Kognitive Systeme

Robotik III

Montag, 24.Juli 2017

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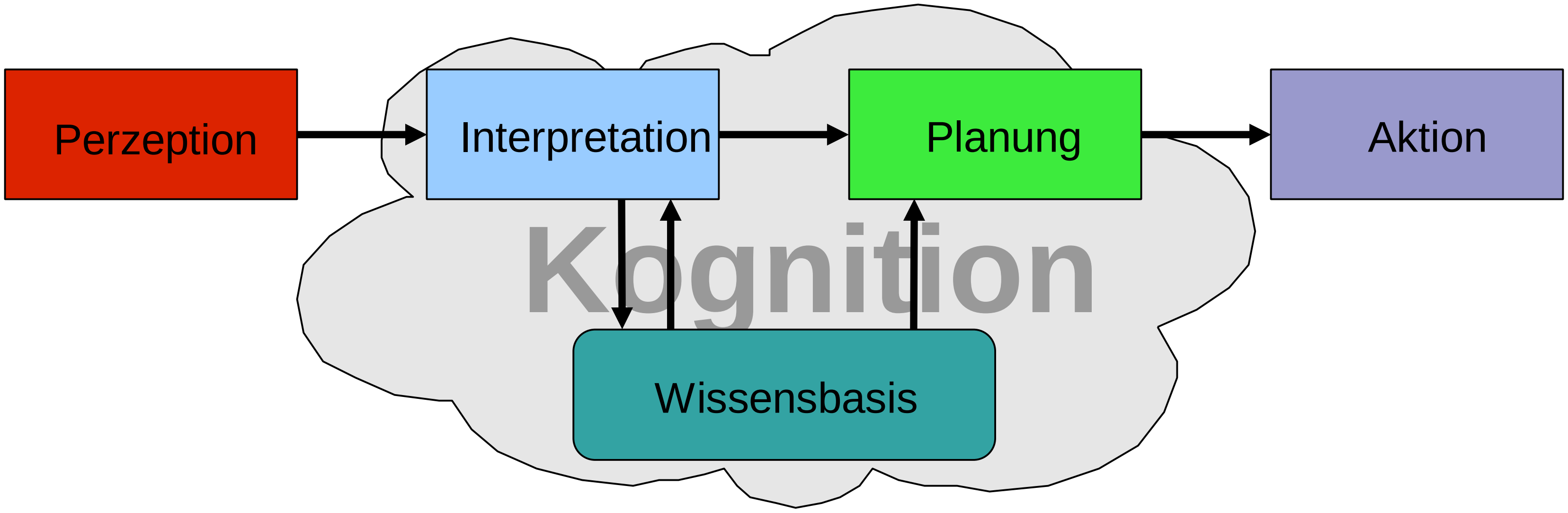
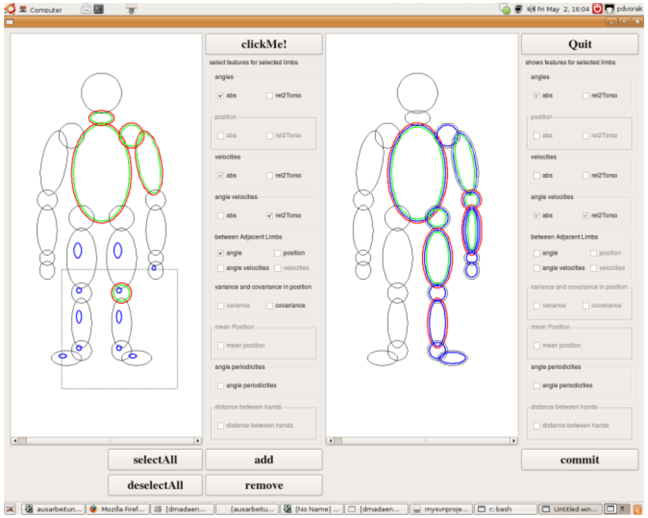
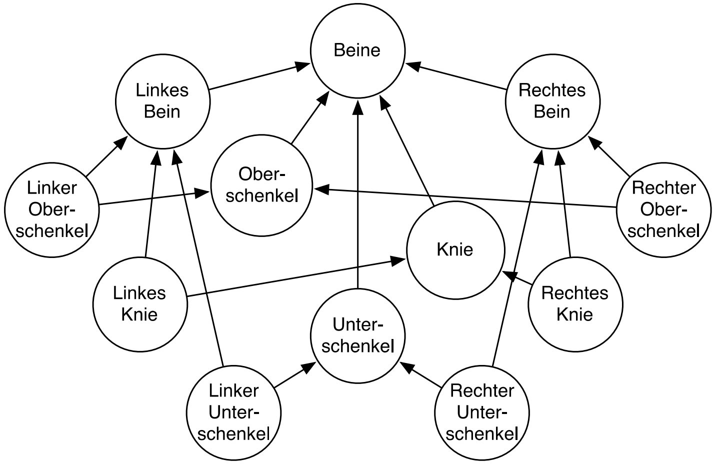
Überblick


Perzeption
Interpretation
Planung
Aktion
Kognition
Wissensbasis

Interaktion in der Merkmalsauswahl



- Einbindung des Trainers über GUI
  - Vorauswahl beteiligter/unbeteiligter Körperteile
  - „Art“ der Aktivität
- Verbindung von Benutzereingaben zu Merkmalen über Modellierung von Merkmalstaxonomien
  - Modellierung des Zusammenhangs zwischen Merkmalsmengen als azyklische Graphen
  - Taxonomien haben Verbund-Struktur



Ausblick Aktivitätserkennung

- *Vision: Autonomes Lernen und Erkennen von Aktivitäten durch robotische Systeme*

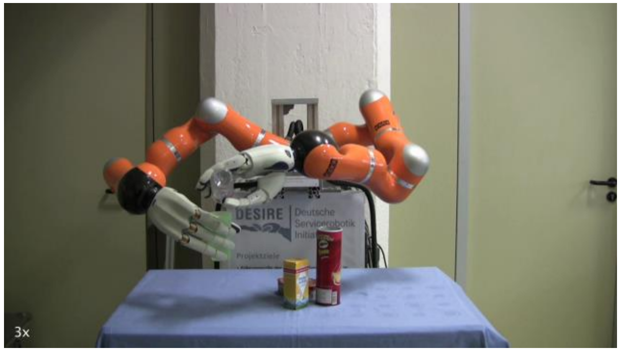
- Integration des Lernystems auf Roboter
  - Lernen vollständig in Interaktion mit Roboter statt Verwendung getrennter Rechner

- Verringerung des Aufwandes für Training durch
  - automatische Segmentierung und unüberwachte Lernverfahren
  - Adaptive Anpassung der Erkenner-Struktur abhängig von Aktivität
  - Nutzung von Bewegungsalphabeten
  - Nutzung von Bewegungsbibliotheken

Prinzip: Programmieren durch Demonstration

- Ein Mensch demonstriert auf natürliche Weise eine Handhabungsaufgabe unter Einbeziehung expliziten und impliziten Domänenwissens
- Die Demonstration wird aufgezeichnet und interpretiert

Specific PbD methodology



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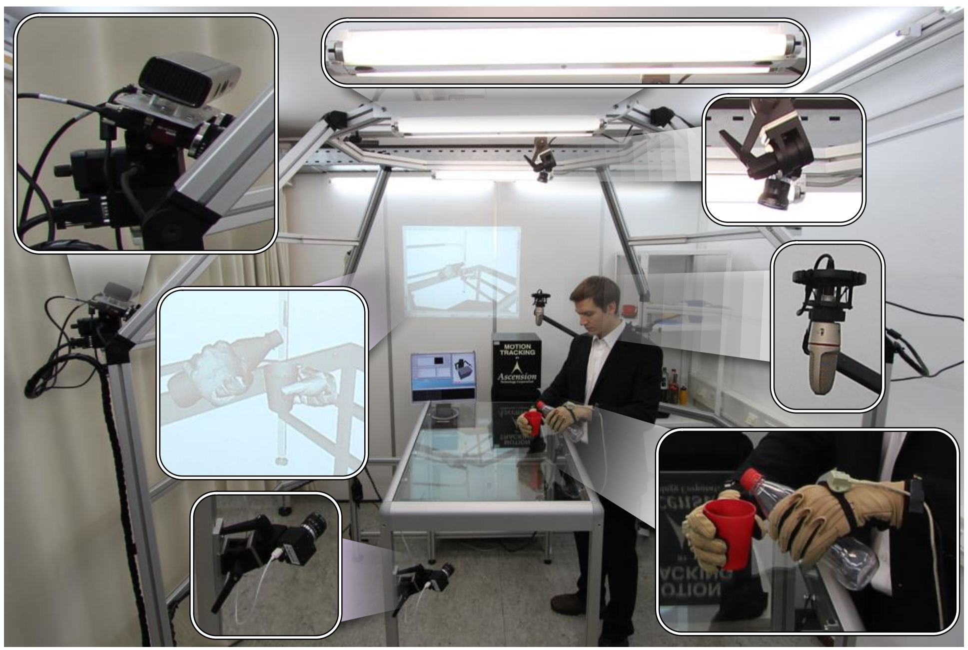
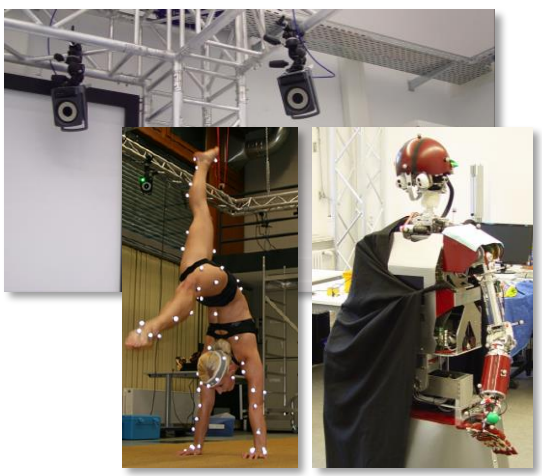
Sensoren zur Handlungsbeobachtung

- Object Modeling Center
  - Generation of high-precision, textured 3D-models
- PbD-Dome
  - Observation of human during manipulation
- Vicon Tracking System

Object Modeling Center



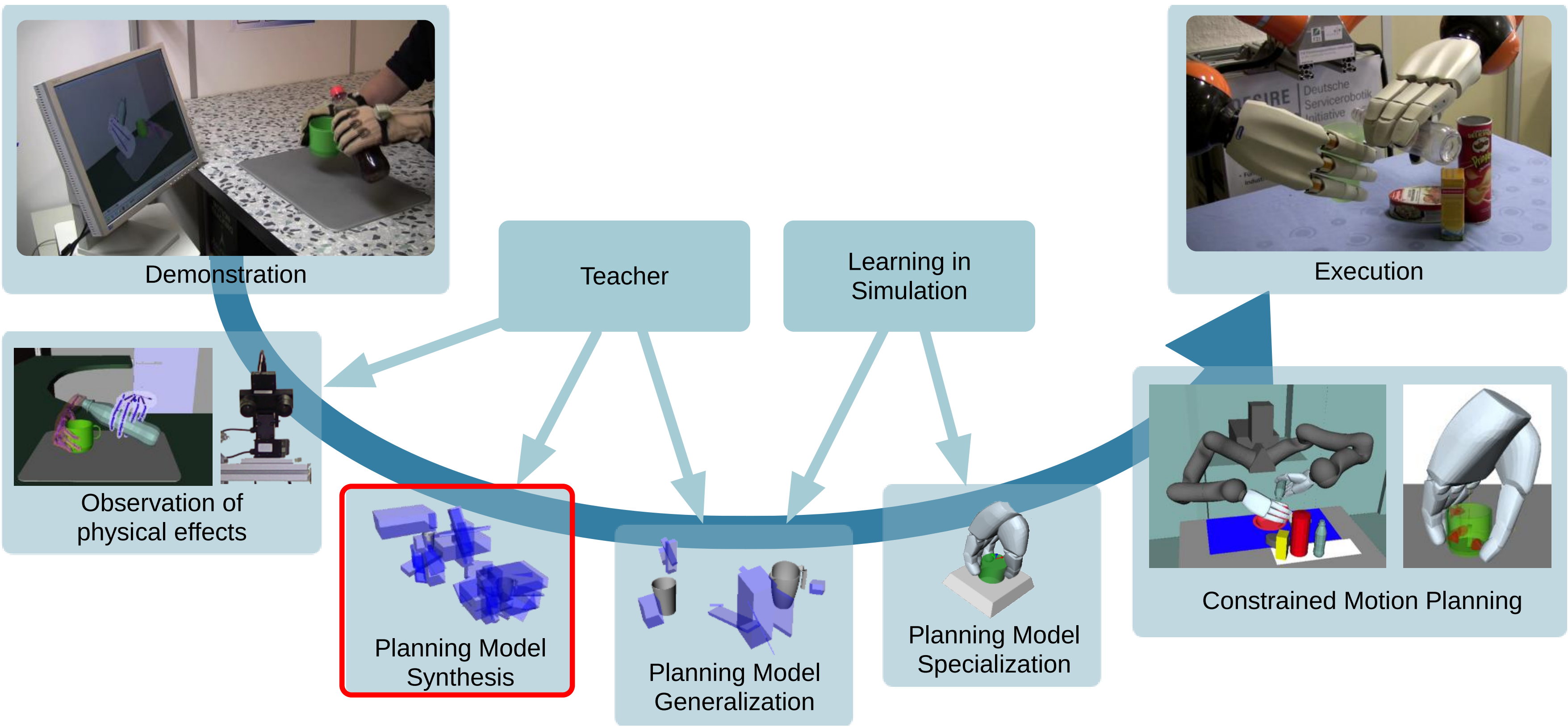
PbD-Dome



Vicon Tracking System

Zyklus – Programmieren durch Vormachen

- PbD-process schema



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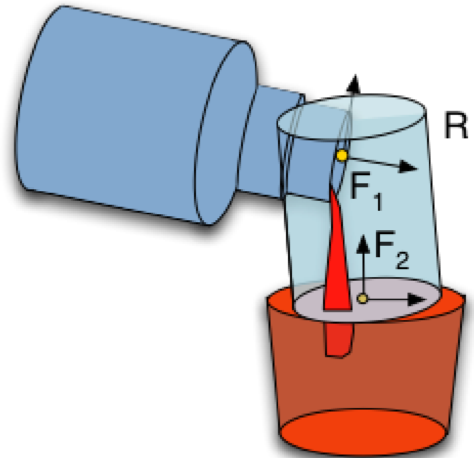
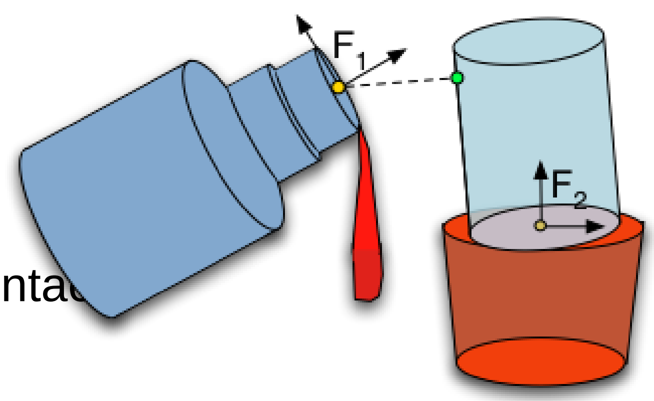
Constraint Representation

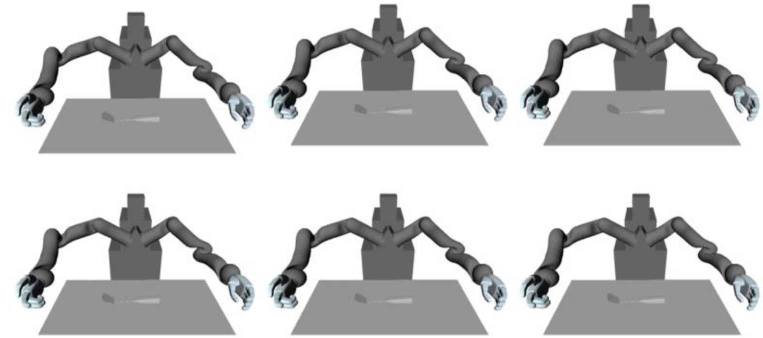
- Definition: position constraint
  - Parameters: coordinate frames F_1, F_2, region R
  - Distance
    - F_1 is transformed into F_2: ${}^2F_1 = F_2^{-1} F_1$
    - Euclidean distance of ${}^2F_1$ to R
  - Random sampling
    - Draw random sample r from R
    - Transformation of r into F_1 using $F_2 \cdot r$
  - Learning
    - For each training data θ_i:
      $F_1(\theta_i)$ is transformed into $F_2(\theta_i)$: ${}^2F_1(\theta_i)$
    - Generate parameters of R: $\forall i$: ${}^2F_1(\theta_i) \in R$
- Other constraints
  - Orientation, direction, force, momentum, contac
  - Compliance, spatial relations, time,…
- Implemented region types
  - cube-, cylinder-, sphere-, cone-sector, GMMs, convex hull





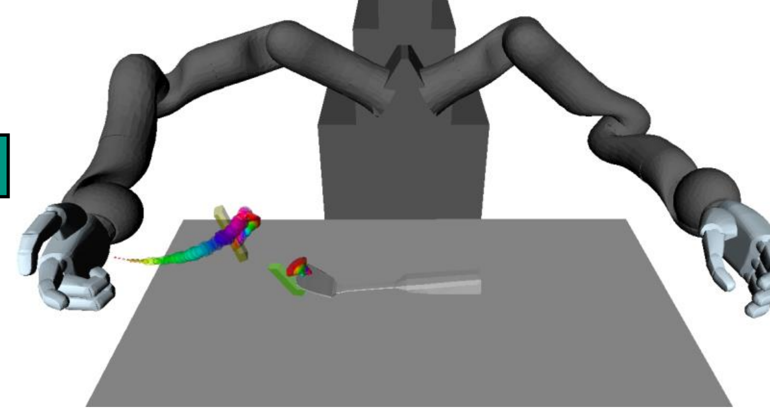
Bewegungensbeispiele

Human demonstrations



(Semi-)Automatic constraint selection

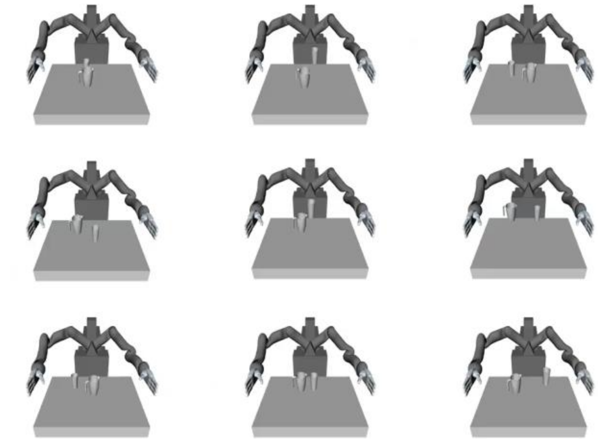
Execution using 2D-vision to localize objects



Automatic constraint optimization

Motions: Automatic model refinement II

- Results
  - 2 Robots, 8 Manipulation tasks
  - 34 CPU cores
  - Planning with/o dynamics simulatio
  - Generalization: 91%
  - Constraint reduction: 47%
  - Optimization time: up to 4h



Parallelized Optimization („pour in“)

Task	Constraints (before)	Constraints (after)	Training data	Test data	Success
Flasche in Kühlschrank	5	2	2	10 (3)	100
Zweihändiges Einschenken	174	60	2	15 (3)	67
Flasche in Kiste	15	13	3	20 (4)	100
Taste auf Tastatur drücken	362	28	3	15 (3)	100
Tasse auf Untertasse	26	15	4	24 (6)	88
Löffel anheben	140	55	1	100 (2)	84
Zudrehen einer Flasche	16	8	1	20 (4)	90
Stuhl anheben	12	6	1	10 (3)	100

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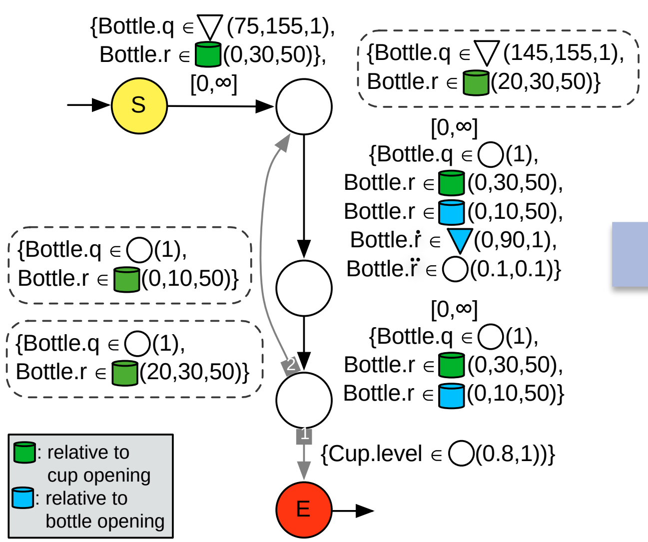
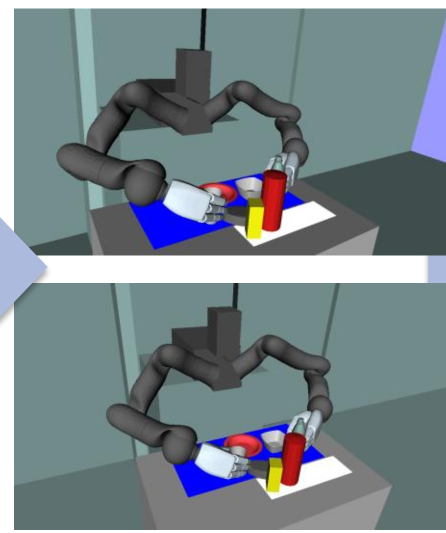
Strategy Learning

Karlsruher Institut für Technologie

- Qualitative description based on domain constraints
- Generalisation and mapping
  → flexible representation of the search space for low-level planning
  → search space automatically adapts to obstacles and objects
- Full exploitation of robot capabilities



Strategy graph
“pouring”



Constrained
Motion Planning

Execution

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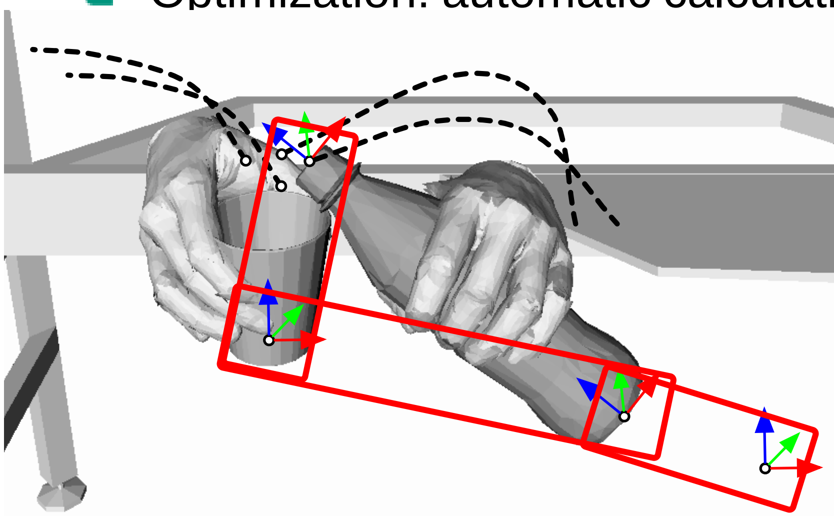
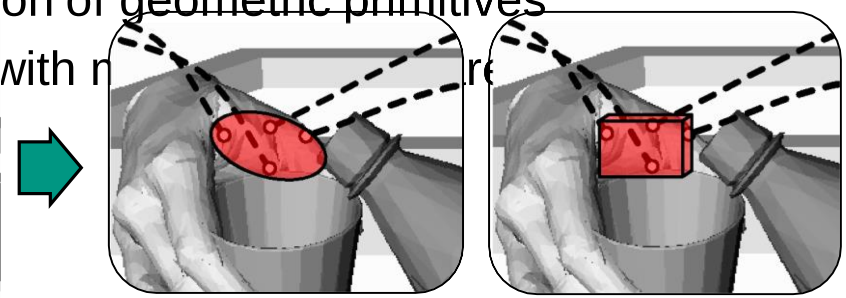
Motions: Preliminary Model generation

- Automatic generation of constraints
  - Basis: Combinations of coordinate systems (fingers, hands, detected objects)
    - Examples: Bottle opening relative to cup, bottle bottom relative to table
  - Optimization: automatic calculation of geometric primitives

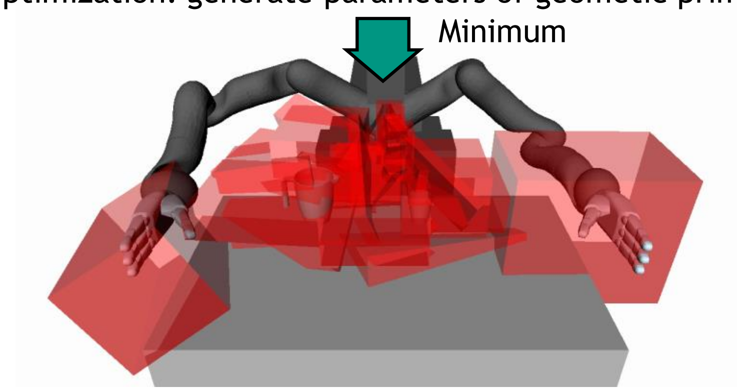


Position: Bottle opening relative to cup
Position: Bottle bottom relative to cup
Position: Bottle bottom relative to table

Multiple human demonstrations



Optimization: generate parameters of geometic primitives



Constraints for combinations of coordinate systems

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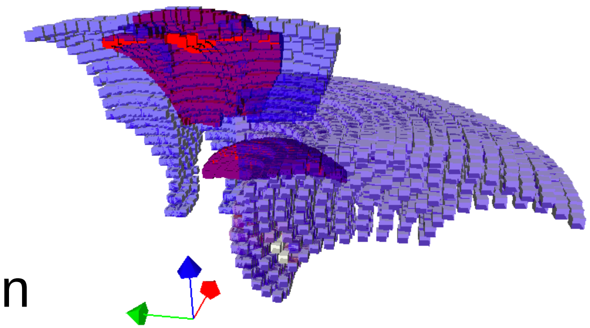
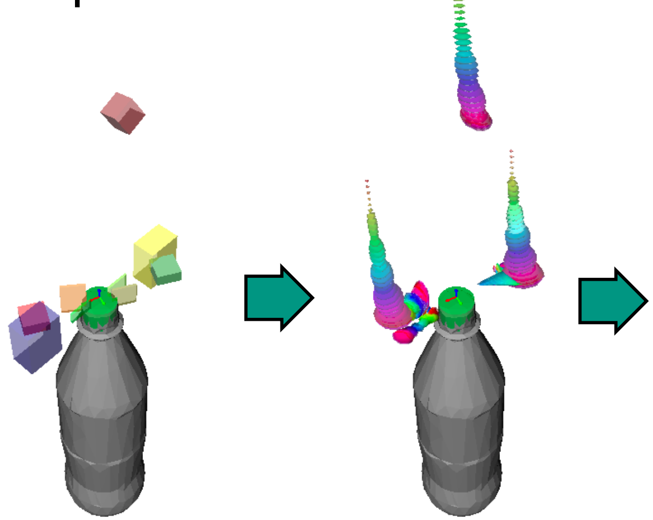
Motions: Correspondence Problem

- Correspondence Problem: „How to consider differences in morphology of human and robot?“ [Skoglund09]

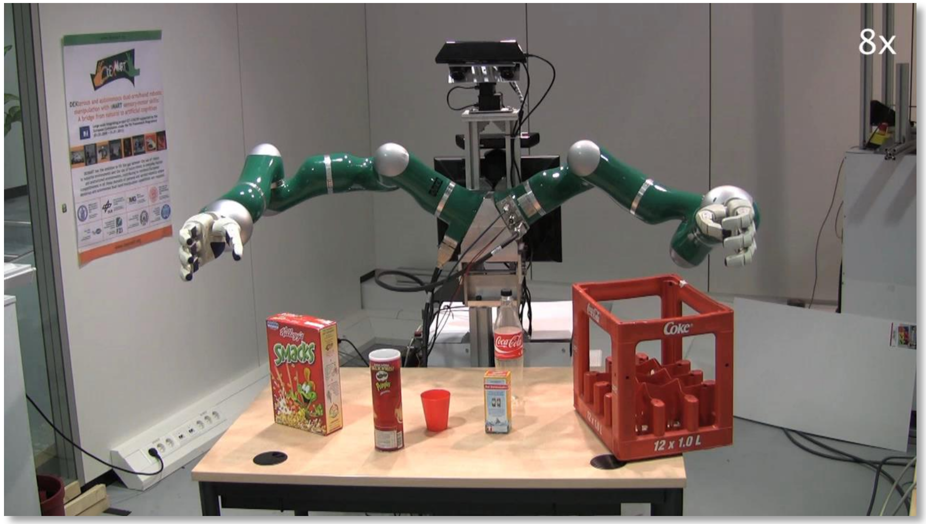
- Relaxation of finger and hand constraints based on workspace differences
- Constraint refinement using cycle-time reduction
→ Specialization to robot morphology



Workspace analysis



Original constraints Optimized constraints



Reduced time to generate complex motions

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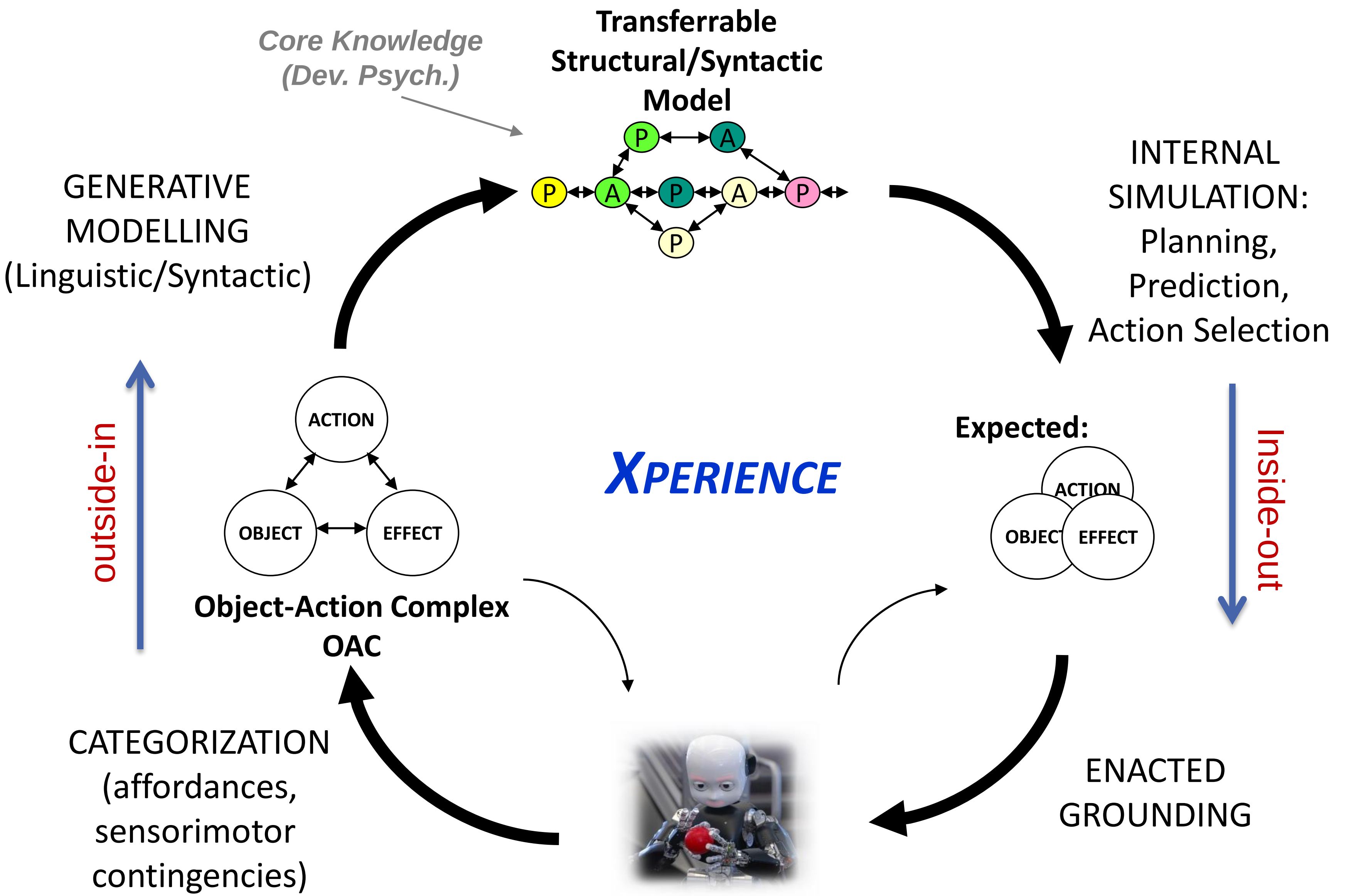
Ansatz zu generativen Lernzyklen

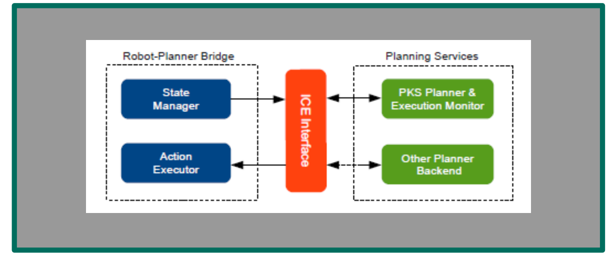


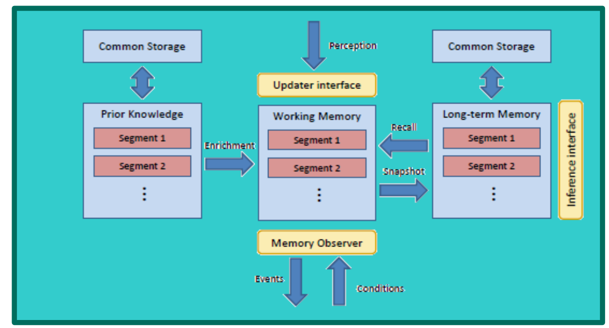
Kognitive Systemarchitektur

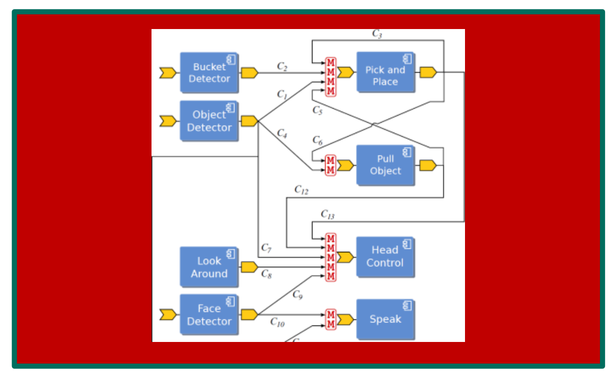
- The Xperience cognitive system architecture
  - Planning level
  - Mid-level (memory)
  - Behavior level

- Bootstrapping examples on all levels utilize grammatical correlations

- Benchmarking

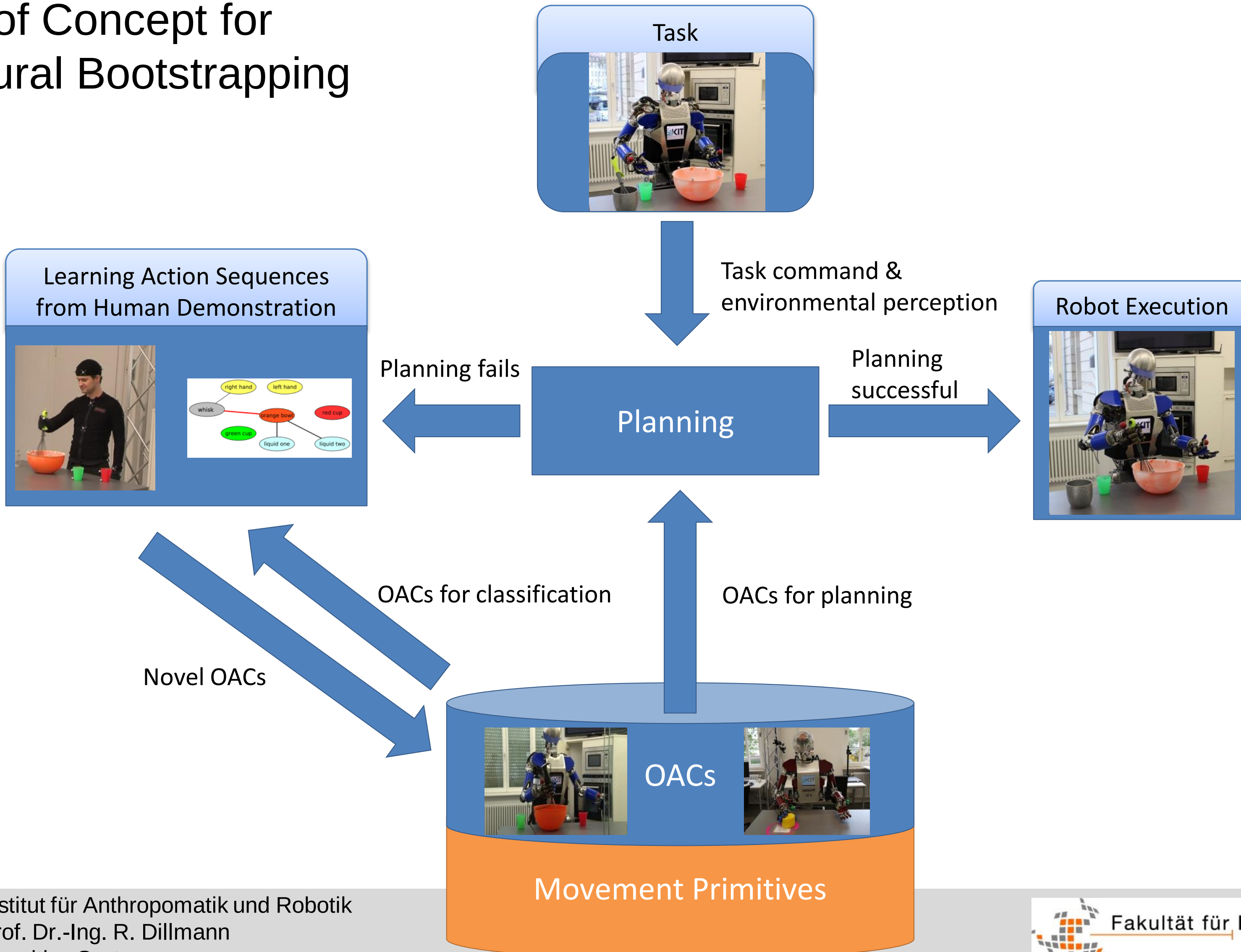






Struktural Bootstrapping von OACs

Proof of Concept for
Structural Bootstrapping



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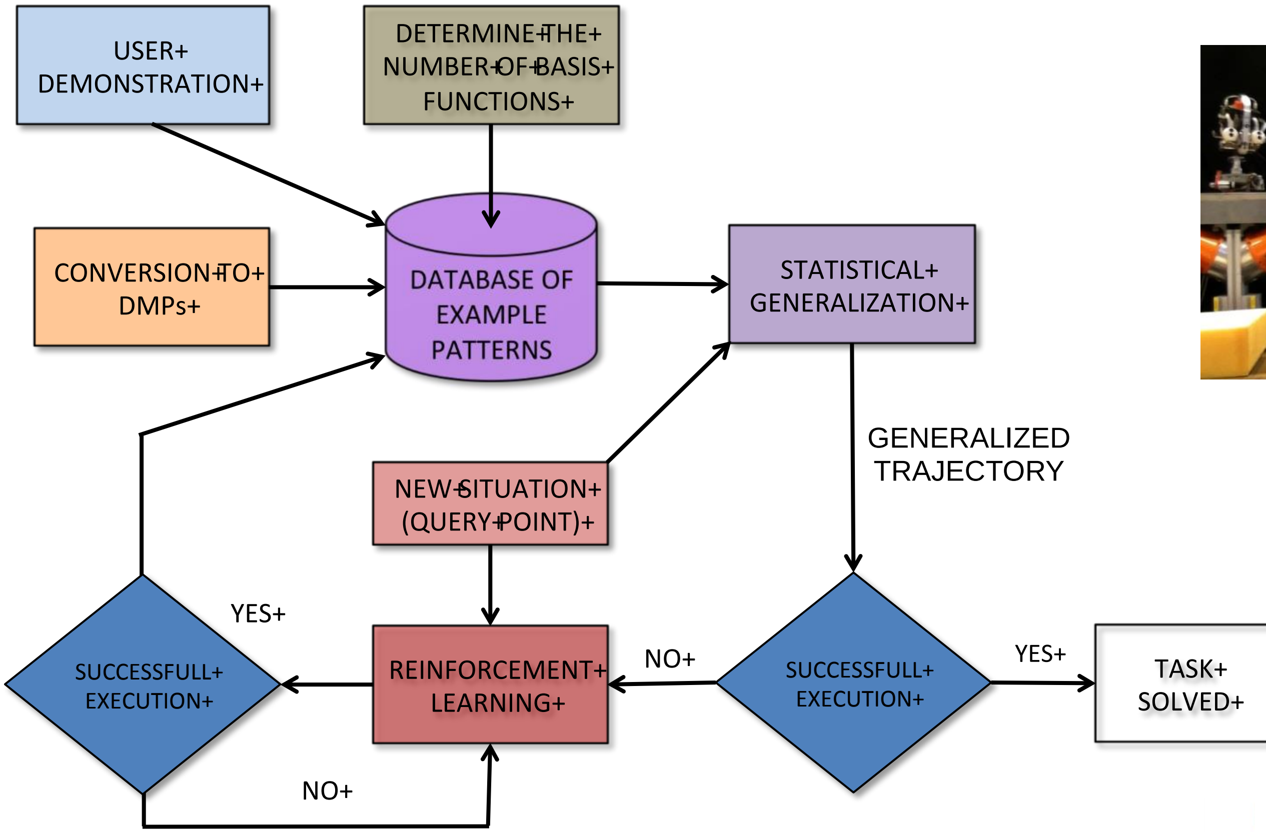
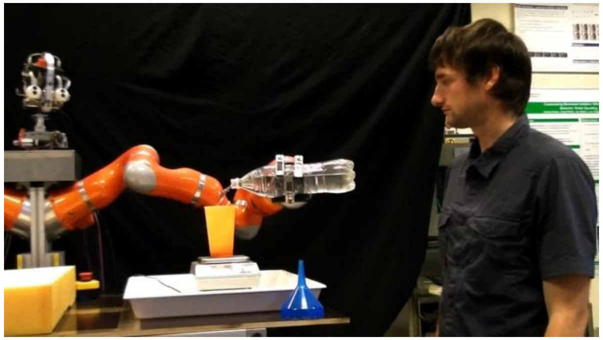
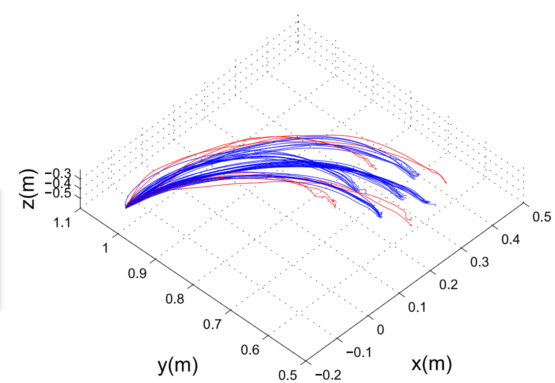
Autonomes Lernen von Skills

Autonomous skill learning by imitation and reinforcement learning







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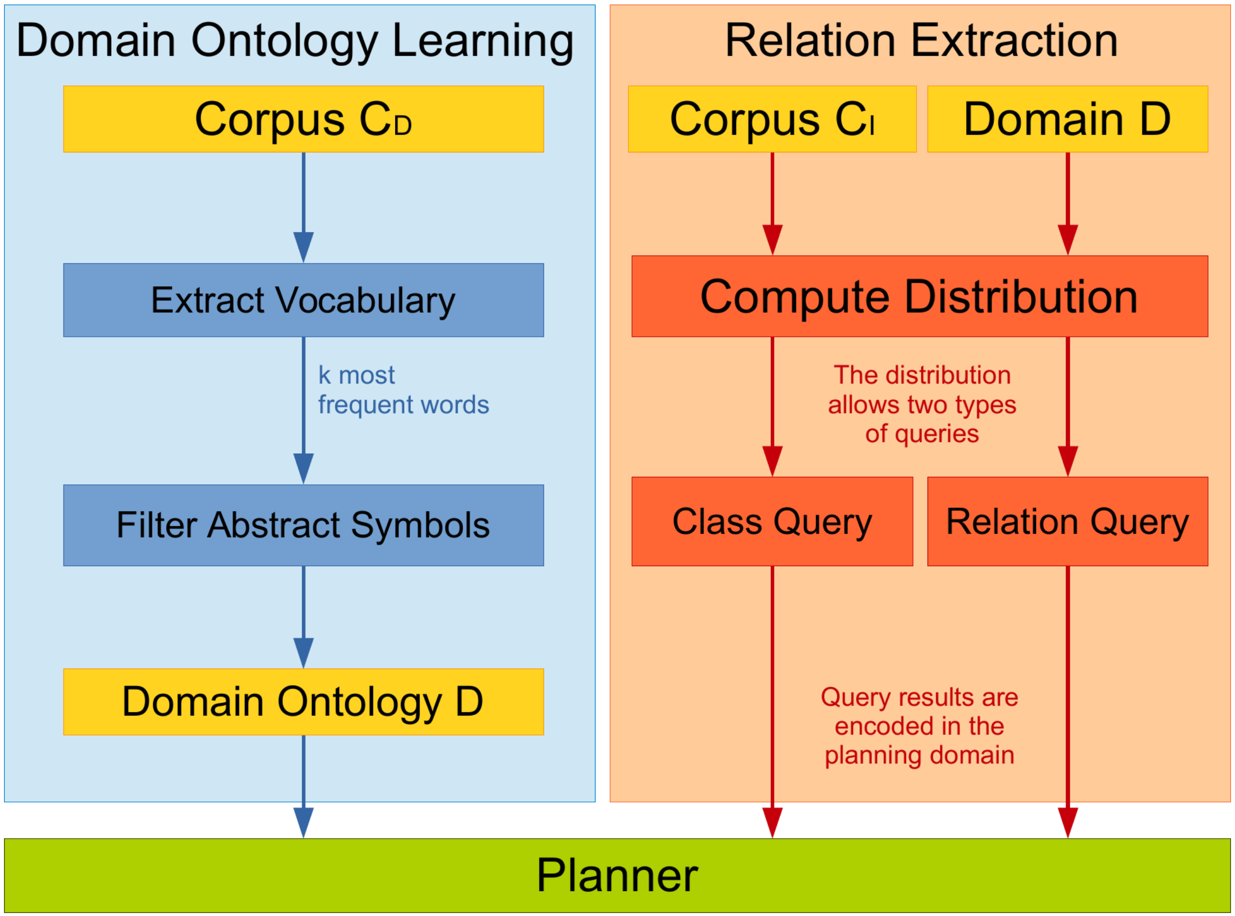
Lernen von Onthologien und Relationen

Learning common sense knowledge for planning



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Forschungsfelder im Human Brain Project

Neuroscience

Integrate what we know about the brain and neural connectivty into computer models and simulations

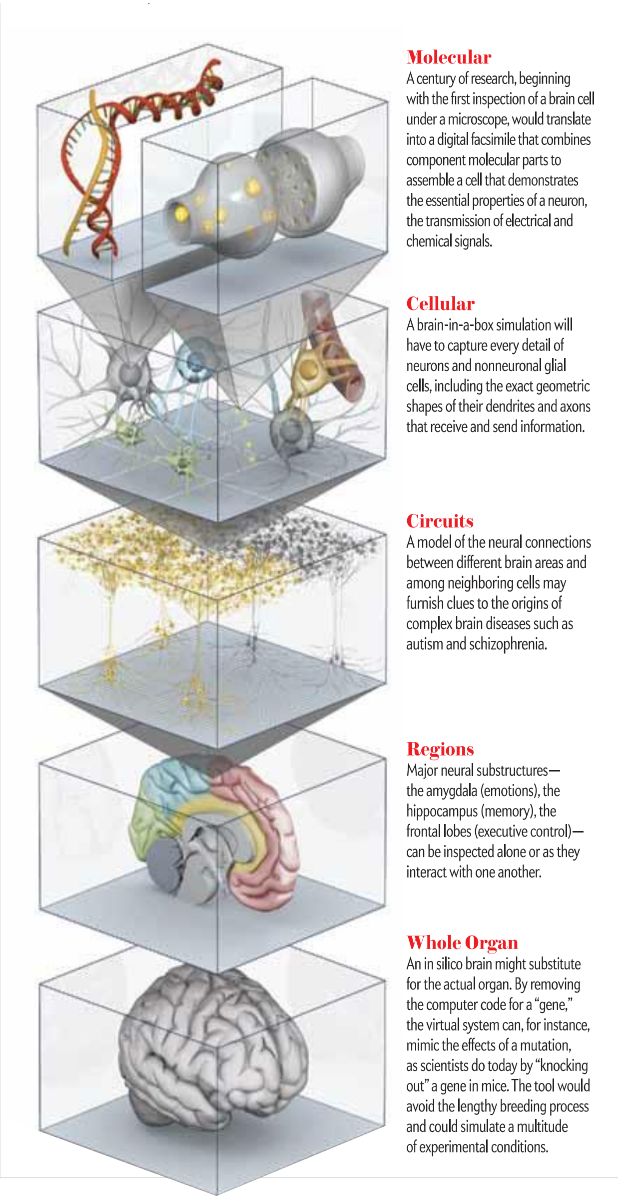
Medicine

Contribute to *understanding, diagnosing and treating* diseases of the brain

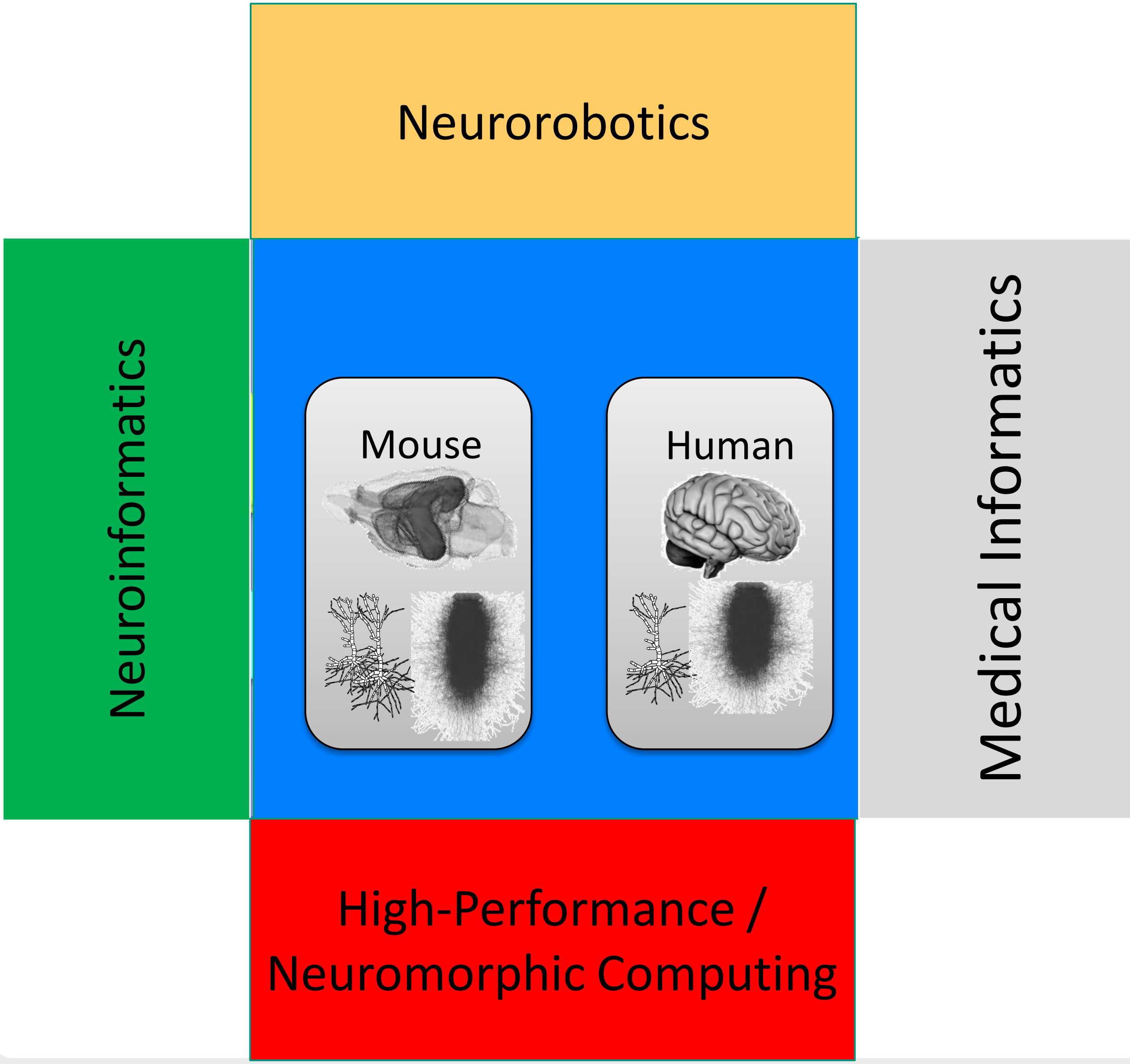
Computing

Learn from the brain how to build future supercomputers and robots of tomorrow

➢ **Virtualization of Brain and Robot Control Functionality: Neuro-Robotics**



Platforms and Research areas in the HBP



Neurorobotics: testing brain models and simulations in virtual environments

Neuroinformatics:
a data repository, including brain atlases

Brain Simulation:
building ICT models and simulations of brains and brain components

Neuromorphic Computing:
ICT that mimics the functioning of the brain

High Performance Computing:
hardware and software to support the other Platforms

Medical Informatics:
bringing together information on brain diseases

Vision of Neurorobotics

Robotics

- Apply findings and effective mechanisms from neuro-science
- Overcome limitations of standard control architectures towards higher adaptivity and behavior
- Use neuromorphic hardware for robot control tasks

Neuro-Science

- Use robots as a tool for testing hypotheses
- Full observability of brain models during robot interaction with the real environment

Learning

- Use of robotic embodiment to study and develop neuro-biological models of learning
- Implement virtual brains with the desired behavior

Ziel: Experimentelle Verifikation und konkrete Systementwicklung

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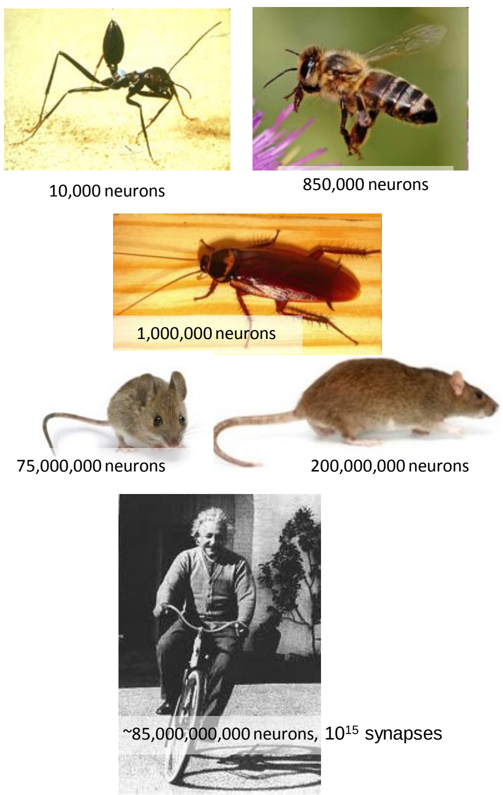
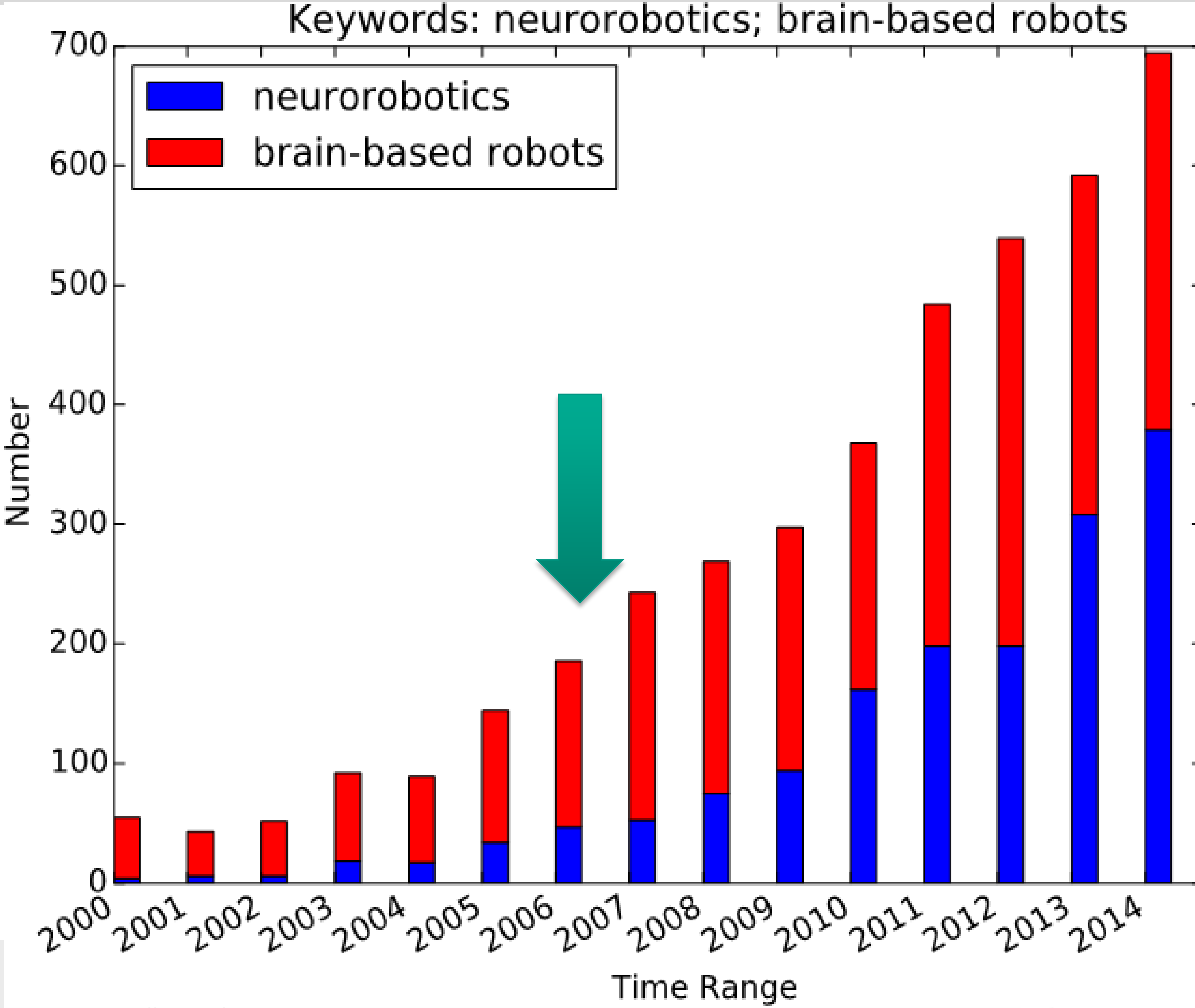
Why Linking Brains to Robots?



- Algorithms are embedded in hardware
- Sensors and effectors operate in real-time
- The brain is massively parallel, but does not suffer from the problems of parallel computing: dead-locks, non-determinism, race-conditions, …
- … and decomposition into parallel tasks is self-organized/evolved
- Architecture is scalable from thousands to billions of “processors”
- Performance is robust – with graceful degradation
- Brains are extremely power and space efficient (“peta-flop computer on 20 Watt”)
- Calls for a “neurorobotics approach”


Keywords: neurorobotics; brain-based robots
neurorobotics
brain-based robots
Number
Time Range
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100
200
300
400
500
600
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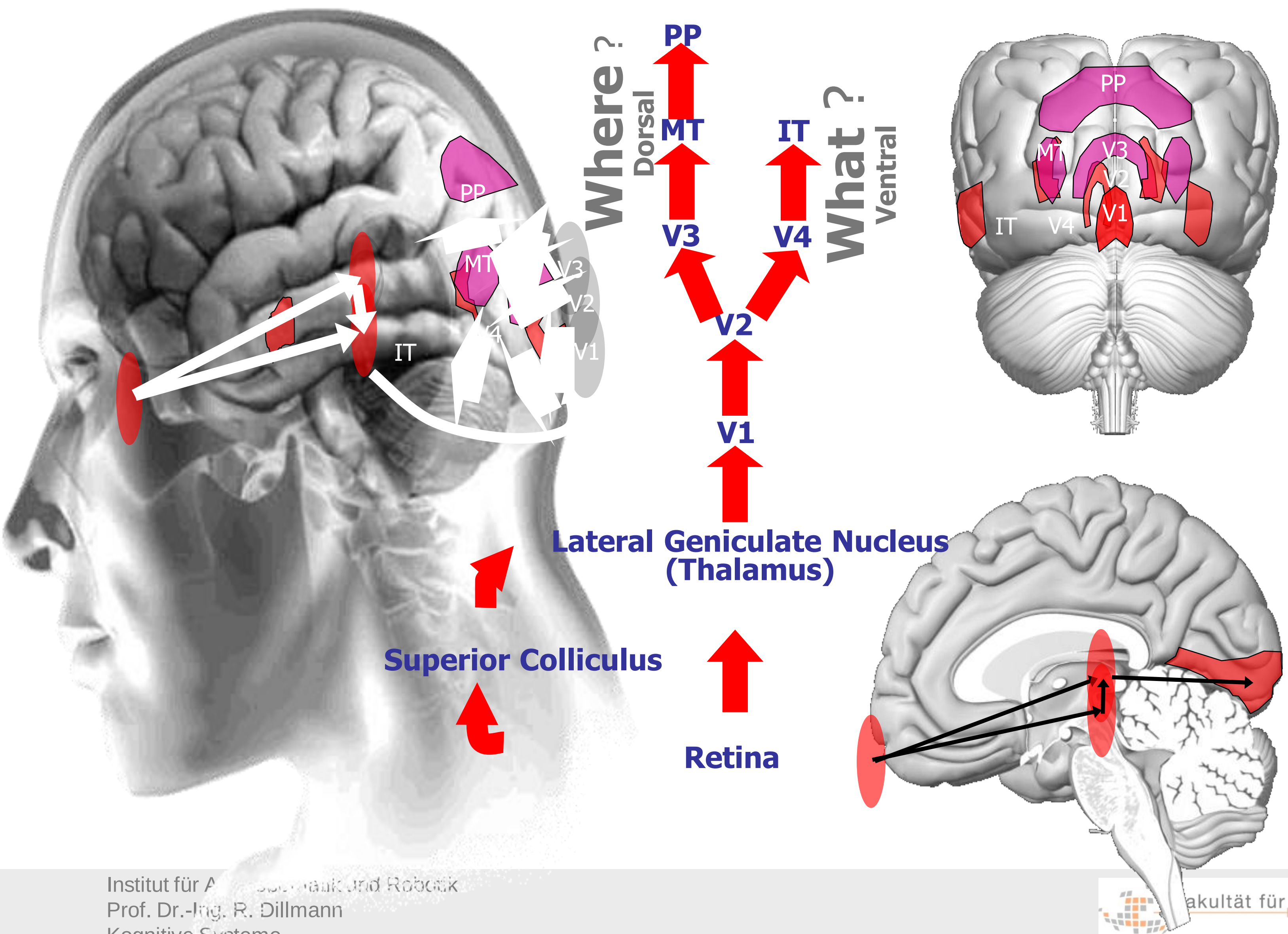
Visuelle Sehnervpfade und ihre Verbindung mit dem Bewegungsapparat

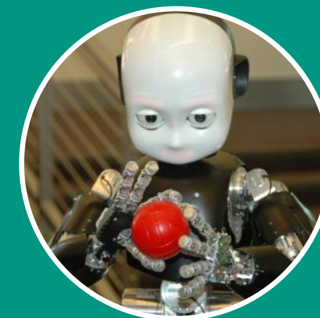


Ansatz: Werkzeuge und Methoden

Observing and modelling of biologic bodies

Simulation of body, sensors and environment in defined experiments

Simulation of robots, sensor-motor controls and environment in defined experiments



Real robots for experiments

iCub
HoLLie
ARMAR
Roboy

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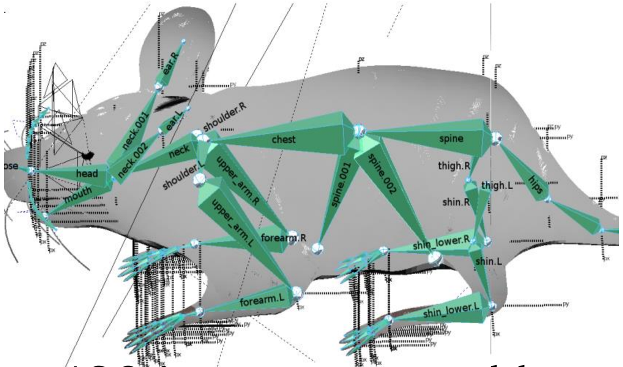
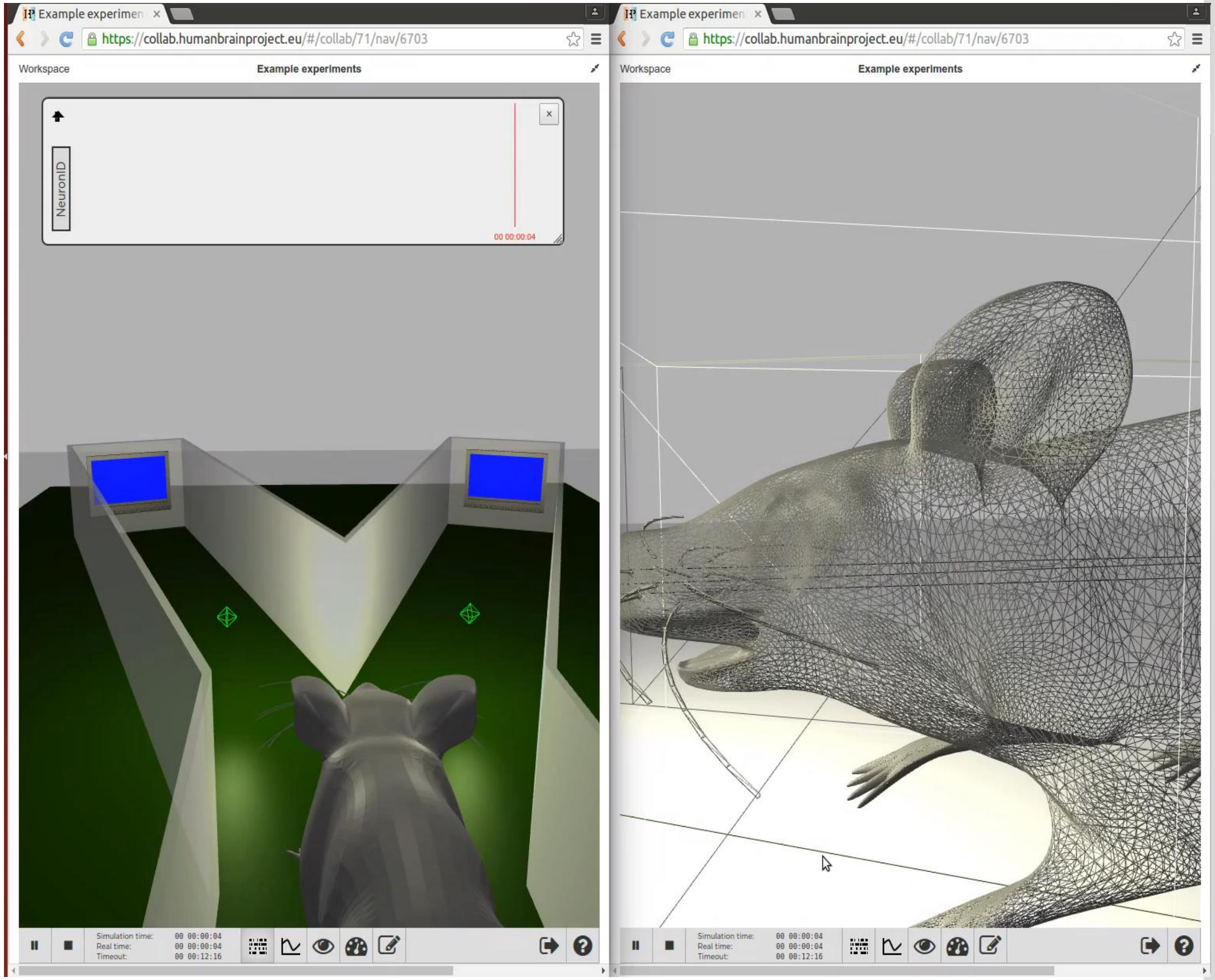
Mouse Experiment



120 interconnected bones

- A mouse model featuring rigging, i.e. <u>deformation</u> of the surface triangles, based on bone movements

- The skin deforms when the mouse turns the head.



Detailed surface model with 135588 triangles

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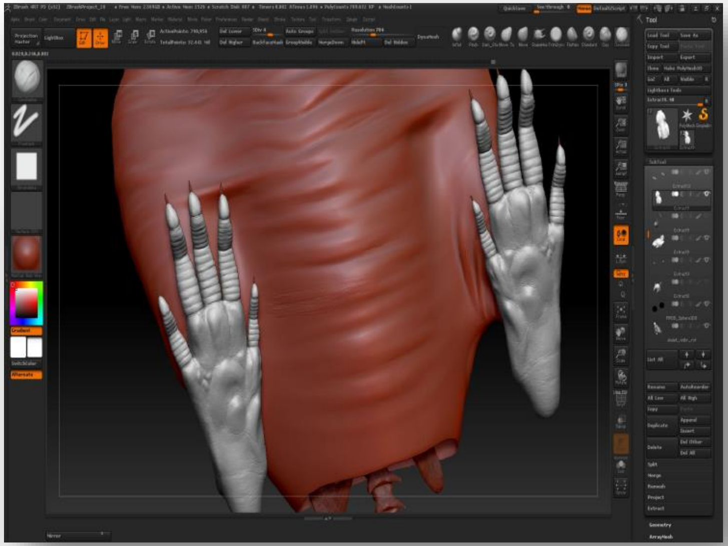
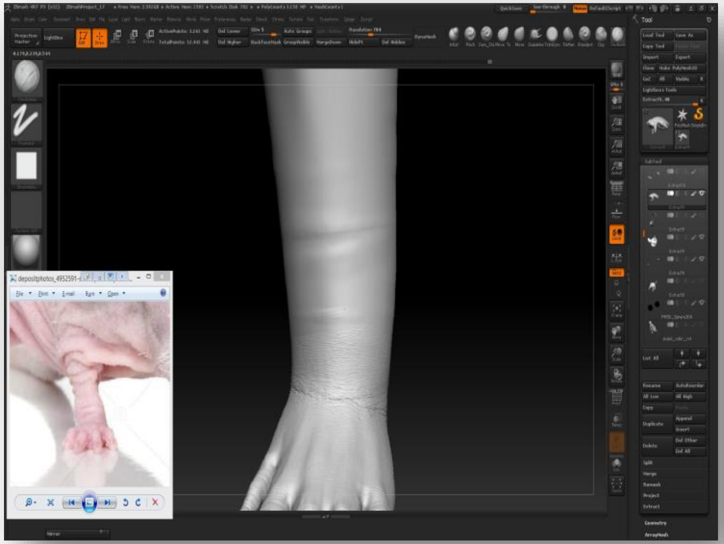
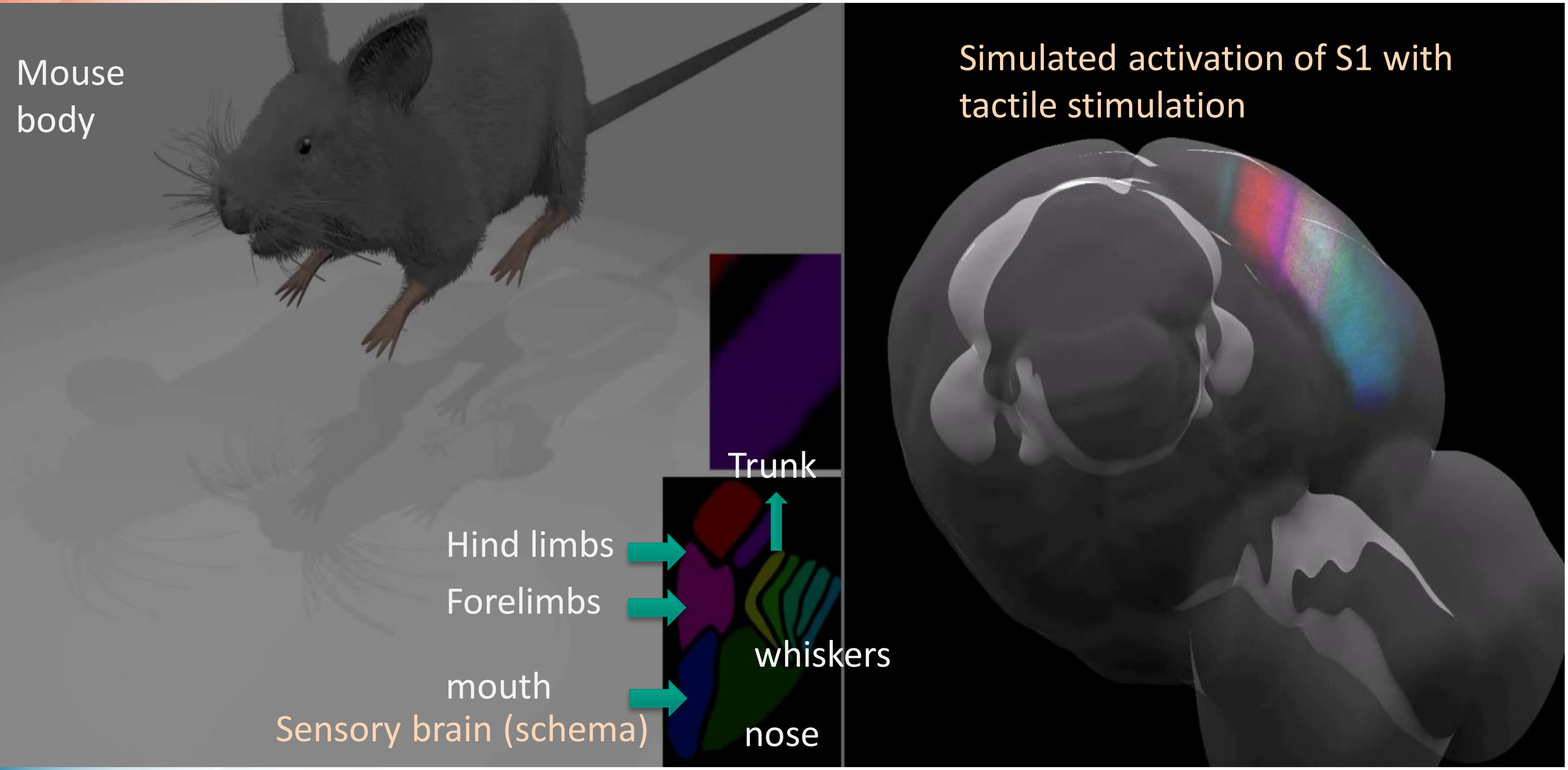
Rodent body model

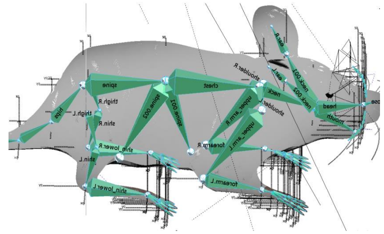




Experiment: Mapping touch to the sensory cortex

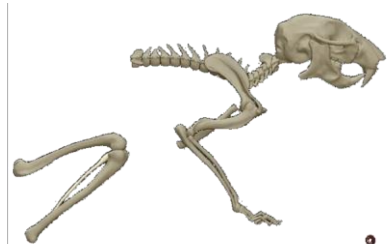


Status quo: virtual mouse



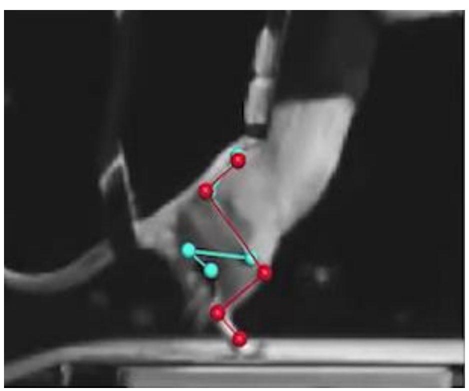
Original ad-hoc model of mouse with skeleton

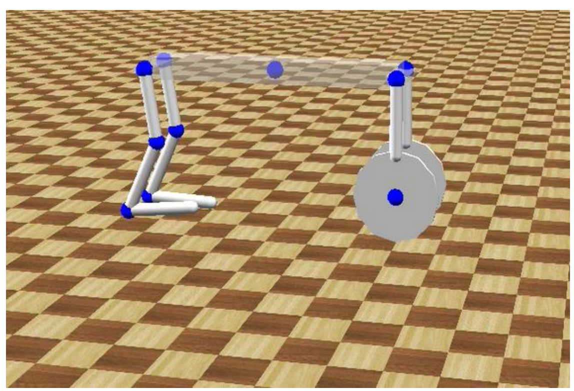
Moby mouse atlas



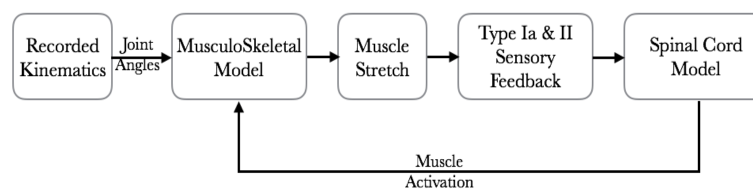
Hi-Fi 3D Model (in progress)

Improved skeleton model, based on MRI reconstructions



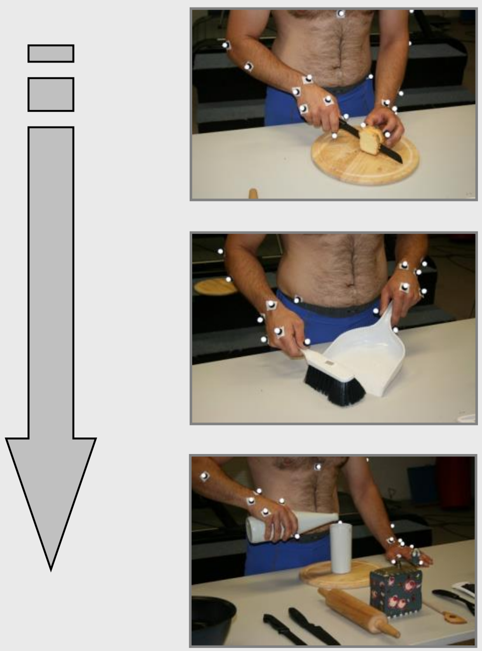


Neuro-musculoskeletal model based on kinematic data

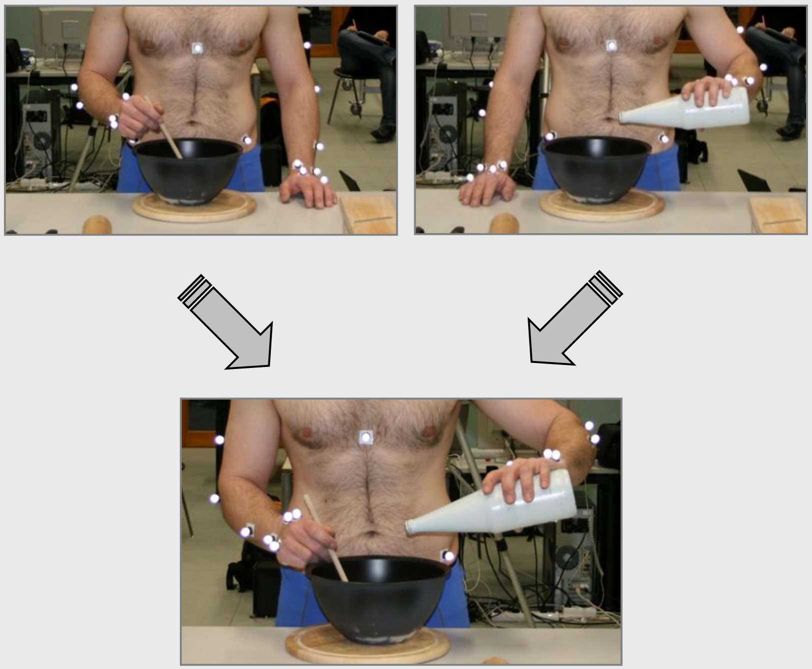


Capture of Human Movement and Interaction

Sequential Motion



Parallel and coordinated Motion



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Mapping of whole-body human motion and handling of objects to avatars

https://motion-database.humanoids.kit.edu/

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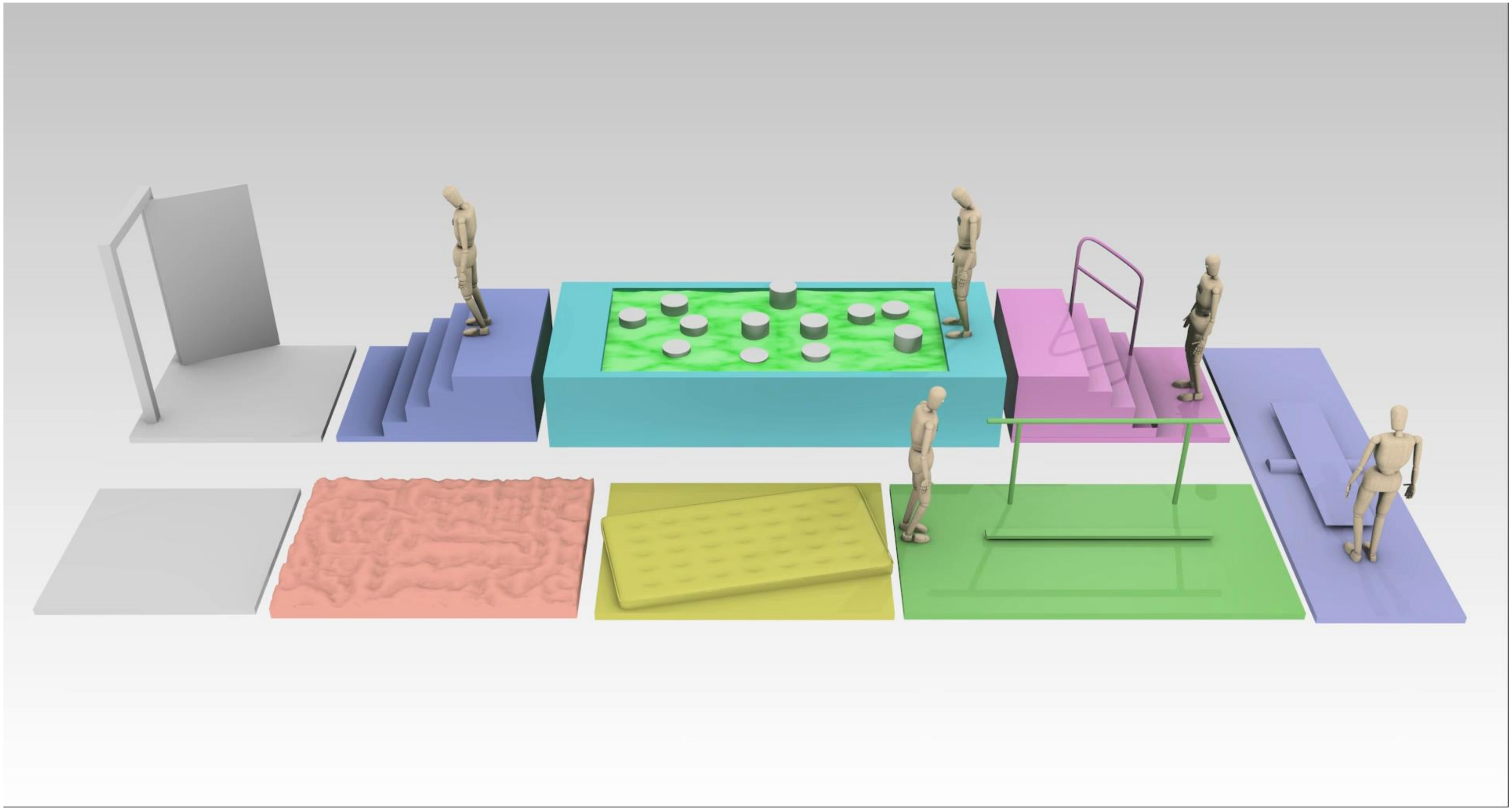
Mapping Human Motion to Master-Moto-Map: MMM



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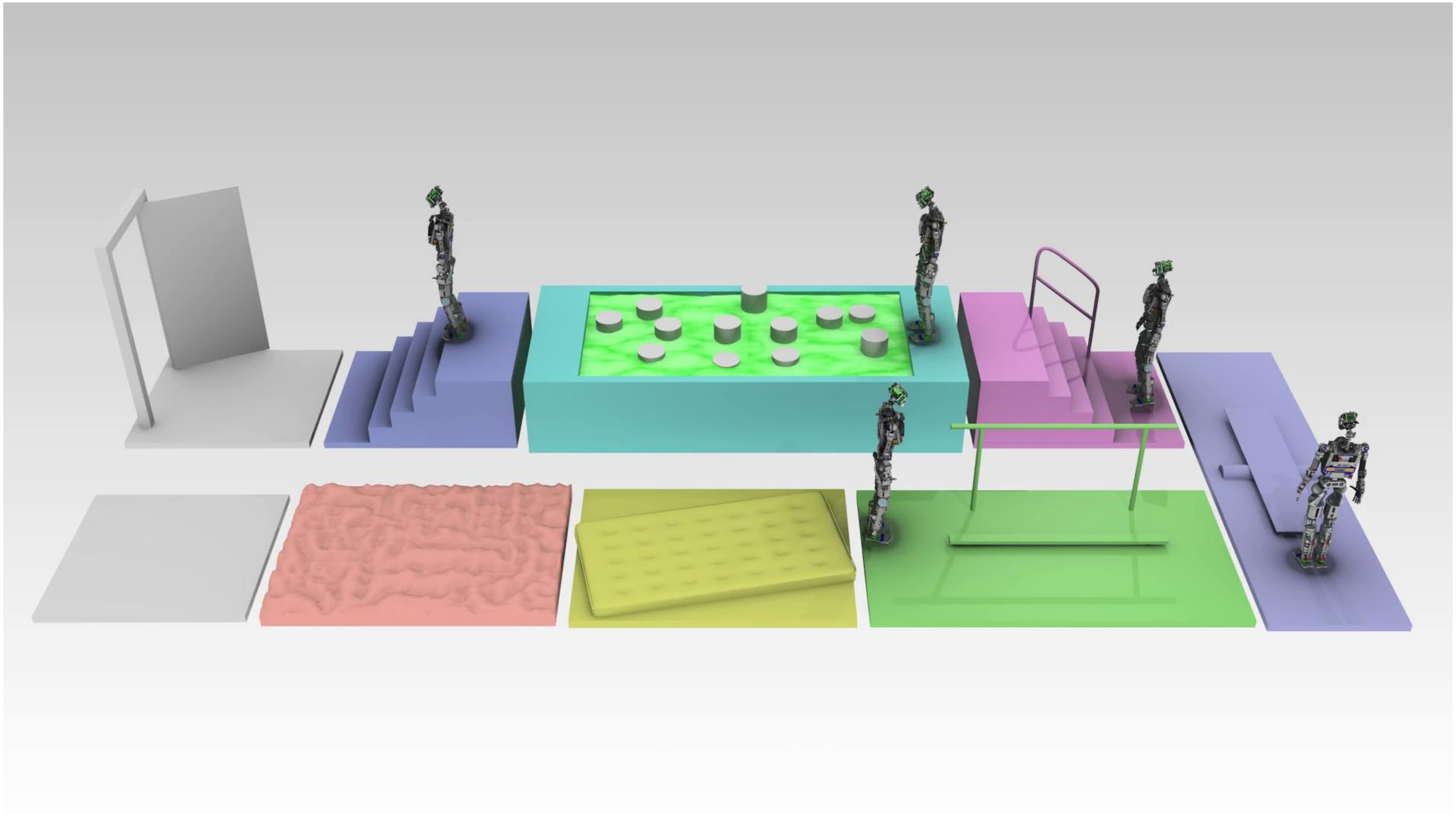
MMM → ARMAR-4



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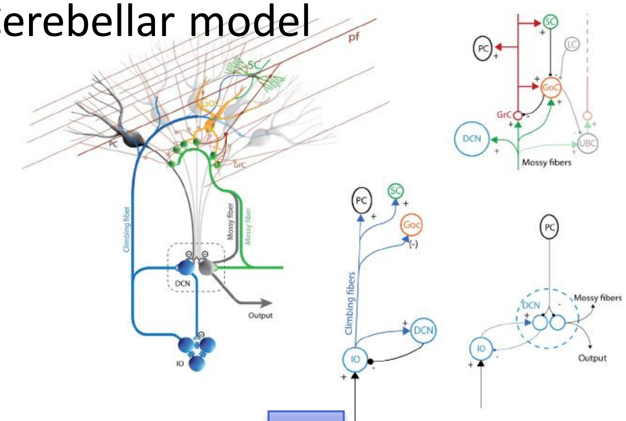
Technology for Neuronal Robot Controls

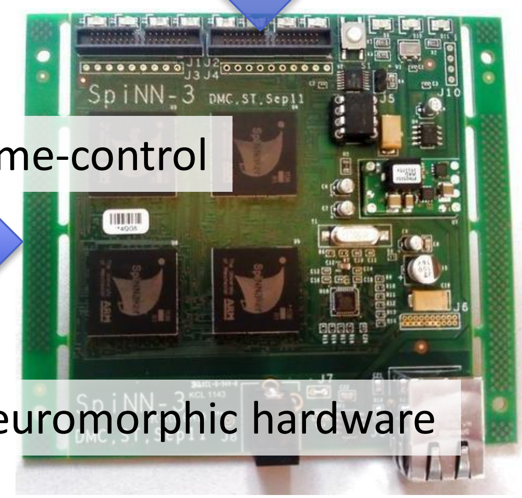
Simulated robot hand

Cerebellar model



Physical robot hand

Ongoing: Realtime-control



Neuromorphic hardware

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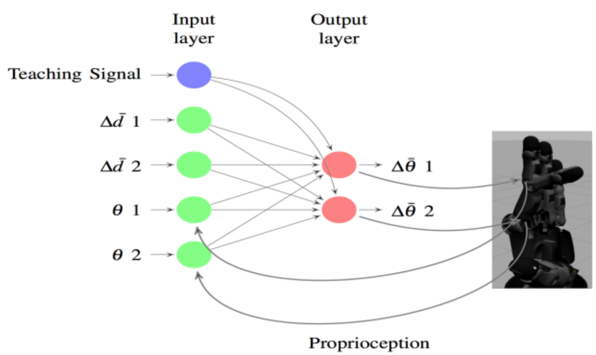
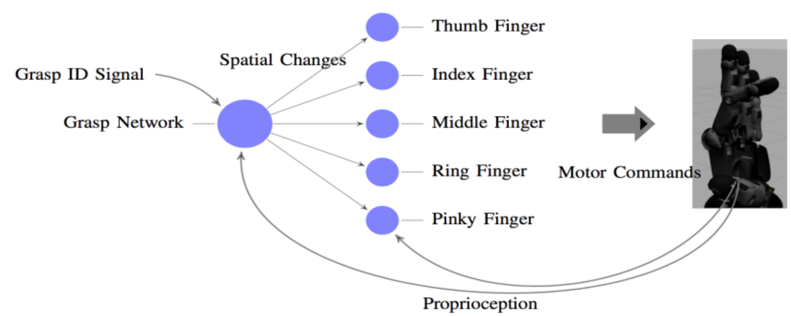
Coordination of single finger motion

- Associative learning with STDP
- Reuse of single motions
- Hierarchical control
- Motion capture with finger tracker (LeapMotion)





Bouganis and Shanahan. Proc. Int. Jt. Conf. Neural Networks. 2010.
Tieck, Donat, et al. “Towards Grasping with Spiking Neural Networks for an Anthropomorphic Robot Hand”. (Submitted). 2017.

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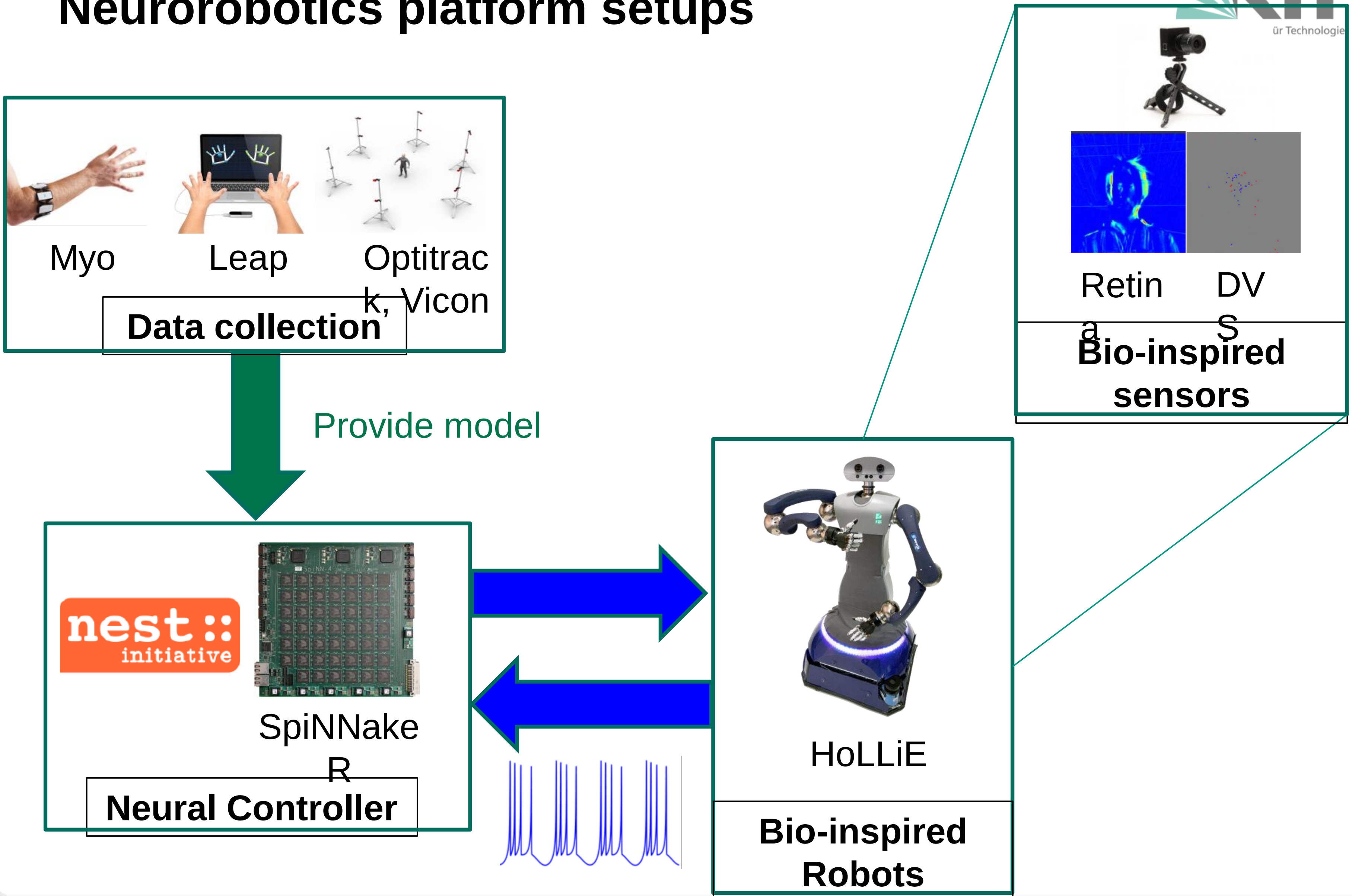
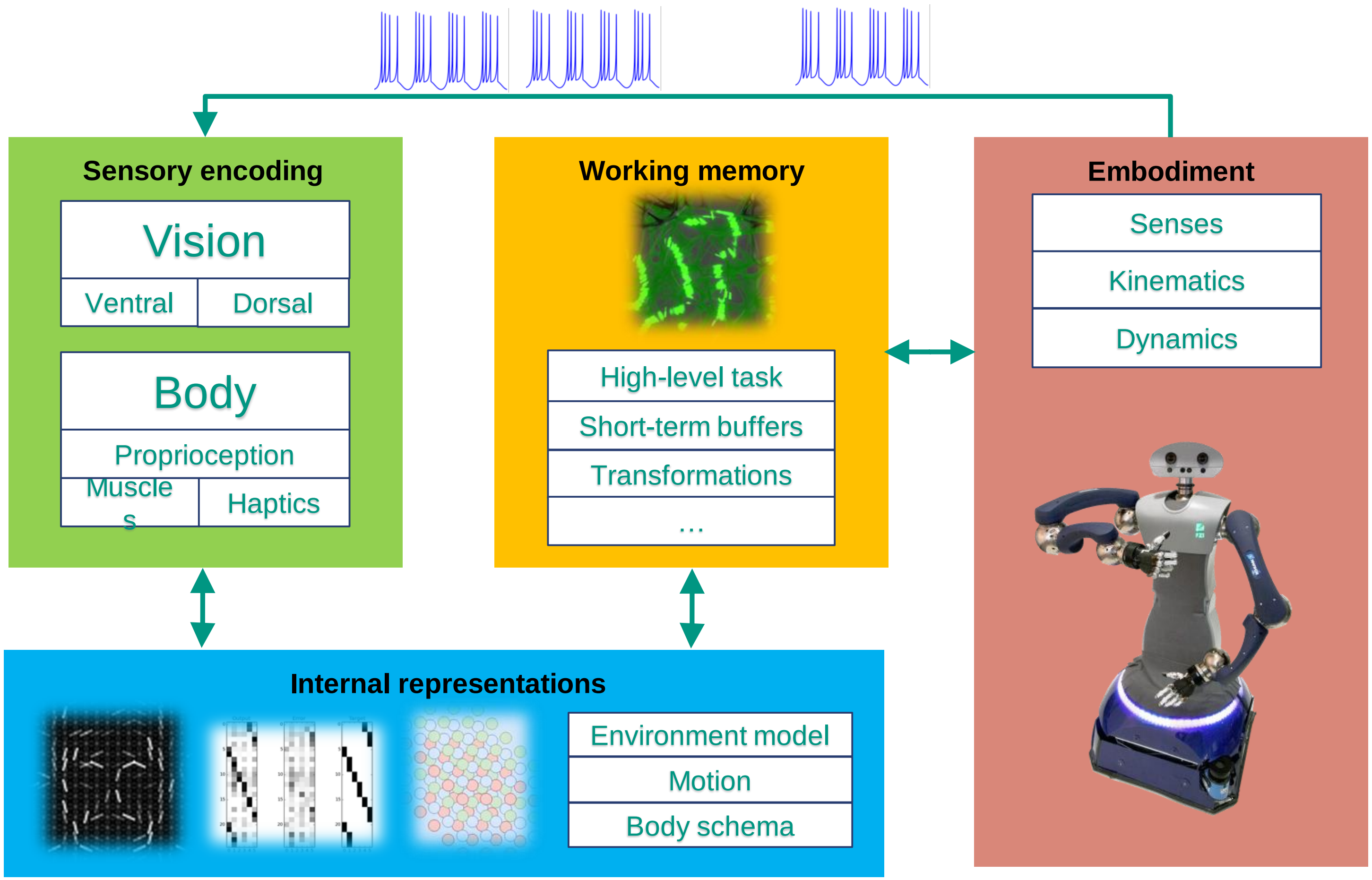
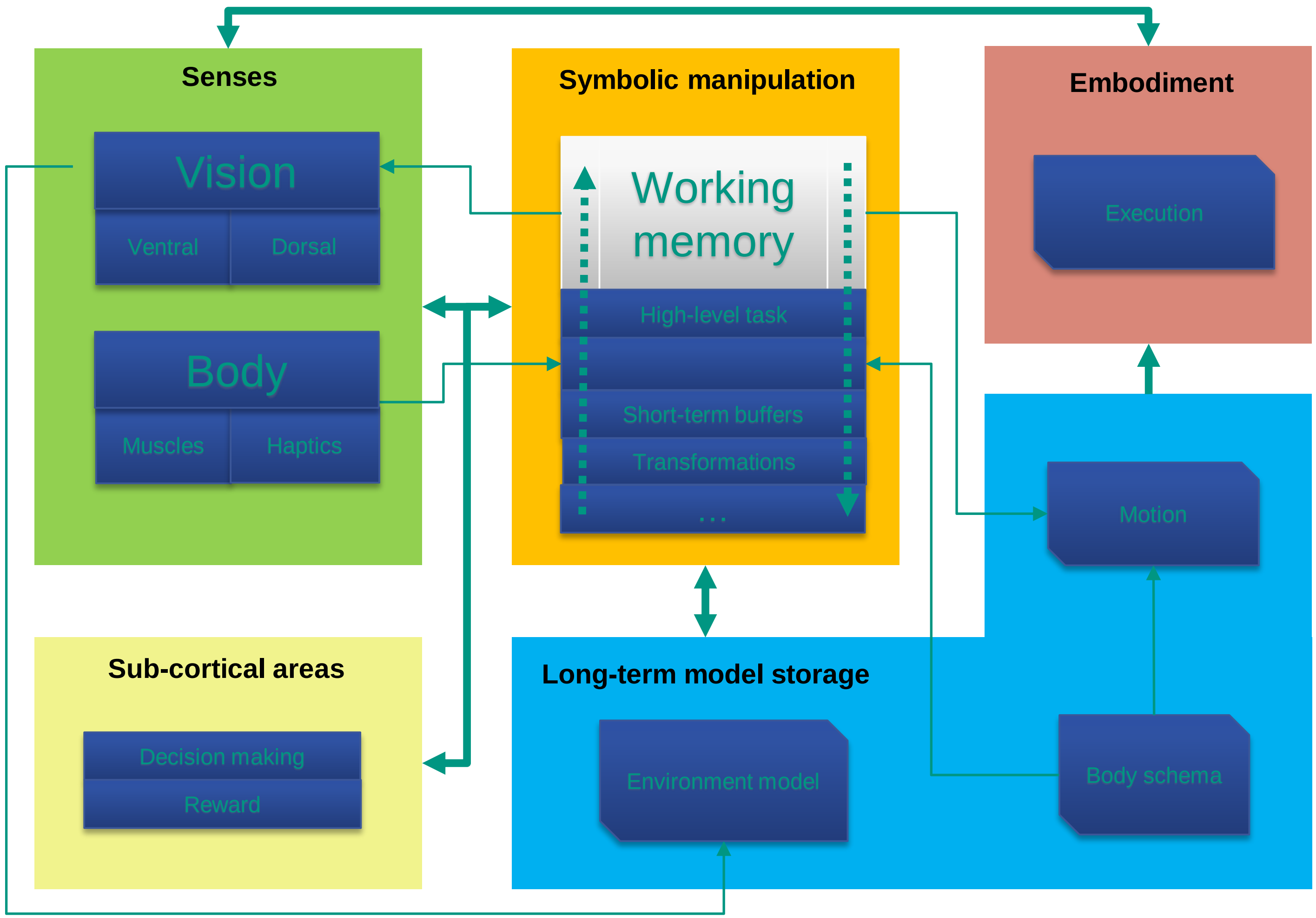
Neurorobotics platform setups



Neural Controller Architecture



Neural Controller Architecture



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Basic Learning Tasks for Neural Controls

Karlsruher Institut für Technologie

Example: Observing a scene and grasping an object that is added by the experimenter

1. Visual cognition
   - “Where is the object?”
   - “What is the object?”
2. Symbolic reasoning
   - “What can/should I do next?”
3. Manipulation and grasping
   - “How to reach the object?”
   - “How to move the fingers to grasp

- Additional question
  - How to combine principles form robotics and machine learning with neuroscie e?

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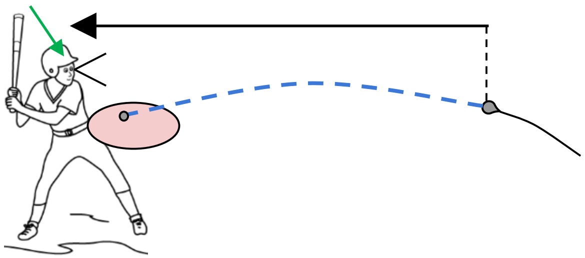
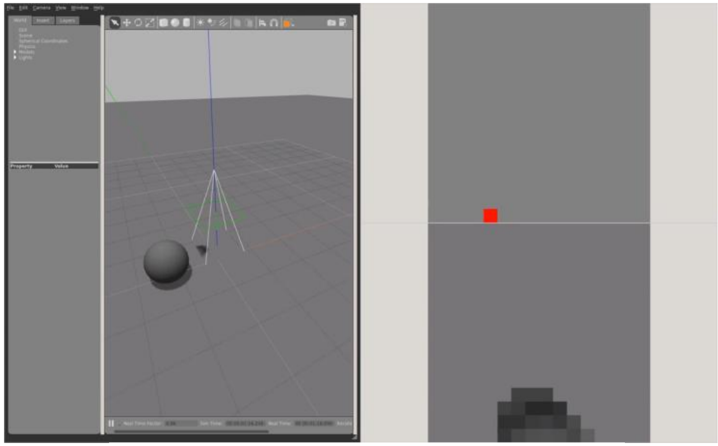
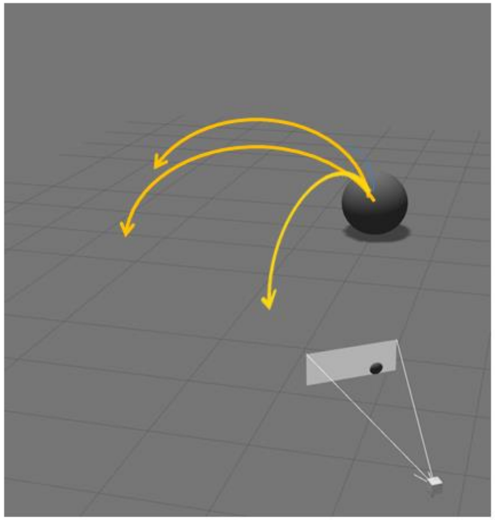
Vision for action: Dorsal pathway



- "Where is the object and where will it be next?"
  - Detection of motion / Saliency
  - Optical flow
  - Localization
- Input data:
  - Address events (DVS-Camera)
- Output:
  - Prediction of future address events
- Neural candidate:
  - Liquid State machines





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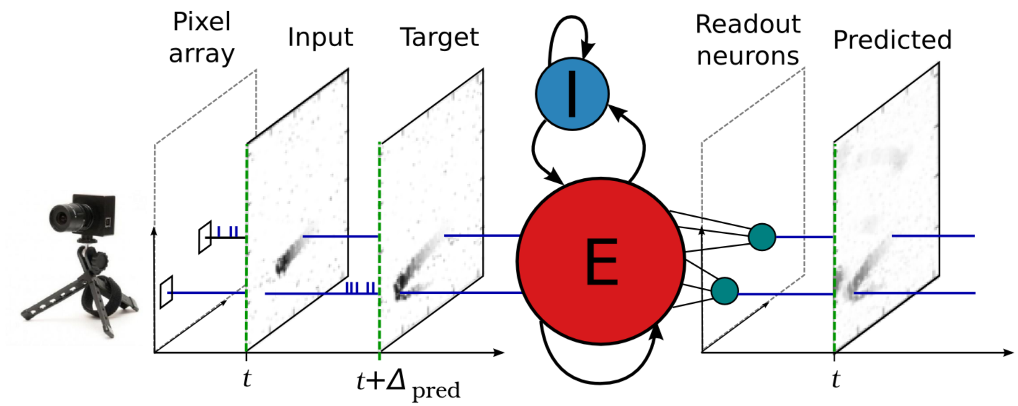
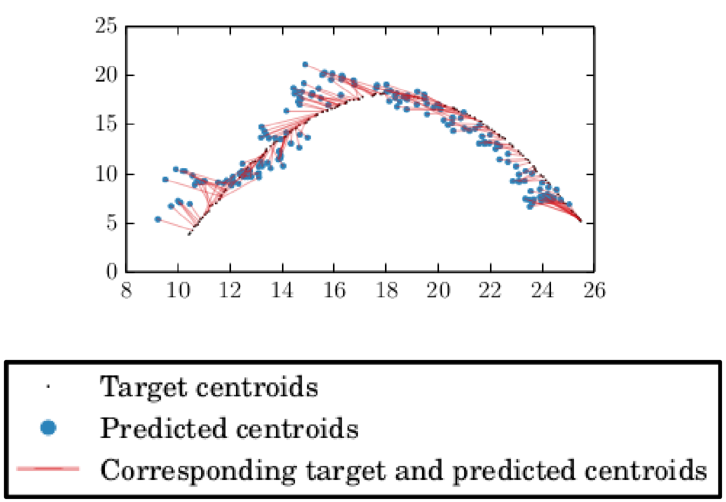
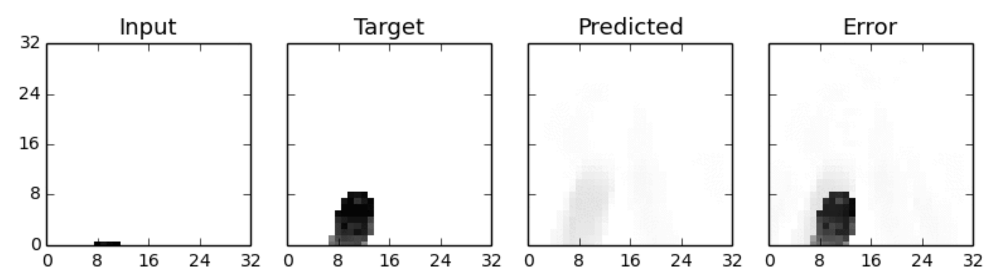
Liquid State Machines

- Reservoir Computing
  - randomly recurrently connected neurons
- Simple training
  (linear regression on readout weights) yet complex behaviour
  (nonlinear dynamics)
- Asynchronous computing

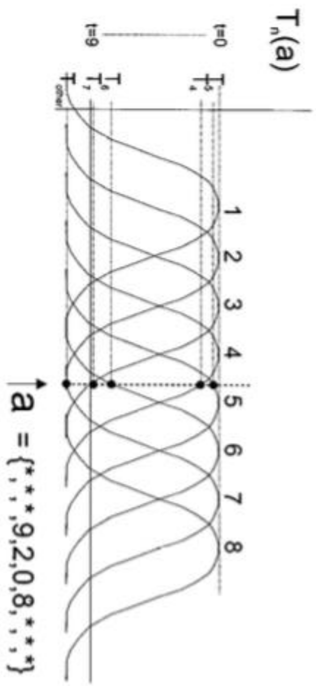


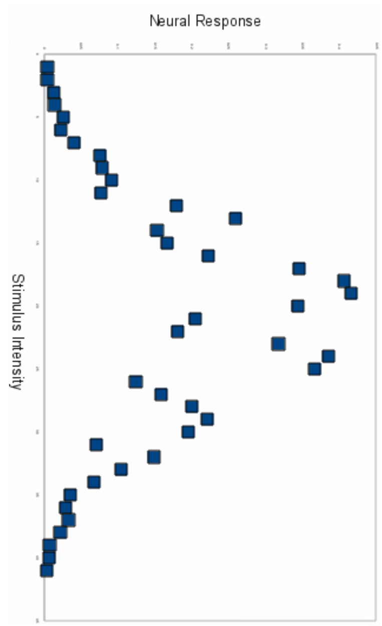


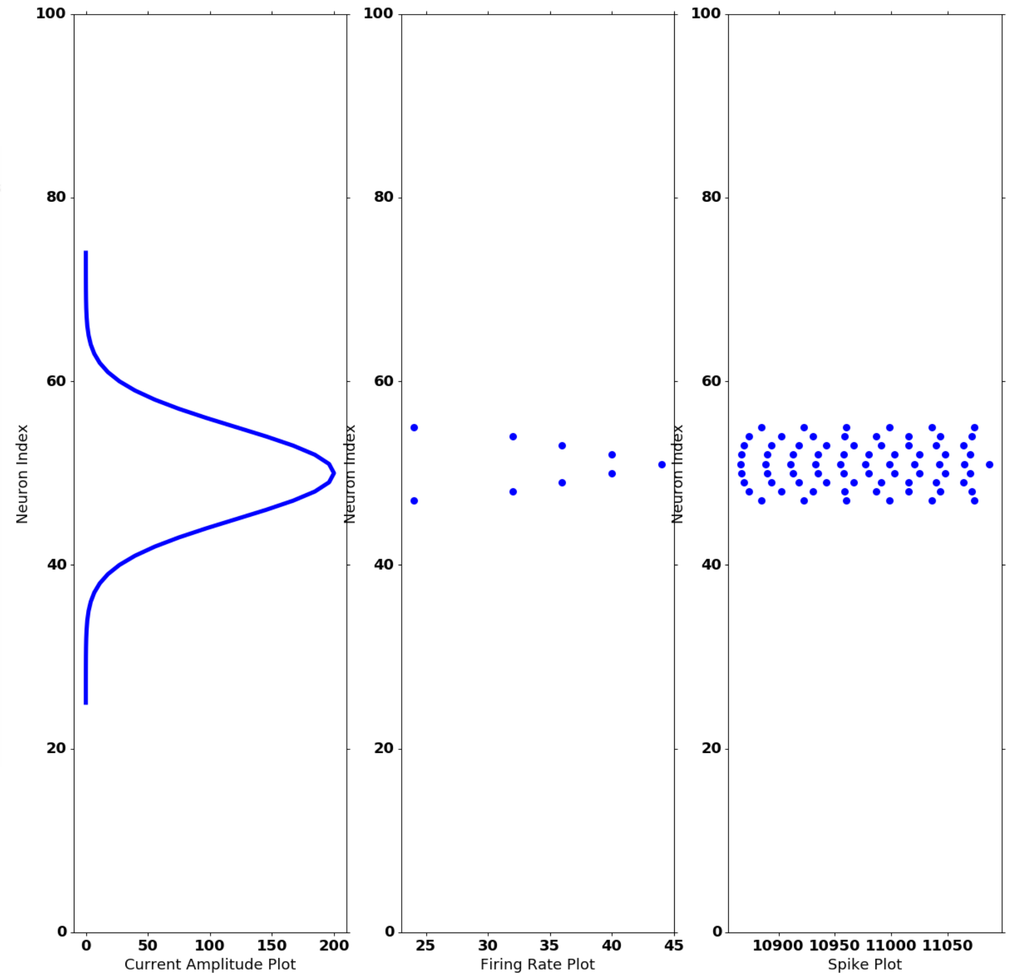


"Scaling up liquid state machines to predict over address events from dynamic vision sensors" , Jacques Kaiser, Rainer Stal, Anand Subramoney, Arne Roennau, Rudiger Dillmann , Bioinspiration & Biomimetics 2016

Spiking neuron model and spiking representations







- Population position Gaussian neural coding

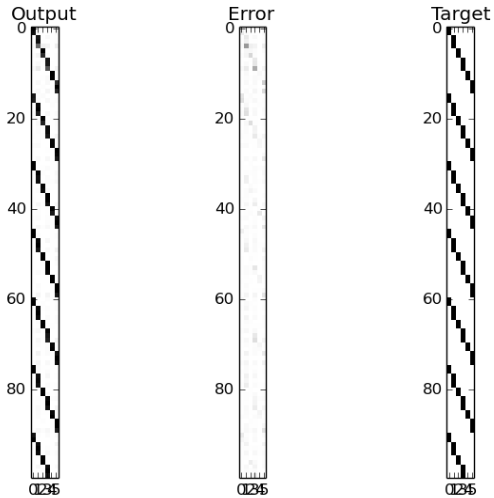
Bohte et al. 2002

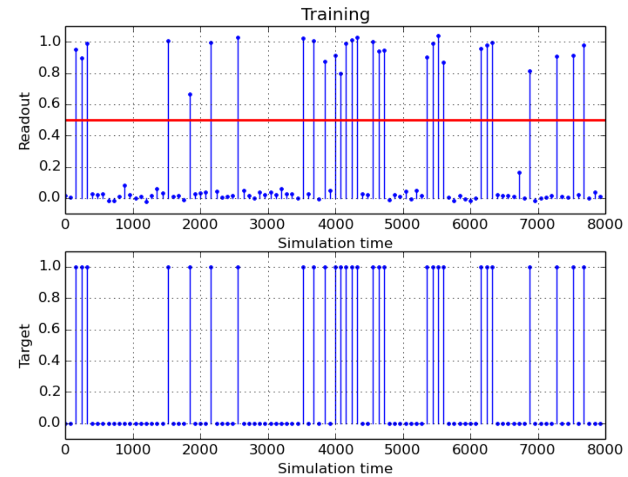
Spiking activity prediction

- Prediction of successive spiking (6 neurons)

Prediction of randomly generated pattern (2 neurons)

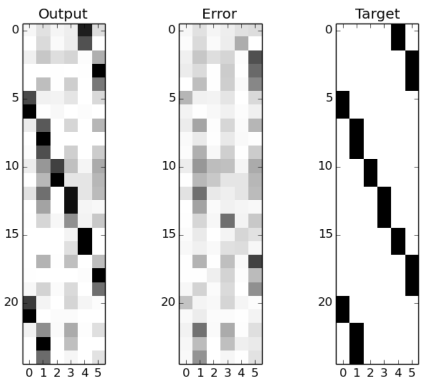
training

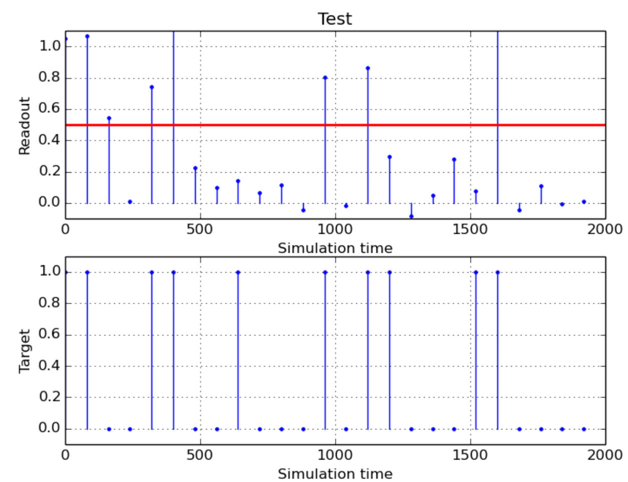




training

test





test

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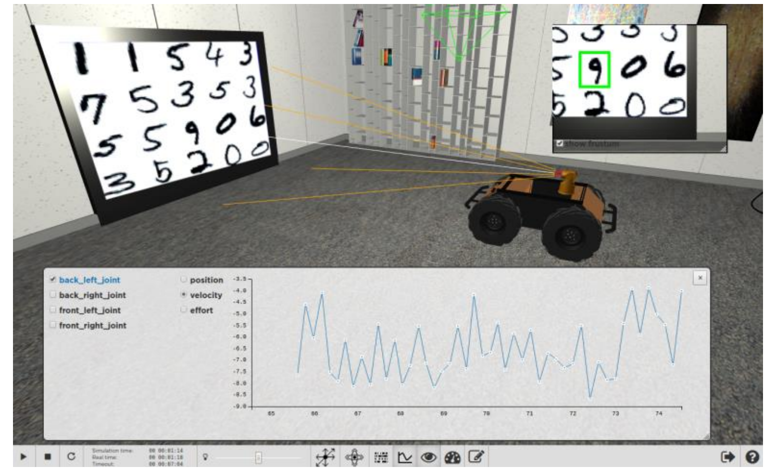
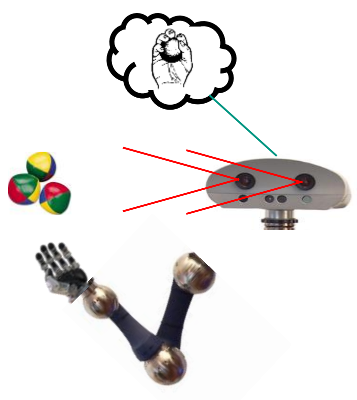
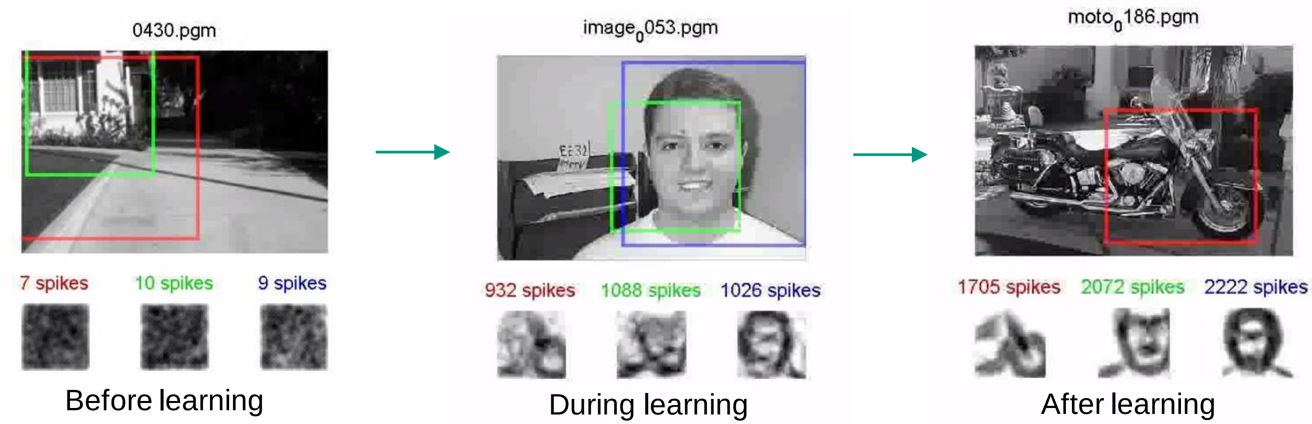
Visual Cognition: Ventral pathway

- “What is the object?”
  - Object recognition
  - Prediction of affordances
- Input data:
  - Camera image stream (RGB)
  - Address events (DVS)
- Output: Grasp type, Object name, Object location, …
- Neural candidates:
  - Spiking Convolutional Restricted Boltzmann Machine
  - HMAX



Desired outcome of recognition experiment

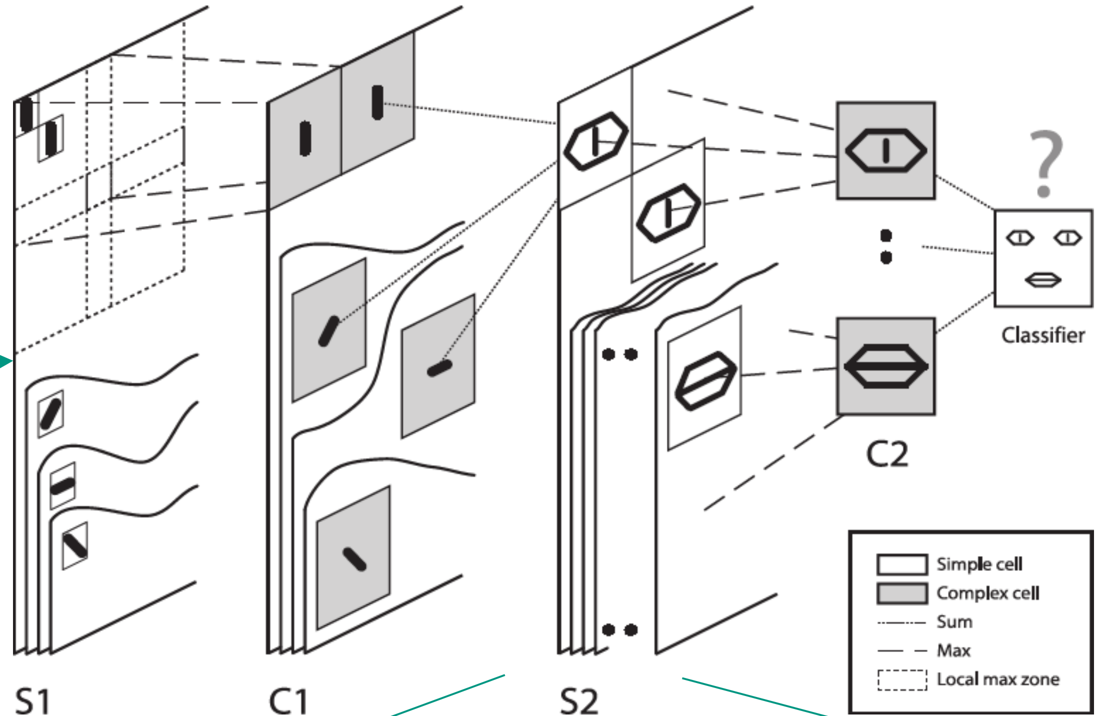


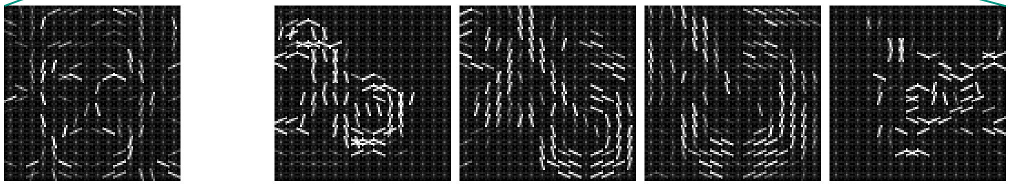


Masquilier T, Thorpe 2007

Learning best visual features in spiking convolutional networks

Image (pixels)

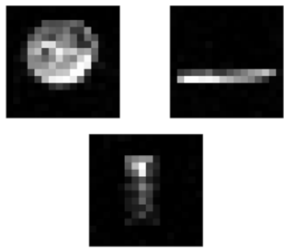




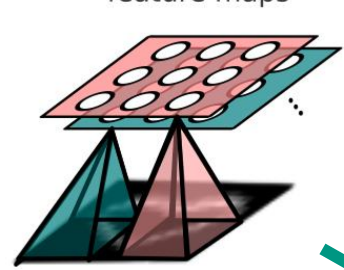
Architecture from Masquilier T, Thorpe 2007

Learning object affordances

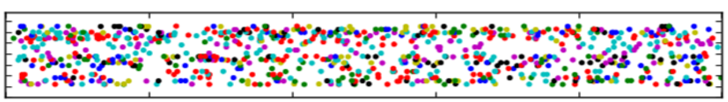
DVS events

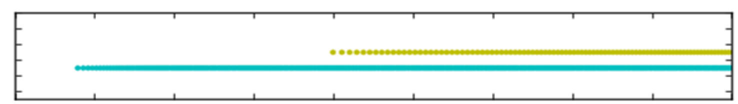


Convolutional Spiking Restricted Boltzmann



Grasp type





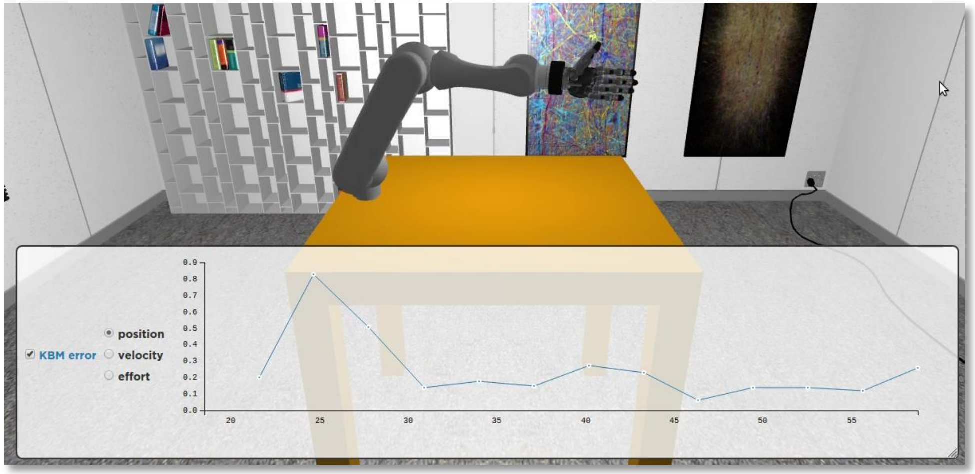
Self-recorded dataset of balls, cans and pens

„Spiking convolutional deep belief networks" , Jacques Kaiser, David Zimmerer , J. Camilo Vasquez Tieck, Stefan Ulbrich, Arne Roennau, Rudiger Dillmann, ICANN 2017

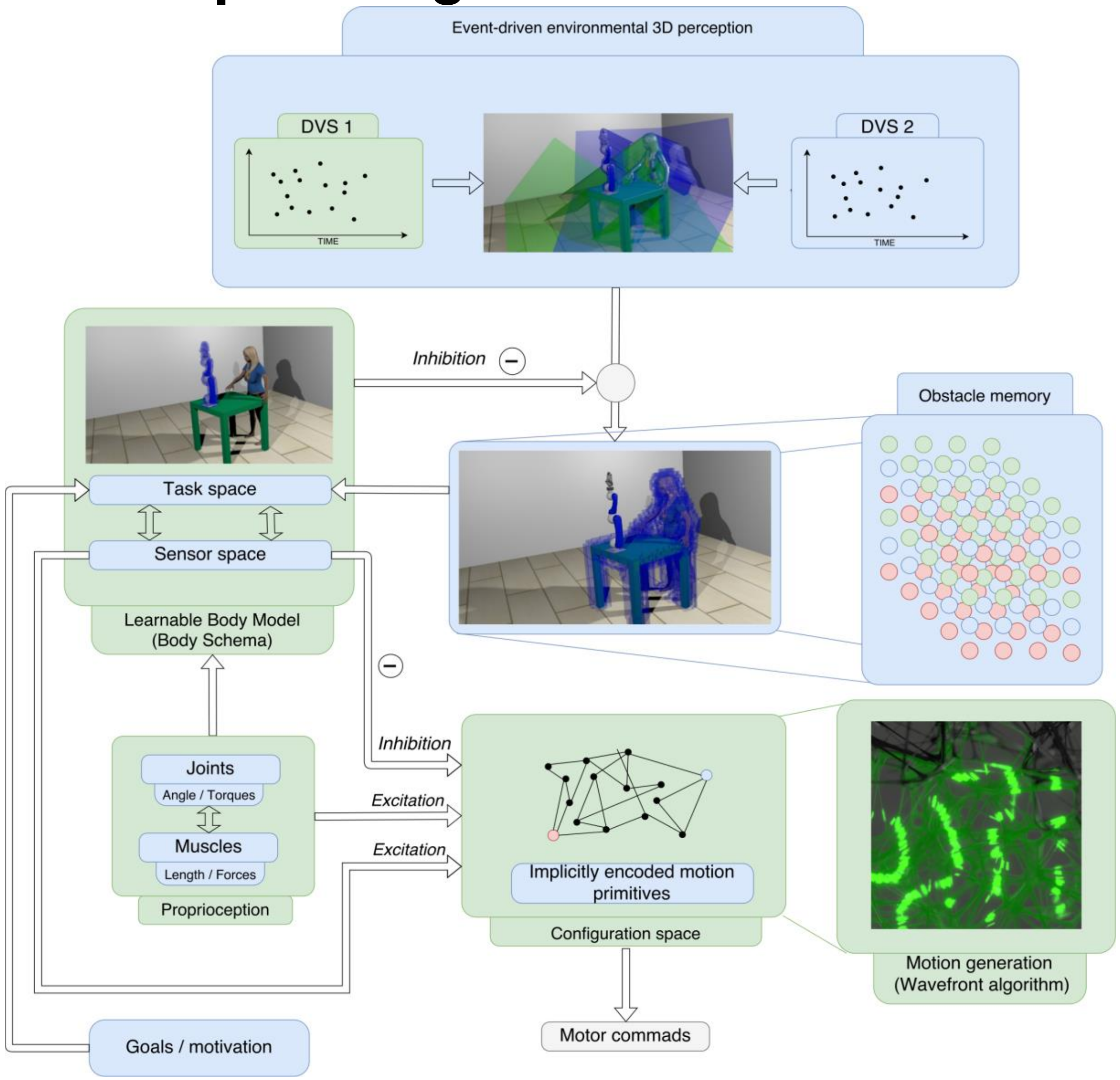
Manipulation and grasping: arm motion

- “How to reach the object?”
- Input data:
  - Target position
  - Arm proprioception (joint configuration)
  - TCP position (error/reward measurement)
- Output:
  - Motor commands

- Classical approaches
  - Programming by demonstration
  - Imitation learning
- Neural Candidates
  - Reinforcement learning
  - Model-based learning of kinematic/dynamic model



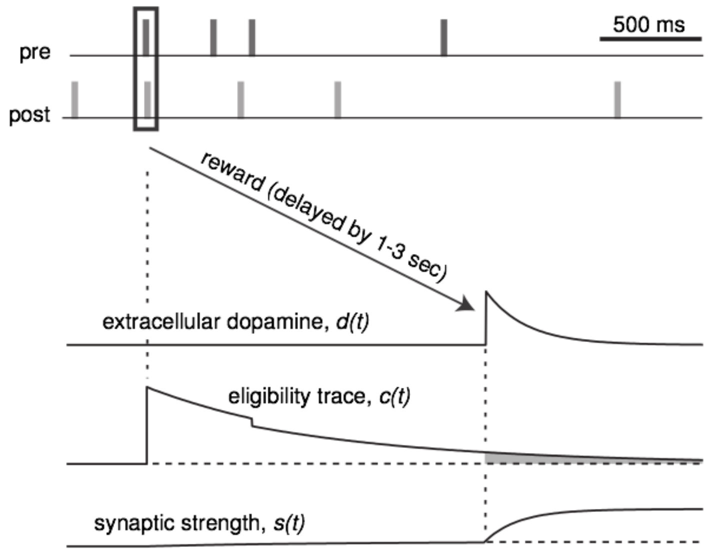
Motion planning

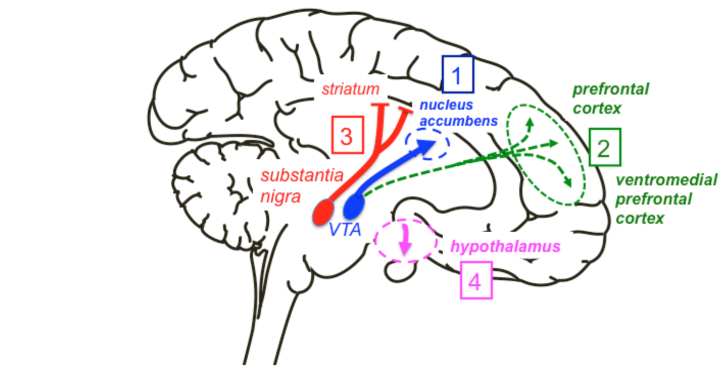


- 3D dynamic vision
  - From stereoscopic DVS
- Active occupancy memory (grid)
  - Sensing robot
  - Sensing obstacles
  - Wavefront planning and control in configuration space
    - Occupancy memory works together with learnt body schema to prohibit planning wave traveling through configurations resulting in collision

Reward-based synaptic plasticity for controlling robotic arm

- Classical STDP (spike-timing dependant plasticity) has no concept of reward
- Biological implementation of reinforcement learning
  - Gives possibility to enter feedback in a spiking neural network
- Reward is not immediately available
  - Spiking eligibility trace solves this problem

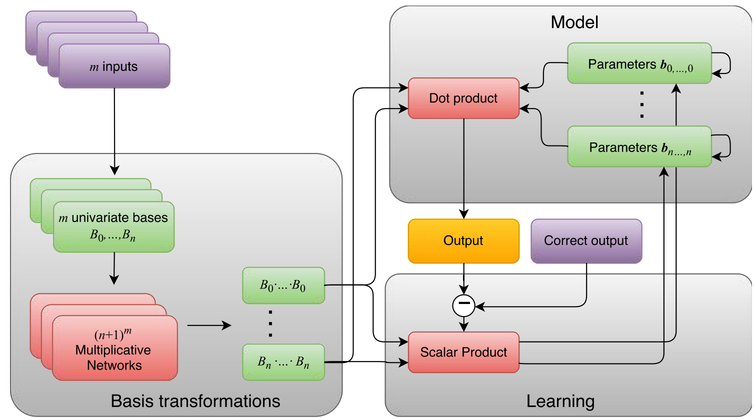


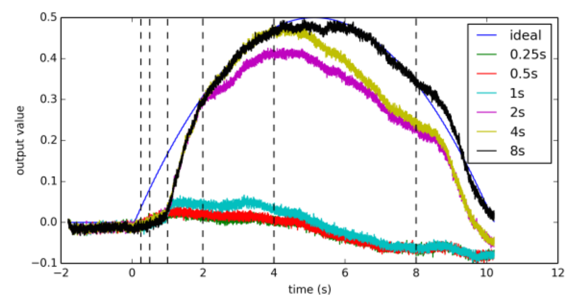


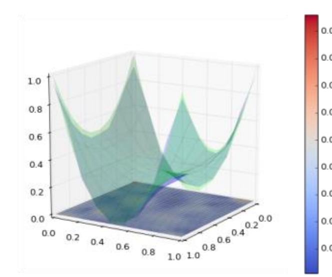
Izhikevich et. al. "Solving the distal reward problem through linkage of STDP and dopamine signaling"

Model-based Polynomial Function Approximation

- Neural architecture for learning polynomial functions
- Use cases
  - Prediction of parabola flight
  - Learning of lens distortion
- Future work
  - Implementation of a body image (mental spatial representation of the own body)
  - Translation from Nengo to NEST/PyNN



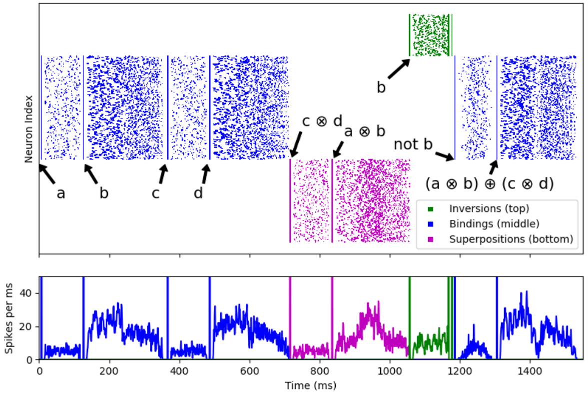


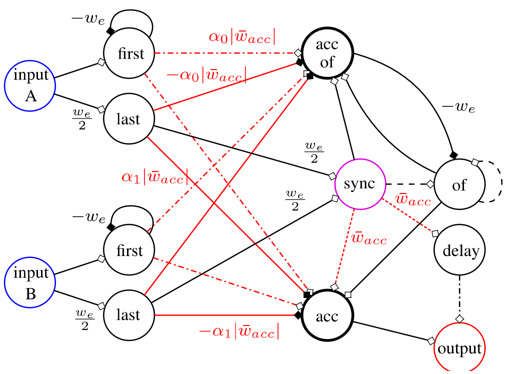


S.Ulbrich et al. “Model-based Polynomial Function Approximation with Spiking Neural Networks”, IEEE Intnl. Conf. Cognitive Informatics & Cognitive Computing, 2017

Convolutional Associative Memories

- Neural memory circuit based on convolutional associative memories
- Functional, constructed network
- Based on
  - mathematical operations
  - implemented with exact spike timing
  - “Spike Timing Interval Computational Kernel” (STICK)
- Implemented in NEST/PyNN

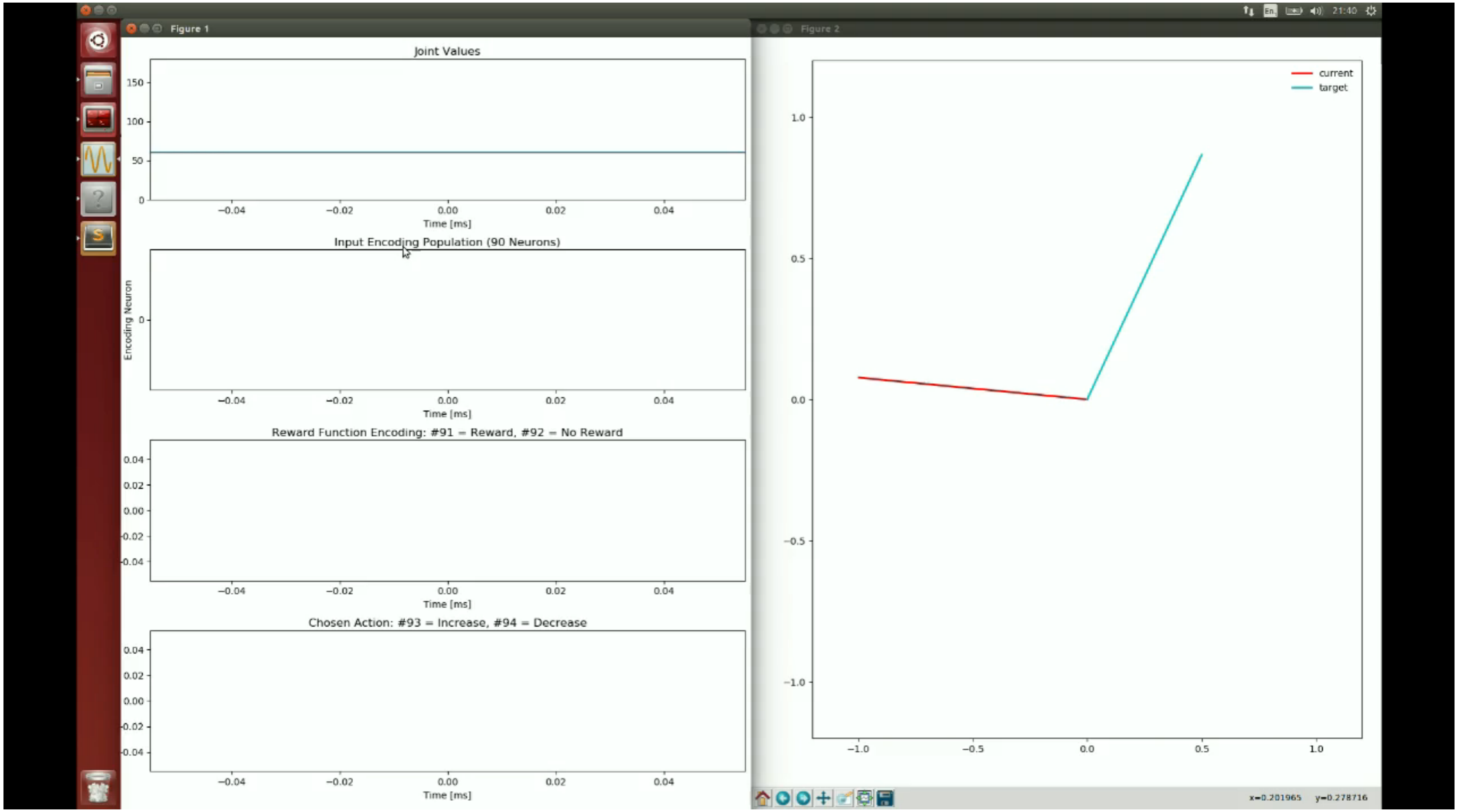




I. Peric et al. “Exact Spike Timing Computational Model of Convolutional Associative Memories”, IEEE Intnl. Conf. Cognitive Informatics & Cognitive Computing, 2017

Example – learning 1 DoF neural controller

- A population of neurons learning to approach a single target



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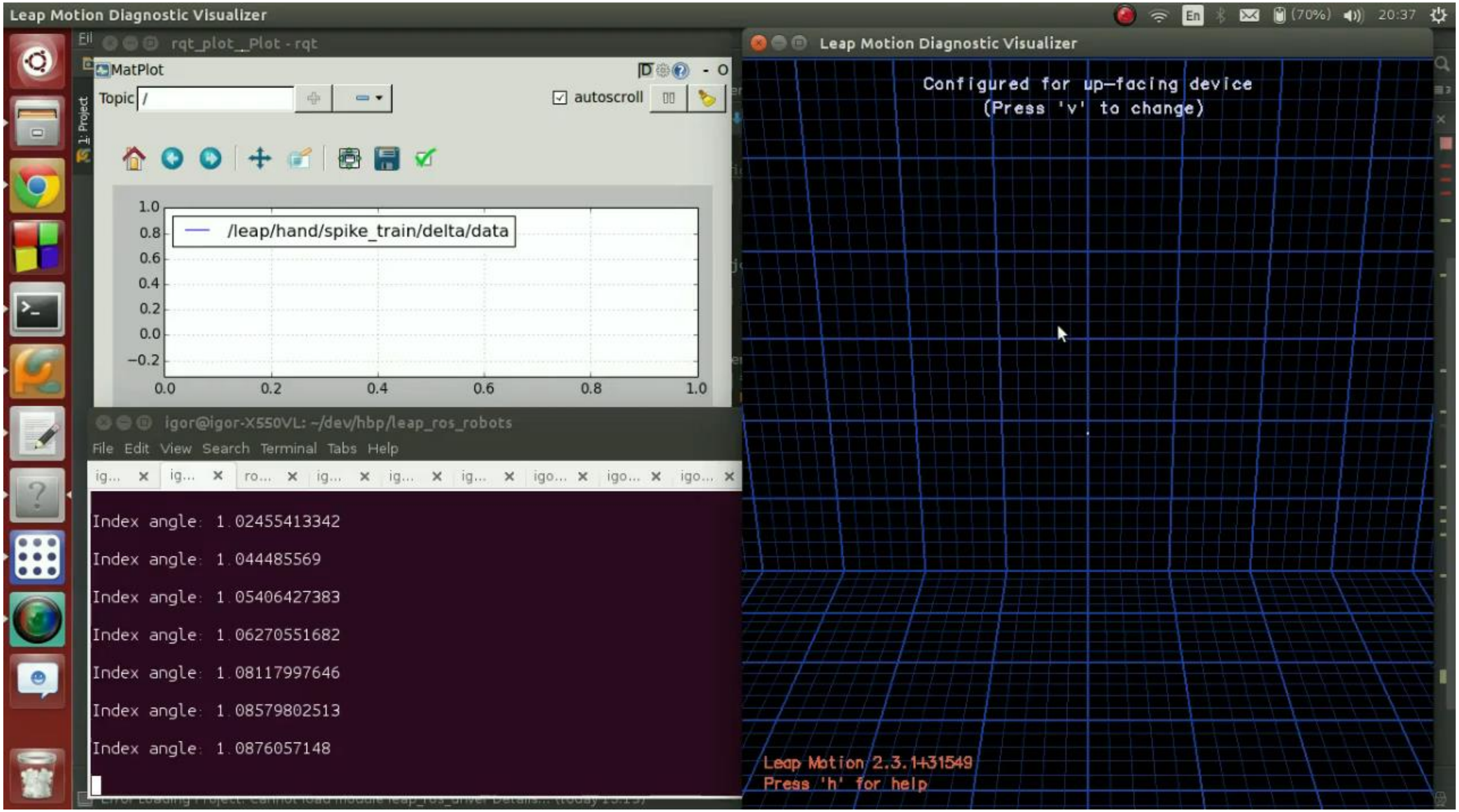
Spiking motion encoding from interactive hand tracker



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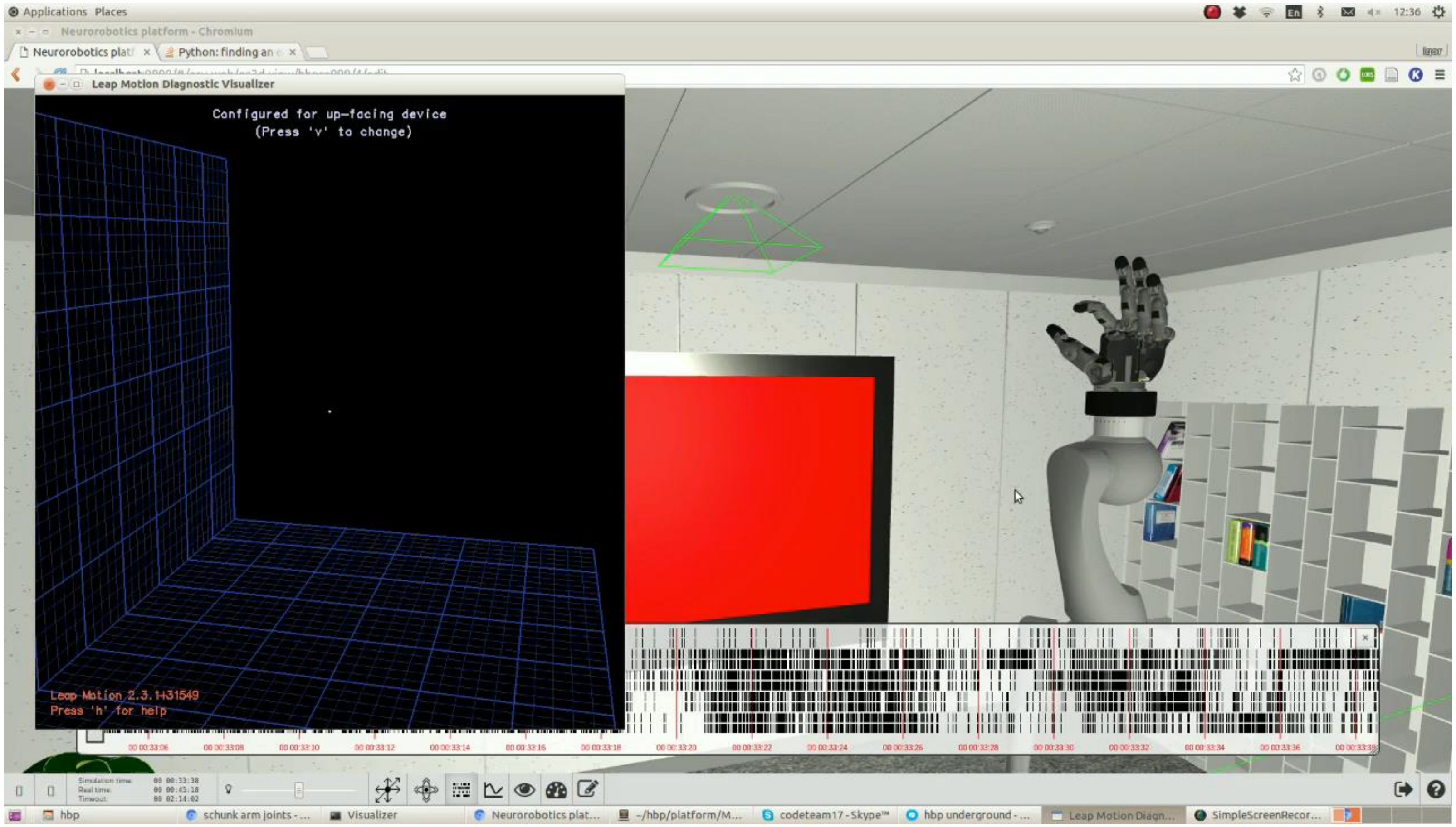
PbD for interactive manipulation training for neuro-robot control



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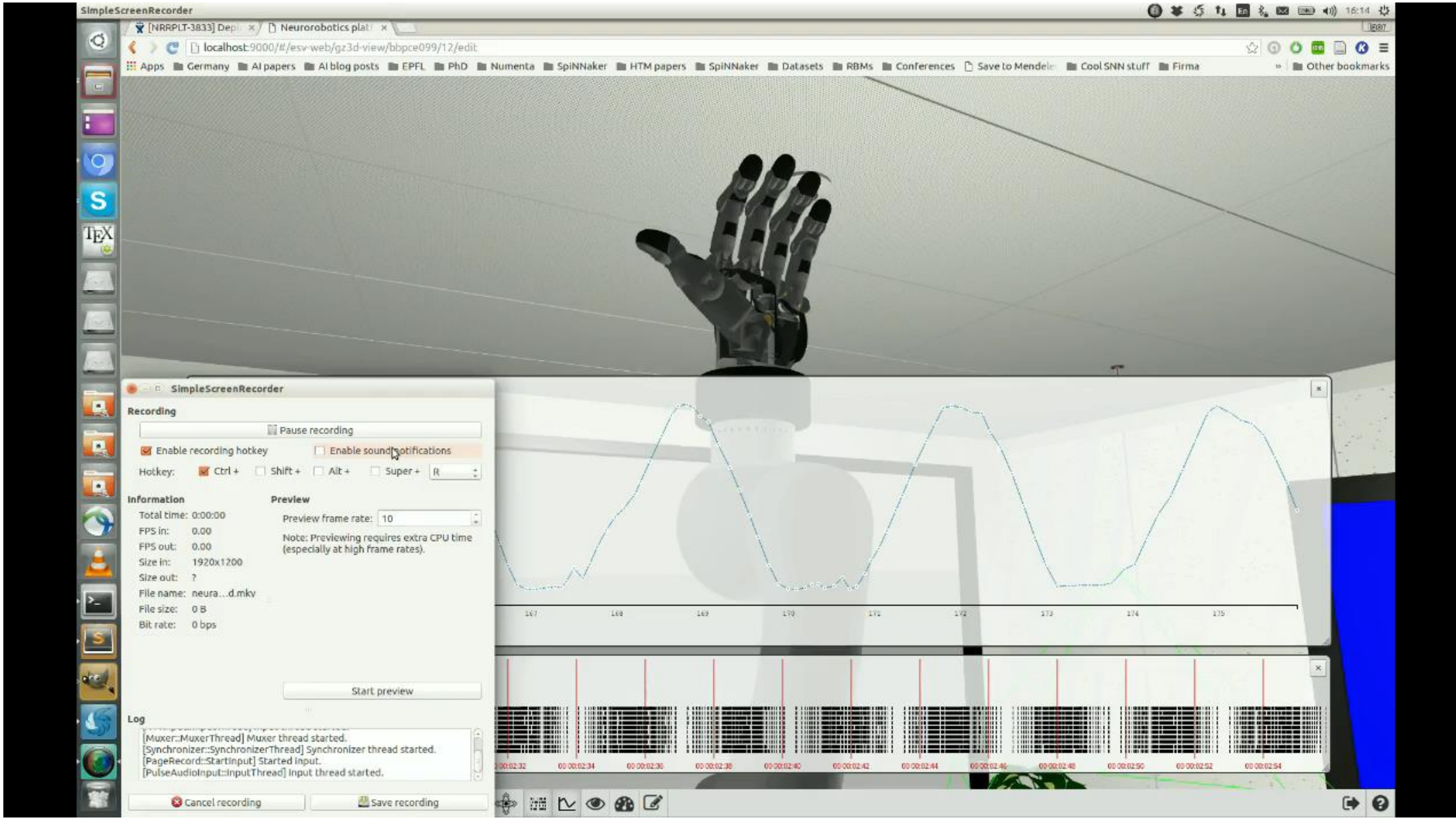
Central pattern generator for hand motion

Karlsruher Institut für Technologie



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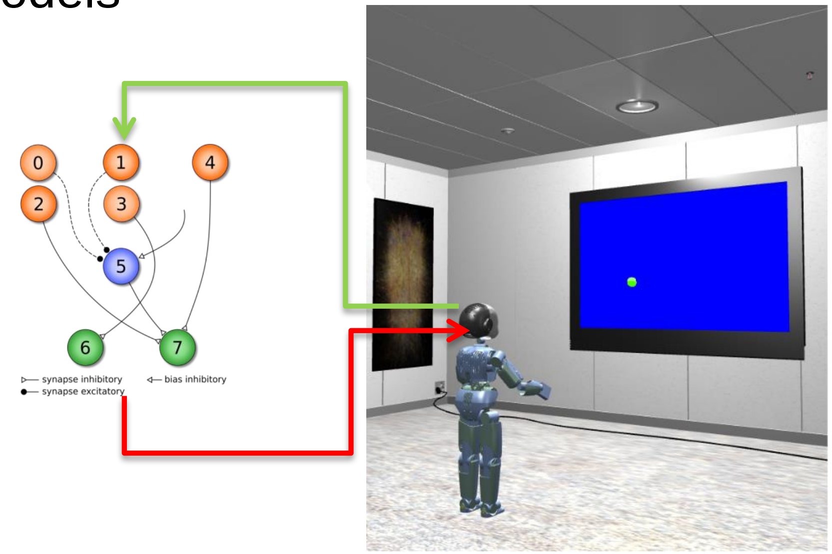
Visual Tracking Experiment

- The goal of the visual tracking experiment is twofold:
  - from a scientific point of view, to embed a retina model in a visual tracking controller
  - from a technical point of view, to assess the capabilities of the platform in dealing with complex transfer functions and integrating neuroscientific models



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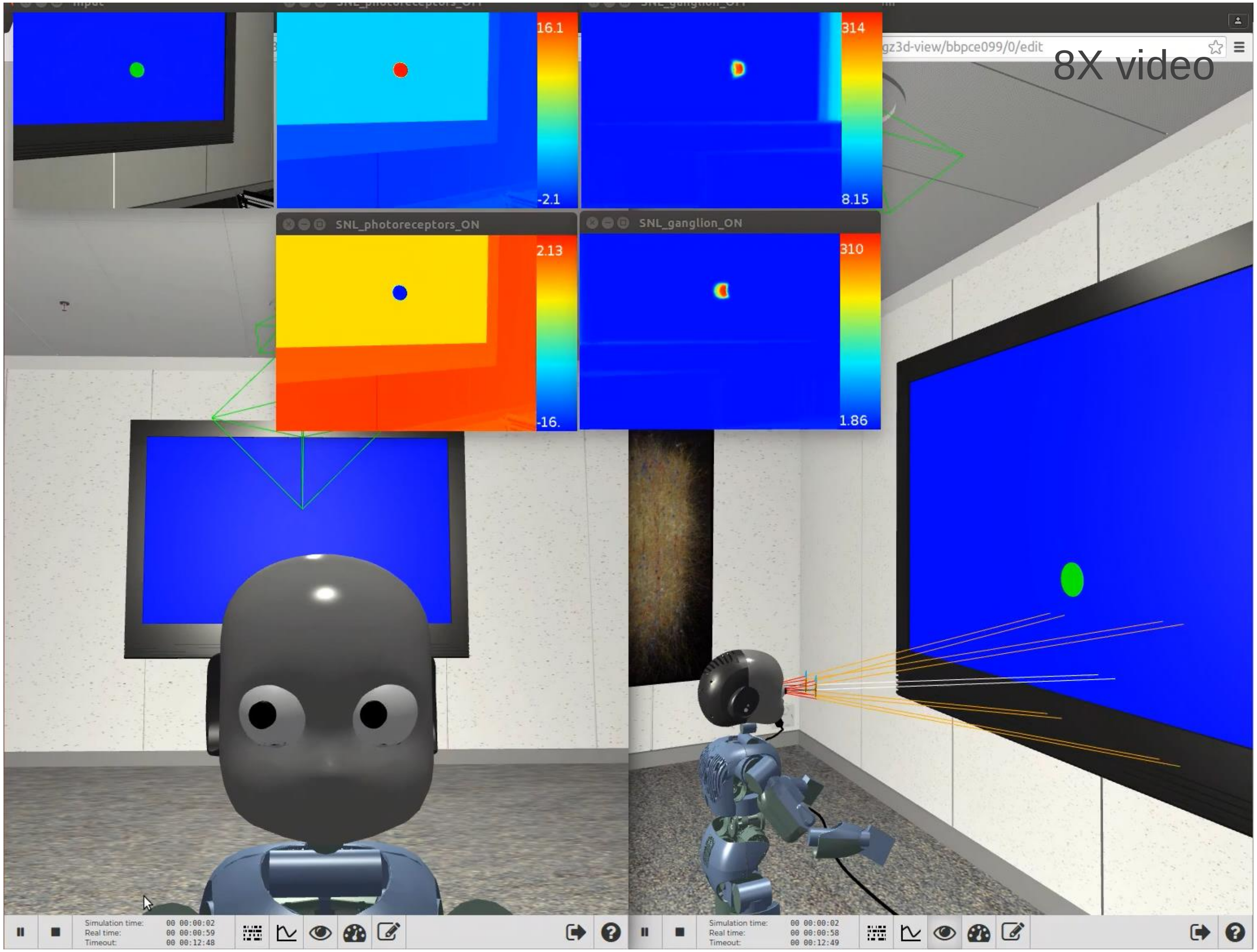
Retina Model integrated in a visual tracking controlle



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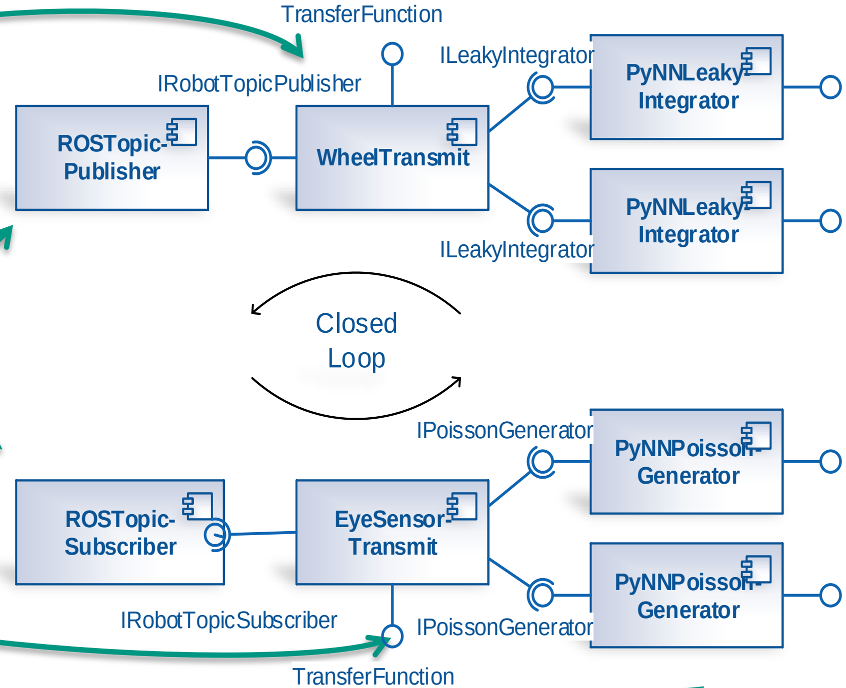
Future development of the NRP

- Experimenting with many different robot embodiments
  - Humanoid robots
  - Biomimetic models
    - Animals
    - Human
    - Muscle and deformable tissue simulation
  - Novel sensors (e.g., addressing event sensors)
- Catalogue of
  - Predefined experiments
  - Experimental environments
  - And objects
- Application to real robots
  - Connections to real robots and sensors
  - Standard installation

Simulation Tool: Closed Loop Engine data flow

- Actuators
  1. Spikes input is read from Nest over Python interface
  2. Transfer Function prepares (converts) them for **robotic body control**
  3. ROS Topic Publisher delivers them to **controllers**

- Senses
  1. ROS sends Image input
  2. Transfer function encodes (converts) it into **sensory spike rates**
  3. Spikes output is sent to Nest over Python interface



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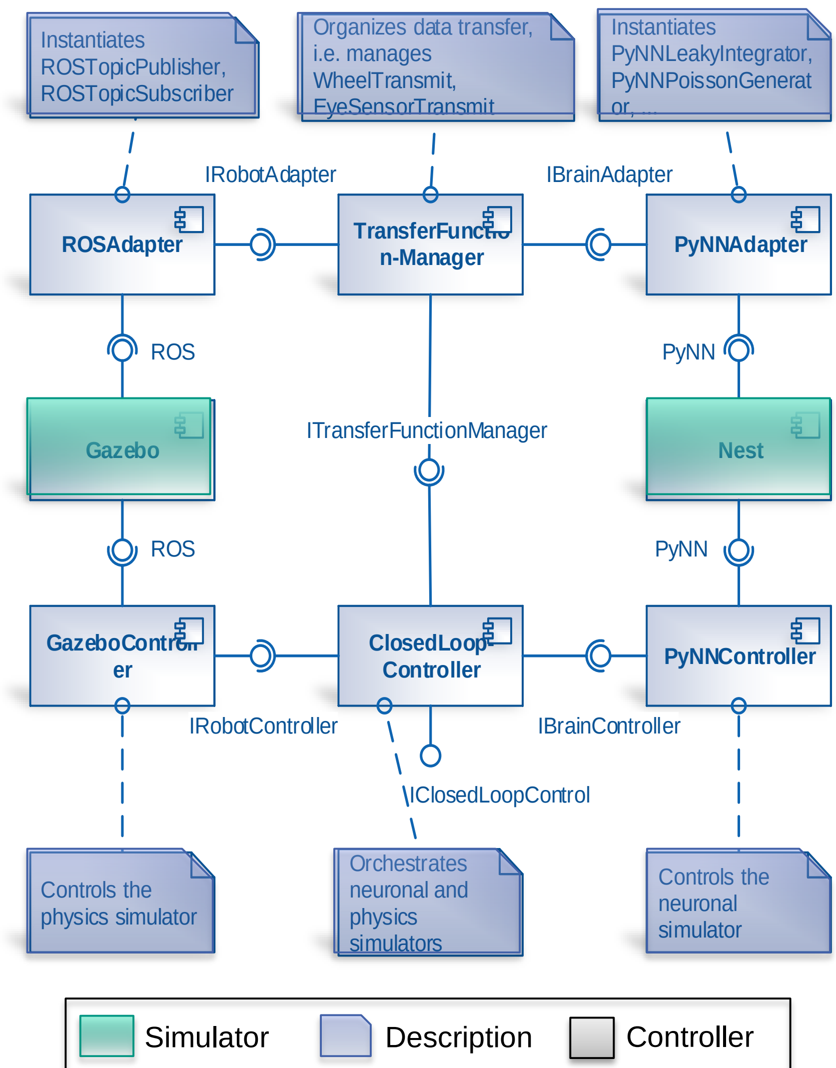
Simulation Tool: Closed Loop Engine components



- Core of CLE is **Closed Loop Controller**, orchestrating:
  - Neural network simulation (PyNNController)
  - Physics simulation (GazeboController)
  - Two-way data transfer (TransferFunctionManager)
- **PyNN ad ROS adapters** augment functionalities of base classes and wrap management capabilities for controller (higher-level) classes

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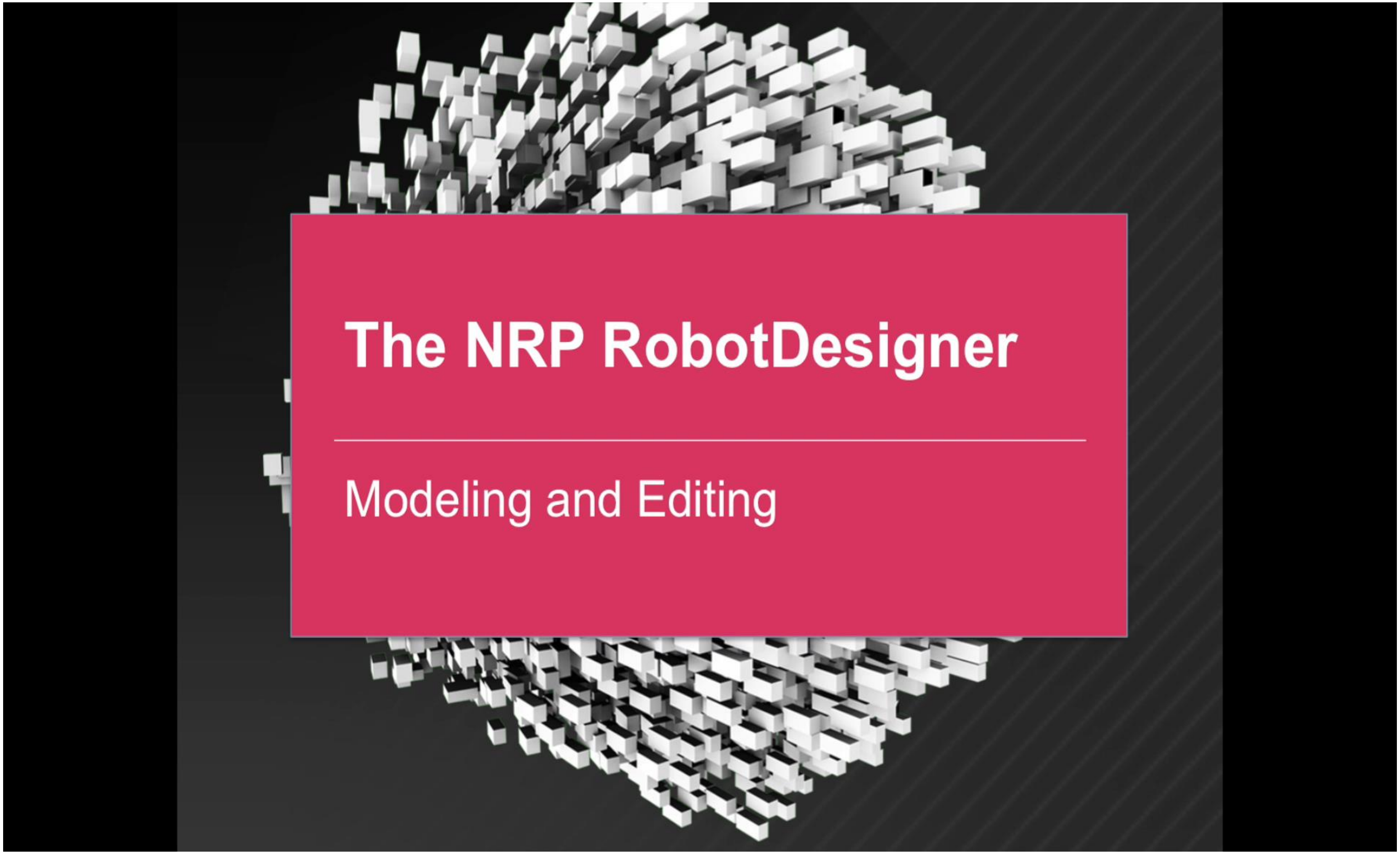
The Robot designer



Klausur: 14. September 2017

Die Hörsääle werden noch bekannt gegeben