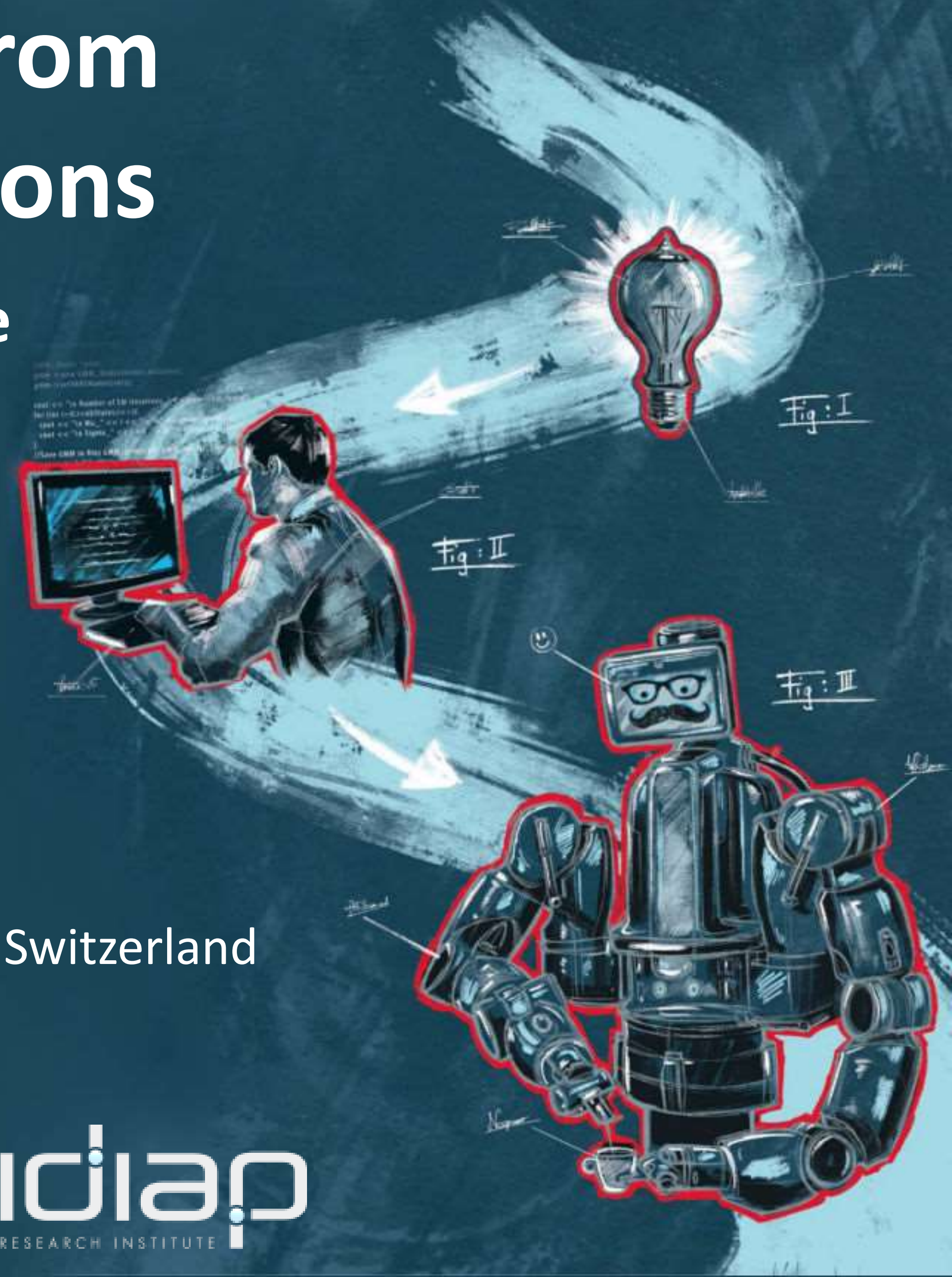
Robot learning from few demonstrations

by exploiting the structure and geometry of data



Sylvain Calinon

Senior Researcher

Idiap Research Institute, Martigny, Switzerland

Lecturer

EPFL, Lausanne, Switzerland

External Collaborator

IIT, Genoa, Italy

idiap
RESEARCH INSTITUTE

Artificial Intelligence for Society

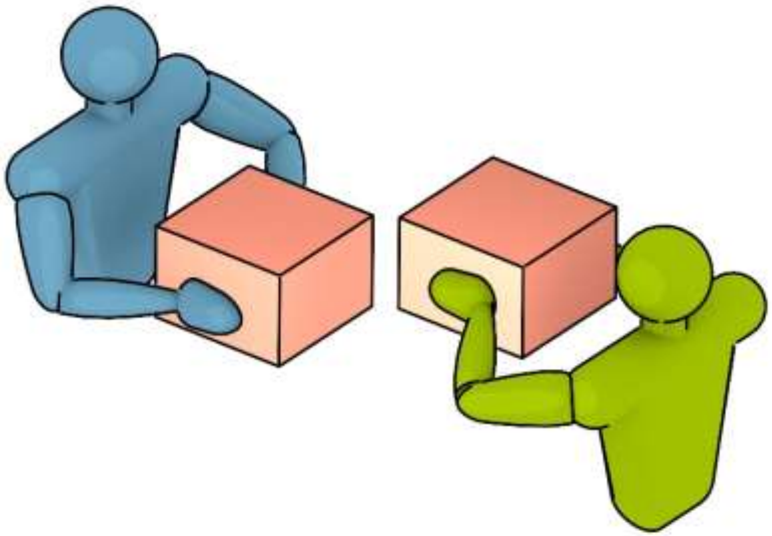
Research Groups:

- Speech & Audio Processing
- Perception & Activity Understanding
- Computer Vision & Learning
- Social Computing
- Biometric Person Recognition
- Applied Machine Learning
- Natural Language Processing
- **Robot Learning & Interaction**
- Computational Bioimaging
- Uncertainty Quantification and Optimal Design

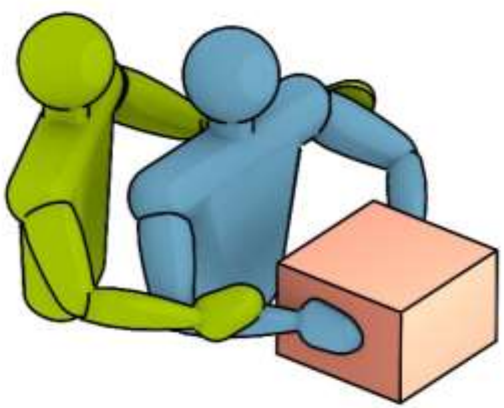
Research
Education
Technology transfer

Learning from demonstration as an intuitive interface to transfer skills to robots

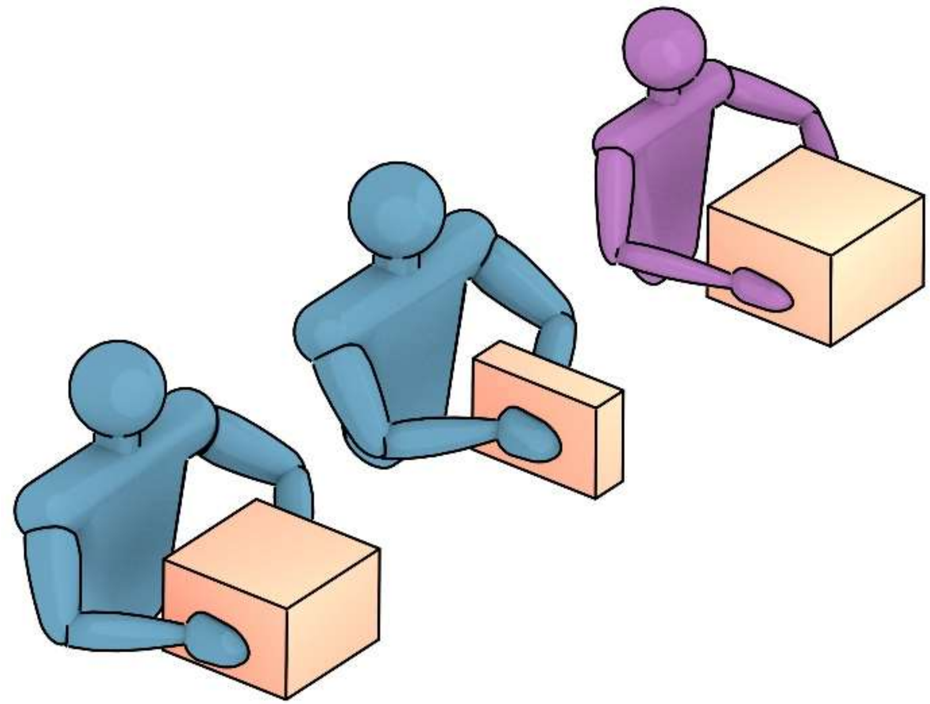
Learning from demonstration - Challenges



Observational learning

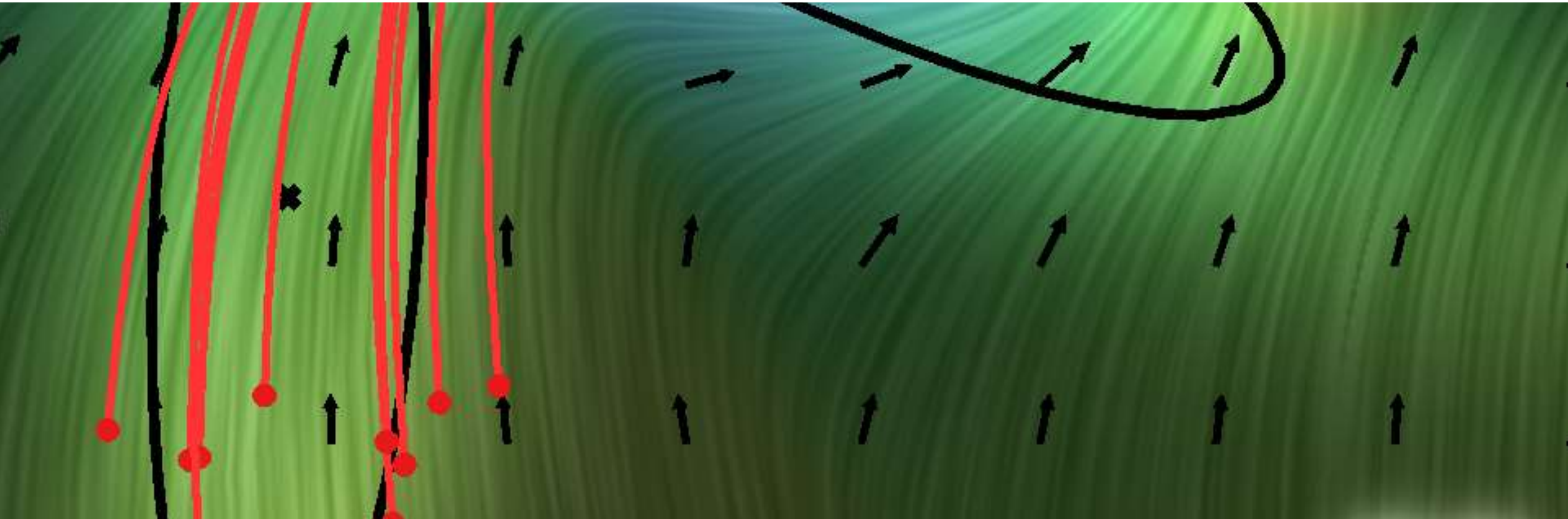


Kinesthetic teaching



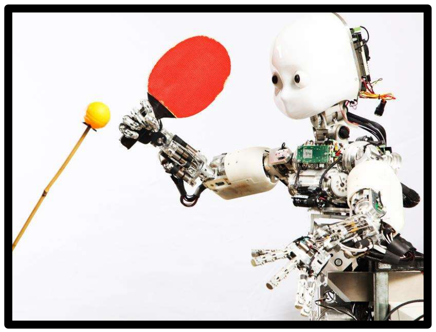
Correspondence problems

Finding *Priors* that are expressive enough to be used in a wide range of tasks

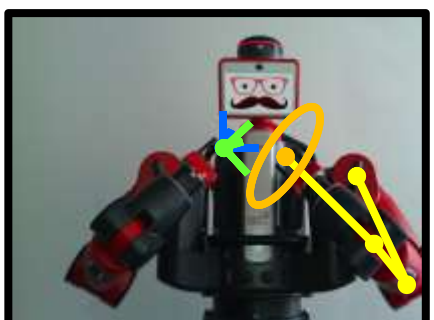


Outline

Prior 1: Movements are smooth and continuous

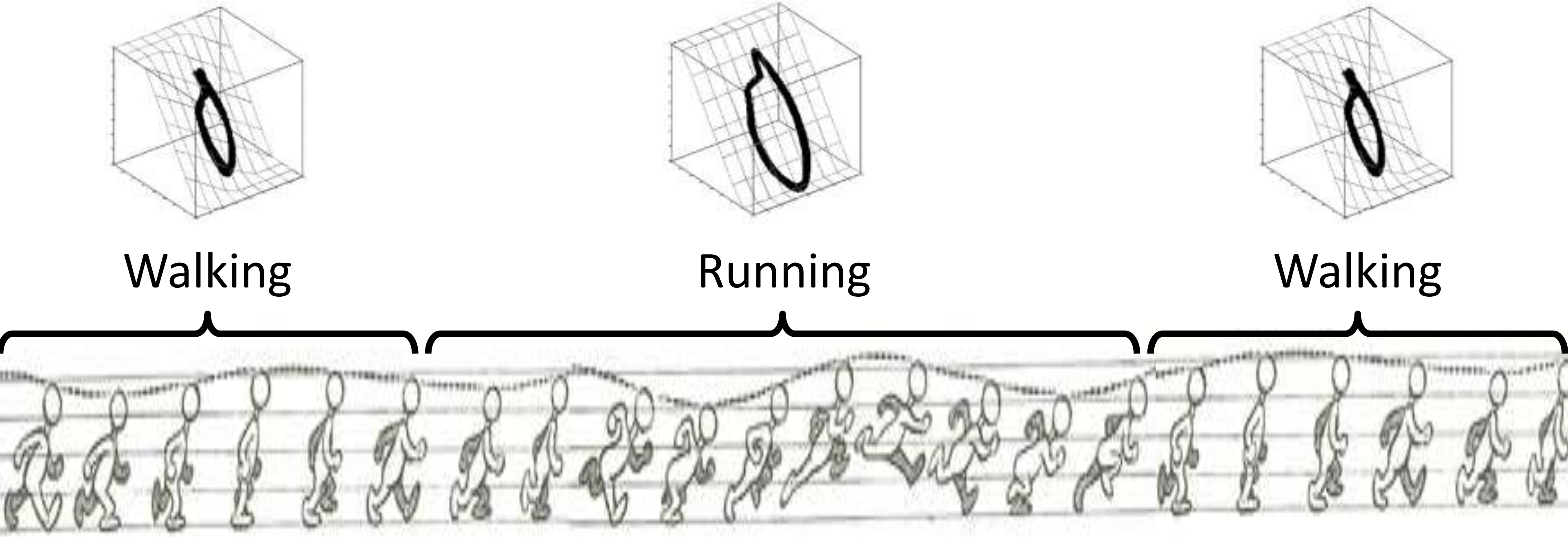


Prior 2: Actions often relate to objects, tools or body landmarks



Prior 3: Data spaces in robotics have geometries and structures

Movement generation as a mix of clustering, subspace analysis and optimal control



We look for a **compact and modular representation** of **continuous movements and skills** that can learn from **few interactions** (with user and environment), that can **exploit variation and coordination**, and that can **adapt to new situations** in a fast manner.

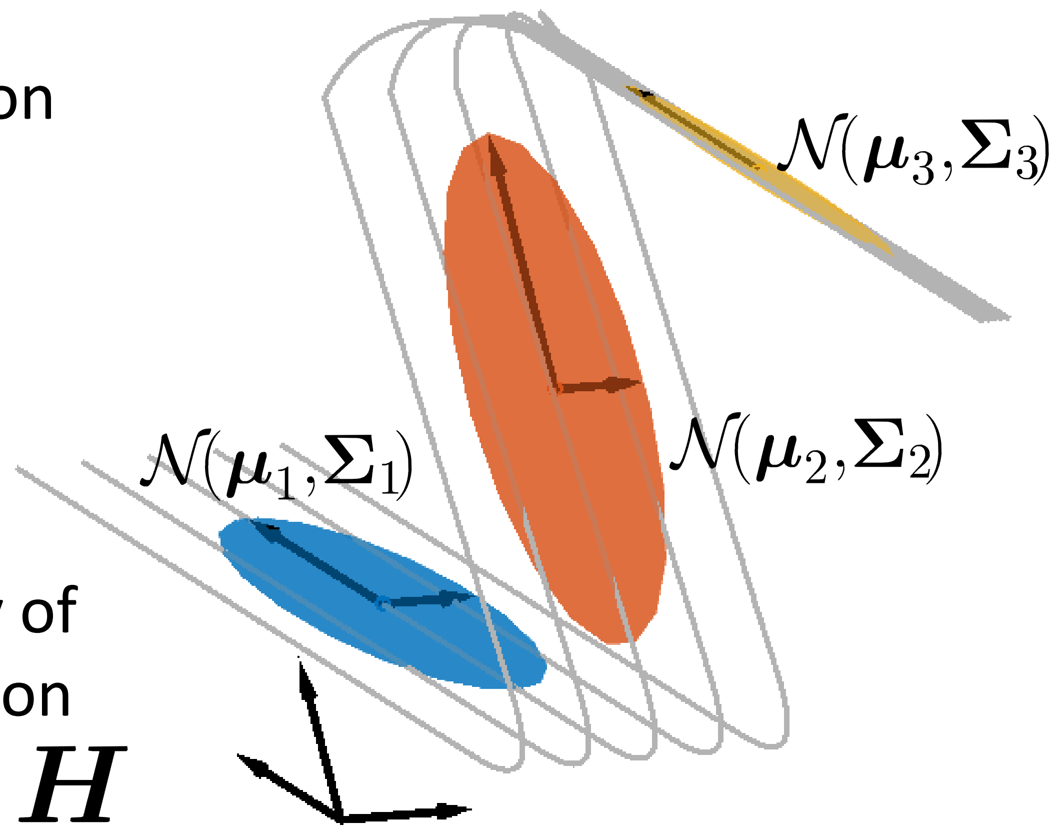
Learning of motions from few demonstrations

$\boldsymbol{\mu}_i$ center

$\boldsymbol{\Sigma}_i$ covariance matrix

Sharing of local coordination patterns with:

$$\boldsymbol{\Sigma}_i = \boldsymbol{H}\boldsymbol{\Sigma}_i^{(diag)}\boldsymbol{H}^\top$$



Dictionary of coordination patterns: $\boldsymbol{H}$

[Tanwani and Calinon, IEEE RA-L 1(1), 2016]

Learning minimal intervention controllers

Track path! Use low control commands!

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \boxed{\left\|\hat{\boldsymbol{x}}_t - \boldsymbol{x}_t\right\|^2_{\boldsymbol{Q}_t}} + \boxed{\left\|\boldsymbol{u}_t\right\|^2_{\boldsymbol{R}_t}}$$

$$\text{s.t.} \quad \boxed{\dot{\boldsymbol{x}}_t = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\boldsymbol{u}_t}$$

System plant

$\boldsymbol{x}_t$ state variable (position+velocity)

$\hat{\boldsymbol{x}}_t$ desired state

$\boldsymbol{u}_t$ control command (acceleration)

$\boldsymbol{Q}_t$ tracking weight matrix

$\boldsymbol{R}_t$ control weight matrix

Approach: solving analytically a basic form of **model predictive control (MPC)** in task space with a **double integrator** as constant linear system

[Calinon, Bruno and Caldwell, ICRA'2014]

Learning minimal intervention controllers

Track path! Use low control commands!

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \left\|\hat{\boldsymbol{x}}_t - \boldsymbol{x}_t\right\|^2_{\boldsymbol{Q}_t} + \left\|\boldsymbol{u}_t\right\|^2_{\boldsymbol{R}_t}$$

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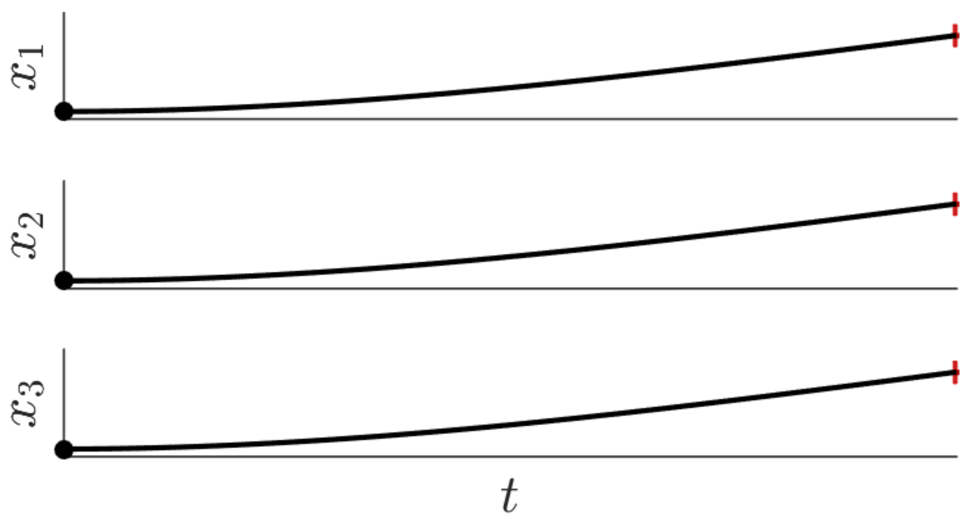
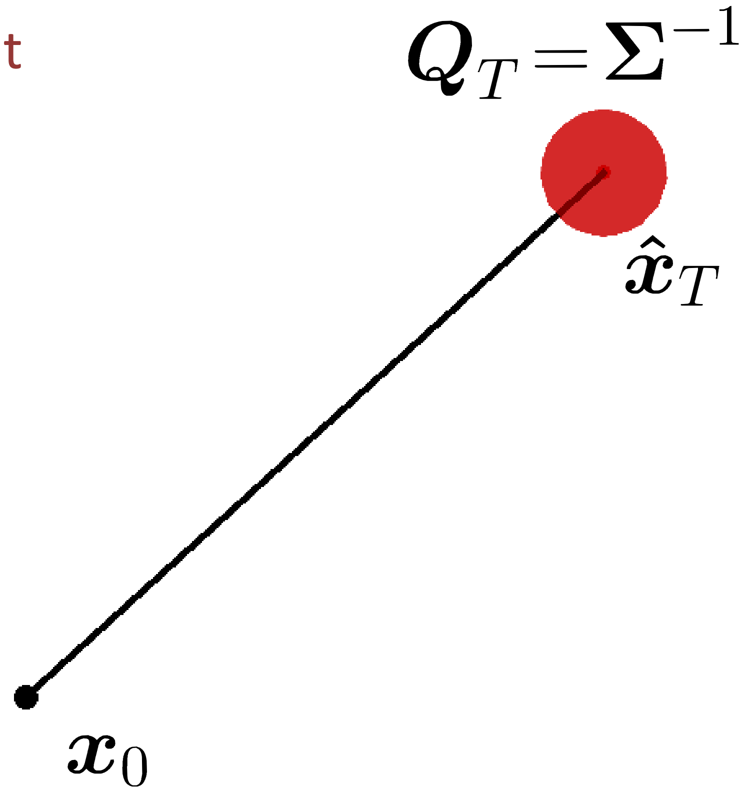
System plant

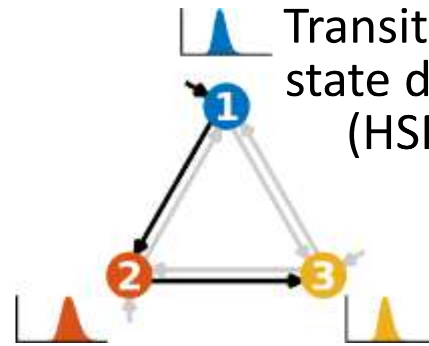




[Calinon, Bruno and Caldwell, ICRA'2014]

Learning minimal intervention controllers

➡ **Analytical solution to generate motion control by following a minimal intervention principle**

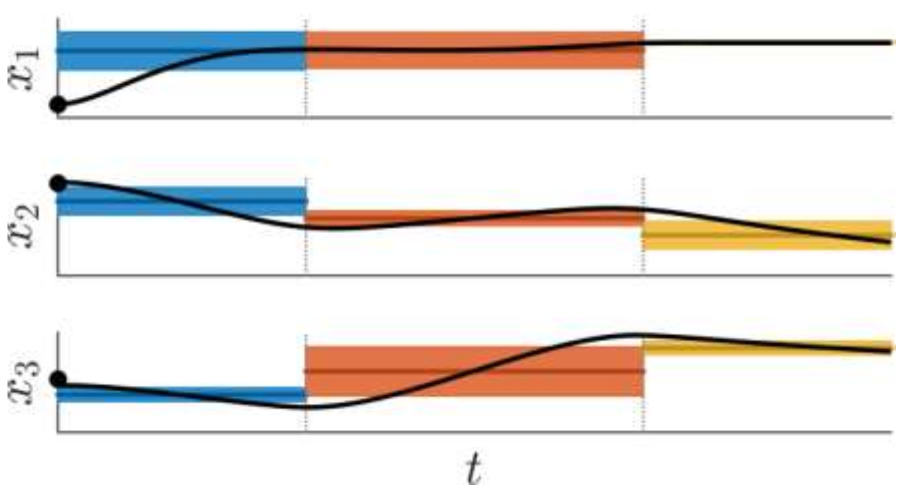


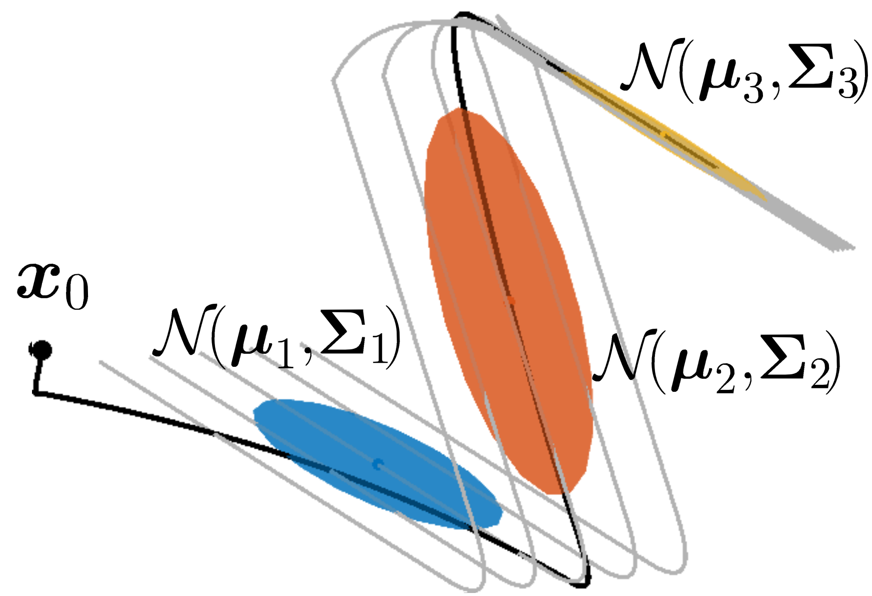
Transition and state duration (HSMM)

Stepwise reference with:

$$\hat{\boldsymbol{x}}_t = \boldsymbol{\mu}_{s_t} \quad \boldsymbol{Q}_t = \boldsymbol{\Sigma}_{s_t}^{-1}$$

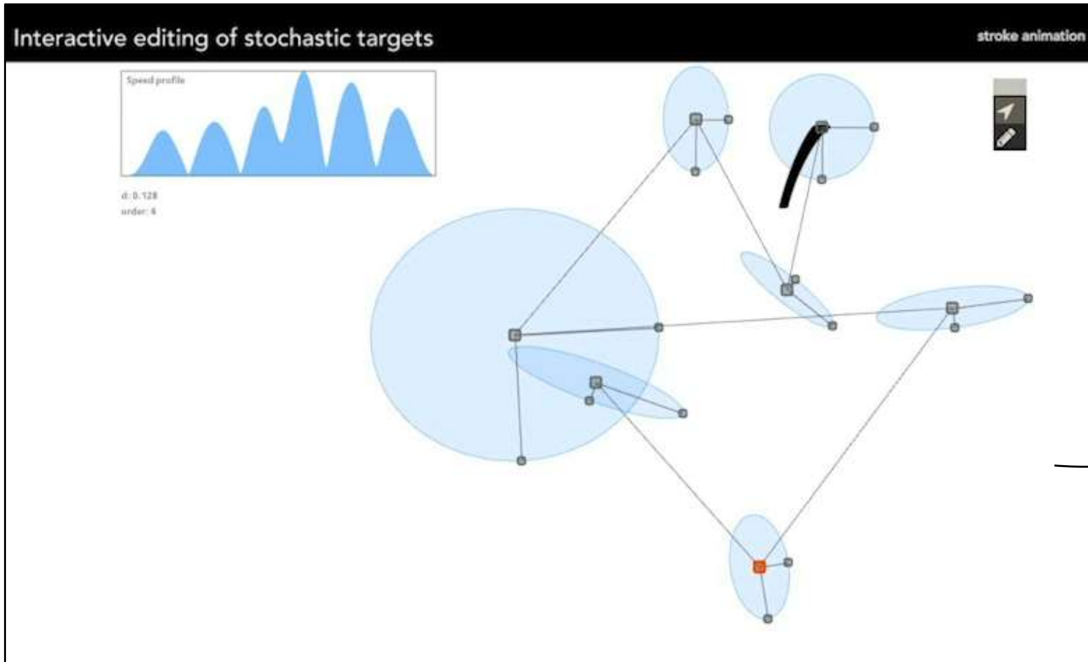
s_t **111111112222222222222333333333**





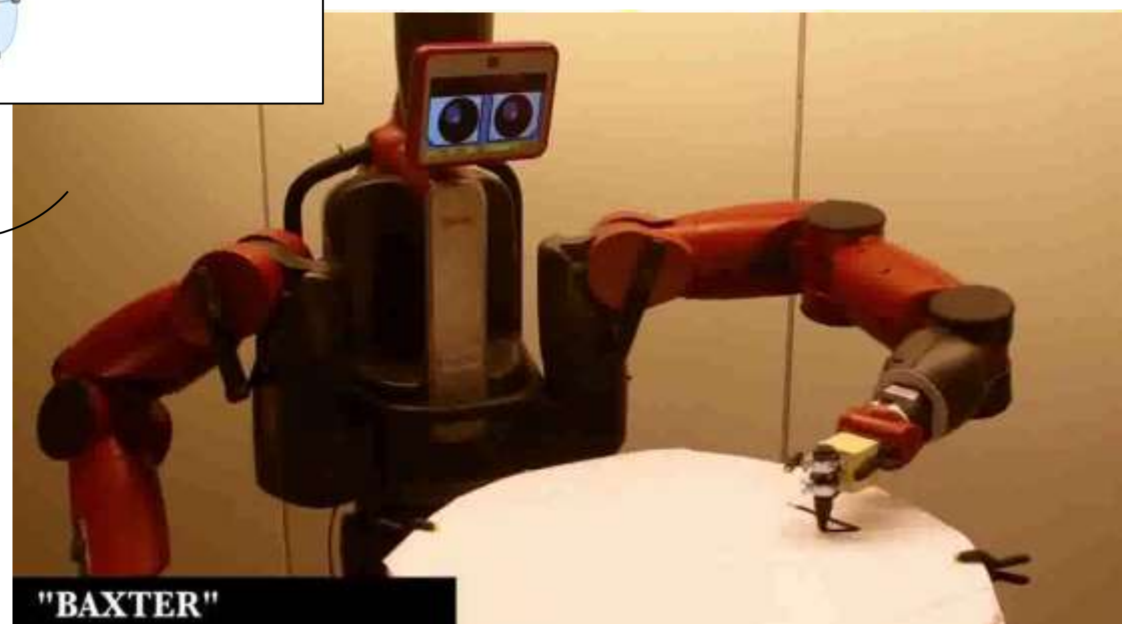
[Calinon, Bruno and Caldwell, ICRA'2014]

Application: Designing motions with variations



User interface to edit and generate natural and dynamic motions by considering variation and coordination

Compliant controller to retrieve safe and human-like motions



Daniel Berio

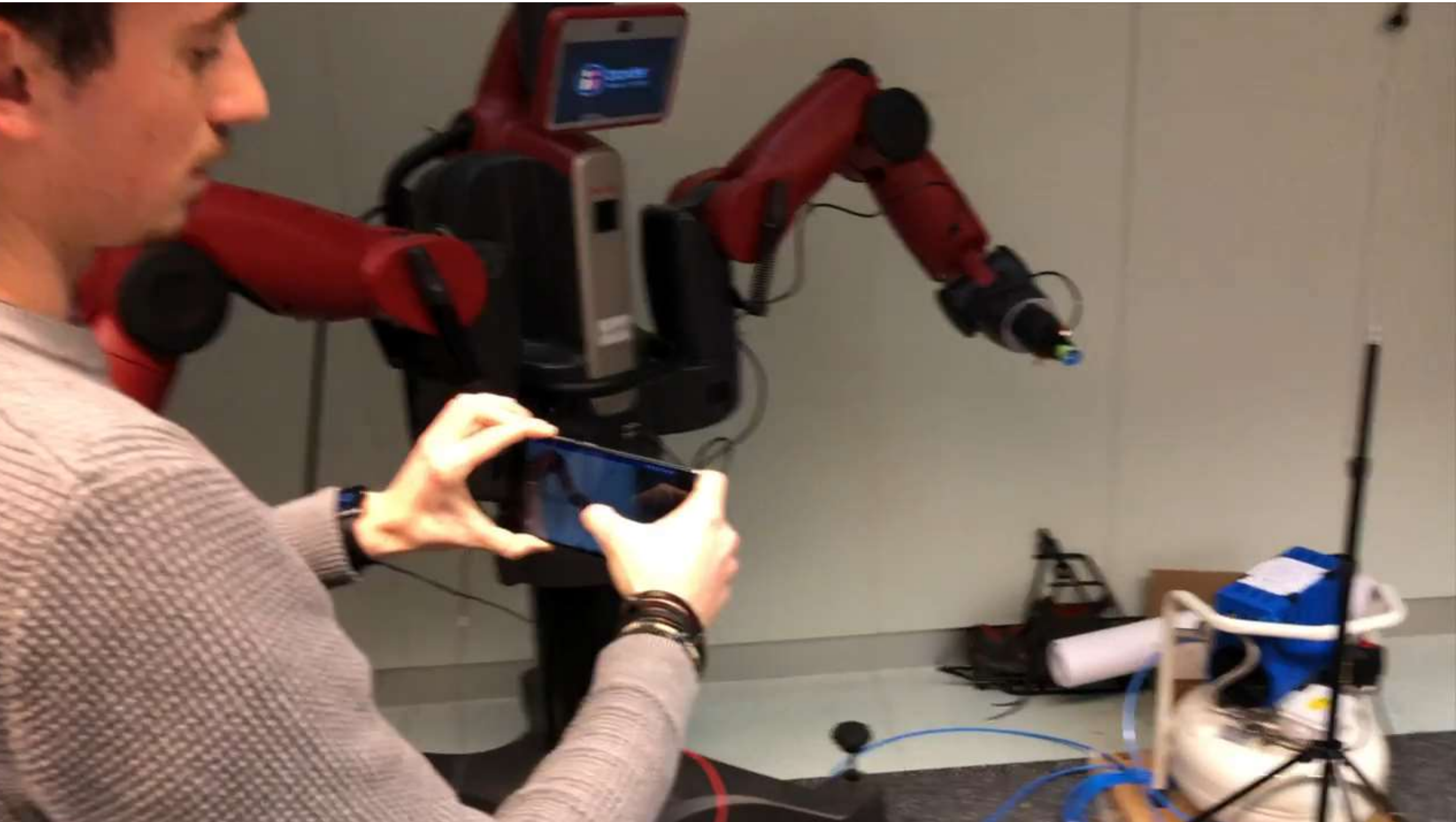
Frederic Fol Leymarie

idiap RESEARCH INSTITUTE

Goldsmiths UNIVERSITY OF LONDON

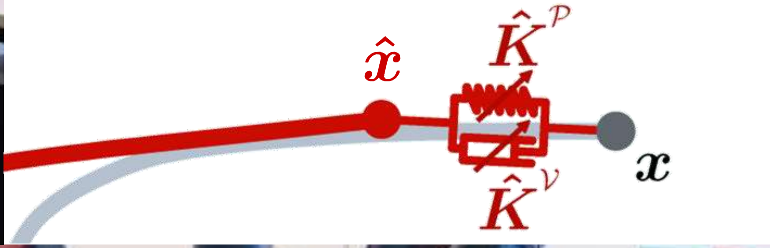
[Berio, Calinon and Leymarie, IROS'2016] [Berio, Calinon and Leymarie , MOCO'2017]

Extension to mobile augmented reality interface to visualize and program robot movements



Learning impedance controllers

Personalized assistance using **haptic and visual** information, with compliant controllers following a **minimal intervention principle**



Emmanuel Pignat

[Pignat and Calinon, RAS 93, 2017]

Outline

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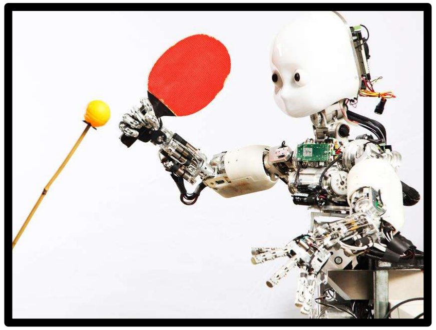

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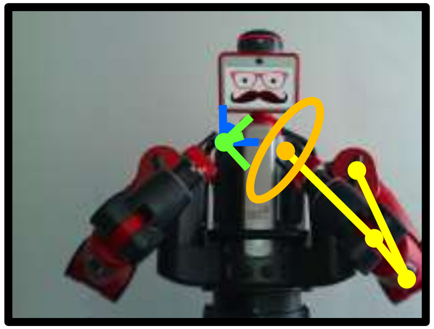

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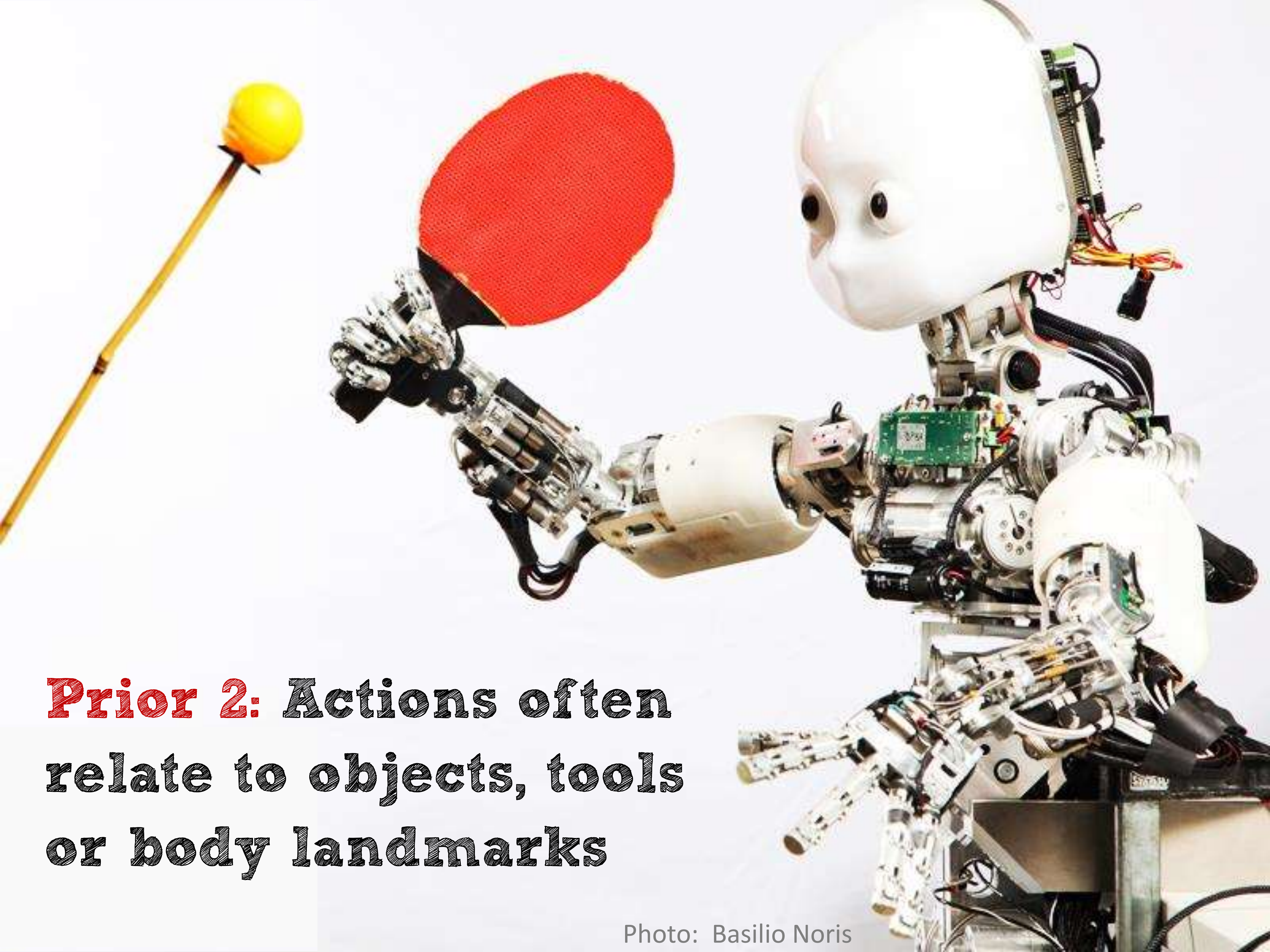


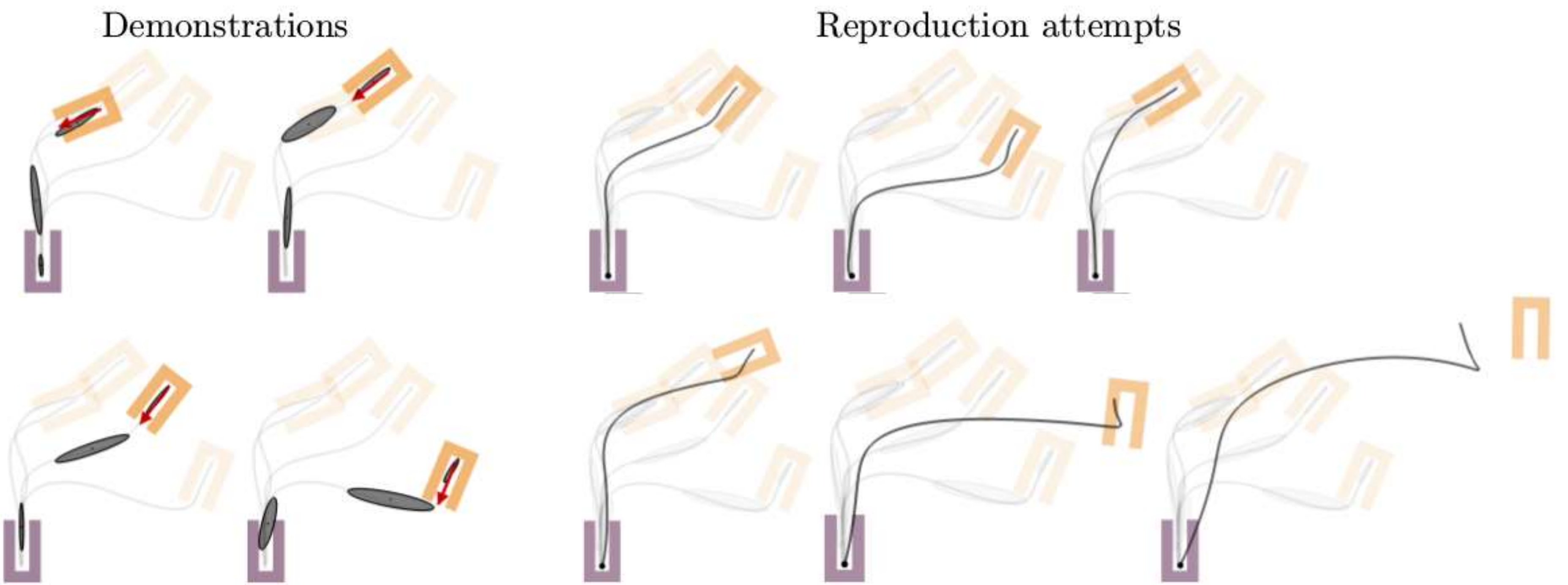
Prior 2: Actions often relate to objects, tools or body landmarks

Photo: Basilio Noris

Task-parameterized motions

Regression with a context variable *c*:

- Learning of $\mathcal{P}(\boldsymbol{c}, \boldsymbol{x})$
- Retrieval with $\mathcal{P}(\boldsymbol{x}|\boldsymbol{c})$



→ Generic approach, but limited generalization capability

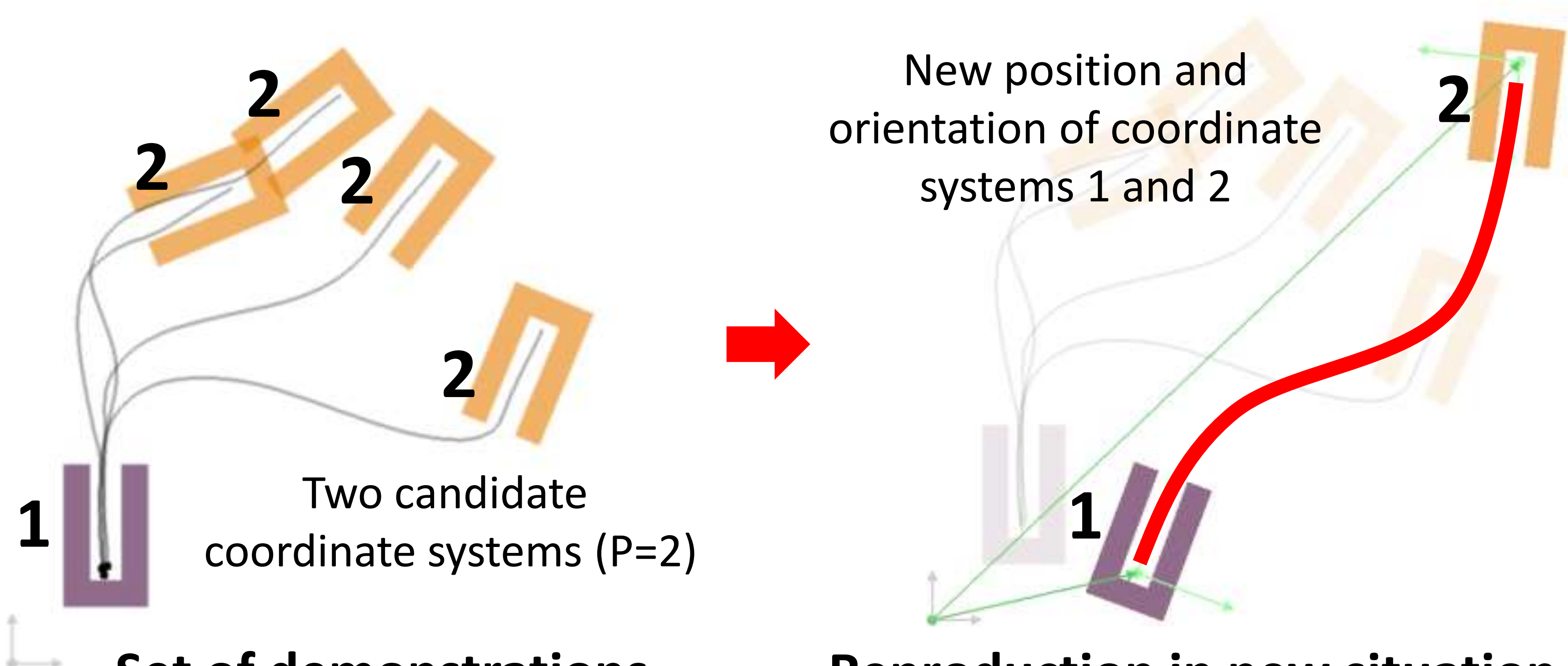
Control in multiple coordinate systems

Track path in coordinate system j

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\| \hat{\boldsymbol{x}}_t^{(j)} - \boldsymbol{x}_t \right\|^2_{\boldsymbol{Q}_t^{(j)}} + \left\| \boldsymbol{u}_t \right\|^2_{\boldsymbol{R}_t}$$

Use low control commands!

$$\text{s.t.} \quad \dot{\boldsymbol{x}}_t = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\boldsymbol{u}_t$$



Set of demonstrations **Reproduction in new situation**

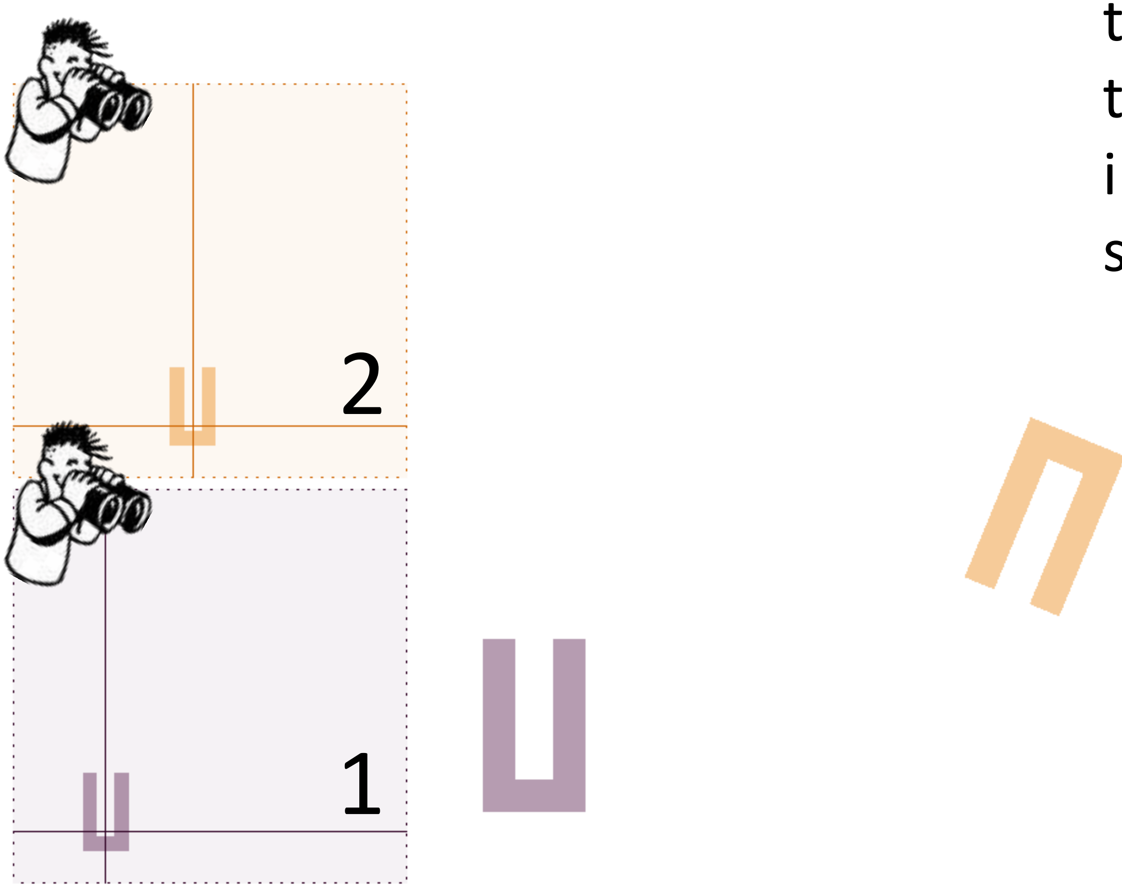
[Calinon, HFR'2016]

Control in multiple coordinate systems

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\| \hat{\boldsymbol{x}}_t^{(j)} - \boldsymbol{x}_t \right\|^2_{\boldsymbol{Q}_t^{(j)}} + \left\| \boldsymbol{u}_t \right\|^2_{\boldsymbol{R}_t}$$

$$\text{s.t.} \quad \dot{\boldsymbol{x}}_t = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\boldsymbol{u}_t$$

In many robotics problems, the parameters describing the task or situation can be interpreted as coordinate systems

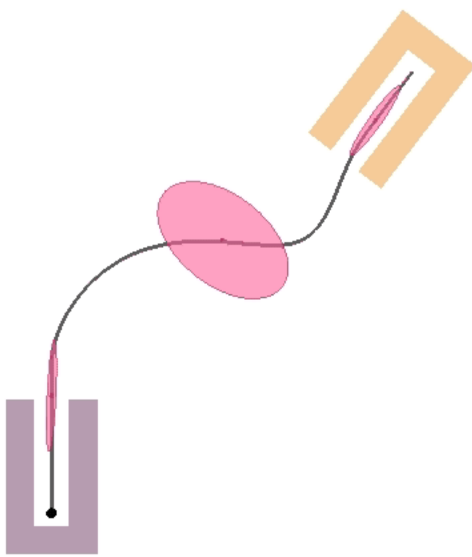


[Calinon, HFR'2016]

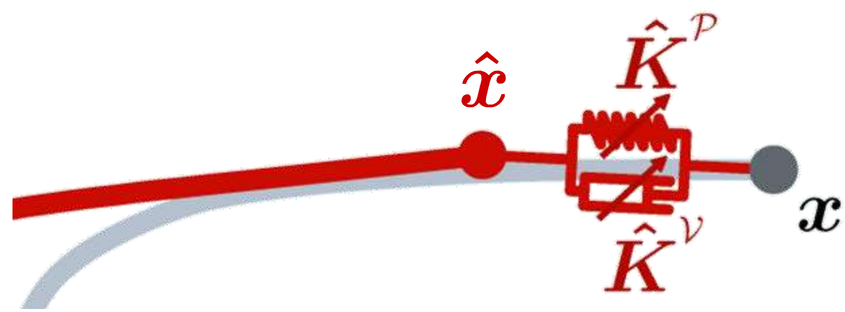
Control in multiple coordinate systems

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\| \hat{\boldsymbol{x}}_t^{(j)} - \boldsymbol{x}_t \right\|^2_{\boldsymbol{Q}_t^{(j)}} + \left\| \boldsymbol{u}_t \right\|^2_{\boldsymbol{R}_t}$$

$$\text{s.t.} \quad \dot{\boldsymbol{x}}_t = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\boldsymbol{u}_t$$



➡ **Learning of a controller**
(instead of learning a trajectory)
that adapts to new situations
while regulating the gains
according to the precision and
coordination required by the task



[Calinon, HFR’2016]

Control in multiple coordinate systems

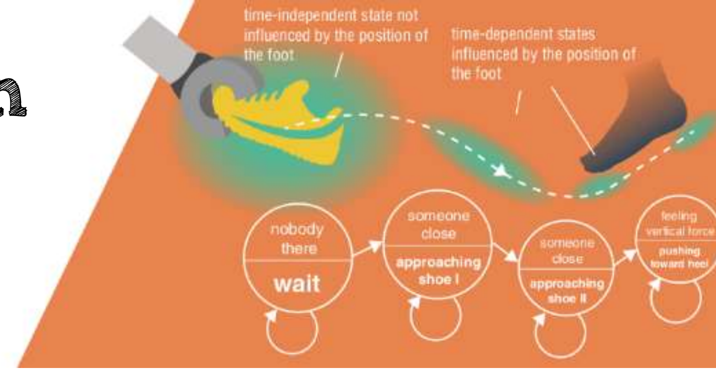
$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\| \hat{\boldsymbol{x}}_t^{(j)} - \boldsymbol{x}_t \right\|_{\boldsymbol{Q}_t^{(j)}}^2 + \left\| \boldsymbol{u}_t \right\|_{\boldsymbol{R}_t}^2$$

$$\text{s.t.} \quad \dot{\boldsymbol{x}}_t = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\boldsymbol{u}_t$$

➡ Retrieval of control commands in the form of trajectory distributions, facilitating exploration and adaptation (in either control or state space)

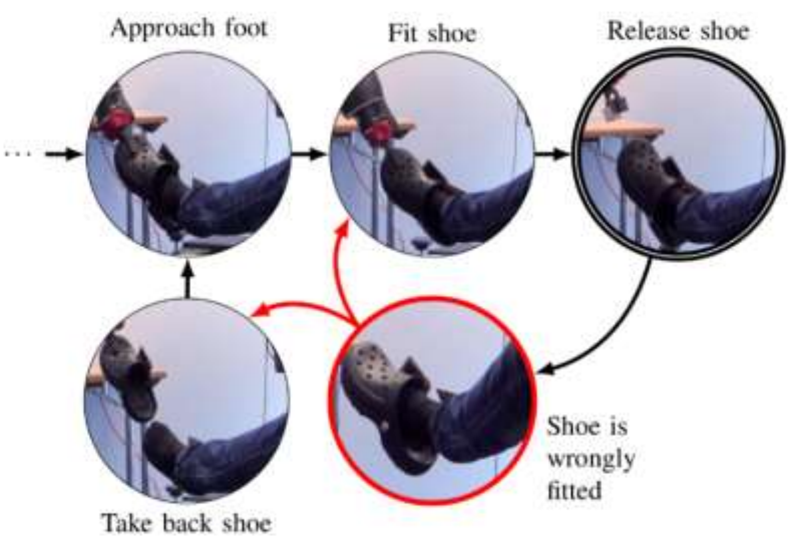
[Calinon, HFR’2016]

Assistive dressing application



I-DRESS
Assistive interactive robotic system for support in dressing

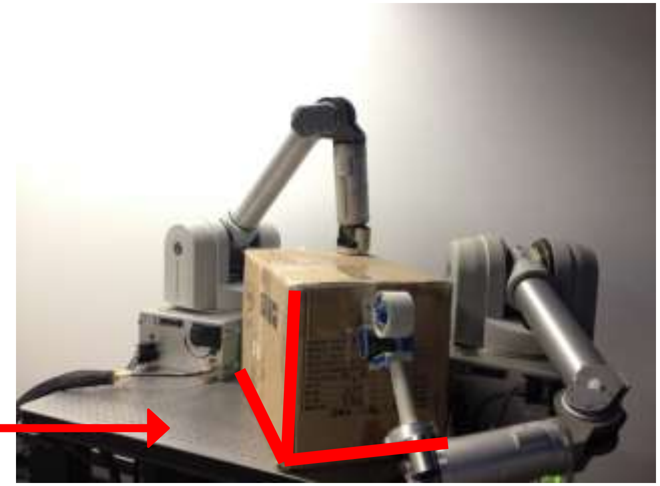
SNSF, CHIST-ERA (2015-2018)



[Canal, Pignat, Alenya, Calinon and Torras, ICRA'2018]

Adaptation to different object shapes

Coordinate system as task parameter



[Calinon, Alizadeh and Caldwell, IROS'2013]

Bimanual coordination and co-manipulation

[Silvério et al., IROS'2015]

[Rozo et al., IROS'2015]

[Rozo et al., IEEE T-RO 32(3), 2016]

ISTITUTO
ITALIANO DI
TECNOLOGIA

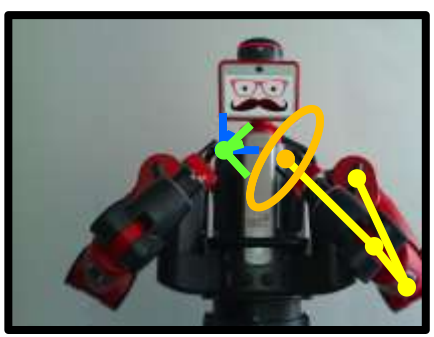
Dr Leonel Rozo

Dr João Silvério

Outline

Prior 1: Movements are smooth and continuous

Prior 2: Actions often relate to objects, tools or body landmarks



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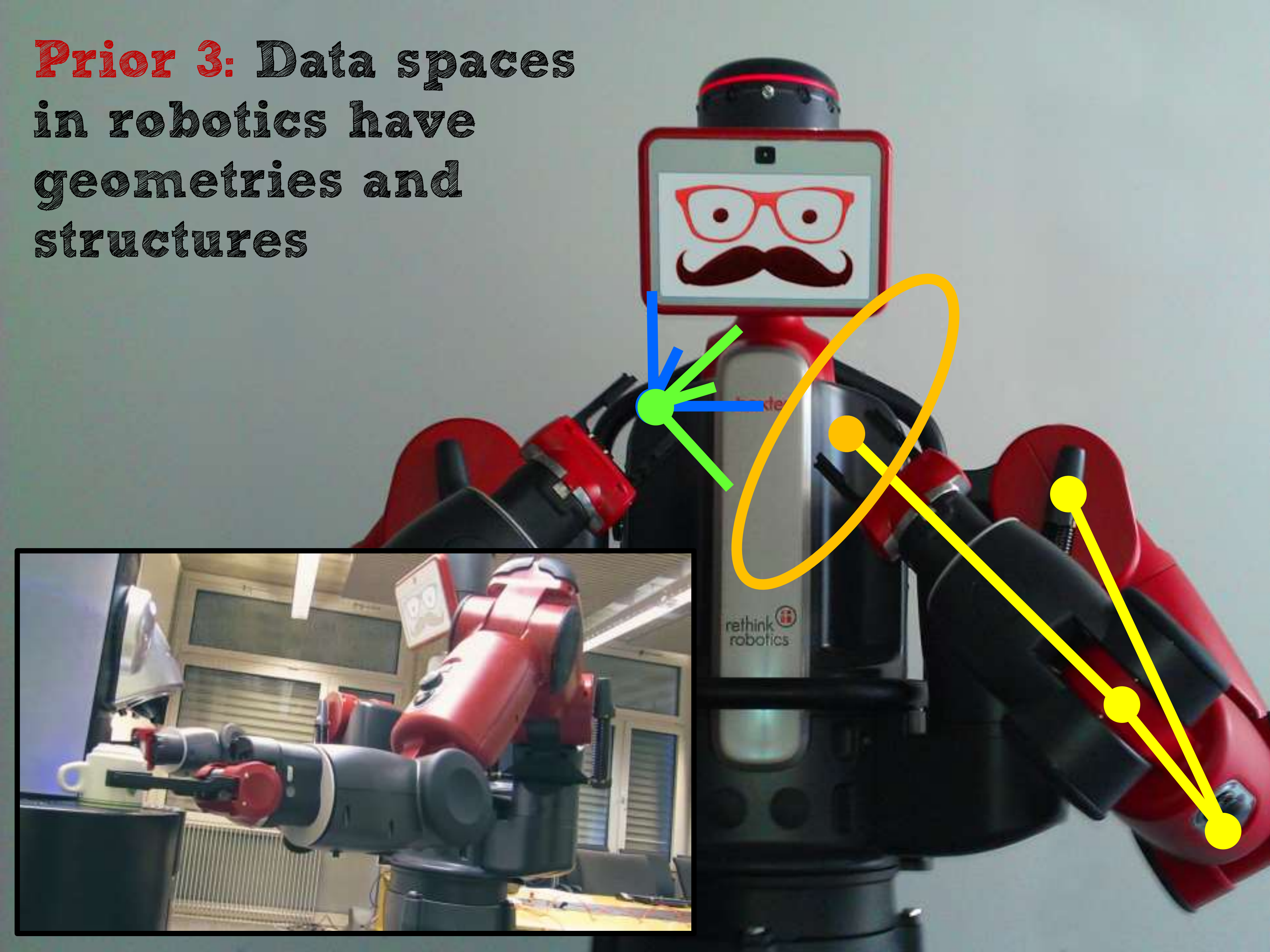
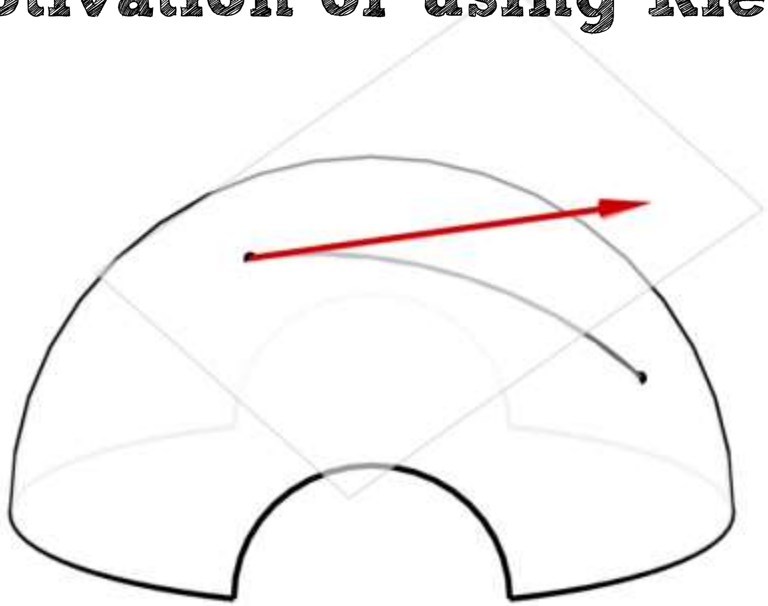
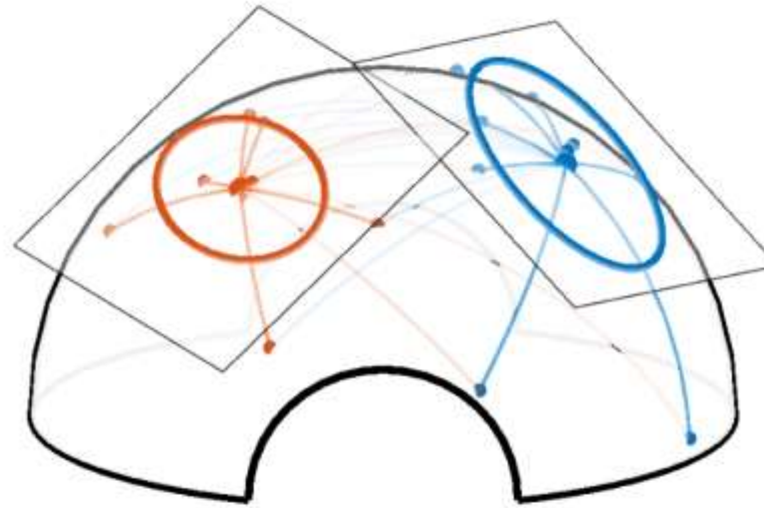


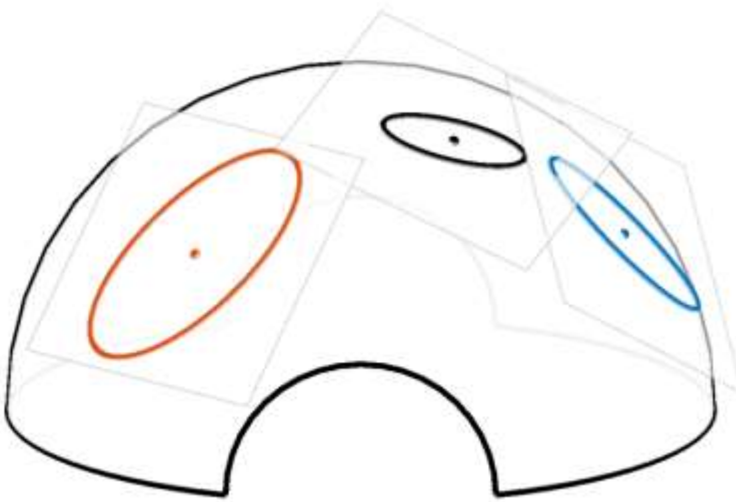
Motivation of using Riemannian manifolds



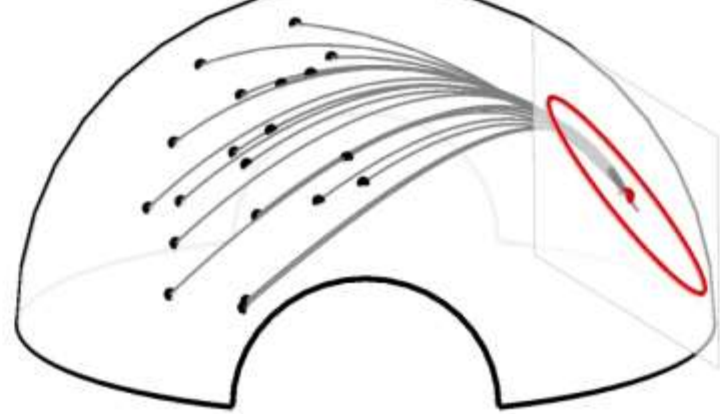
Interpolation and extrapolation



Clustering and distribution



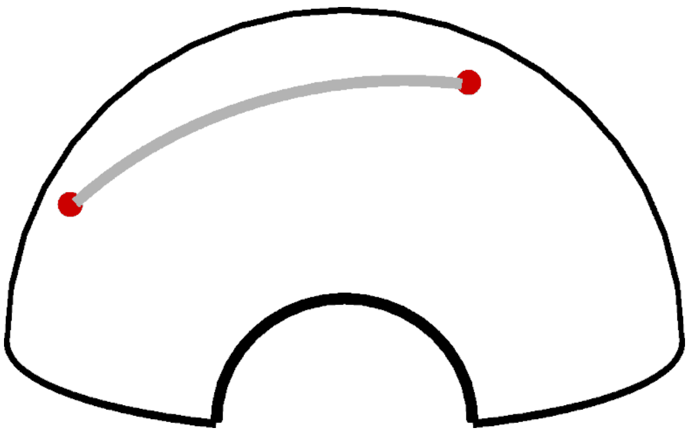
Fusion of sensing/control information

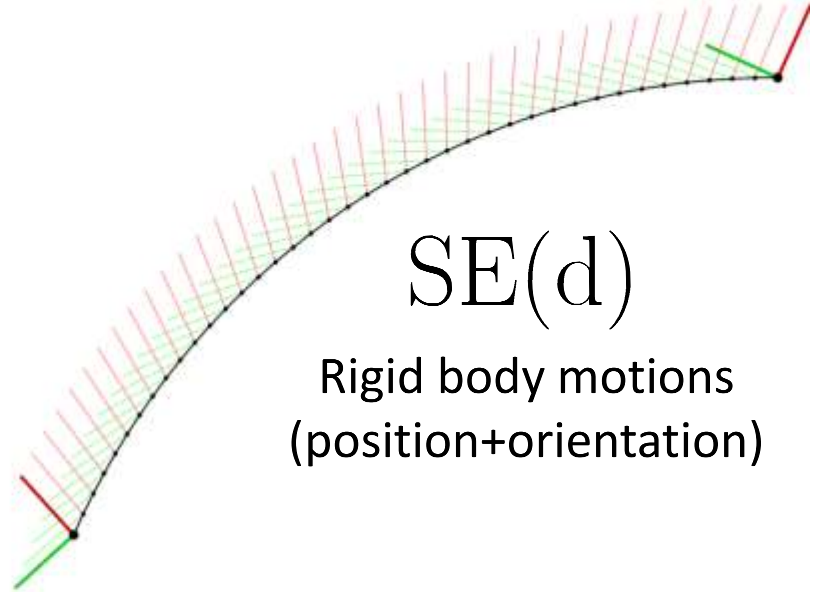


Linear quadratic tracking

Interpolation on Riemannian manifolds

Orientation
(unit quaternions) $\mathcal{S}^d$

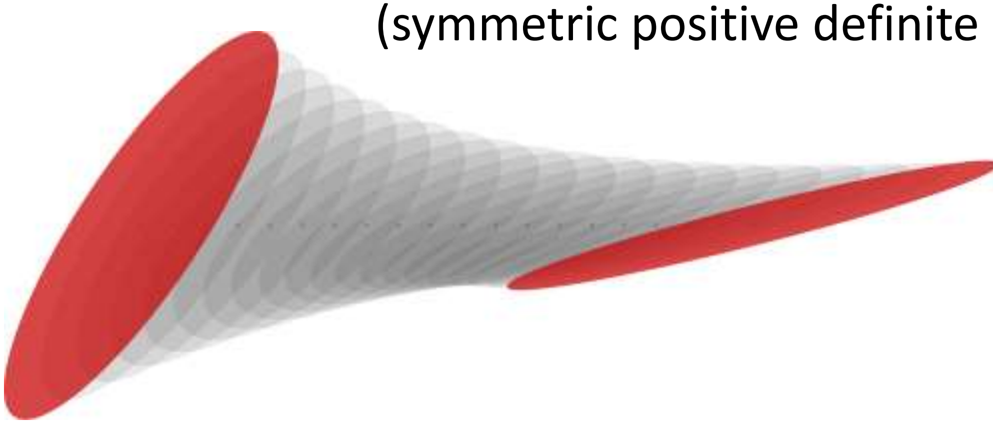


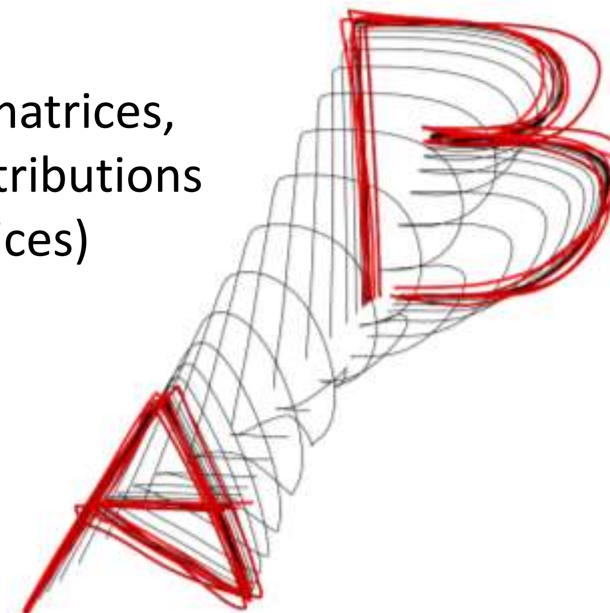


$\mathrm{SE(d)}$

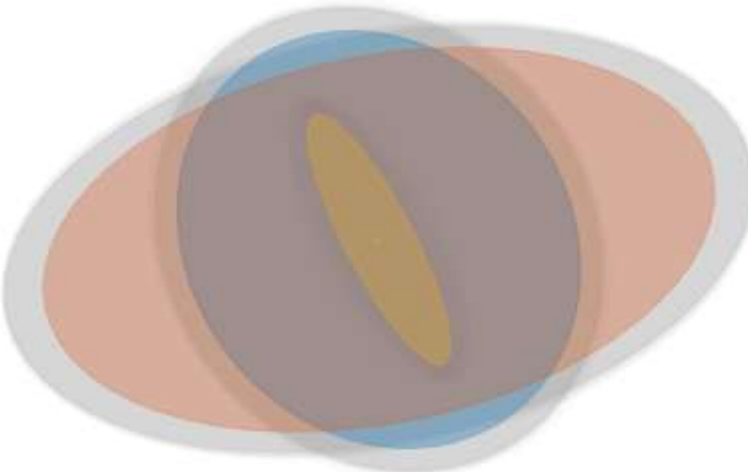
Rigid body motions
(position+orientation)

$\mathcal{S}^d_{++}$ Covariance features, inertia and gain matrices,
manipulability ellipsoids, trajectory distributions
(symmetric positive definite matrices)



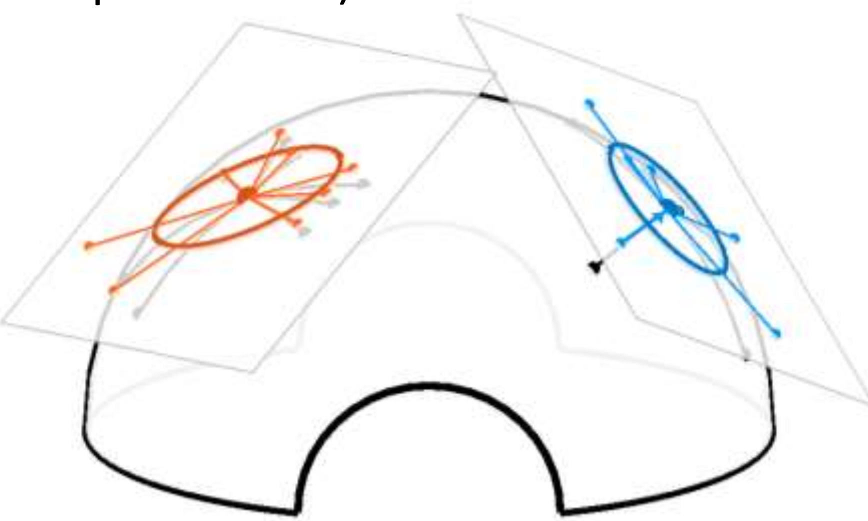


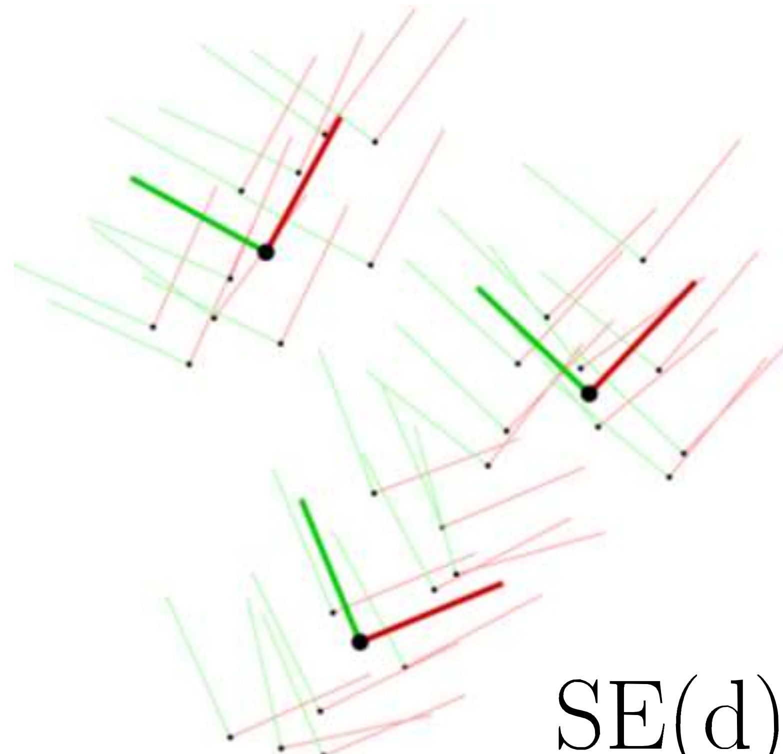
Clustering on Riemannian manifolds



$\mathcal{S}^d_{++}$ Covariance features, inertia and gain matrices, manipulability ellipsoids, trajectory distributions (symmetric positive definite matrices)

Orientation (unit quaternions) $\mathcal{S}^d$





$\mathrm{SE(d)}$

Rigid body motions (position+orientation)

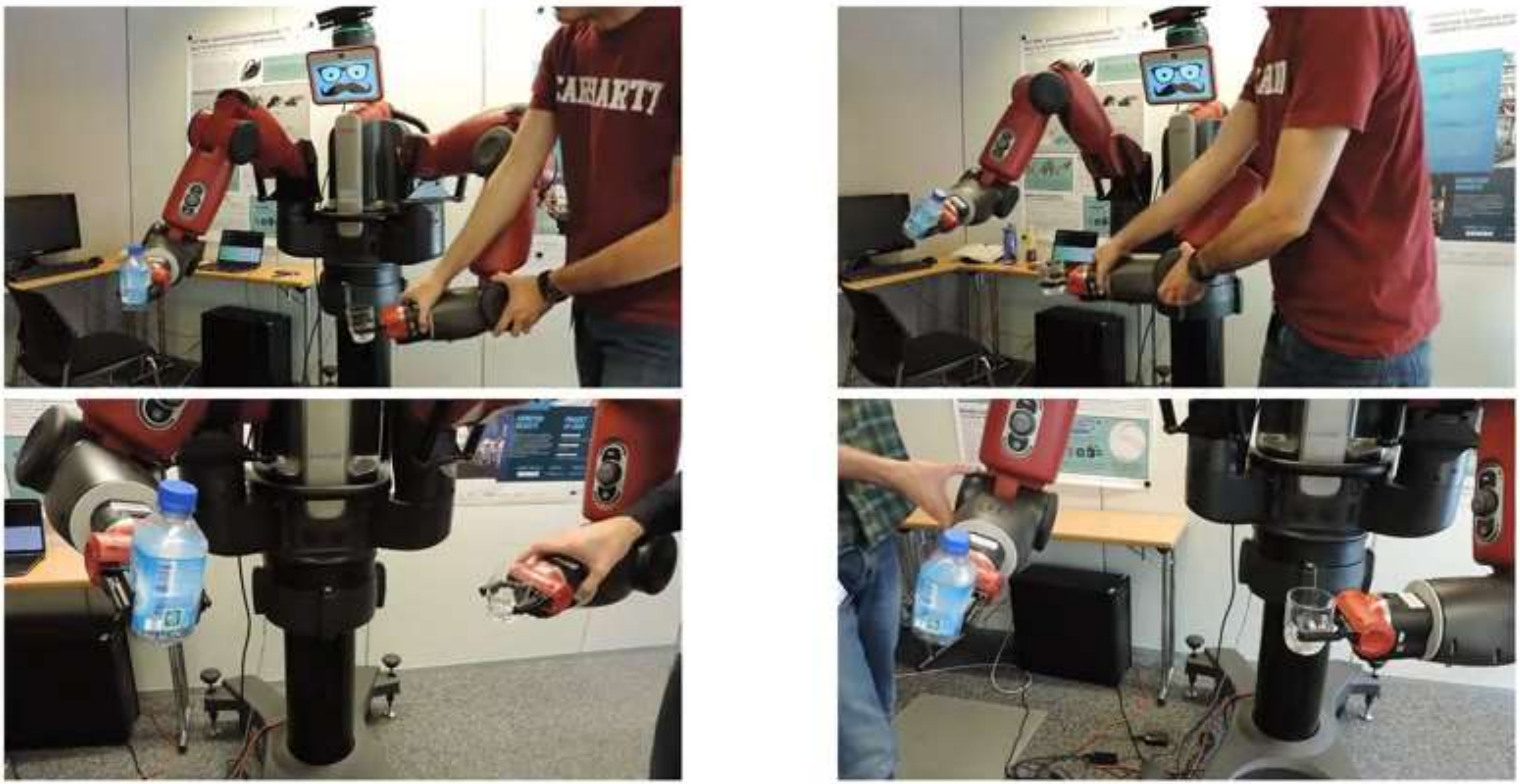
Regression with orientation and position data

Four demonstrations of coordinated bimanual movement

[Zeestraten, Havoutis, Silvério, Calinon and Caldwell, IEEE RA-L 2(3), 2017]

Regression with orientation and position data

Four reproductions with perturbations by the user

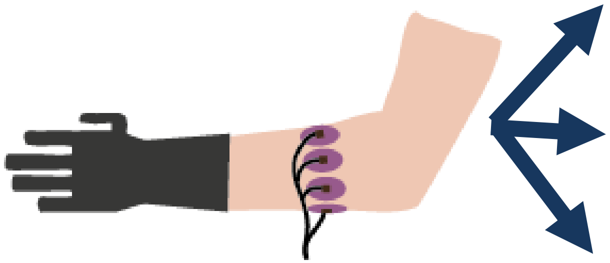


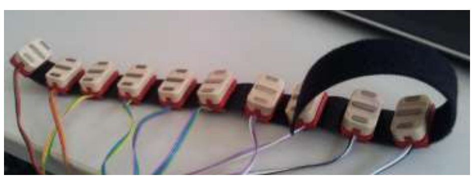
[Zeestraten, Havoutis, Silvério, Calinon and Caldwell, IEEE RA-L 2(3), 2017]

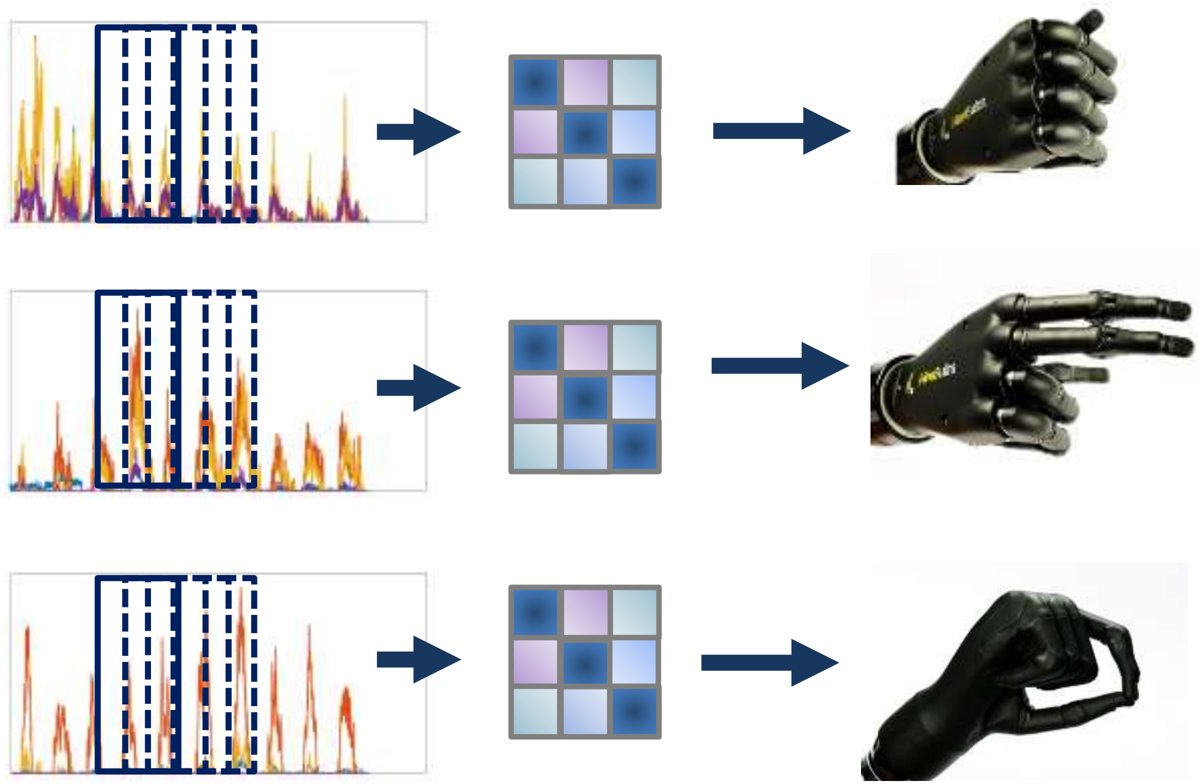
Regression with sEMG sensory data

TACT-HAND
SNSF, D-A-CH (2016-2019)

Noémie Jaquier







Surface electromyography (**sEMG**) measurements

Transformation in **spatial covariances** (SPD matrices)

Control of the corresponding hand pose

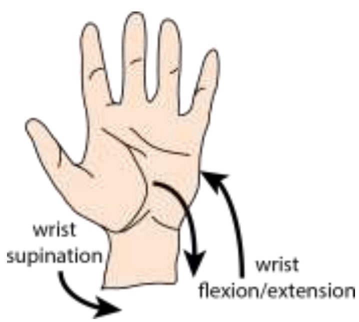
[Jaquier and Calinon, IROS 2017]

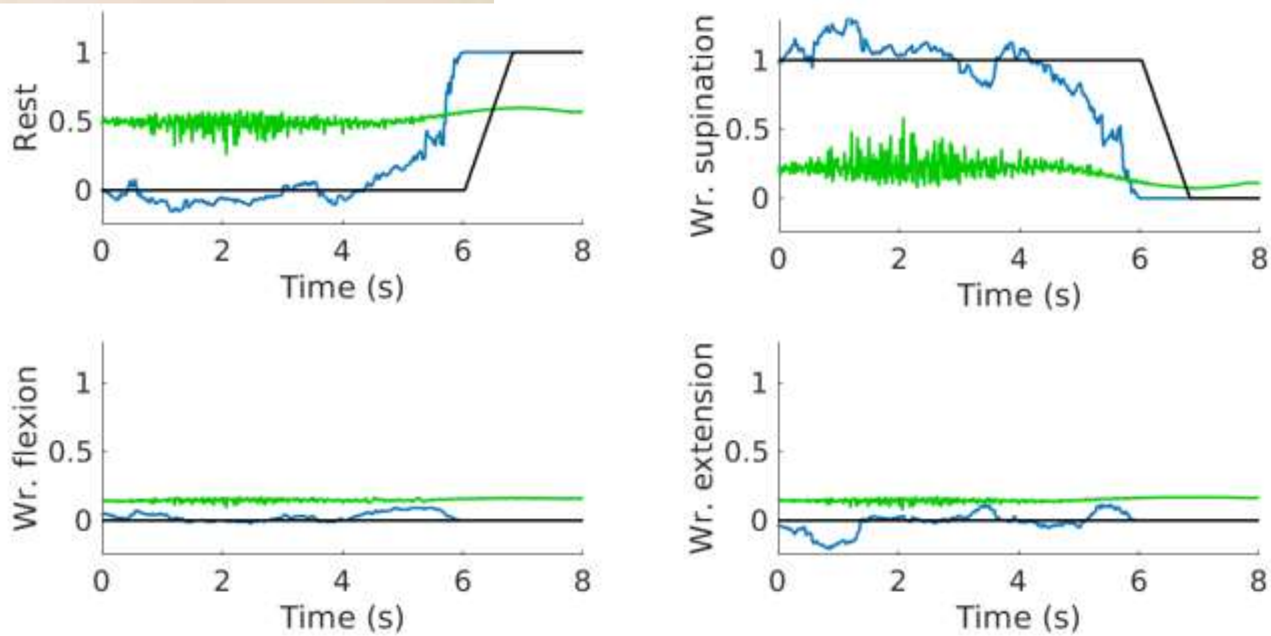
Comparison: standard GMR vs geometric GMR

sEMG data from Ninapro database processed as spatial covariances:

Input $\in \mathcal{S}_{++}^{12}$

Output $\in \mathbb{R}^4$

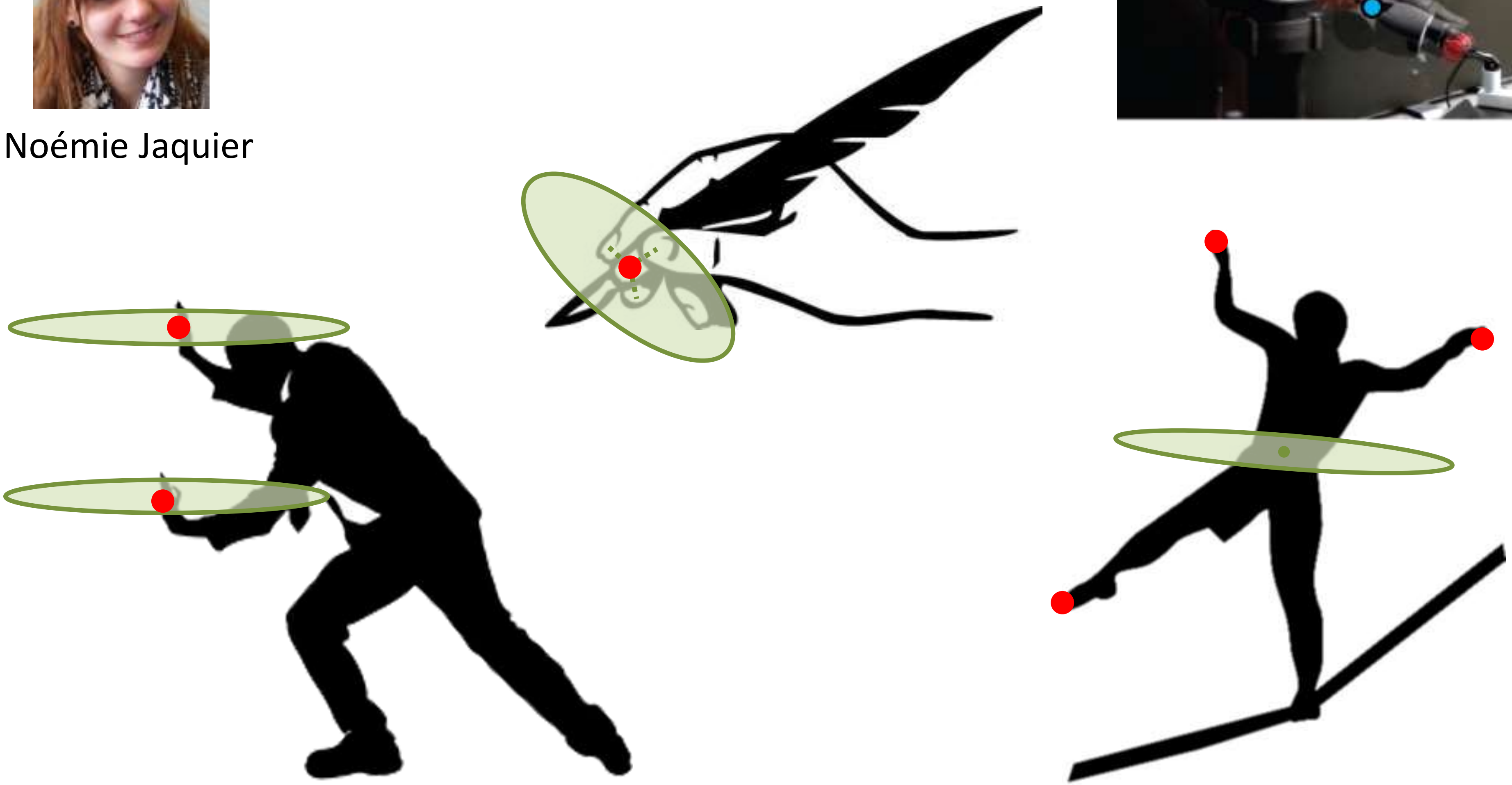


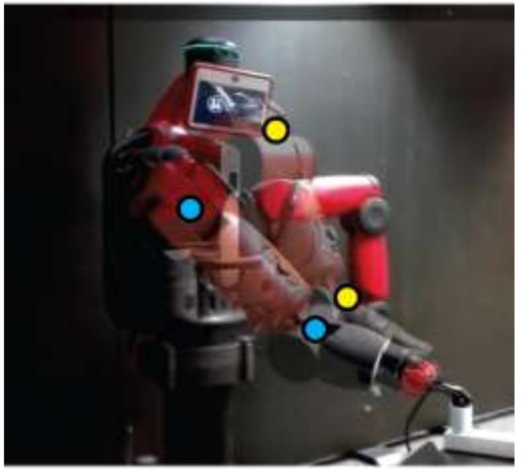


[Jaquier and Calinon, IROS 2017]

Manipulability ellipsoid tracking

Noémie Jaquier

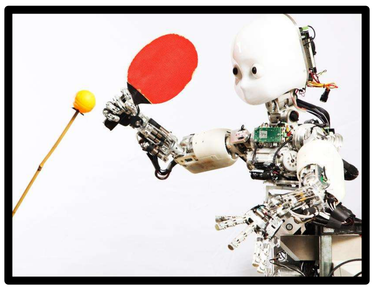




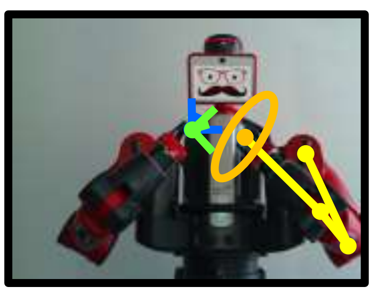
[N. Jaquier, L. Rozo, D.G. Caldwell and S. Calinon, RSS'2018]

Conclusion

Combining **statistical learning** techniques and **model predictive control** provides a generative approach to the **transfer of skills and movements**



Statistical learning in **multiple coordinate systems** can be exploited to learn robot skills and movements from few demonstrations, with **adaptation to new situations**



Robotics is rich in **structures** and **geometries** that can be exploited to acquire skills and movements from a **small set of interactions** (with user or environment)

Source codes (Matlab/Octave, C++ and Python):

http://www.idiap.ch/software/pbdlib/

Contact:

sylvain.calinon@idiap.ch

http://calinon.ch

Robot Learning & Interaction Group at Idiap:

Dr Andras Kupcsik

Dr Antonio Paolillo

Noémie Jaquier

Emmanuel Pignat

Thibaut Kulak

Nicolas Desprès

Hakan Girgin

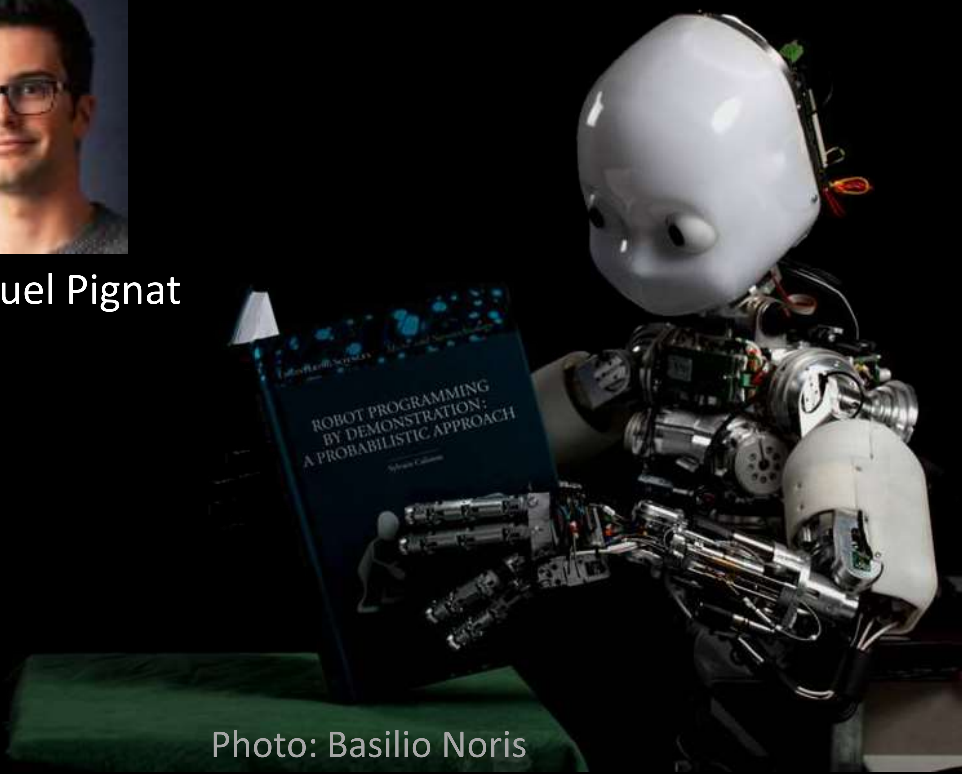


Photo: Basilio Noris