Movement Learning and Control for Robots in Interaction

Dr.-Ing. Michael Gienger
Honda Research Institute Europe
Carl-Legien-Strasse 30
63073 Offenbach am Main

innovation through science

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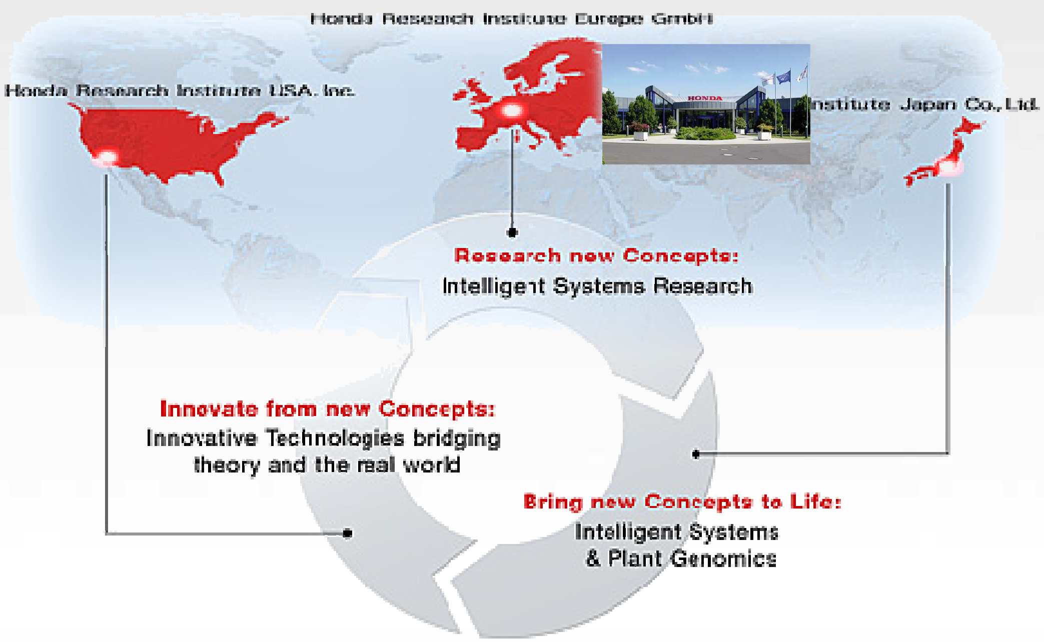
The Honda Research Institutes



The Honda Research Institutes

- 3 institutes world-wide
- collaborating with scientific community
- broad research span: material science, genomics, intelligent systems, neuroscience …
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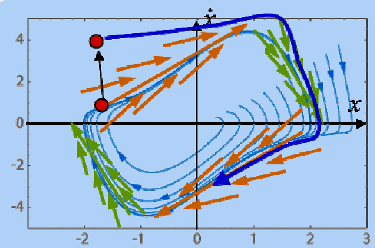
Honda Research Institute Europe: Core Themes regarding Movement Generation

Skill Learning

- Learning by observation
- Physical teaching
- Explorative learning
- Open-ended skill acquisition

Movement Coordination

- Transient between MPs for sequential / parallel behavior
- Hierarchical organization
- Preparatory movements

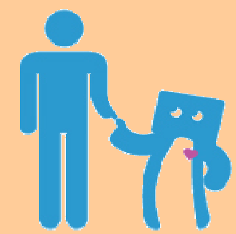


Movement Representation

- Movement primitives (MP)
- Dynamical systems
- Reference frames
- Generalization

Dynamical Environments

- Error recovery
- Decision making
- Short- and long-term prediction



Human-Robot Interaction

- Physical, safe interaction
- Situation binding / context
- Cooperative tasks
- Intention recognition

1. Whole-body movement control

- Redundant control
- Task descriptors

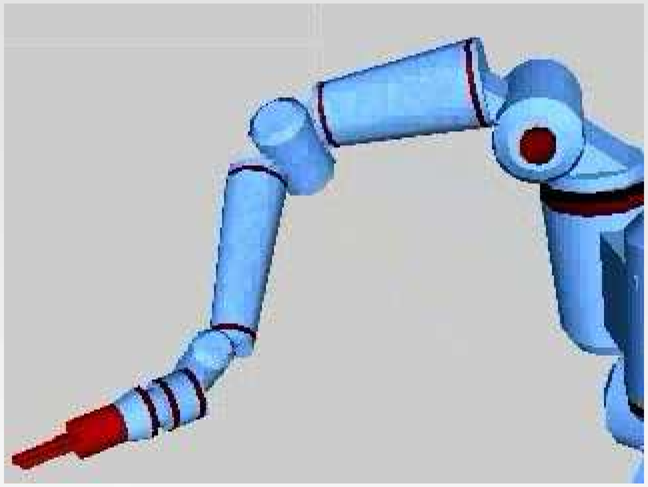
2. Movement primitives

3. Optimal movements

4. Learning from demonstration

Redundant Control concepts

Redundant control: more degrees of freedom than controlled variables



Redundant velocity / acceleration control
(Liegeois, Nakamura, Maciejewski, Siciliano...)

- Computation of joint displacements according to task- and nullspace motion
- Framework for position controlled robots

Redundant torque control (Khatib, Brock, ...)

- Approach using dynamic equations of motion
- Computation of joint torques
- Framework for torque controlled robots

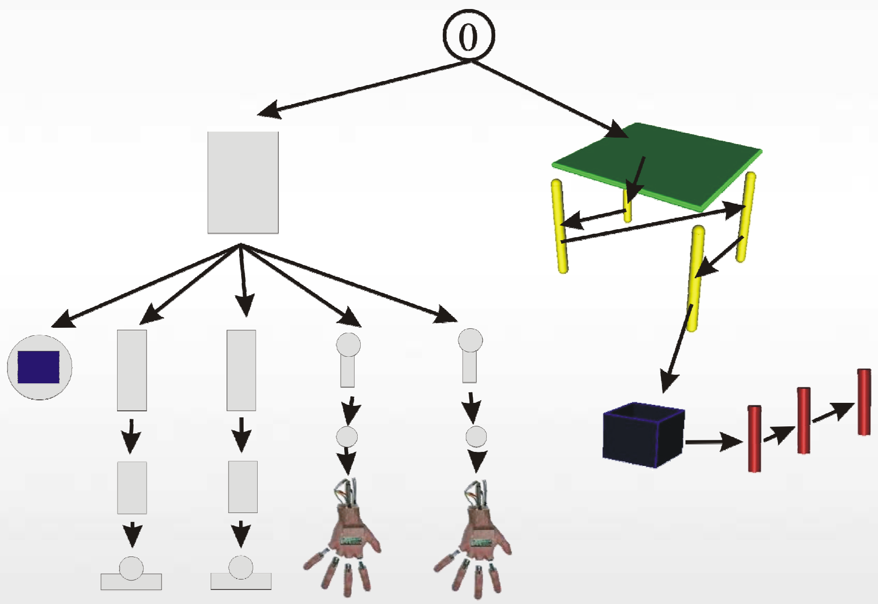
Searching (planning) methods (Latombe, Kuffner, Khavraki ...)

- Computationally expensive (usually not real-time capable)
- Optimal solution can be found
- A-star, dynamic programming, ...

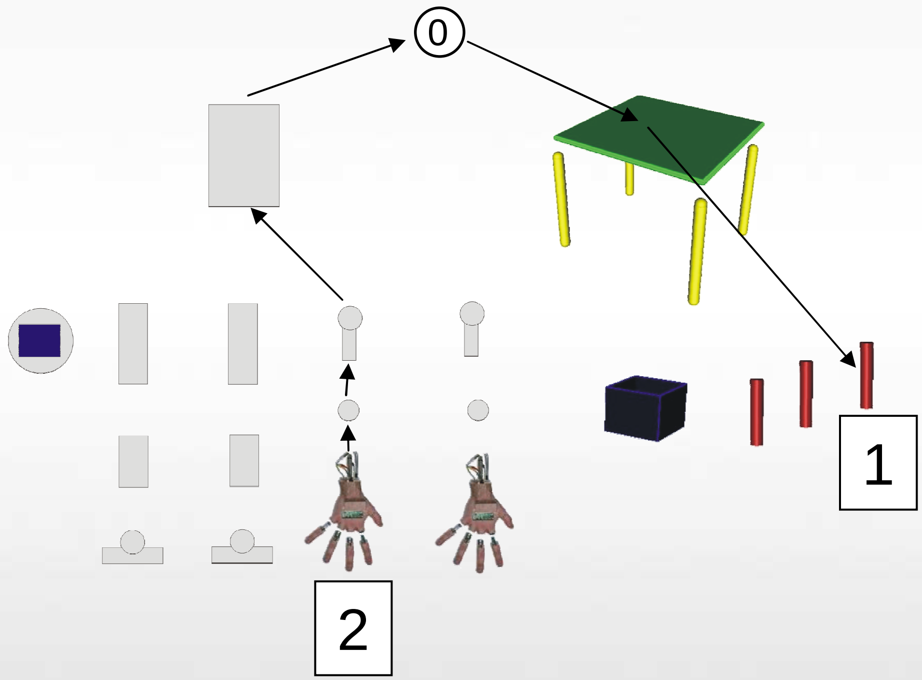
Kinematic rigid body model

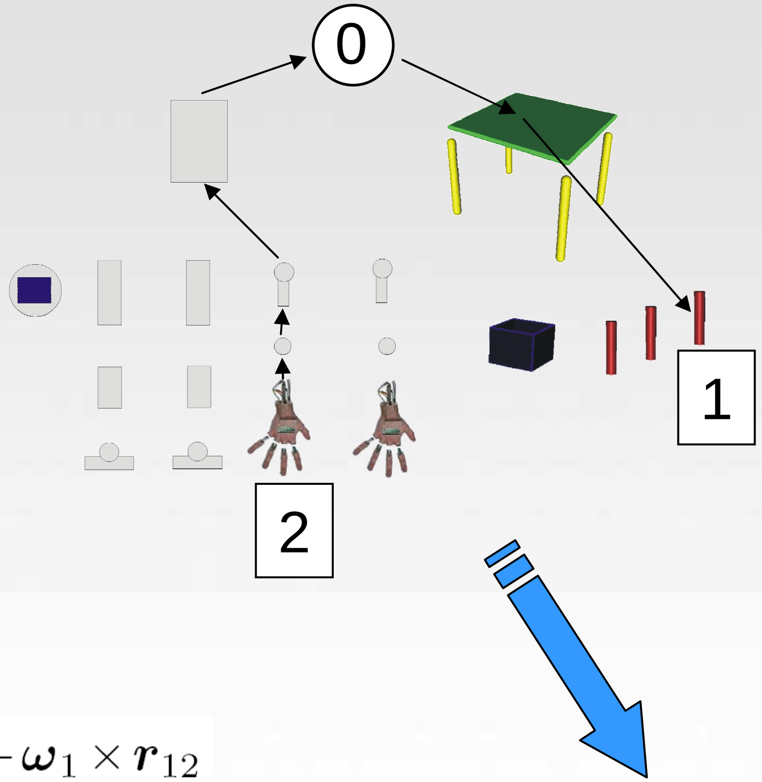
- Rigid-body model of robot & environment represented as kinematic tree
- Parent-child hierarchy: parent influences movement of children
- Basis for all kinematic computation

Forward kinematics



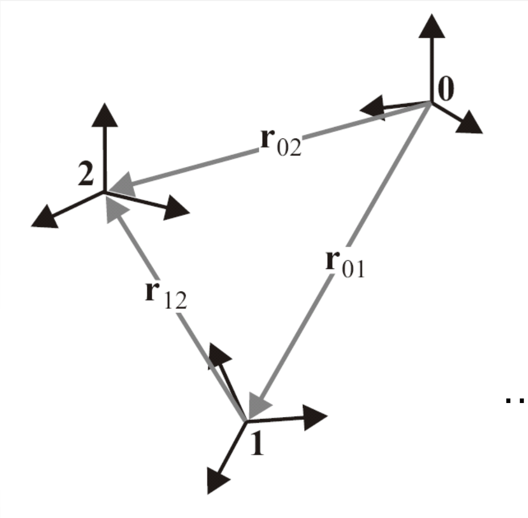
Inverse kinematics





Kinematic task descriptors

- movement of a body with respect to another body
- is defined through the shortest paths to the root node
- for instance: hand-world, hand-heel, object, hand-hand, camera-object …



Relative position $\boldsymbol{r}_{12} = \boldsymbol{r}_{02} - \boldsymbol{r}_{01}$

Relative velocity $\dot{\boldsymbol{r}}_{12} = \dot{\boldsymbol{r}}_{02} - \dot{\boldsymbol{r}}_{01} + \boldsymbol{\omega}_1 \times \boldsymbol{r}_{12}$

… in joint coordinates $= \boldsymbol{A}_{10} \left({}_0\boldsymbol{J}_{T,2} - {}_0\boldsymbol{J}_{T,1} + {}_0\tilde{\boldsymbol{r}}_{12}^T \; {}_0\boldsymbol{J}_{R,1} \right) \dot{\boldsymbol{q}} = {}_1\boldsymbol{J}_{T,rel} \; \dot{\boldsymbol{q}}$

→ We can compute the movement of any object with respect to any other object
→ We can express the movement in terms of the joint angles, velocities (also acceleration / torque)

- Dynamic properties like linear and angular momentum can be formulated using kinematics
- Linear projections into joint space can be computed by summing up over robot links

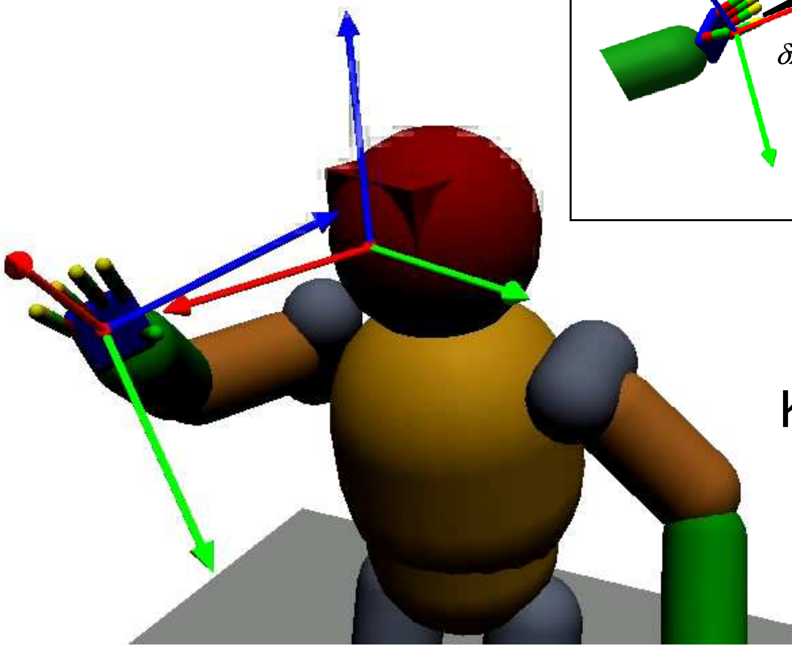
Linear momentum

$$r_{cog} = \frac{1}{m} \sum_{i=1}^{bodies} m_i r_{cog,i} \qquad \dot{r}_{cog} = \frac{1}{m} \left\{ \sum_{i=1}^{bodies} m_i J_{T,cog,i} \right\} \dot{q} = J_{cog}\, \dot{q}$$

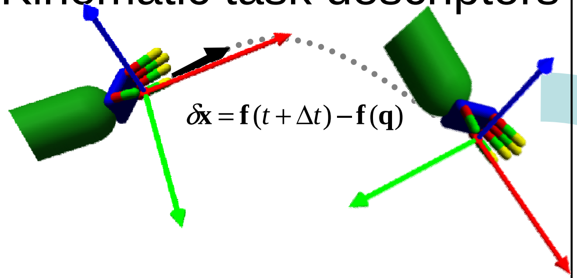
Angular momentum

$$L = \sum_{i=1}^{bodies} m_i r_{cog,i} \times \dot{r}_{cog,i} + I\omega = \left\{ \sum_{i=1}^{bodies} m_i\, \tilde{r}_{cog,i} J_{T,cog,i} + I_i J_{R,i} \right\} \dot{q} = J_{am}\, \dot{q}$$

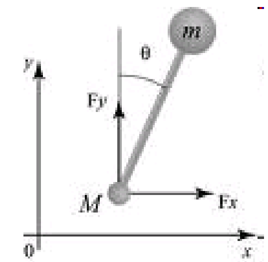
Whole-body control



Kinematic task descriptors



Dynamic task descriptors



Inverse Kinematics

$$\dot{\boldsymbol{q}} = \boldsymbol{J}^{\#}\,\dot{\boldsymbol{x}} - \alpha\,\boldsymbol{N}\boldsymbol{W}^{-1}\left(\frac{\partial H}{\partial \boldsymbol{q}}\right)^{T}$$

Cooperative balance control

Linear / angular momentum

Whole-body control

ZMP control

Body shift

Redundant Control approach (Liegeois):

- Velocity control
- End effektor movement described in task space
- Redundant nullspace used to satisfy additional criteria

1. Reactive movement control

2. Movement primitives

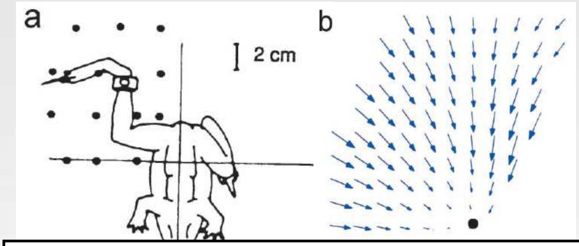
- How to compute the trajectories?

3. Optimal movements

4. Learning from demonstration

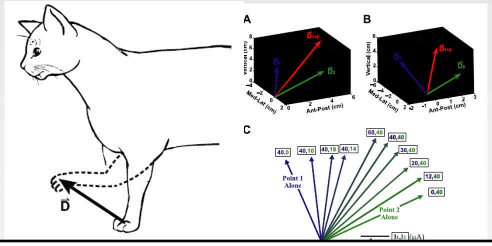
Movement Primitives – biological perspective

- Spinal system of frog encodes “force fields”
- Limb movement is summation of force fields



E. Bizzi, A. d’Avella, P. Saltiel, and M. Tresch:
Modular Organization of Spinal Motor Systems

- Motor cortex encodes behavioral relevant movements (defense, prey-catching)
- Cortical output combines nearly linearly



C. Ethier, L. Brizzi, W. G. Darling, and C. Capaday
Linear Summation of Cat Motor Cortex Outputs

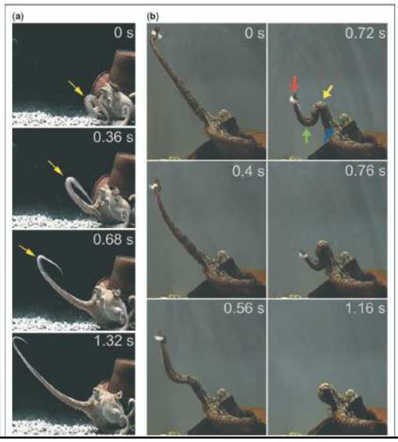
Functional view

Attractor dynamics
Effector movements
Behavioral relevant

⇓

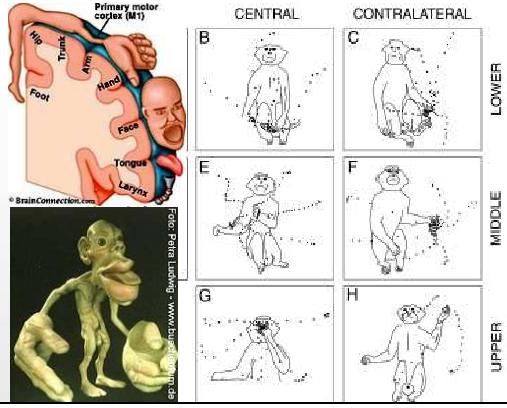
high flexibility
good generalization
low complexity

- Reduce the complexity of movement generation



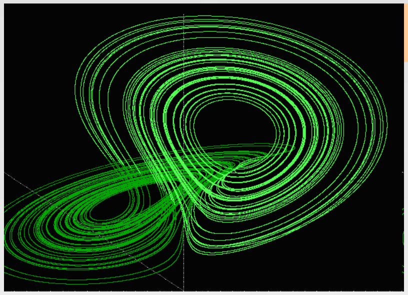
T. Flash and B. Hochner:
Motor primitives in vertebrates and invertebrates

- Often encode effector movements



M. Graziano:
The organization of behavioral repertoire in motor cortex

Movement Primitives – State of the art



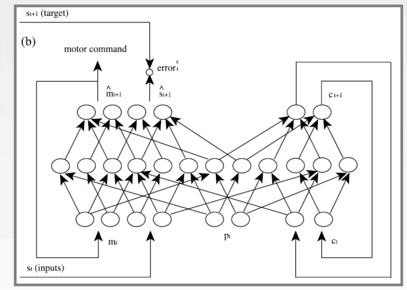
Dynamical systems approaches

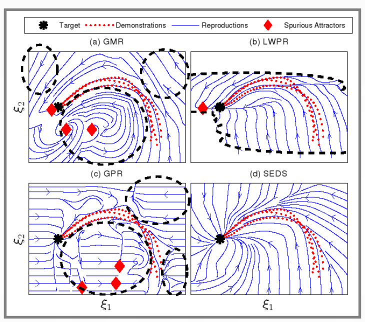
(e.g. DMP: Schaal, Peters ...*)*

- autonomous differential equations
- attractor / periodic movements
- Local sensor feedback

Neural approaches (e.g. RNNPB Tani)

- layered recurrent neural network (RNN) representation
- primitives may be represented as attractors implicitly inside a RNN.



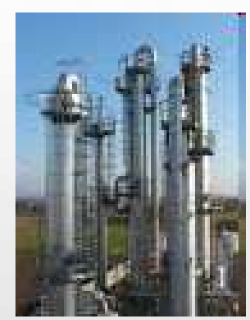


Probabilistic approaches (e.g. Billard)

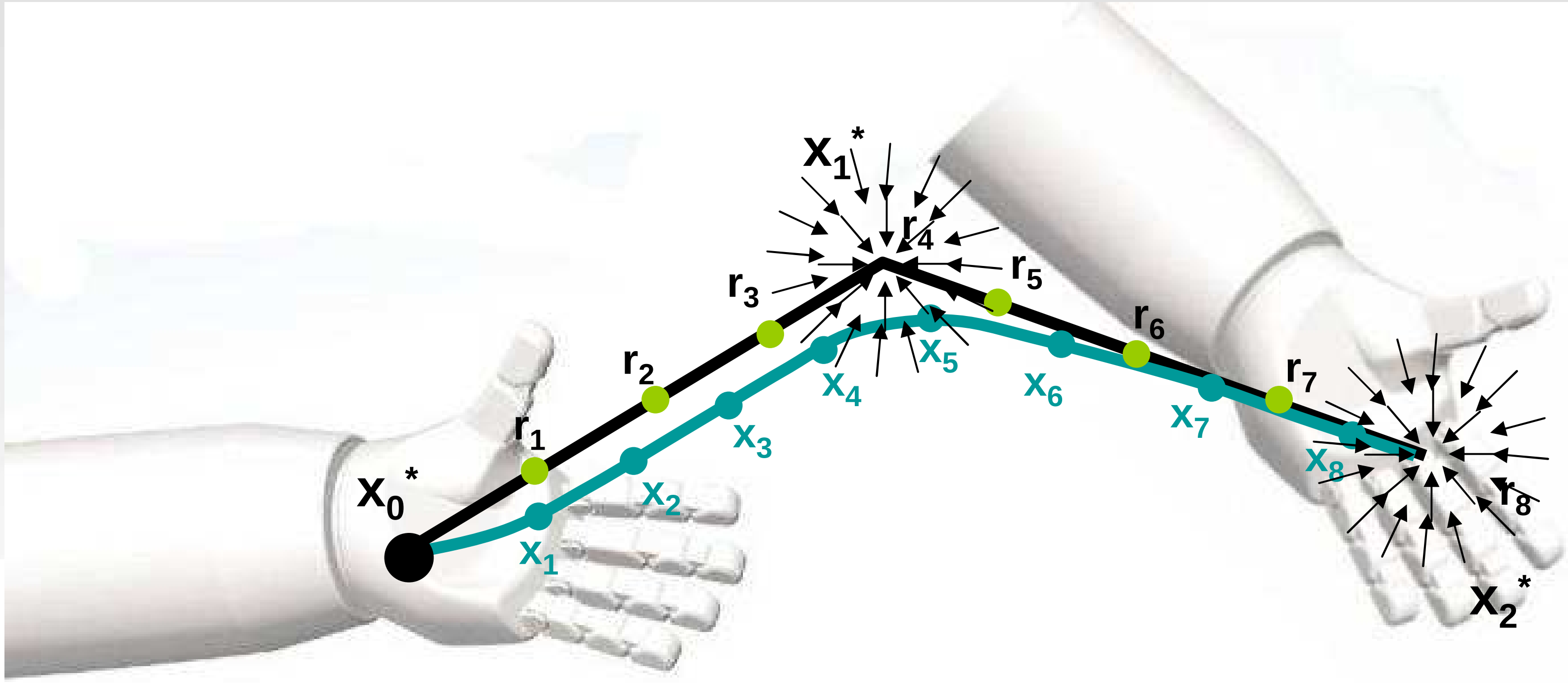
- GMM / HMM representations
- movement generated by regression

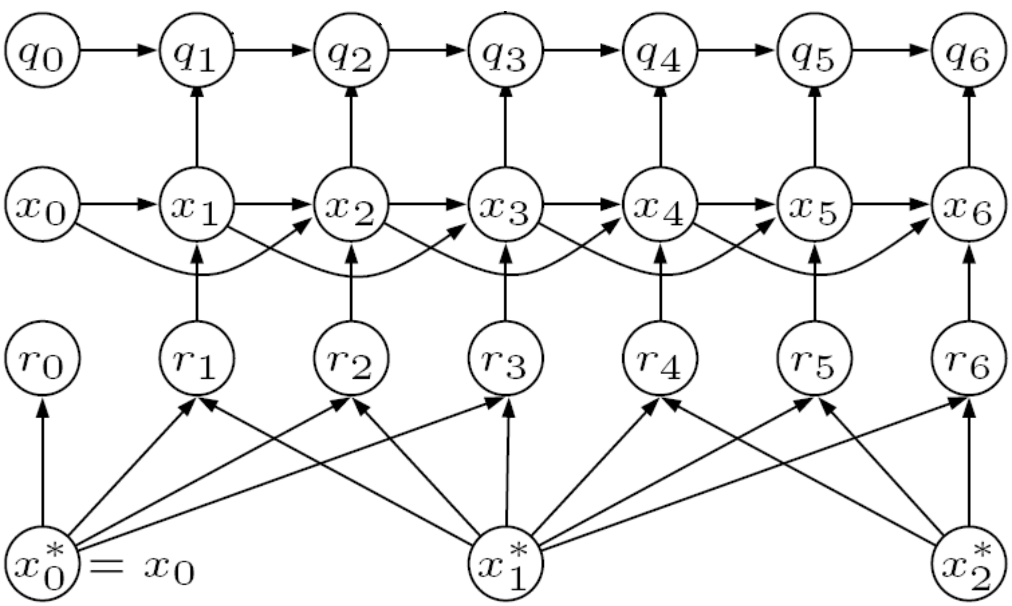
Optimal control approaches (Bellmann, Jacobson, Todorov, Popovic ...)

- future prediction & anticipation
- local approaches are feasible for real-time
- computer graphics, now starting in robotics



Task-level attractor system

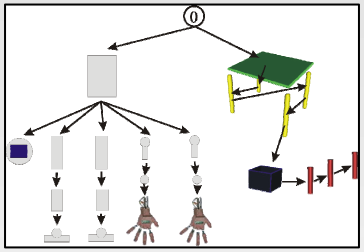


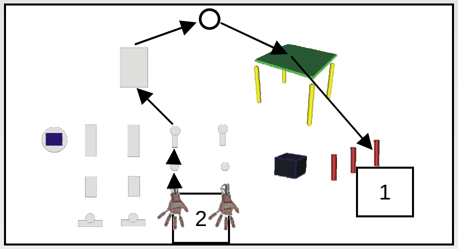


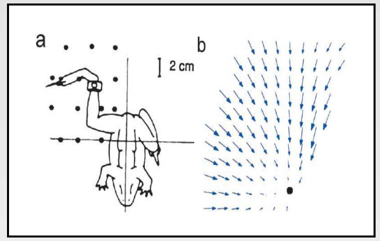
Task space → ***Whole body control***

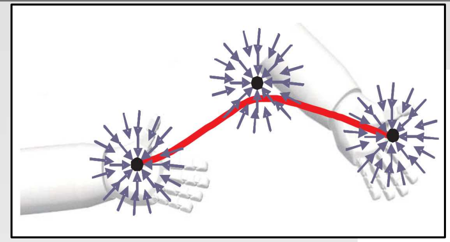
Attractors → ***Attractor dynamics***

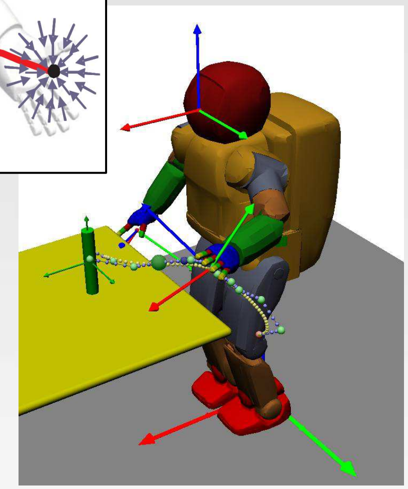
Movement primitives – our approach











Generalization

Joint space representation	Task space representation	Attractor representation
Robot embodiment, full description of movement capabilities	**Low-dimensional task space description**	**Movement primitives: time-sparse, low-dimensional task space description**

Whole body control → **Abstraction of embodiment**

Attractor dynamics → **Loss of „arbitrary“ movement capabilities**

Movement primitives

- Attractor points similar to motor behaviour created by Movement Primitives
- Attractors are formulated in task-coordinates (hand positions, gaze direction, grasp angle …)
- Attractors may be composed of different sets of variables
- Whole body motion is used to track trajectories

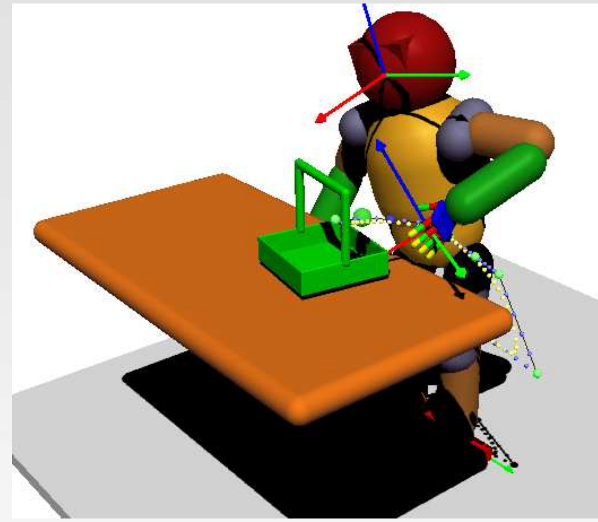
1. Reactive movement control

2. Movement primitives

3. Optimal movements

- Attractor-based movement optimization: Anticipate a future time horizon

4. Learning from demonstration



Formulation of trajectories as sequence of attractors

Cost function

$$C = \sum_{t=0}^{T-1} \left\{ \sum g_i(\mathbf{q_t}) + \sum h_i(\mathbf{q_t}, \mathbf{q_{t+1}}) \right\}$$

- ***Reaching the target***
- ***Joint limit avoidance***
- ***Collision avoidance***
- ***Postural similarity***

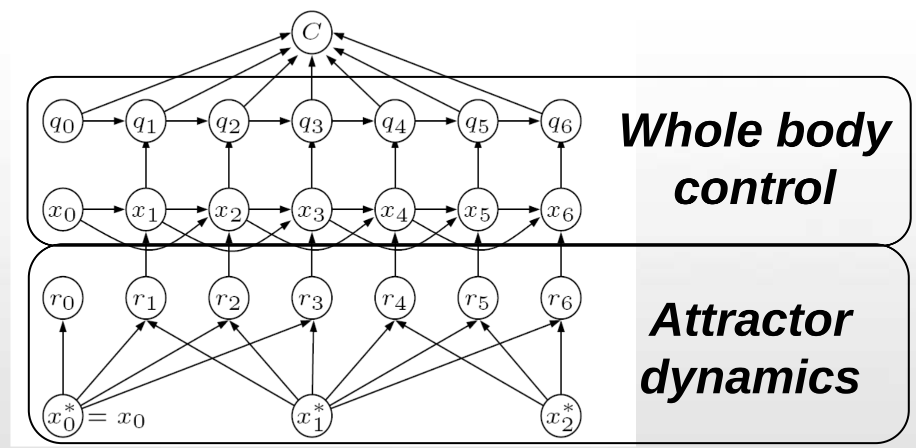
...

- ***Minimal path length***
- ***Speed at a certain point***

...

Gradient-based optimization

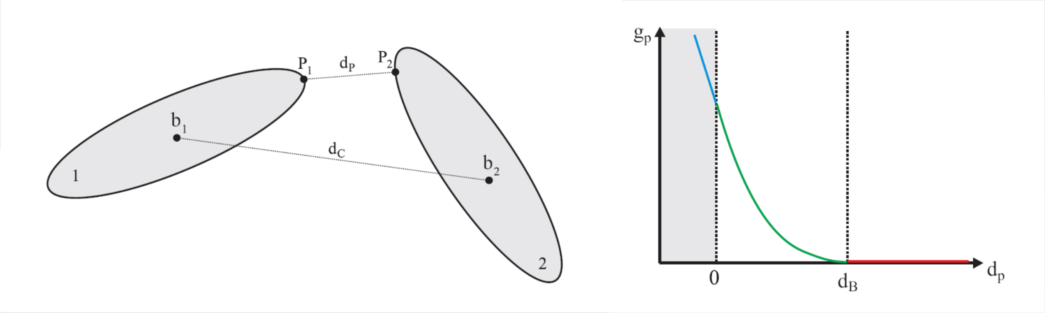
$$\frac{dC}{d\mathbf{x}^*} = \sum_{\text{children } \mathbf{y_i} \text{ of } \mathbf{x}^*} \frac{dC}{d\mathbf{y_i}} \frac{\partial \mathbf{y_i}}{\partial \mathbf{x}^*}$$



M. Toussaint, M. Gienger, Ch. Goerick: ***Optimization of sequential attractor-based movement for compact behaviour generation***, Humanoids 2007

Collision avoidance

$$Q(q) = \sum_{i}^{pairs} g_p(d_{p,i}) + g_c(d_{p,i}, d_{c,i})$$



Target precision

$$|\tilde{\phi}(q_T) - \hat{x}|^2$$

Joint limit avoidance

$$\frac{1}{2}\sum_{i=1}^{\text{dof}} w_i(q_i - q_{0,i})^2$$

Length of the movement in joint space

$$\sum_{t=1}^{T}(q_t - q_{t-1})^T W (q_t - q_{t-1})$$

Similarity to teachers movement

$$c_{im}(t) = (\phi(\mathbf{q}_t) - \hat{\boldsymbol{\mu}}_t)^2 \cdot \mathbf{w}_t$$

Others: Speed, energy efficiency, dynamics …

1. Reactive movement control

2. Movement primitives

3. Optimal movements

4. Lerning from demonstration

Collaboration with CoR-Lab, Uni Bielefeld

- Transfer skills from a human tutor
- Acquire a model of the movement
- Generalize observations towards a goal

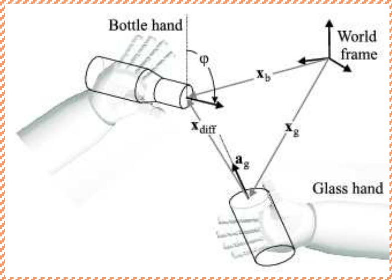
Imitation Learning – our focus

Gesture imitation

„Replaying" of demonstrators movements without understanding (e.g. gestures, dancing etc.)

Goal-directed imitation

Infering the goal of the movement (e.g. object handling / manipulation)



- ***learning*** of goal-directed object movement skills
- ***representing*** it independent from a concrete situation
- ***imitating*** it in novel situations using adaptation methods
- ***Interaction*** supports learning and imitation

Intention imitation

Understanding the goal of the demonstrator and possibly finding other ways to achieve it

State of the art in robotics

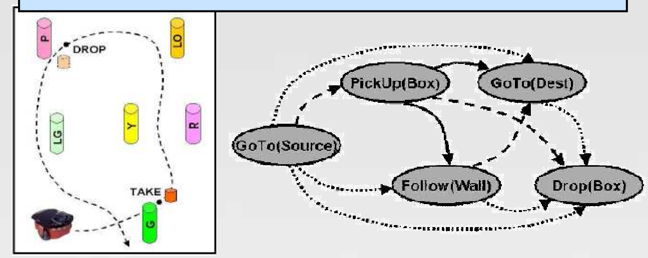
[Calinon and Billard 2008]

- Movement representation with Gaussian Mixture Models
- Generalization by exploiting variance of multiple demonstrated movements

[Ijspeert et al. 2003]

- Dynamic Movement Primitives (DMPs) represent discrete or rhythmic movements
- Generalization by inherent robustness of DMPs wrt. spatial and temporal perturbations

[Nicolescu and Matarić 2006]



- Problem of movement learning shaped into the problem of learning a state chart structure
- Generalization by learning the skill as a coordination of predefined complex behaviors

probabilistic **dynamical systems** **symbolic**

observation

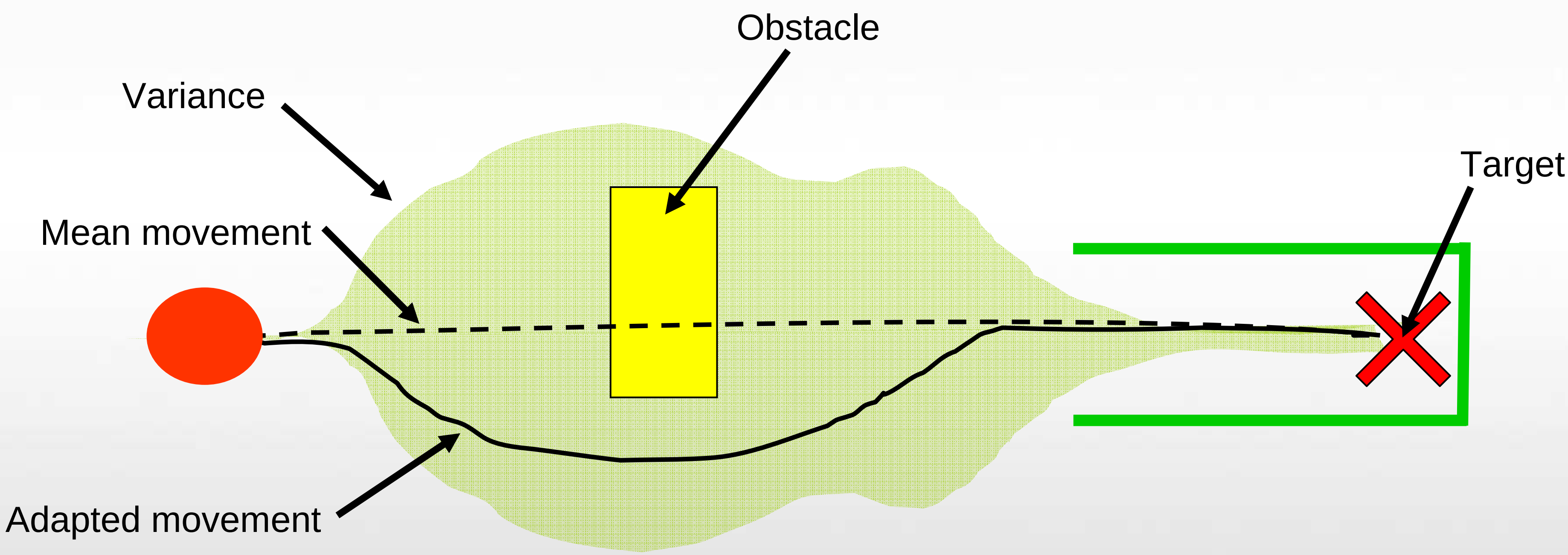
generalization → **Representation** → **binding**

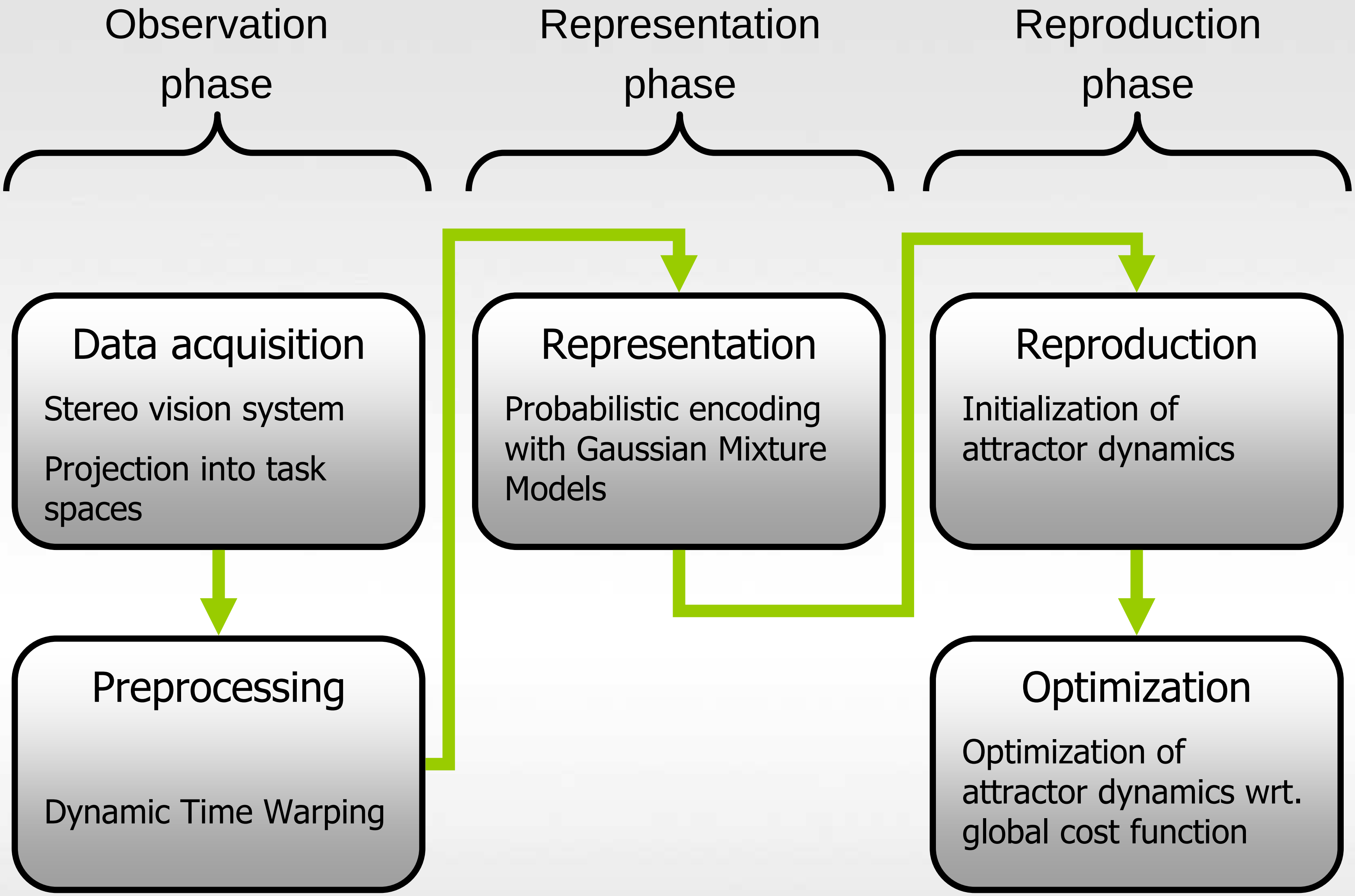
new situation

Images from: Humanoid Robots Lab, University of Freiburg

Concept: Variance-based imitation

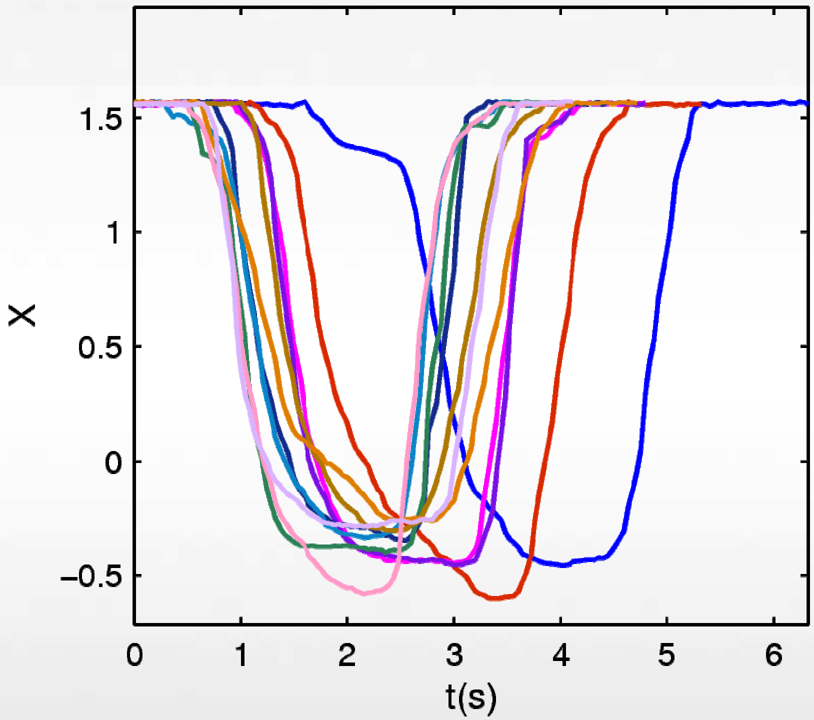
- Exploiting the statistics of a number of demonstrations
- Inter-trial variance as an importance measure:
  - Low variance → important for the task
  - High variance → less important for the task
- Movement may be different in less important parts → Improve other criteria: collisions, energy …

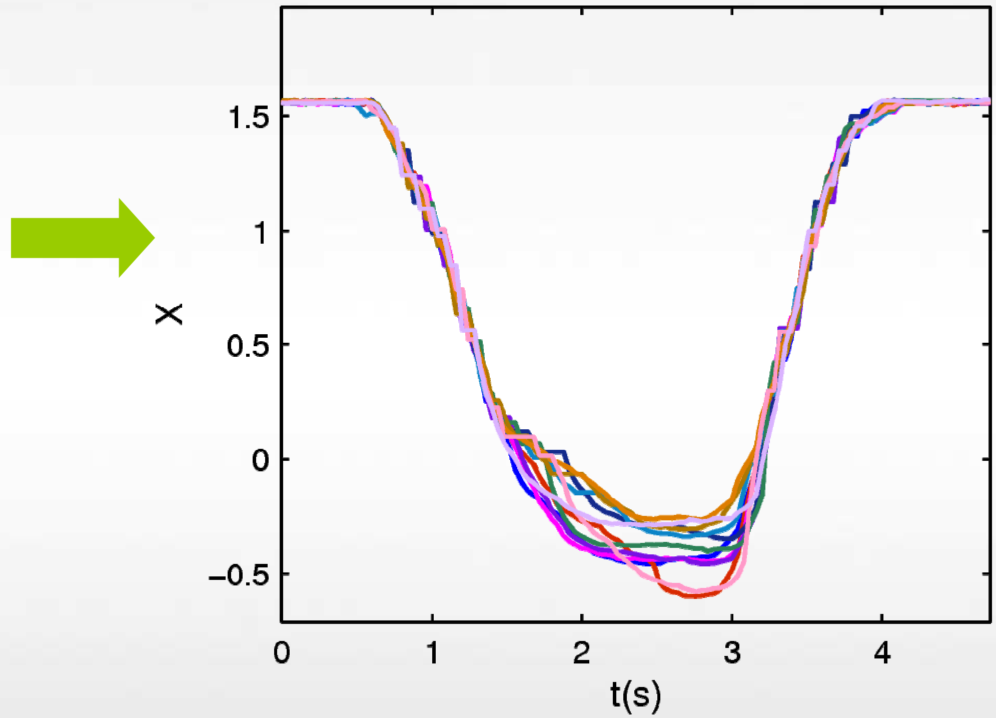




M. Mühlig, M. Gienger, S. Hellbach, J. J. Steil, and C. Goerick, "Task-level Imitation Learning using Variance-based Movement Optimization," in *Proc. IEEE International Conference on Robotics and Automation*, 2009.

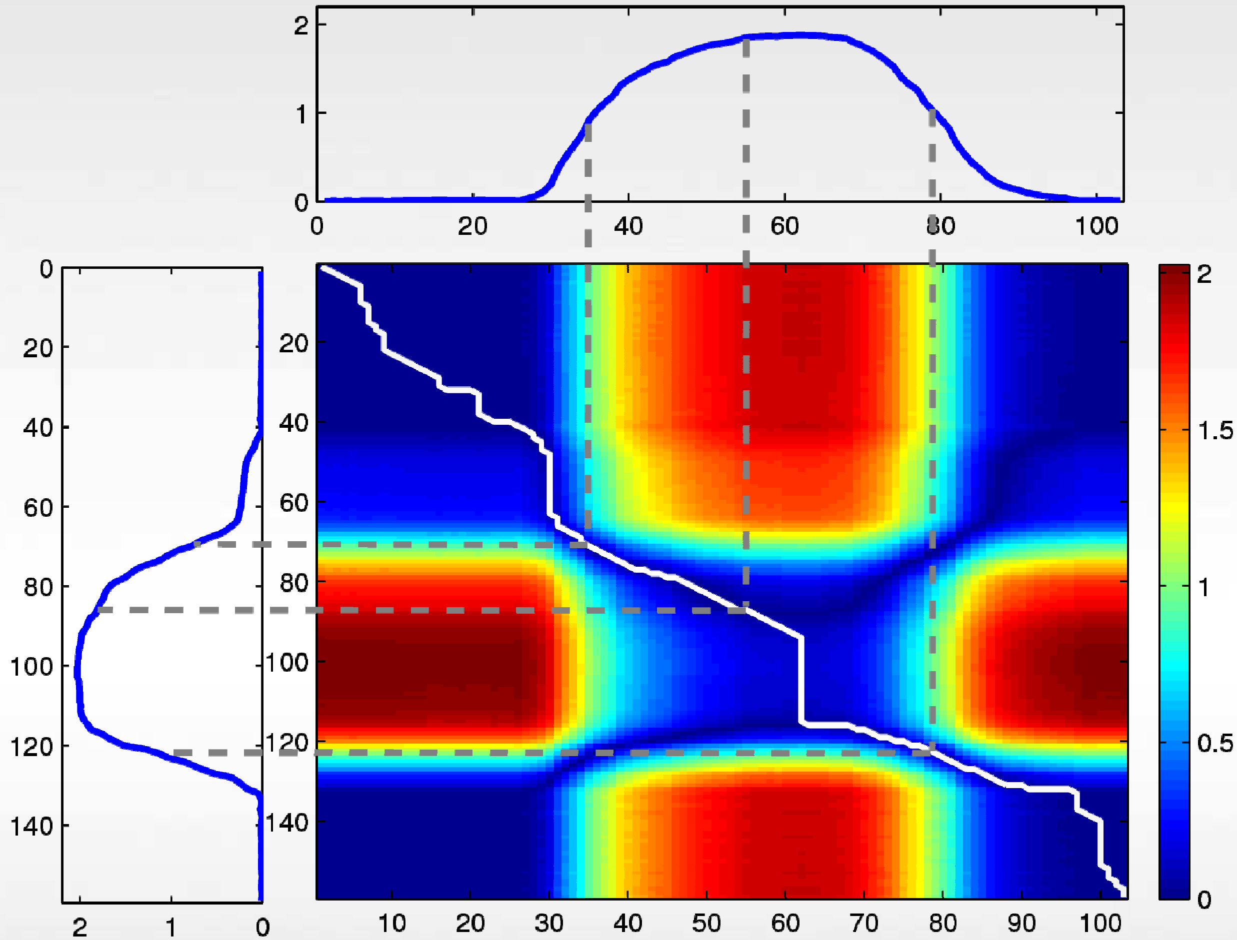
- Inter-trial variance from multiple demonstrations serves as importance measure
- Problem: different demonstrations may have different temporal properties → inappropriate variance information
- Therefore: Dynamic Time Warping for temporal alignment





S. Calinon and F. Guenter and A. Billard:
On Learning, Representing and Generalizing a Task in a Humanoid Robot, IEEE Transactions on Systems, Man and Cybernetics, Part B. Special issue on robot learning by observation, demonstration and imitation", 2007

Dynamic Time Warping (DTW) - temporal alignment



1. Calculate distance matrix
2. Recursive search of the minimal path
3. Indices of the minimal path define the transformation of one signal to match the other

Gaussian Mixture Models

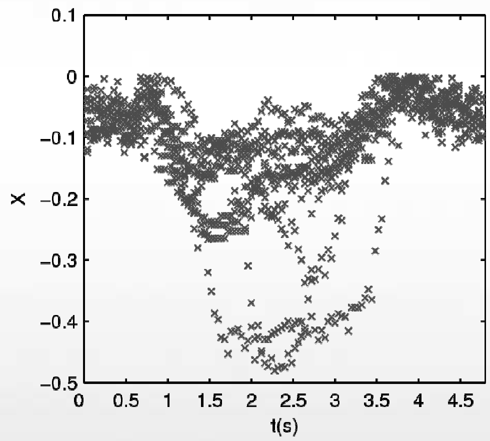
$$p(\mathbf{x}_i) = \sum_{k=1}^{K} p(k)p(\mathbf{x}_i|k)$$

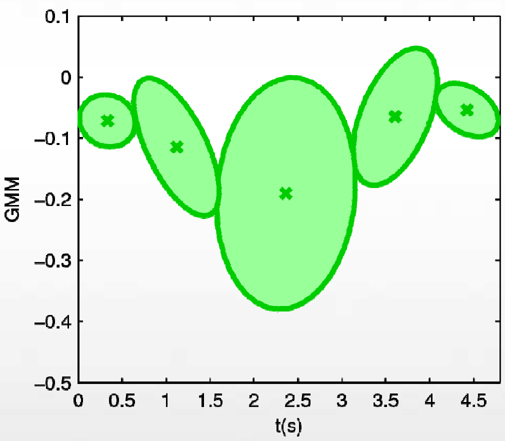
$$p(k) = \pi_k$$

$$\begin{aligned} p(\mathbf{x}_i|k) &= \mathcal{N}(\mathbf{x}_i; \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k) \\ &= \frac{1}{\sqrt{(2\pi)^D \cdot |\boldsymbol{\Sigma}_k|}} \cdot e^{-\frac{1}{2}\left((\mathbf{x}_i-\boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}_i-\boldsymbol{\mu}_k)\right)} \end{aligned}$$

Parameters π_k, μ_k, Σ_k of all multivariate Gaussian components *k* define the GMM

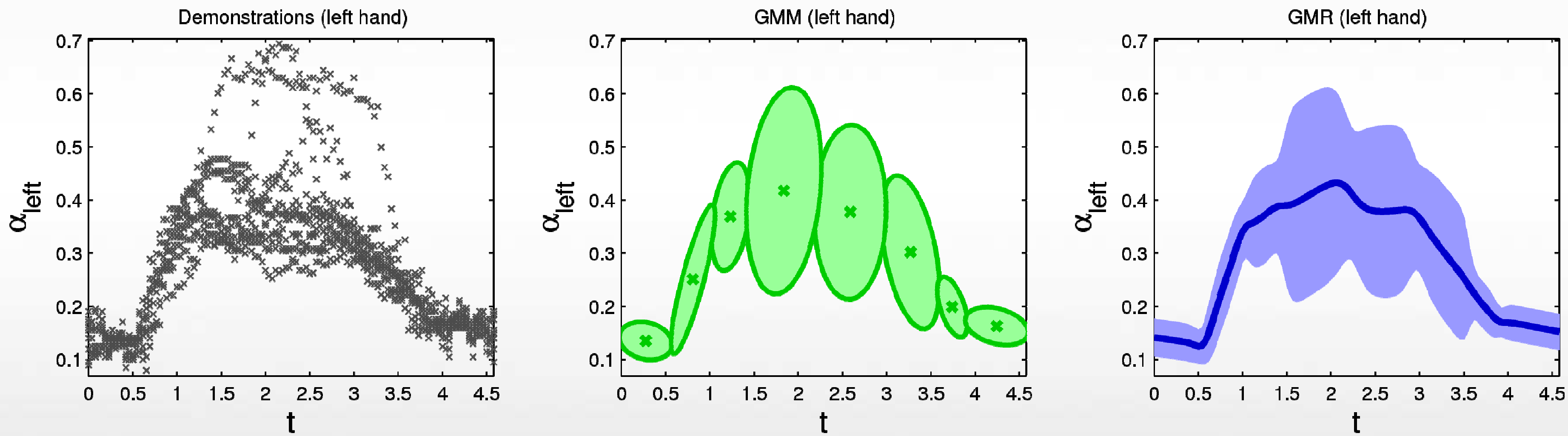
- Input: temporally aligned demonstrations
- Expectation Maximization training
- Bayesian Information Criterion based heuristic for estimating the number of Gaussians





Gaussian Mixture Regression (GMR)

- Extraction of the generalized (mean) movement and the according inter-trial variance information
- Any dimension(s) of the encoded movement data can serve as an input (here: the time dimension)
- Values of the remaining dimensions of the task space are interpolated, depending on the information encoded in the GMM



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Next step:

- Initialization of the attractor dynamics [Toussaint, Gienger et al., 2007]
- Attractors are defined in the task space and are initialized with the mean movement of the GMR

We are not done!

- Attractor points do not necessarily reside on the actual trajectory
- Additional criteria not yet regarded

Optimization-based movement imitation

- Similarity of demonstrated movement is one out of several criteria
- Criterion weighted with variance

→ Imitation is „strong“ in phases with low variance, weak“ in phases with high variance
→ Robot‘s limitations are considered

Movement curvature

$$\sum_{t=1}^{T}(q_t - q_{t-1})^T W (q_t - q_{t-1})$$

Target precision

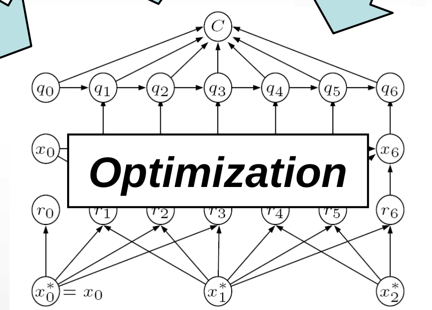
$$|\tilde{\phi}(q_T) - \hat{x}|^2$$

Collision avoidance

$$Q(q) = \sum_{i}^{pairs} g_p(d_{p,i}) + g_c(d_{p,i}, d_{c,i})$$

Joint limit avoidance

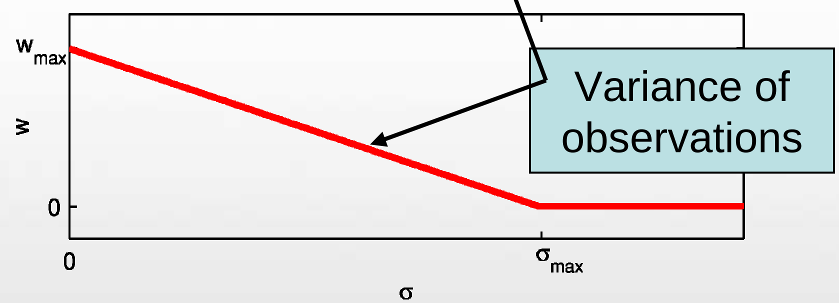
$$\frac{1}{2}\sum_{i=1}^{\text{dof}} w_i(q_i - q_{0,i})^2$$



Robot‘s movement

Teacher‘s mean movement

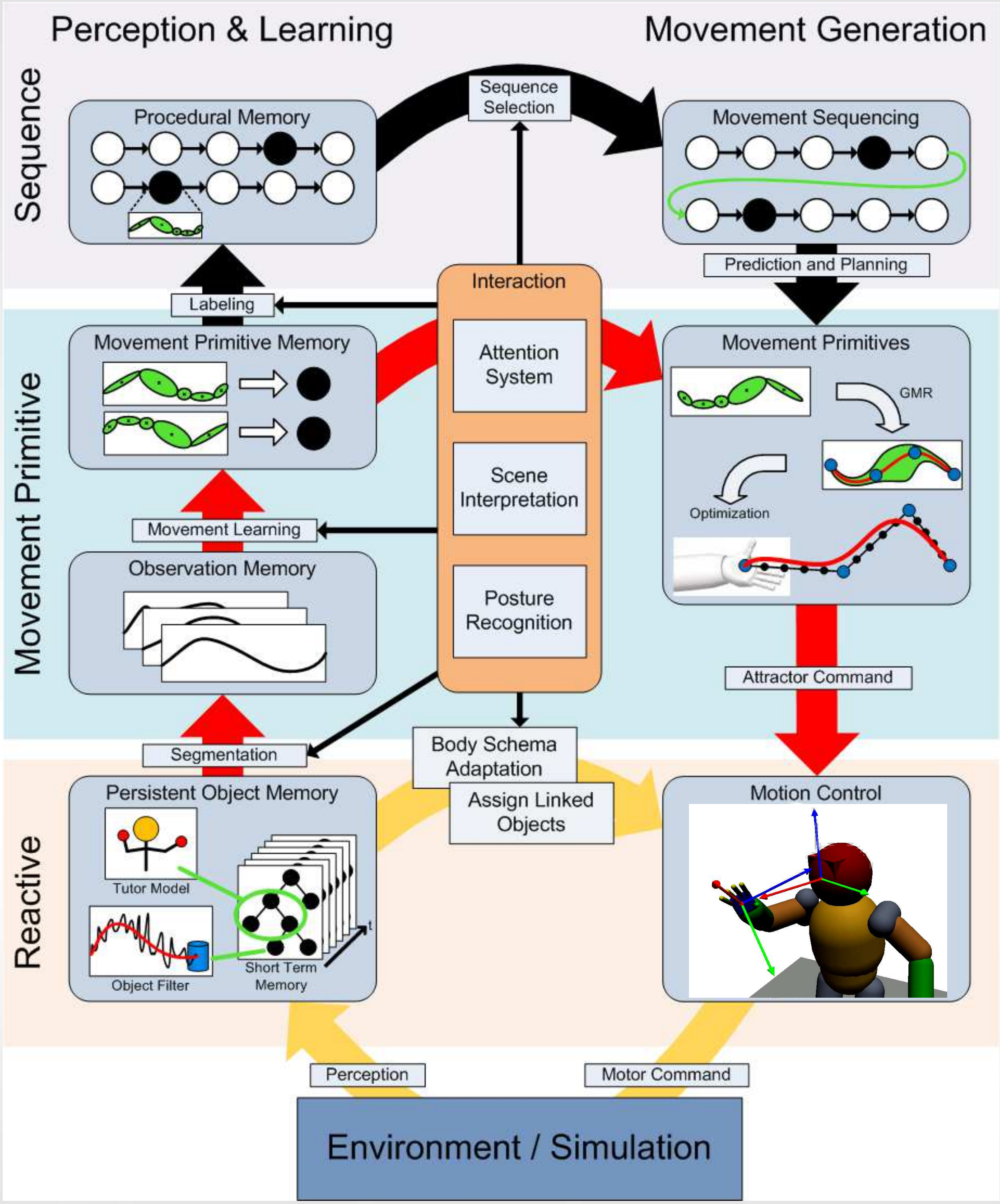
$$c_{\text{im}} = (\mathbf{x}_t - \hat{\boldsymbol{\mu}}_t)^T \mathbf{W}_t (\mathbf{x}_t - \hat{\boldsymbol{\mu}}_t)$$



System imitates teacher as good as possible, but respects limitations such as collisions, joint limits, etc.

System architecture

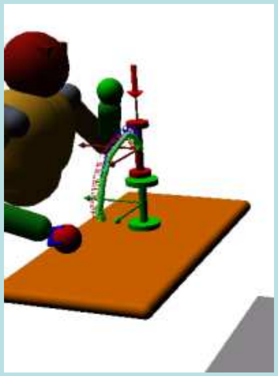
- Simple table scenario: human teaches robot to stack or put objects
- Interactive scenario – teacher interacts with robot to learn & imitate
- Pre-defined preparatory movements – combined with learnt ones



M. Mühlig, M. Gienger, and J. J. Steil, "Human-Robot Interaction for Learning and Adaptation of Object Movements," in *Proc. IEEE International Conference on Intelligent Robots and Systems,* 2010.

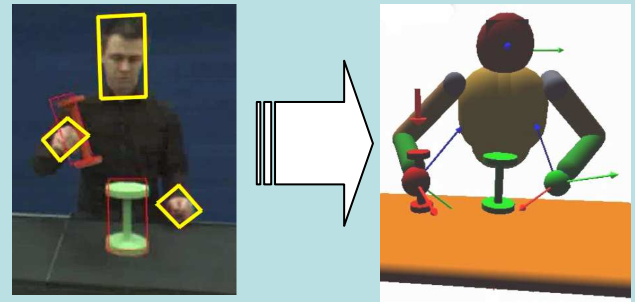
M. Gienger, M. Mühlig, and J. J. Steil, "Imitating Object Movement Skills with Robots – A Task-Level Approach Exploiting Generalization and Invariance," in *Proc. IEEE International Conference on Intelligent Robots and Systems,* 2010.

3D object memory



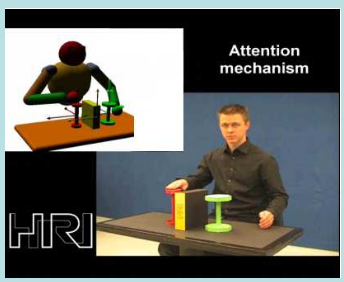
- Fusion of sensor data to a 3D scene
- System’s mental image of the scene
- Basis for all subsequent processing

Tutor model



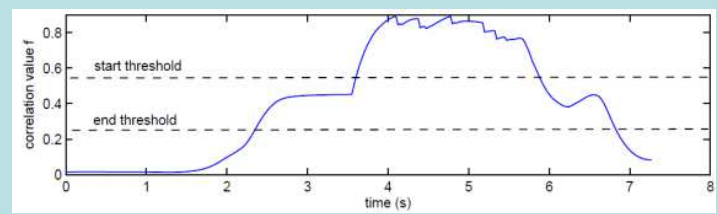
- Tutor’s kinematics modeled (average size human)
- 3D skin color blobs acquired by vision system
- Blobs assigned to hands and head of the model
- Posture estimated using inverse kinematics

Attention system



- Each object is associated with a saliency
- Saliency decays over time, and increases by making the object interesting to the robot
  - by shaking it
  - by pointing to it
- Robot tracks interesting objects

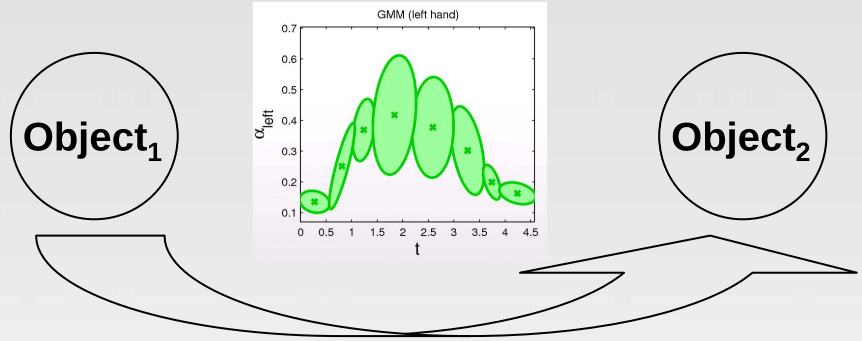
Movement segmentation

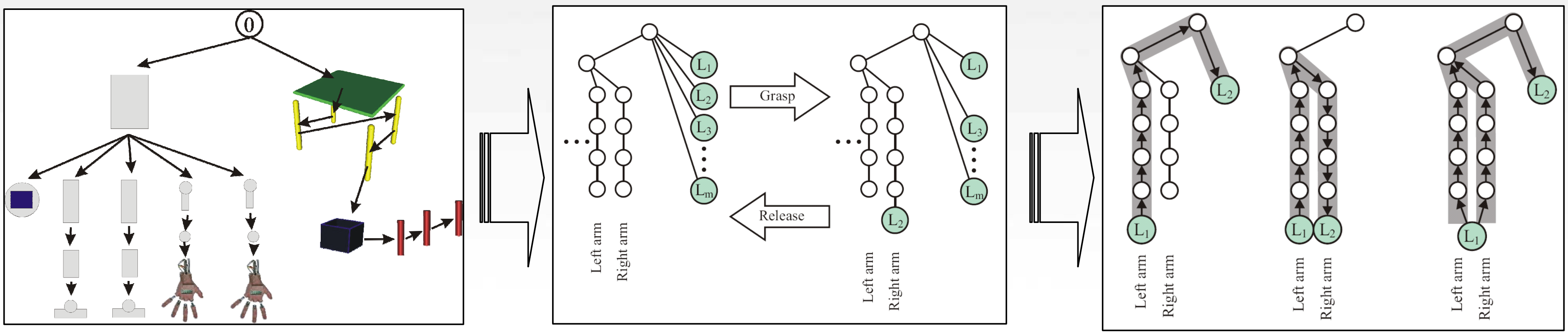


- Coherent hand-object movement is important
- Movement segmentation:
  - Hand is close to object
  - Hand and object have same velocity
- Start & stop thresholds avoid oscillations

Imitating in different styles

- Movement is learnt independent of robot's embodiment → in object coordinates
- Changing the topology of the model allows to generate the movement in different styles

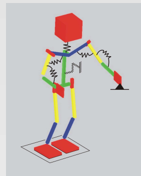




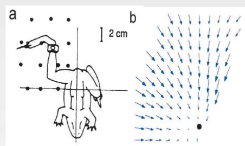
Adapting the body schema allows to
→ create movements with different end effectors
→ create movement one-handed or bi-manual
→ deal consistently with collision avoidance etc.

Conclusions

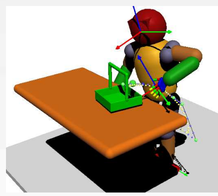
Summary



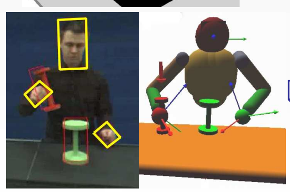
- Whole body movement control



- Movement primitives



- Optimization of movement



- Imitation learning

Interesting future questions

- Relation of action and effects → the basis for inference
- Intuitive learning in interaction
- Integration of sensory modalities
- …

Thank you very much for your attention!