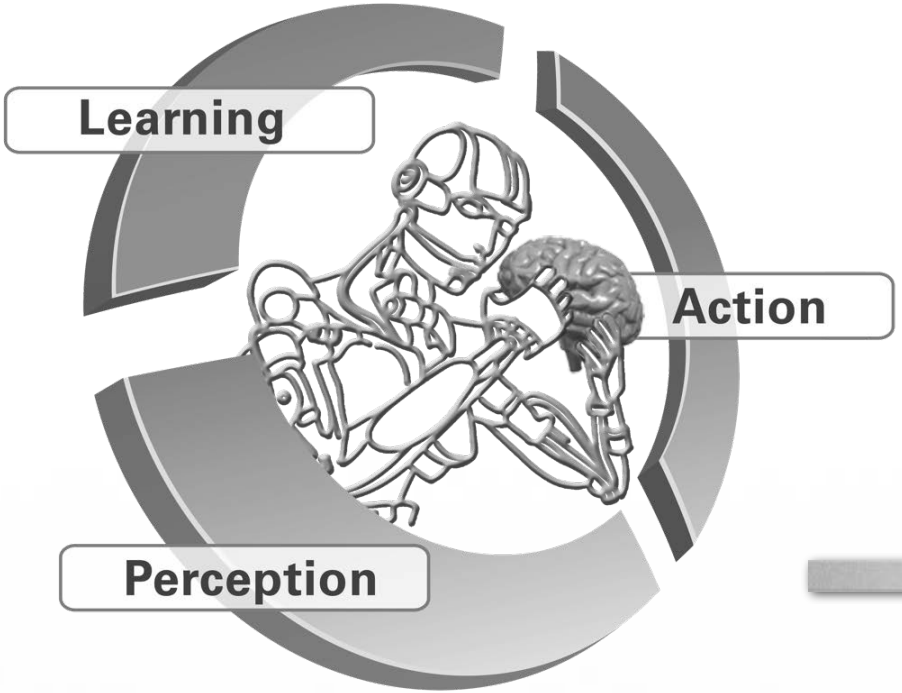

Explorations in Manipulation and Locomotion

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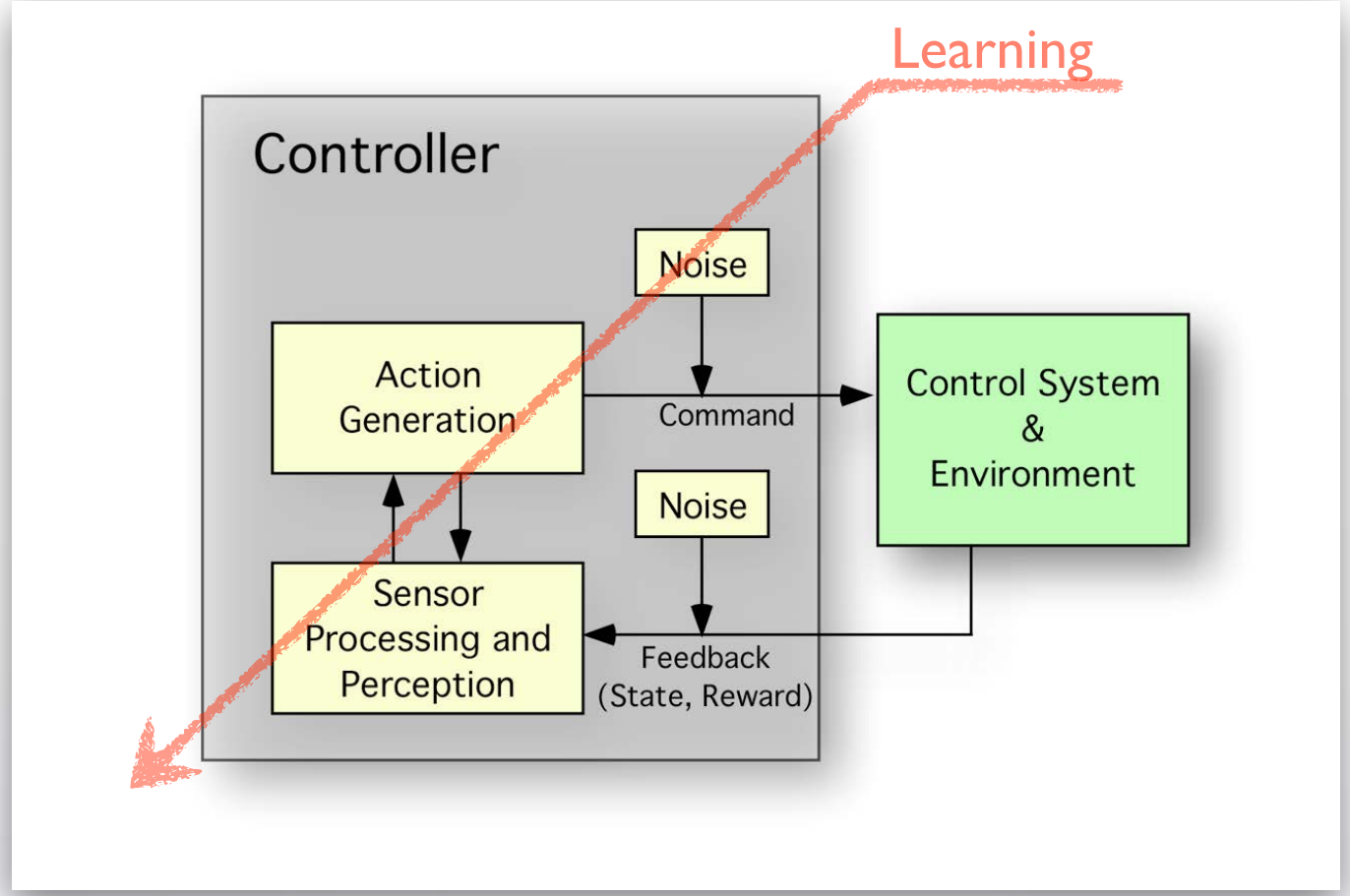
In Collaboration With:

Learning in Perception-Action Loops as Common Ground for Autonomous Systems



System Model: $\dot{\mathbf{x}} = \mathbf{f}\left(\mathbf{x}, \mathbf{u}, t, \varepsilon_{\mathbf{x}}\right)$

Observation Model: $\mathbf{y} = \mathbf{h}\left(\mathbf{x}, \mathbf{u}, t, \varepsilon_{\mathbf{y}}\right)$

Why the Divide Between Manipulation and Whole Body Control?

Equations of motion: $\mathbf{M}\ddot{\mathbf{q}} + \mathbf{h} = \mathbf{S}^T \boldsymbol{\tau} + \mathbf{J}_c^T \boldsymbol{\lambda}$

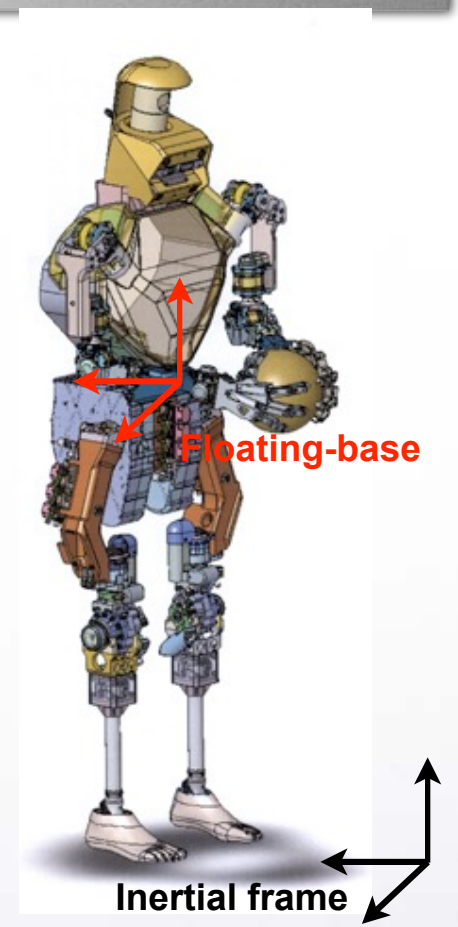
(under) actuation

contact forces

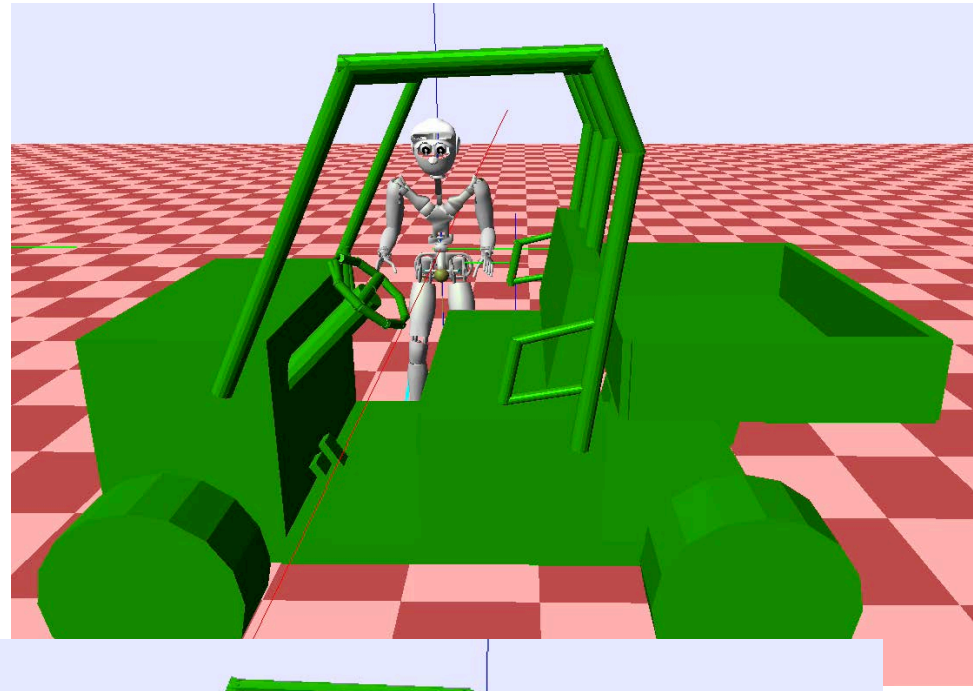
Contact constraints: $\mathbf{J}_c \ddot{\mathbf{q}} = \mathbf{b}(\mathbf{q}, \dot{\mathbf{q}})$

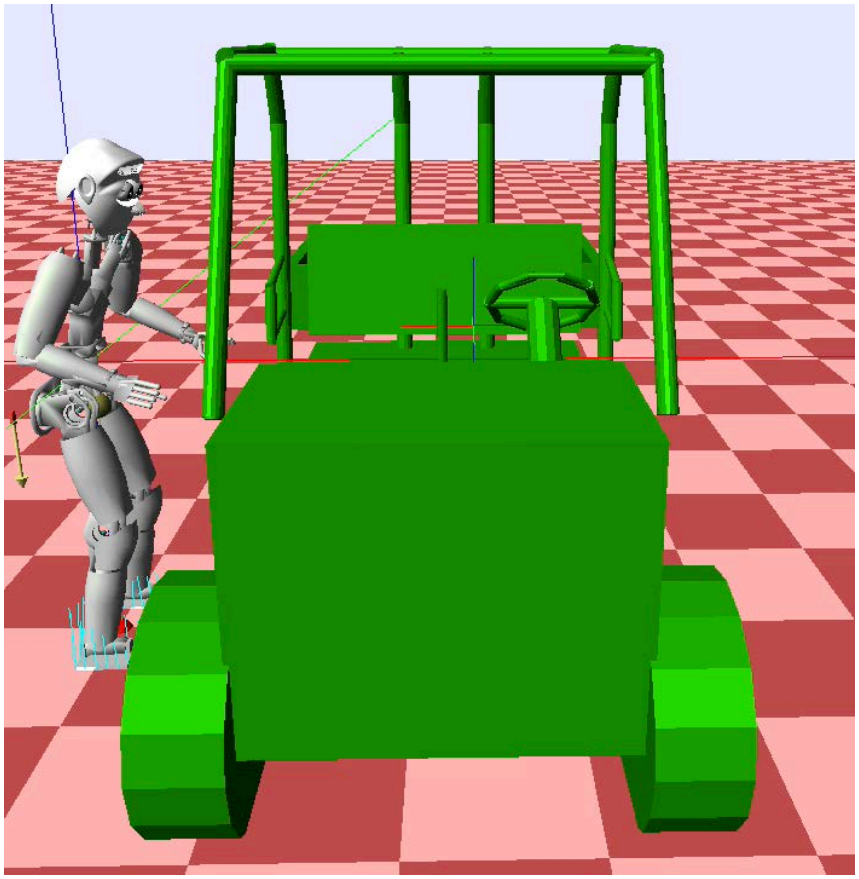
Physical limitations:
(cones of friction, center of pressure, torque saturation, joint limits, etc...)

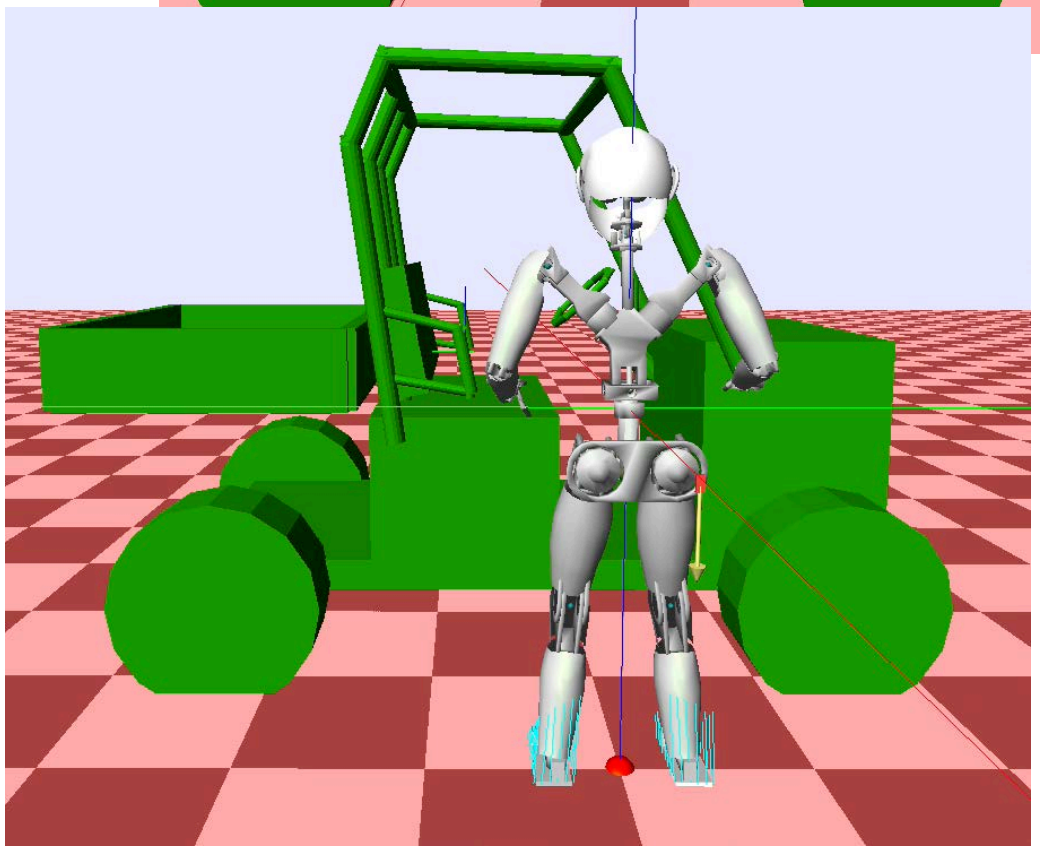
$$\mathbf{A} \begin{bmatrix} \ddot{\mathbf{q}} \\ \boldsymbol{\tau} \\ \boldsymbol{\lambda} \end{bmatrix} \leq \mathbf{b}$$



Control problem: find actuation torques to achieve a desired position/force policy





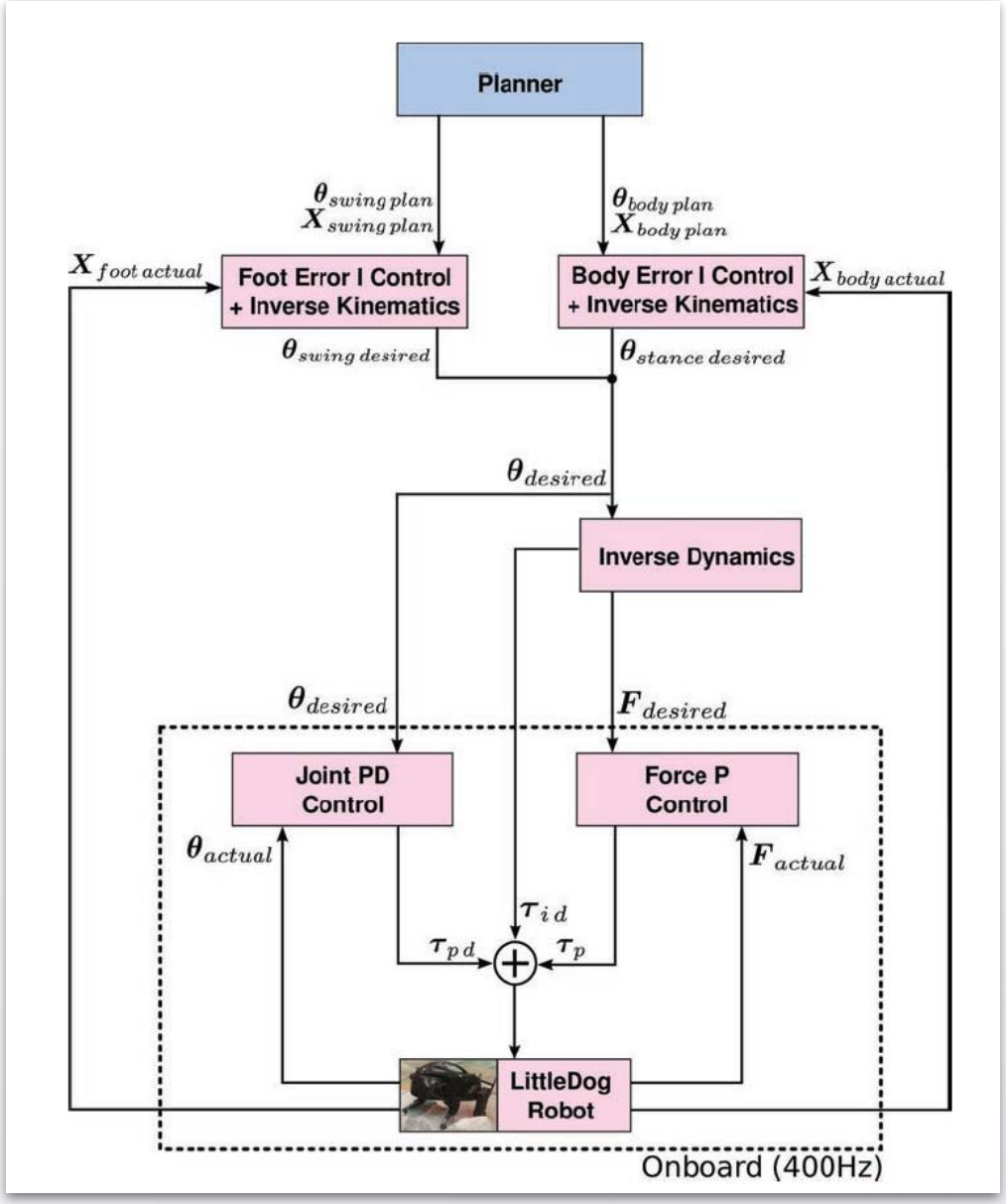


Some Example Projects

- Agile locomotion control with Little Dog
  - force control
  - model-based control
  - constraint-based planning and control
- Nonparametric foothold planning
  - Learning to score perceptual events (affordances) from rather raw sensory data
- Exploiting sensory feedback
  - Mapping sensory data directly into the control loop and switching controllers (prediction)
- Nonparametric grasp planning
  - Learning to score perceptual events (affordances) from rather raw sensory data
- Task-based control
  - hierarchies (algebraic, could also be time-based hierarchies)
  - desired task dynamics
  - constraint-based planning and control
  - force control
- Planning primitives
  - simplified models for preview planning
  - movement primitives and on-line adaptation

Little Dog Control

- Some key features
  - on-line corrections of plans (integral controllers)
  - Model-based inverse dynamics control
  - Constraint-based control
  - Contact prediction and control, i.e., force control
  - Fast control loop for balance/ force control, while slower planning loop

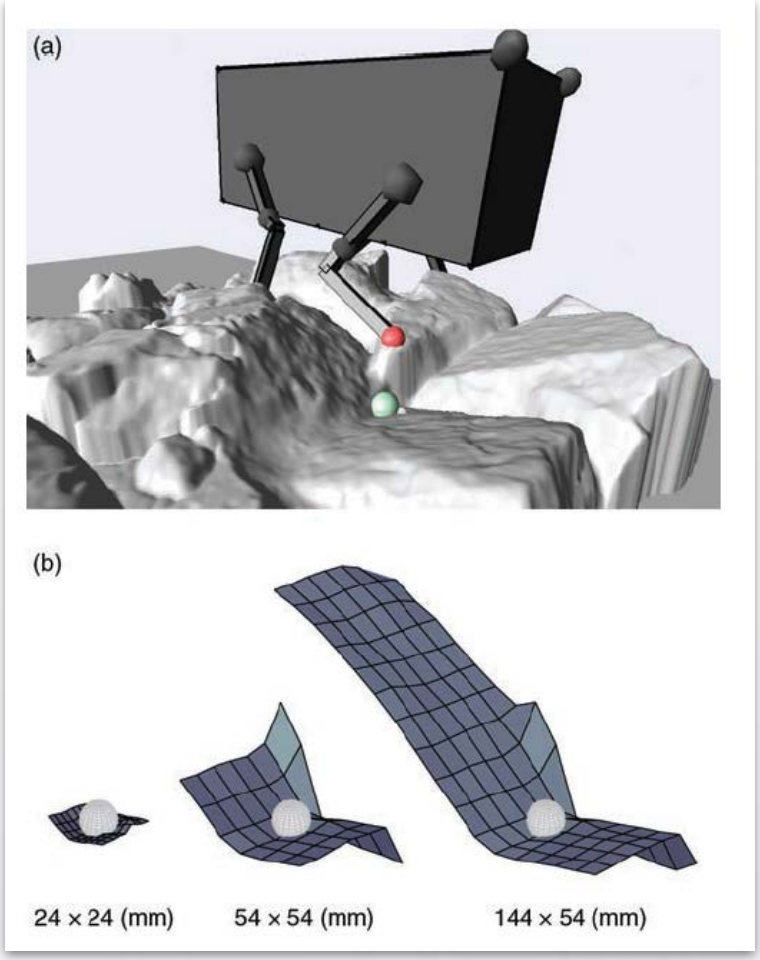


Example: Compliant Task Space Control

Mrinal Kalakrishnan, Jonas Buchli, Peter Pastor, Michael Mistry

Nonparametric Foothold Planning

- Some key features
  - Rather direct 3D perception of terrain (raw sensory data)
  - Foothold templates (foothold affordances)
  - Machine learning to score templates
  - Can be an ever adjusting number of templates (nonparametric)
  - Avoids human feature design (although manual features can improve performance)

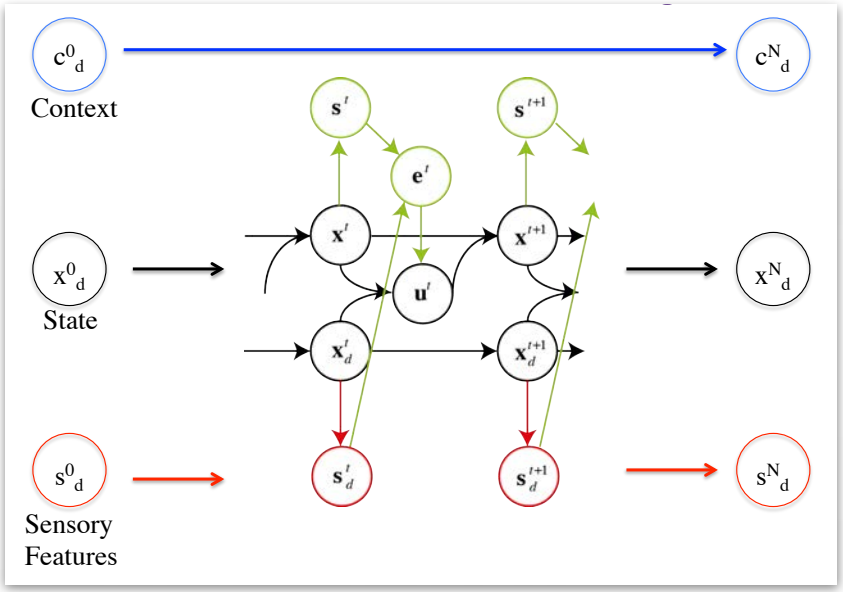


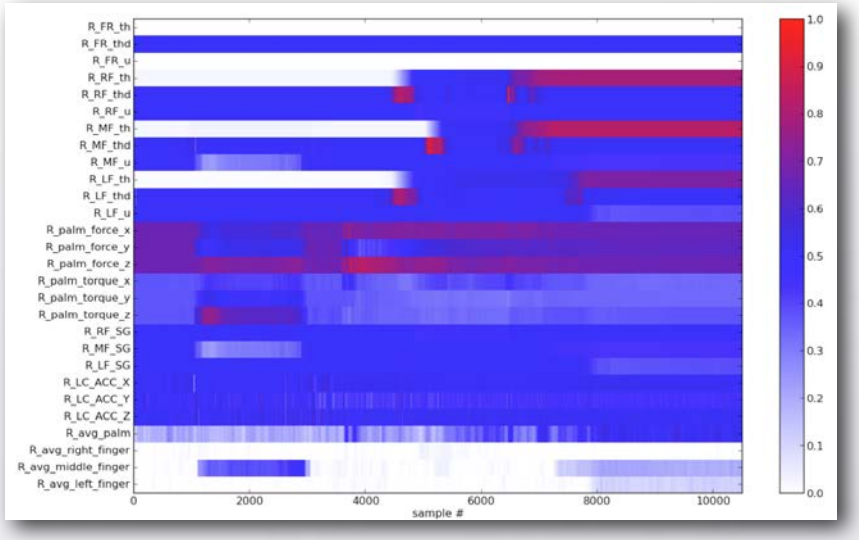
Example: Walking Over Rough Terrain

Mrinal Kalakrishnan, Jonas Buchli, Peter Pastor, Michael Mistry

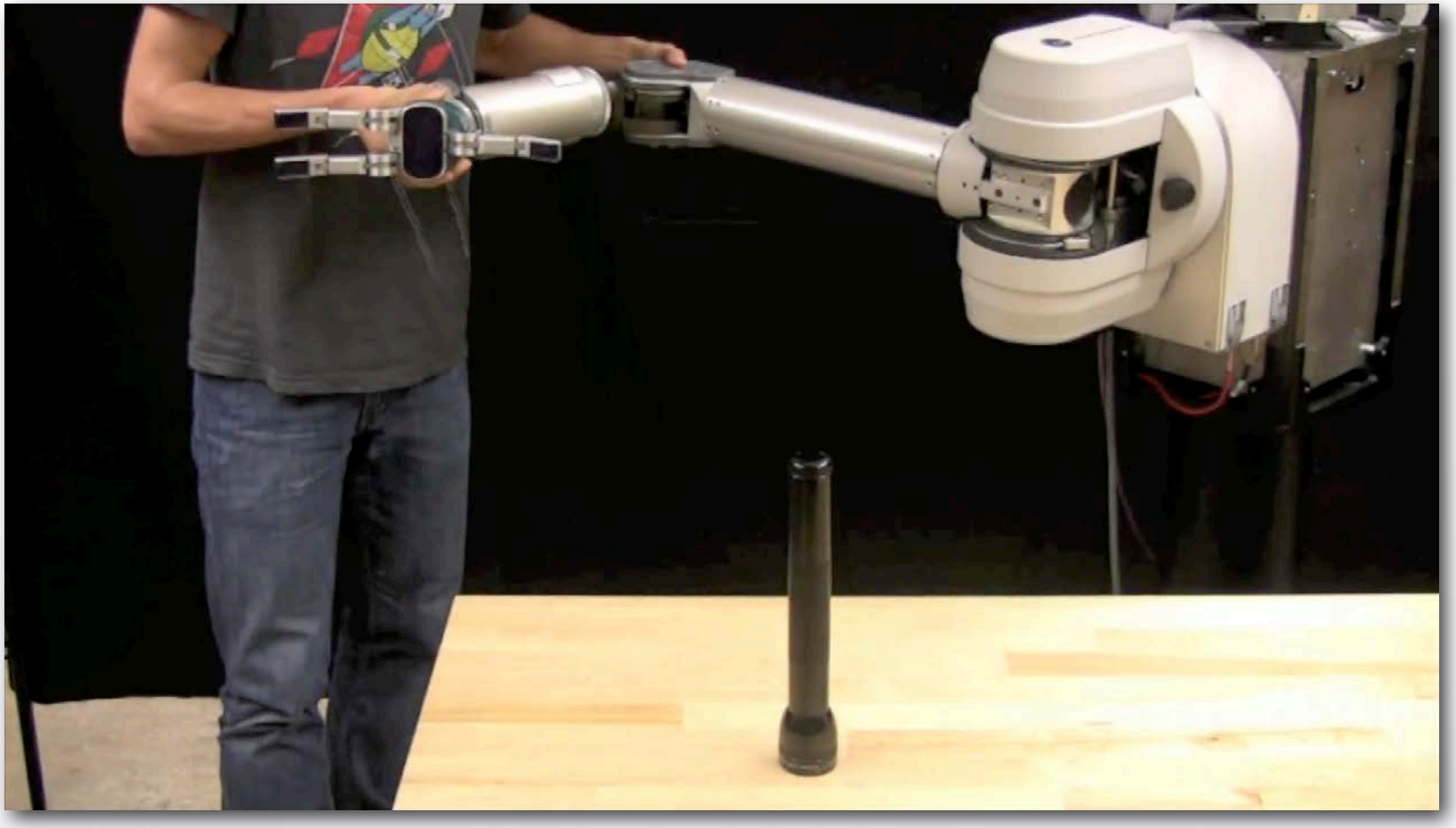
Exploiting Sensory Feedback

- Some key features
  - Remember (associate) all sensory data with movement trajectories (skills)
  - Raw data and manual features
  - Exploit to create on-line
    - feedback correction
    - switching
    - prediction
    - sequential planning
  - a modest “big data” approach to robotics?
  - explored in manipulation, but should extend to locomotion/ whole body control





Example: On-line Correction of Grasping Given Misperceived Object

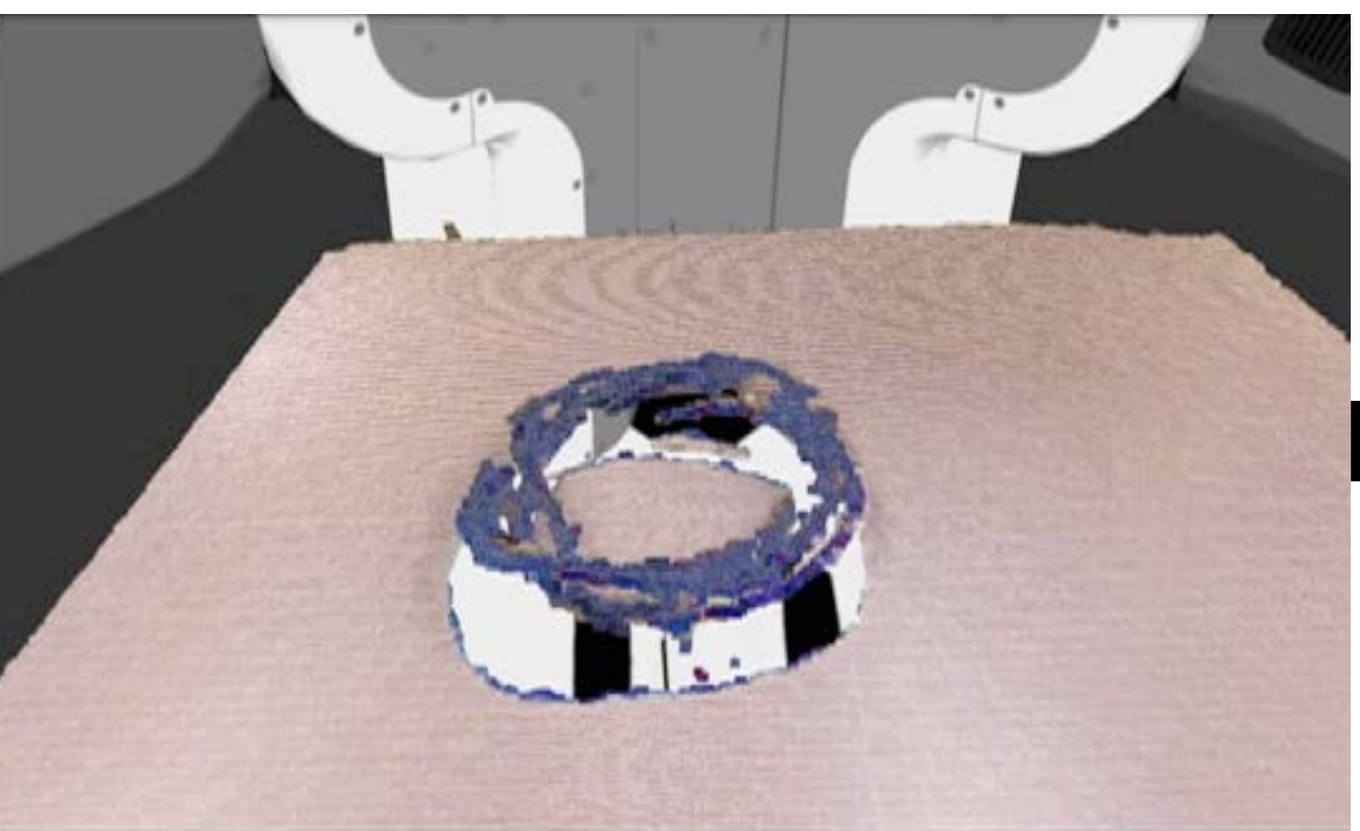


Peter Pastor, Mrinal Kalakrishnan, Ludovic Righetti

Template-based Grasp Selection

no object model, just point cloud

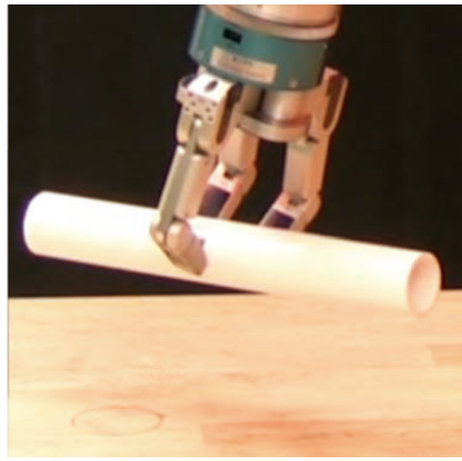
necessary component: find **6d gripper pose** and **joint configuration** on object



?

Template-based Grasp Selection

similarly shaped objects ⟶ similar grasps



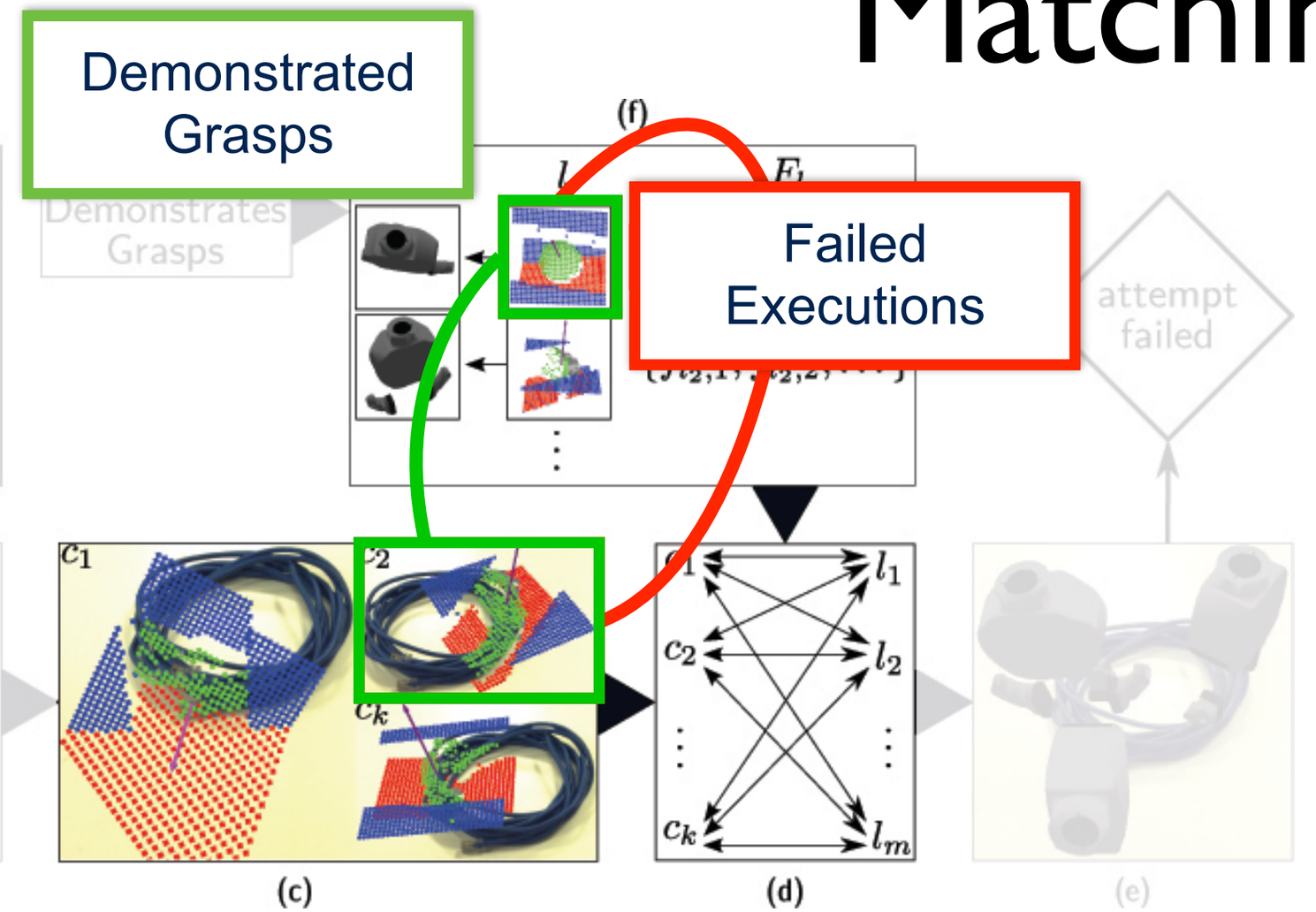
object shape encoded by
local grasp shape descriptor

library of grasp **templates** is
stored from user demonstrations

apply learned grasps to
unknown objects

improves over time

Matching



Compute Similarities

$\alpha =$ Sample & Demonstration

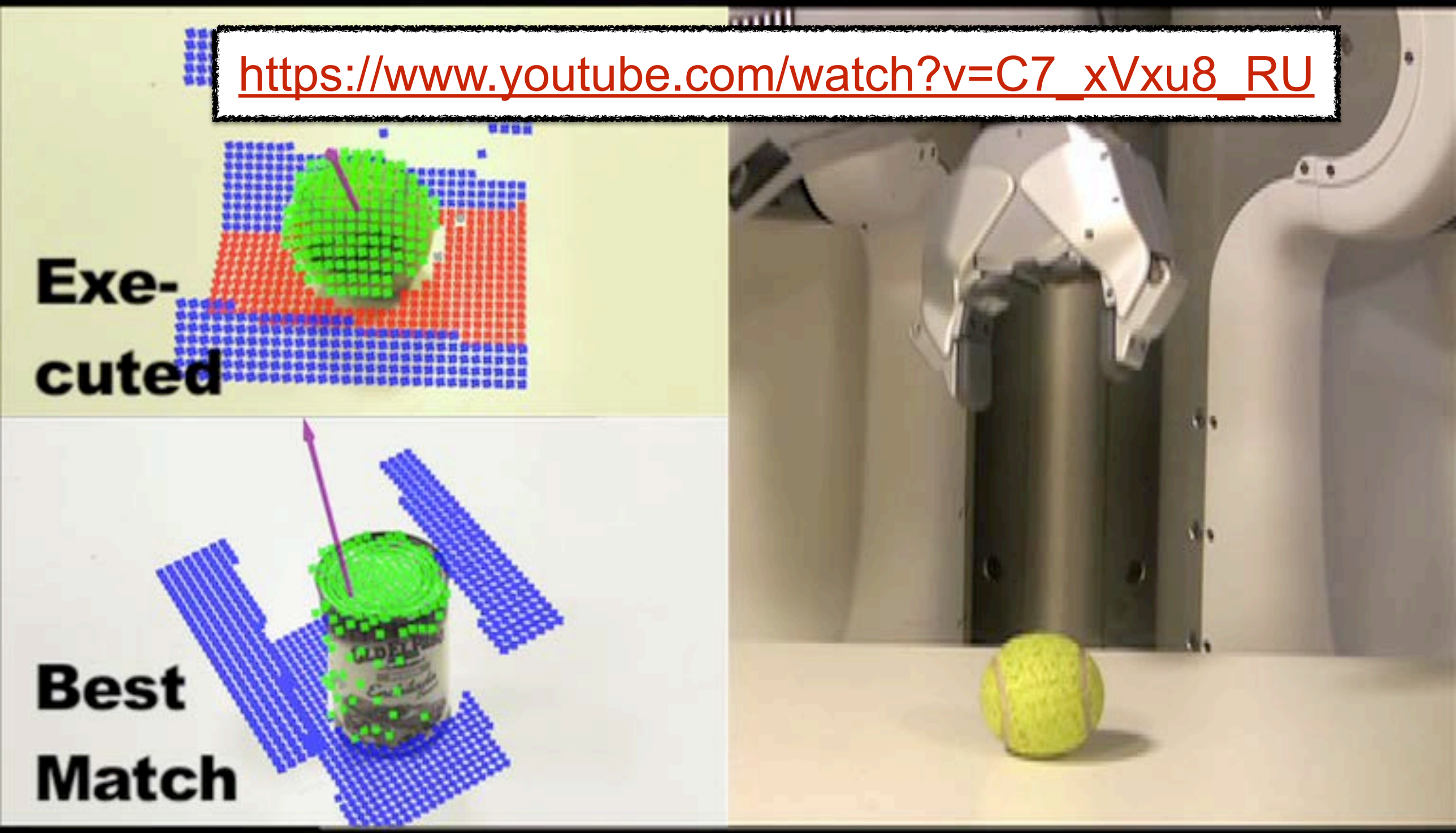
$\beta =$ Sample & Failures

$\gamma =$ Failure & Demonstration

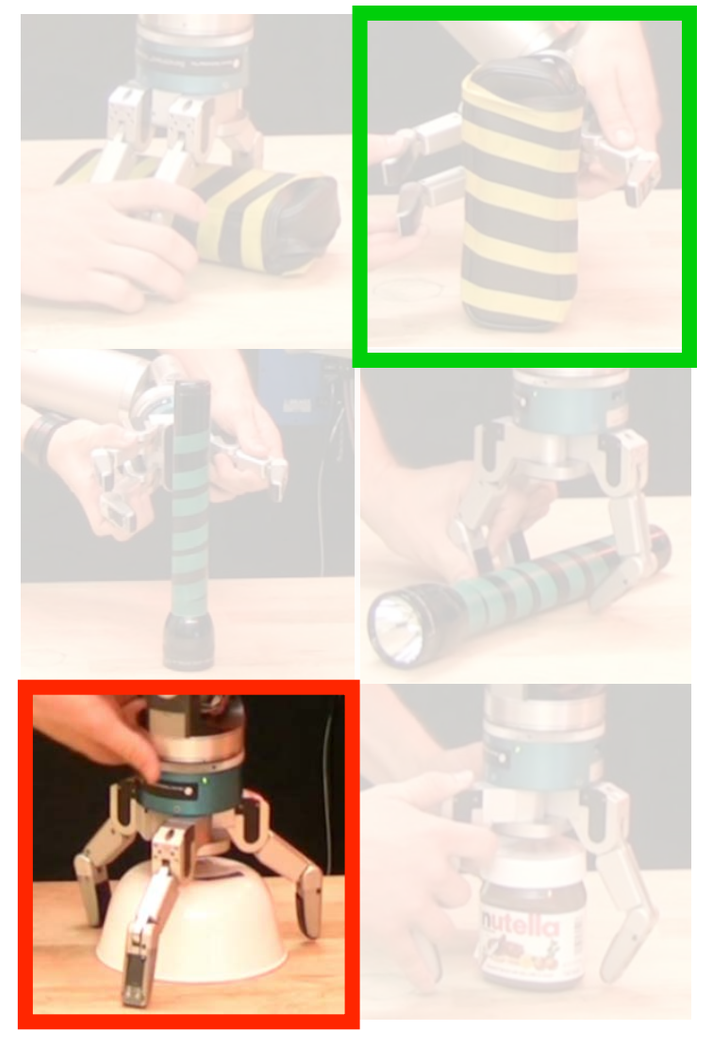
$$\mathrm{m}(\mathbf{c}, \mathbf{l}, \mathbf{F_l}) = \frac{\alpha}{[1 - \exp(-\mathrm{k}_1 \beta^2)][1 - \exp(-\mathrm{k}_2 \gamma^2)]}$$

[Herzog et al., Auton. Rob, 2014]

https://www.youtube.com/watch?v=C7_xVxu8_RU



Improvement using Feedback on Barrett WAM robot



improvement over
30% after 39 trials

autonomously adapts to
more stable grasps

[Herzog et al., Auton. Rob, 2014]

- inspired by little dog footstep selection
- (object-) model free approach
- rough contact shape with template grasp
- control impedance at fingers (compliance)
- library from user demonstration

team work!

Movement Generation and Control Group

Ludovic Righetti

Alexander Herzog

Nick Rotella

Brahayam Ponton

Sean Mason

Felix Grimminger

MAX-PLANCK-GESELLSCHAFT

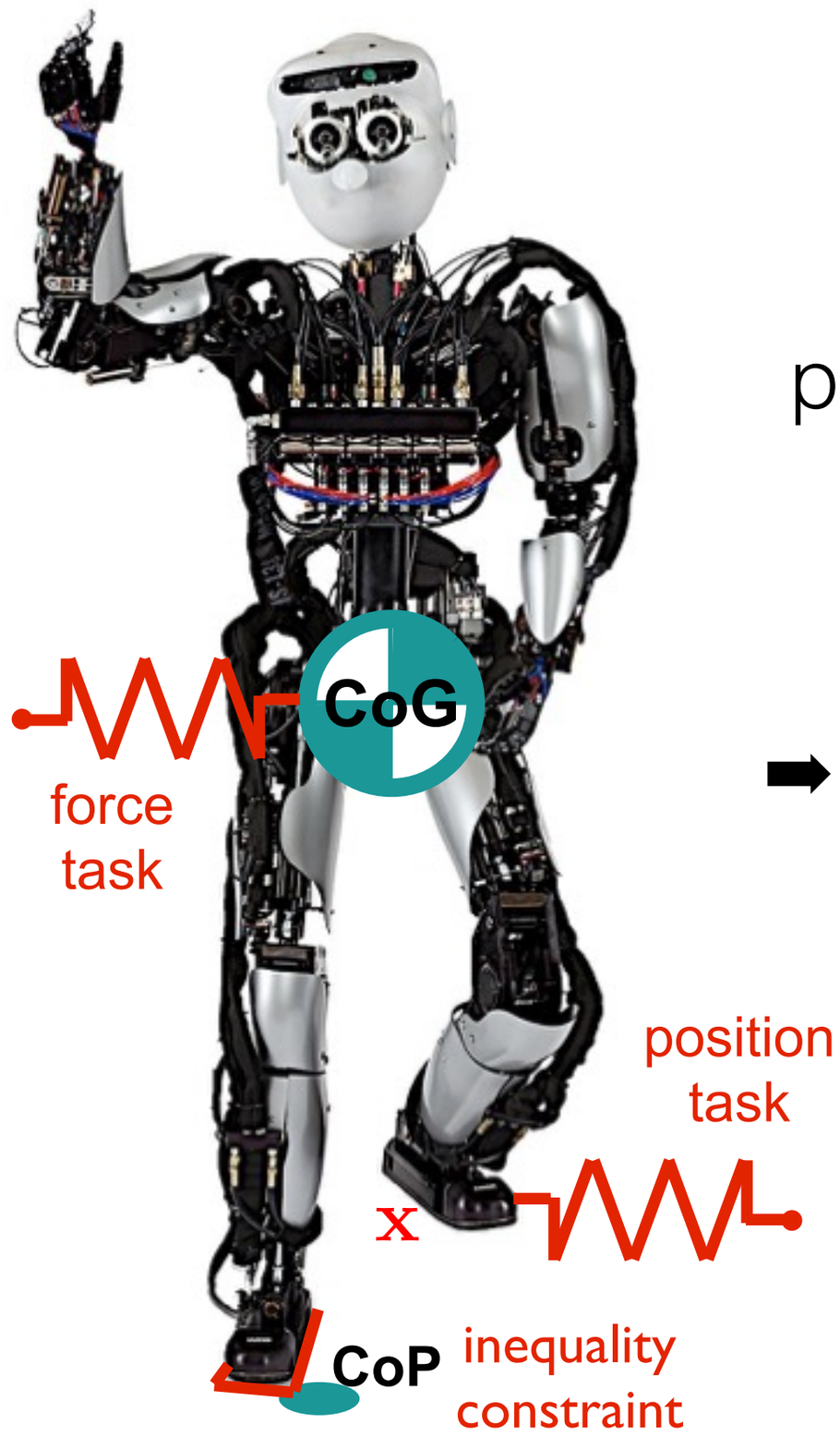
European Research Council

Established by the European Commission

Conflicting Tasks

task vs task

➡ weights



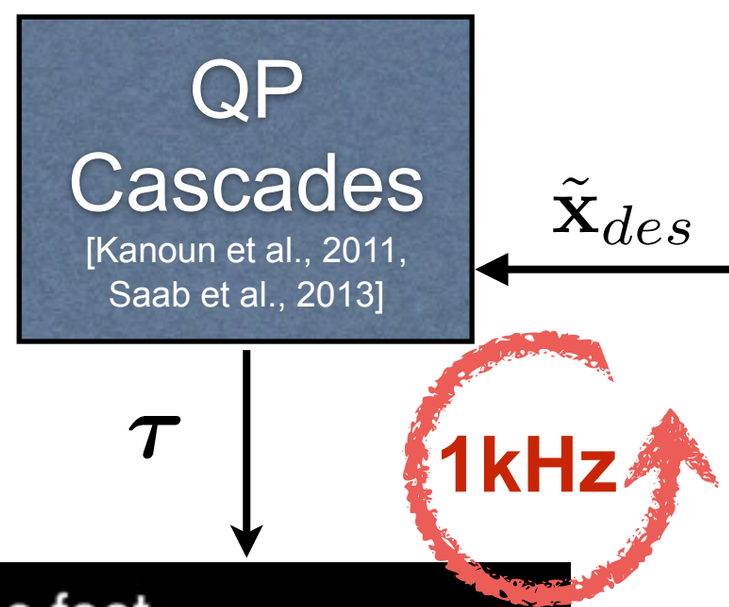
physical constraint
vs
task

➡ hierarchies

Balancing in Single Support

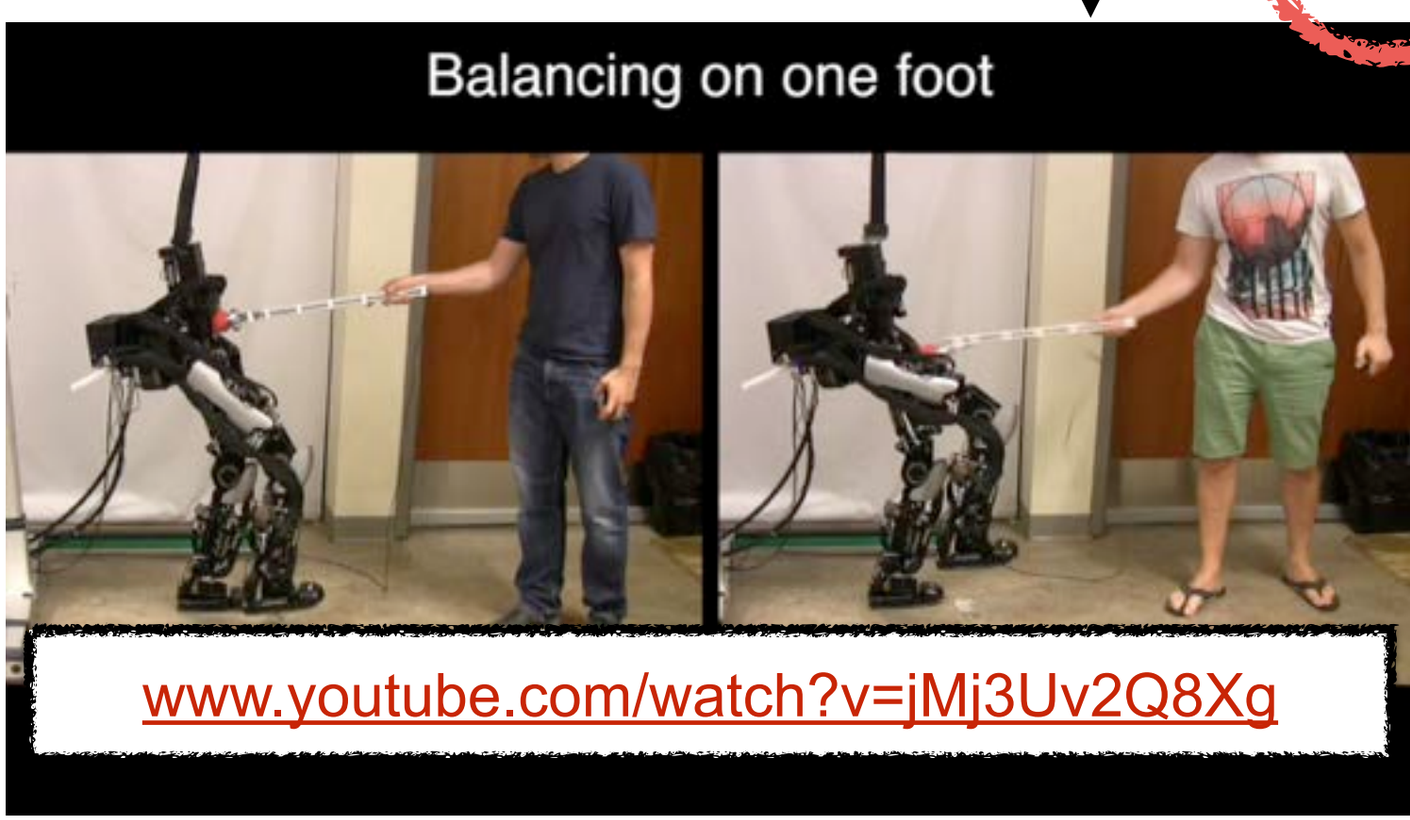
[Herzog, Righetti et al., IROS, 2014]

- feedback in task space
- no joint stabilization
- consistent optimization problem



Task Hierarchy

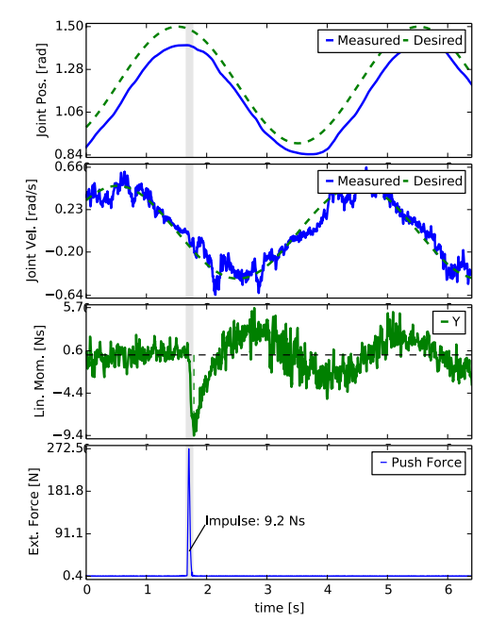
1. $\mathbf{M}\ddot{\mathbf{q}} + \mathbf{h} = \mathbf{S}^T\boldsymbol{\tau} + \mathbf{J}_c^T\boldsymbol{\lambda}$, torque limits
2. **admissible contact forces**, acceleration limits
3. swing leg, posture and **momentum control**
4. Regularization on forces



joint pos. & vel. tracking

momentum tracking

push force



Momentum-based control as a LQR problem

1 Coupling between angular and linear momentum through contact forces

$$\dot{\mathbf{h}} = \begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & \dots \\ [\mathbf{x}_{cog} - \mathbf{x}_i]_\times & \mathbf{I}_{3\times3} & \dots \end{bmatrix} \boldsymbol{\lambda} + \begin{bmatrix} m\mathbf{g} \\ \mathbf{0} \end{bmatrix}$$

momentum rate of change

sum of forces (upper)
sum of moments (lower)

interaction forces

2 In practice different gains are necessary for different robot configurations (one foot vs. two feet support)

What are the optimal contact forces to achieve a desired momentum tracking performance?

Momentum-based control as a LQR problem

$$\dot{\mathbf{h}} = \begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & \dots \\ [\mathbf{x}_{cog} - \mathbf{x}_i]_\times & \mathbf{I}_{3\times3} & \dots \end{bmatrix} \boldsymbol{\lambda} + \begin{bmatrix} m\mathbf{g} \\ \mathbf{0} \end{bmatrix} \quad \begin{matrix} \text{(linear)} \\ \text{(angular)} \end{matrix}$$

$$m\dot{\mathbf{x}}_{com} = \mathbf{h}_{lin}$$

Interaction forces as the control input

Desired performance

$$\min \begin{bmatrix} \mathbf{x}_{com} \\ \mathbf{h} \end{bmatrix}^T \mathbf{Q} \begin{bmatrix} \mathbf{x}_{com} \\ \mathbf{h} \end{bmatrix} + \boldsymbol{\lambda}^T \mathbf{R} \boldsymbol{\lambda}$$

Linearization of the dynamics to compute optimal feedback control

$$\boldsymbol{\lambda} = -\mathbf{K} \begin{bmatrix} \mathbf{x}_{cog} \\ \mathbf{h} \end{bmatrix} + \mathbf{k}(\mathbf{x}_{ref}, \mathbf{h}_{ref})$$

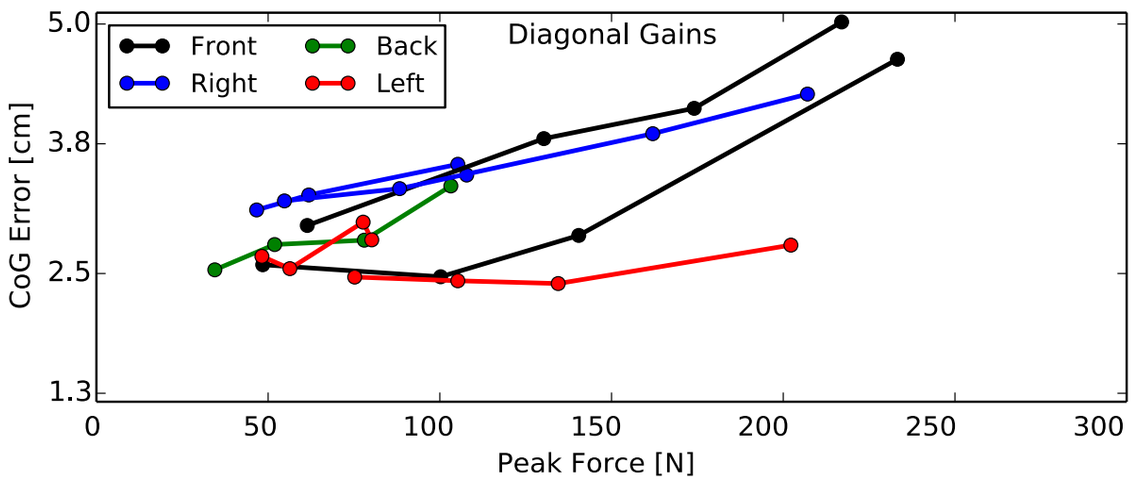
Use control law to define desired closed-loop behavior of the momentum task

$$\begin{bmatrix} \mathbf{I}_{3\times3} & \mathbf{0}_{3\times3} & \dots \\ [\mathbf{x}_i - \mathbf{x}_{cog}]_\times & \mathbf{I}_{3\times3} & \dots \end{bmatrix} \left(\boldsymbol{\lambda} + \mathbf{K} \begin{bmatrix} \mathbf{x}_{cog} \\ \mathbf{h} \end{bmatrix} - \mathbf{k} \right) = 0$$

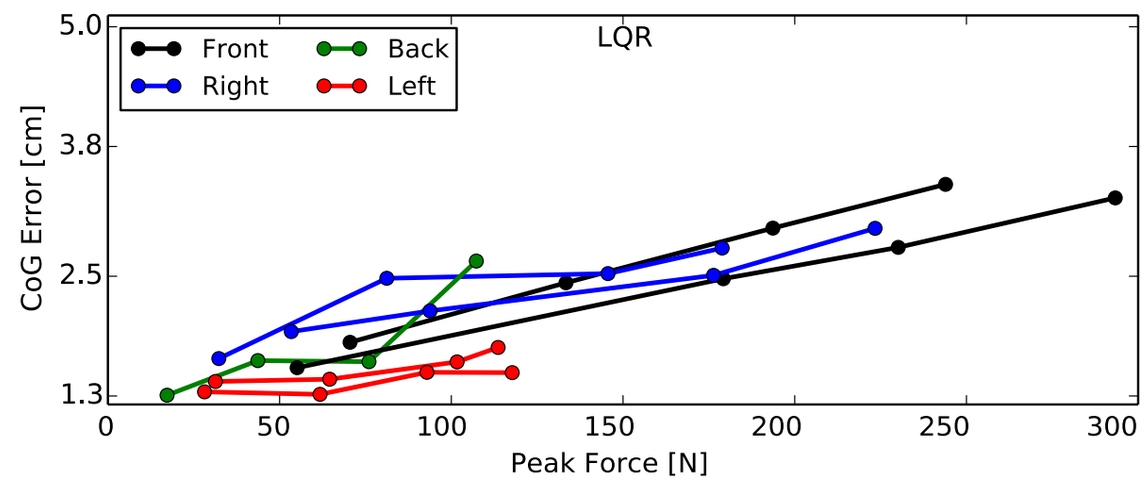
Balance control with LQR momentum control

[Herzog et al., accepted]

Original momentum task

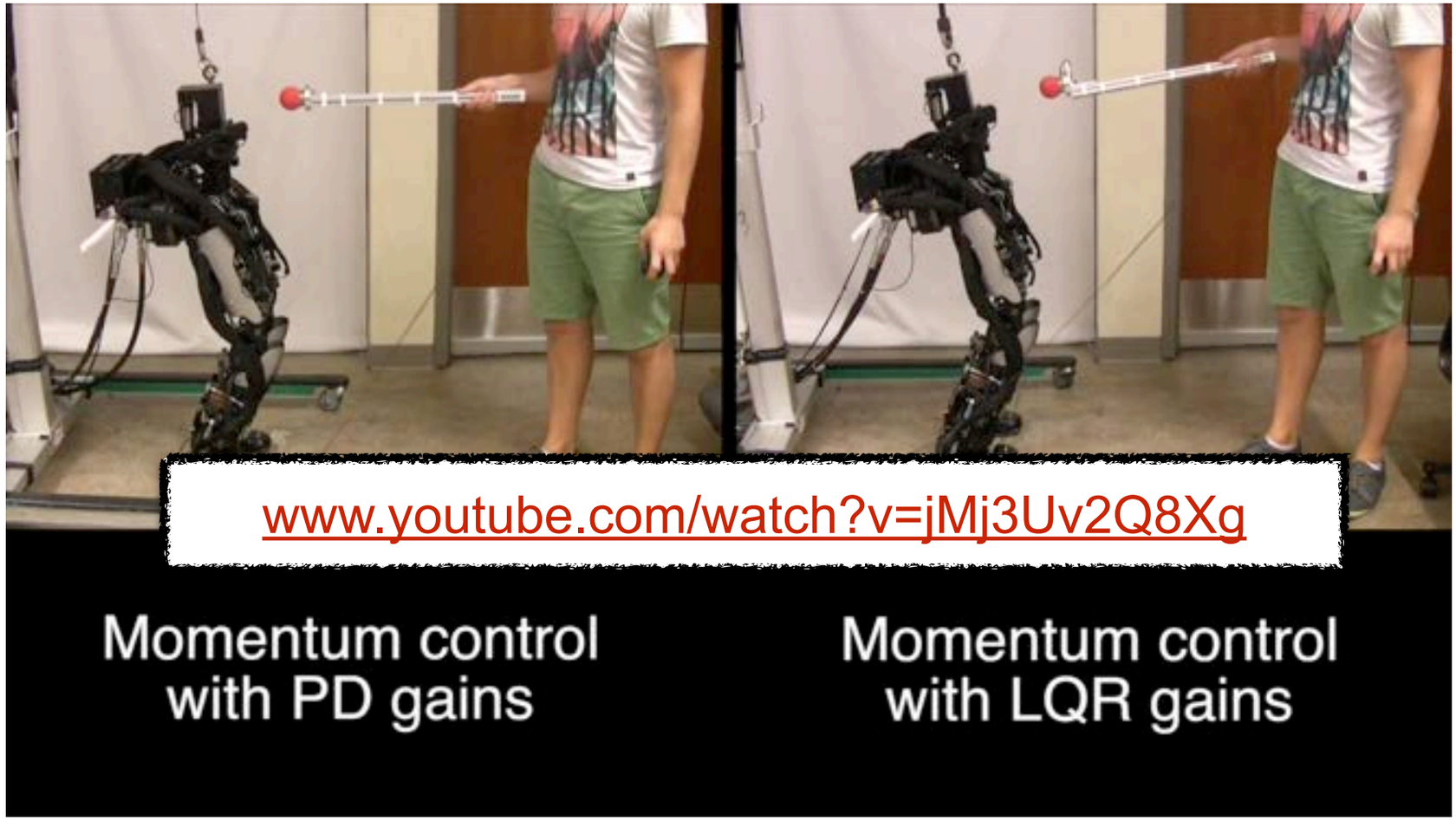


LQR Design



LQR significantly improves performance

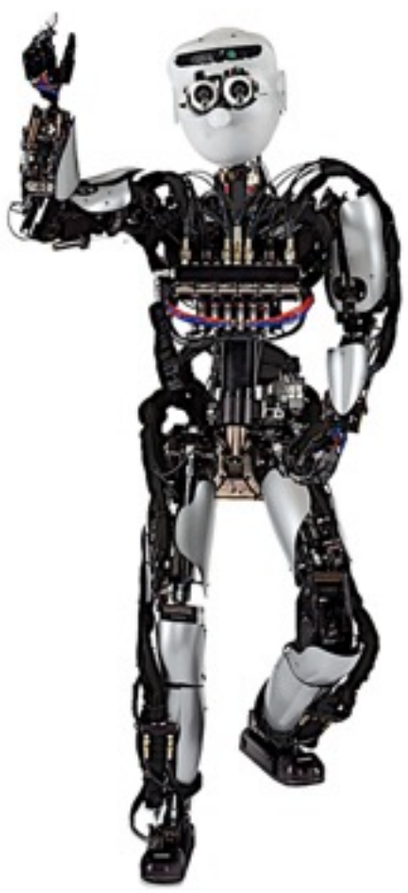
No need for re-tuning when changing contact conditions



- strict prioritization between tasks and constraints
- 1kHz task feedback loop(s)
- LQR feedback design for momentum control
- pure feed forward torques, no joint stabilization

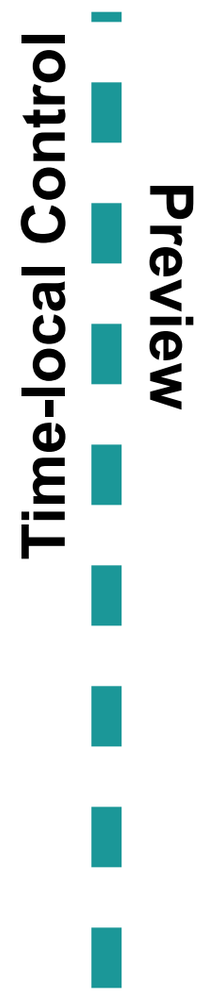
Momentum trajectory generation

- motion requires admissible wrench and momentum trajectories



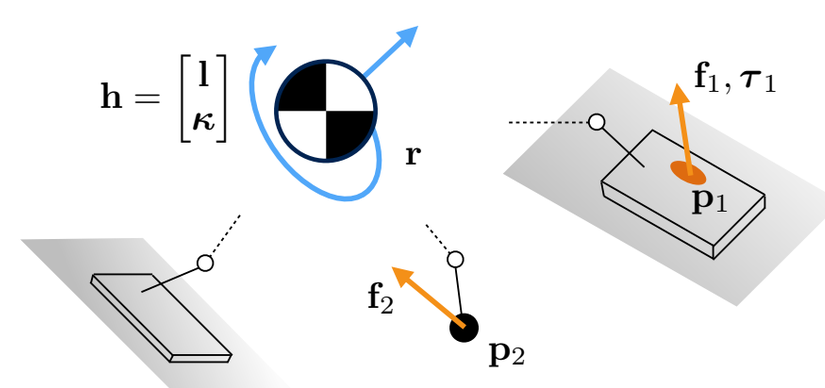
$$\mathbf{M}\ddot{\mathbf{q}} + \mathbf{N} = \mathbf{S}^T \boldsymbol{\tau} + \mathbf{J}^T \boldsymbol{\lambda}$$

Full Dynamics



$$M\dot{\mathbf{r}} = \mathbf{l}$$
$$\dot{\mathbf{l}} = M\mathbf{g} + \sum \mathbf{f}_i$$
$$\dot{\boldsymbol{\kappa}} = \sum \boldsymbol{\tau}_i + \sum (\mathbf{p}_i - \mathbf{r}) \times \mathbf{f}_i,$$

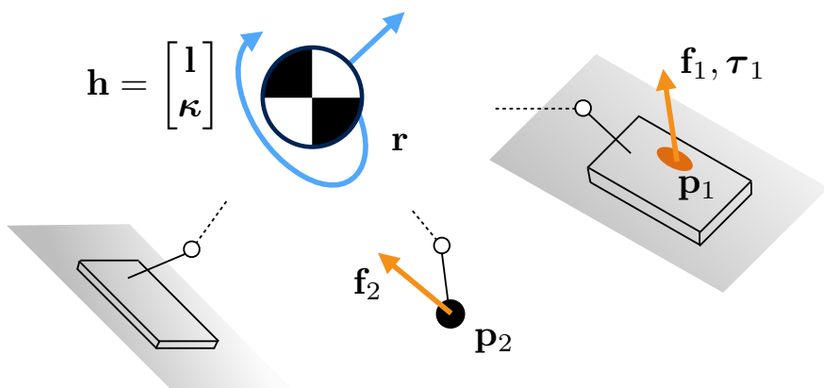
Reduced Dynamics



[Herzog et al., submitted]

Momentum Trajectory Optimization

[Herzog et al., arXiv:1507.04380]



- fix contact timing & design swing leg trajectory (splines)
- acquire **desired angular momentum** from inverse kinematics forward integration
- solve:

$$\min_{\mathbf{w}} \quad \sum_{t_0}^{T} (\|\mathbf{l}_{t_i} - \mathbf{l}_{t_i,des}\|_{W_1}^2 + \|\mathbf{r}_{t_i} - \mathbf{r}_{t_i,des}\|_{W_2}^2 + \|\boldsymbol{\kappa}_{t_i} - \boldsymbol{\kappa}_{t_i,des}\|_{W_3}^2)$$

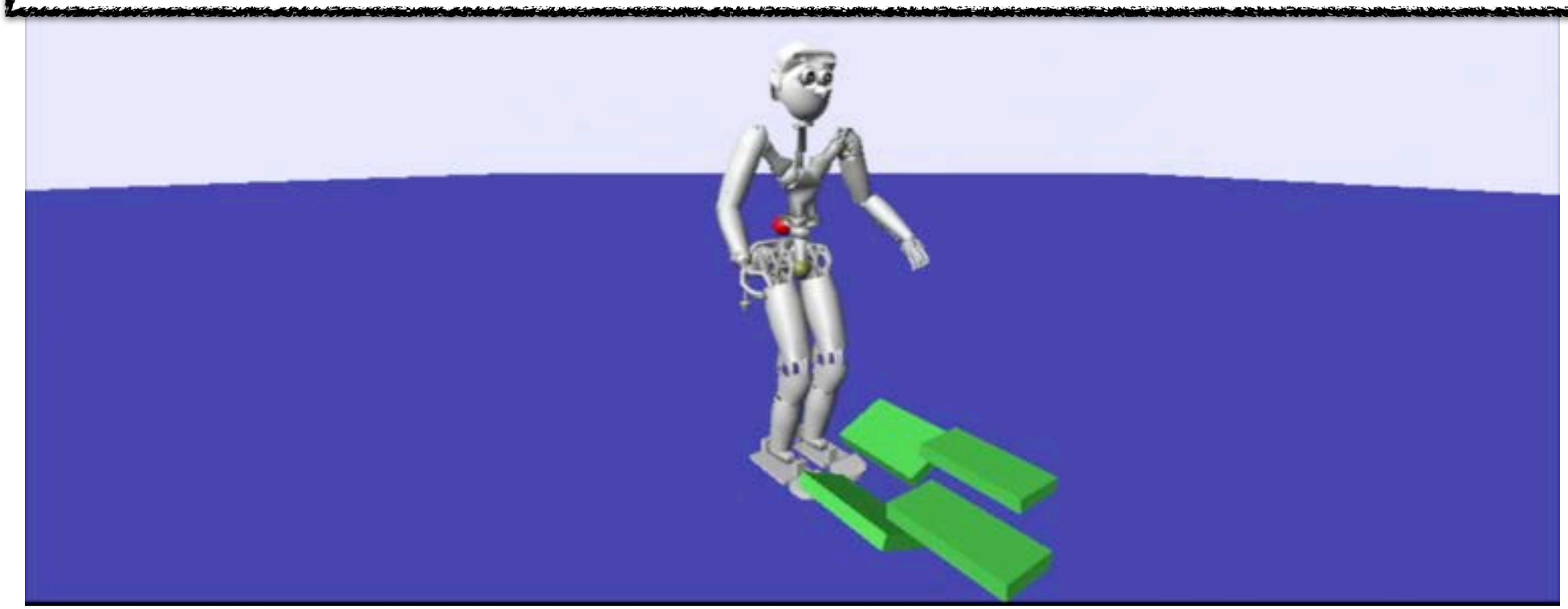
$$\text{s.t.} \quad \mathbf{f}_{t_i}, \mathbf{p}_{t_i}, \boldsymbol{\tau}_{t_i} \text{ admissible}$$

- resulting momentum trajectories come with **admissible contact forces** and respect **motion-induced momentum**
- embed (LQR) **feedback control** on momentum in a **task hierarchy**

Trajectory generation for multi-contact momentum-control

[Herzog et al., arXiv:1507.04380]

http://www-amd.is.tuebingen.mpg.de/~herzog/15_07-Humanoids.mp4



Preliminary results

- We split control into
  - time-local control on full dynamics
  - trajectory optimization with momentum dynamics
- we compute admissible forces from a naive kinematic forward integration
- tracking is achieved with LQR around the momentum

Momentum estimation

[Rotella et al., submitted]

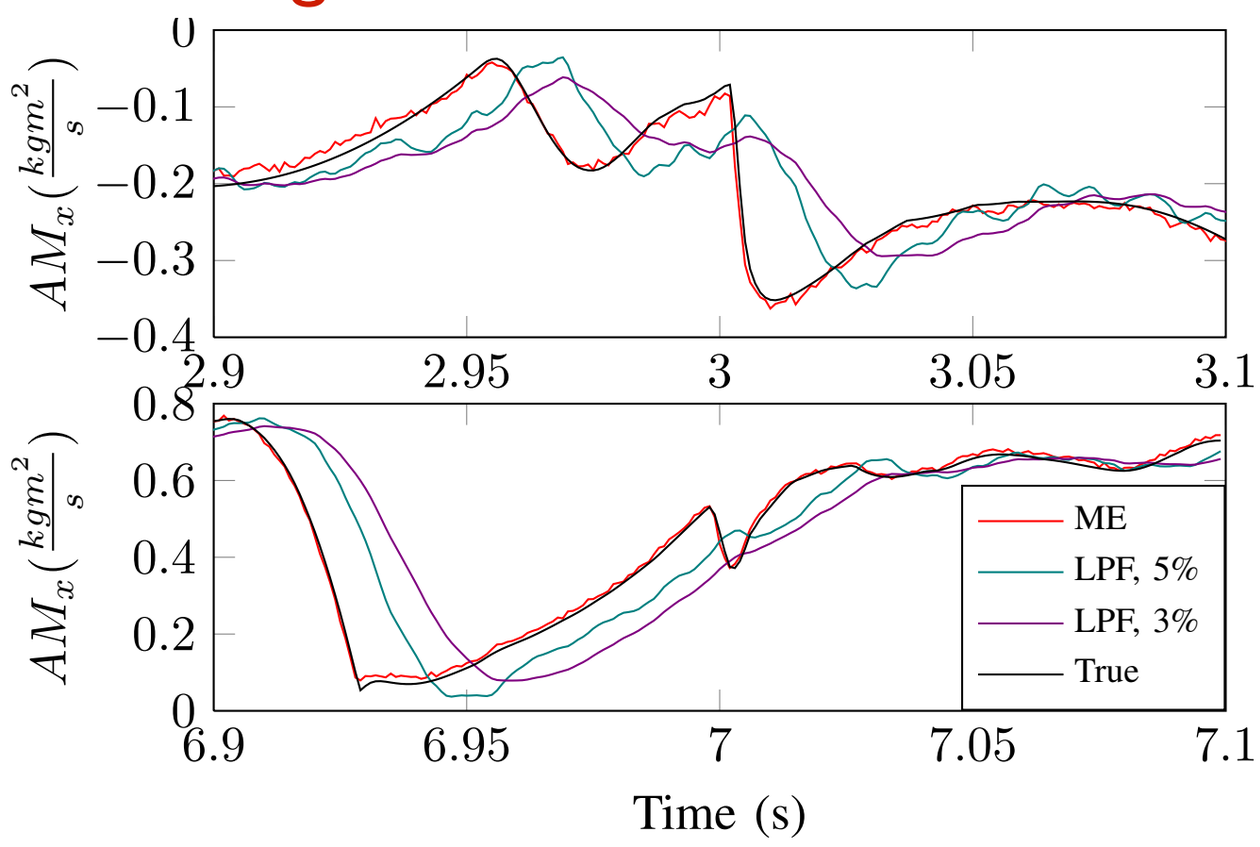
Fusion of kinematics and force information

Process model = momentum dynamics

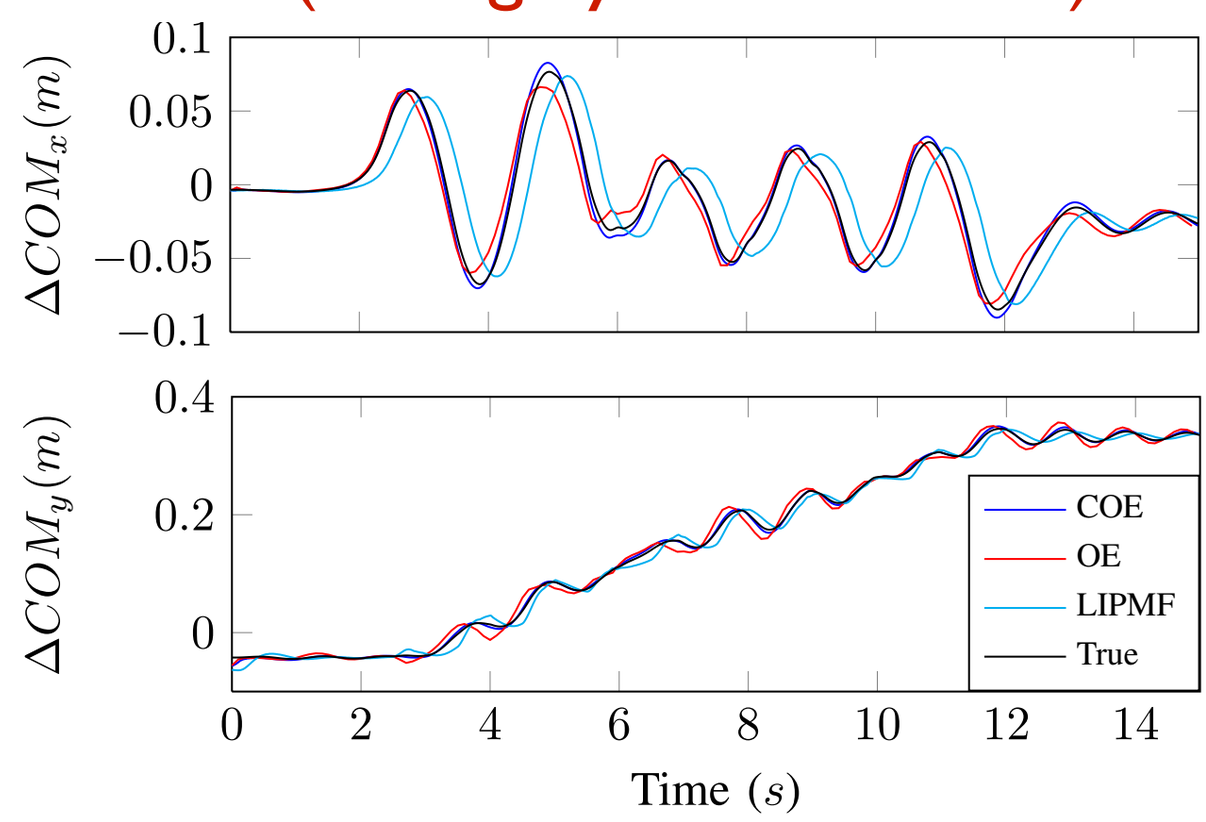
- CoM, linear and angular momentum filtering
- Center of mass offset estimation
- External wrench estimation

Full observability analysis (theoretical limits)

Angular momentum estimation



CoM offsets (wrong dynamics model)



Manipulation & Whole-Body Control
Bridges and Gaps

Manipulation		**Whole-Body Control**
Position/Force Tasks	Model-based Force Control	Hierarchical Inverse Dynamics
-Impedance at finger - rough geometrical description	Contact Modeling	-feed-forward force -model contact surface
- mostly kinematic	Planning Primitives	- optimization over reduced dynamics
Initialization from demonstration	Bootstrapping	captured in (simpler) dynamic models