleration data. If such high frequency components are fed back to the motors, this would lead to unintended power consumption and heat production as well as additional non-linear distortion of the system's lateral movement. Also, the correct phase is needed for a quick buildup of the oscillation. Therefore, the loop is extended by a neural implementation of two first order recursive filters (cf. Figure 7).

The acceleration signal will be low-pass filtered and phase shifted by $\frac{\pi}{4}$ per neuron. Approximately, the filtering neurons' outputs can be regarded sinusoids with almost the same amplitude and fundamental. Thus, mixing those signals yields another one with the same frequency but with different amplitude and phase. The mix is then fed to the motors. Figure 8 shows the acceleration signal and its low-pass filtered variants, together with the mixed and again phase-corrected motor signal. As can be seen, filtering performed effectively, resulting in a strong reduction of high frequency components and a corrected phase. Moreover, it turned out that damping the high frequencies widens the basin of attraction for the quasiperiodic orbit and therefore increases the robustness of the robot's gait.

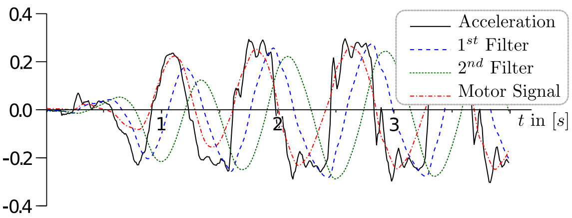

Figure 8: Acceleration data and its low-pass filtered variants; mixed and phase-corrected motor signal.

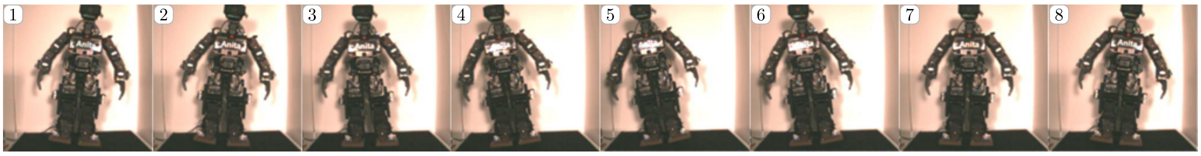

Figure 9: An A-Series humanoid robot performing lateral oscillation.

3.3 Stability of the Walking Pattern

Amplitude and frequency of the gait usually change on different terrain; especially on soft surfaces, e. g. on carpet, the amplitude of the oscillation is strongly decreased. Keeping synaptic weights constant, it can be mentioned that robots of the same series slightly differ in walking amplitude and frequency. This is due to minor variations in construction, material and battery charge level as well as mechanical wearout of gears and soles.

Due to its attractor properties, the gait has an inherent stability against small disturbances, e. g. minor variations in surface structure. For larger disturbances or major environmental variations like changing ground slopes or obstacles, further balancing methods are required.

For now, knee joints have not yet been used, yielding a penguin-like gait. Bending knees, the amplitude of the lateral oscillation can be decreased since the legs need less distance to the ground. This will very likely improve the gait stability once again and reduces the risk to fall over sidewards.

3.4 Starting and Stopping the Motion

At the beginning, the robot is initialised at the stable fixed point, i. e. the upright posture. So far, the robot needs an external impulse, e. g. a gentle push from the experimenter, to get out of the basin of the fixed point, into the basin of the quasiperiodic attractor, and hence, starts the lateral oscillation.

When the robot is to act autonomously the neural controller has to initialise the swinging motion on its own to leave the stable fixed point on a transition to the quasiperiodic orbit. For this, an internal oscillator with almost the same eigenfrequency as the robot's sensorimotor oscillation is temporarily connected to the actuators to initiate the motion smoothly and robustly.

The oscillator is likewise implemented as a neural network (Pasemann et al., 2003) and well dosed through neural gates. When the amplitude has reached a certain threshold, the oscillator is cut off from the sensorimotor loop. On the other hand, if the controller has to stop the motion from inside, the sensory feedback is simply cut off with the use of a neural gate. After this, the oscillation fades out, cf. once again Figure 6.

This means that the lateral oscillation and thus the walking pattern can be started and stopped either from outside the body by an external disturbance or from inside by the controller itself. This equivalence may shed new light on how behaviours of living beings are triggered and merged.

4 CONCLUSION AND OUTLOOK

Using the dynamical systems approach, we have shown that behaviours like walking and standing can co-exist as attractors of the same pure sensorimotor loop. For this, we used a neural implementation of a minimalist control loop where acceleration data are directly fed back to the actuators. We further extended the controller with a filtering mechanism that widens the basin of attraction for the walking pattern and thus enhance the stability of the gait. We state that attractor-based behaviours are inherently robust and can easily be switched while producing smooth transitions among behaviours.

Since no explicit body model is required, the proposed technique is independent of the humanoid robot platform used for walking experiments. We have successfully tested our approach with the humanoid robot Myon (Hild et al., 2011). Although the Myon robot significantly differs in size, weight and the type of actuation, we were able to gain comparable results which will be reported in an upcoming paper. If acceleration sensors are not available, the position sensors of the hip roll joints can be used alternatively.

The proposed sensorimotor loop can be enhanced in terms of reactivity and stability by replacing the aforementioned filtering neurons with a Slow Feature Analysis (Höfer and Hild, 2010). This also extends the robot's capabilities with a fall-over prediction by detecting slow varying changes in sensory data.

Also the shape and elastic properties of legs and feet can increase the stability and efficiency of the gait (Collins, 2005; Schneider, 2006). Arched foot shapes apparently outperform pure flat and rectangular shapes in terms of dynamics and controllability. Current work incorporates the redesign of a humanoid robot's foot under these pure mechanical aspects (Richter, 2011). Furthermore, we currently enhance the sensorimotor gait with recent balance recovery techniques using the humanoid robot Myon (Kubisch et al., 2011).

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REFERENCES

Collins, S. H. (2005). A Bipedal Walking Robot with Efficient and Human-Like Gait. In *Proceedings of IEEE International Conference on Robotics and Automation*, pages 1995–2000.

Guckenheimer, J. and Holmes, P. (1983). *Nonlinear Oscillations, Dynamical Systems and Bifurcations of Vector Fields*. Springer-Verlag, New York.

Hein, D. (2007). Simloid: Evolution of Biped Walking Using Physical Simulation. Master's thesis, Department of Computer Science, Humboldt-Universität zu Berlin.

Hein, D., Hild, M., and Berger, R. (2007). Evolution of biped walking using neural oscillators and physical simulation. In *RoboCup 2007: Proceedings of the International Symposium LNAI, Springer*.

Hild, M. (2007). *Neurodynamische Module zur Bewegungssteuerung autonomer mobiler Roboter*. PhD thesis, Department of Computer Science, Humboldt-Universität zu Berlin.

Hild, M. and Kubisch, M. (2011). Self-Exploration of Autonomous Robots Using Attractor-Based Behavior Control and ABC-Learning. In *Proceedings of the 11th Scandinavian Conference on Artificial Intelligence*, Trondheim, Norway.

Hild, M., Kubisch, M., and Göhring, D. (2007). How to Get from Interpolated Keyframes to Neural Attractor Landscapes – and Why. In *Proceedings of the 3rd European Conference on Mobile Robots*, Freiburg, Germany.

Hild, M., Siedel, T., Benckendorff, C., Kubisch, M., and Thiele, C. (2011). Myon: Concepts and Design of a Modular Humanoid Robot Which Can Be Reassembled During Runtime. In *Proceedings of the 14th International Conference on Climbing and Walking Robots*, Paris, France.

Höfer, S. and Hild, M. (2010). Using Slow Feature Analysis to Improve the Reactivity of a Humanoid Robot's Sensorimotor Gait Pattern. In *Proceedings of the International Conference on Neural Computation (ICNC)*.

Kubisch, M., Benckendorff, C., and Hild, M. (2011). Balance recovery of a humanoid robot using cognitive sensorimotor loops (CSLs). In *Proceedings of the 14th International Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines*.

Martius, G., Fiedler, K., and Herrmann, J. M. (2008). Structure from Behavior in Autonomous Agents. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 858–862.

Pasemann, F., Hild, M., and Zahedi, K. (2003). SO(2)-Networks as Neural Oscillators. In *Proceedings of the International Work Conference on Artificial and Natural Neural Networks (IWANN)*, pages 144–151.

Richter, E. (2011). Redesign und Fertigung eines Fußes für humanoide Roboter. Master's thesis, Leibniz Institute of Polymer Research, Technische-Universität Dresden.

Schneider, A. (2006). *Local Positive Velocity Feedback for the Movement Control of Elastic Joints in Closed Kinematic Chains: A Modelling and Simulation Study of a 2DoF Arm and a 3DoF Insect Leg*. PhD thesis, Department of Biology, Universität Bielefeld.

Solomon, J. H., Wisse, M., and Hartmann, M. J. (2010). Fully Interconnected, Linear Control for Limit Cycle Walking. *Adaptive Behavior*, 18.

Thompson, J. M. T. and Stewart, H. B. (1986). *Nonlinear Dynamics and Chaos*. Wiley, Chichester U.K.

Werner, B. (2008). Sensomotorische Erzeugung eines Gangmusters für humanoide Roboter. Studienarbeit am Lehrstuhl für Künstliche Intelligenz, Humboldt-Universität zu Berlin.