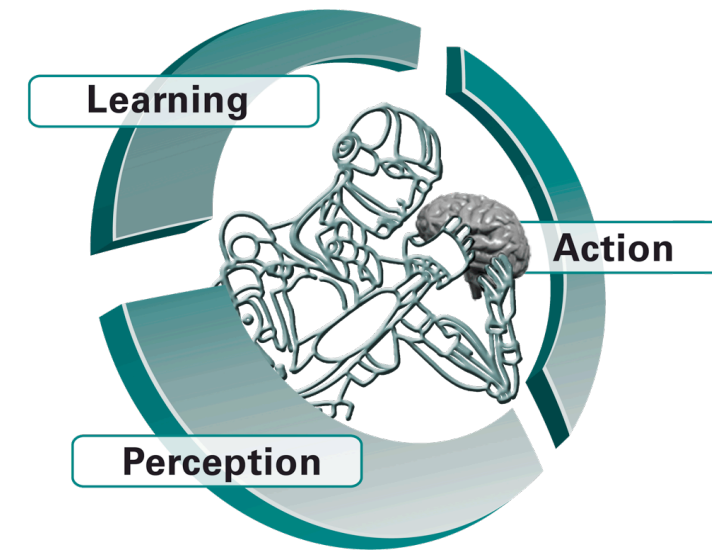


Balancing Experiments on a Torque Controlled Humanoid with Hierarchical Inverse Dynamics

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Max-Planck Institute Intelligent
Systems (Autonomous Motion)



Computational Learning
and Motor Control Lab

Low-level control of Sarcos humanoid



- Lower body of Sarcos humanoid
- 17 DOFs
- Linear hydraulic actuators
- Moog 30 Series valves
- Load cells and position sensors at each joint
- 6-axis force sensors in the foot
- 1KHz control loop

Control of hydraulics

- How do we implement a “torque source” with hydraulics?

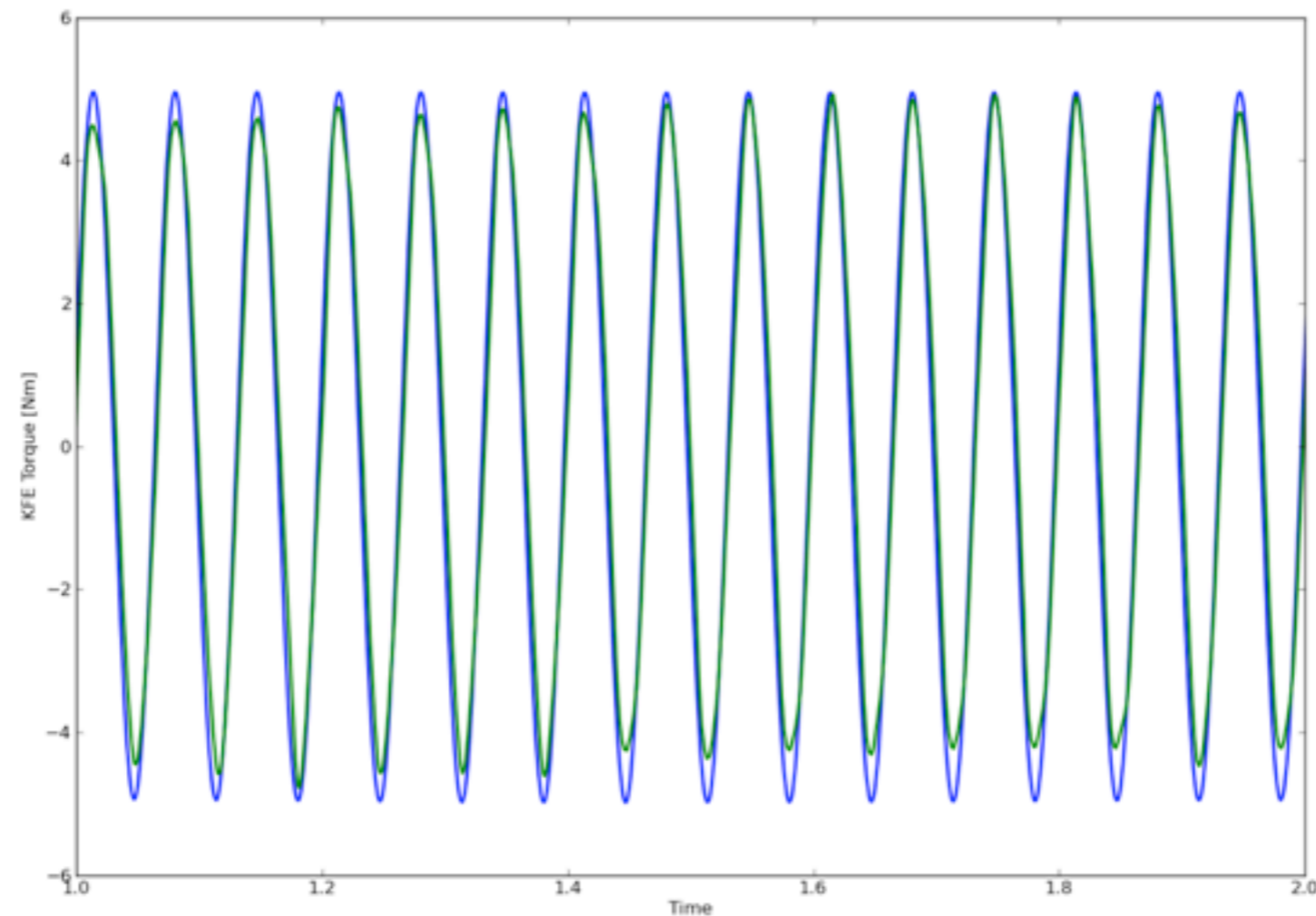
[Boaventura et al. 2012]

$$v = PID(F_{des}, F) + K\dot{x}_{piston} + c$$

- This controller was key to good force control performances
- Special care in calibration and tuning of controller to maximize performance

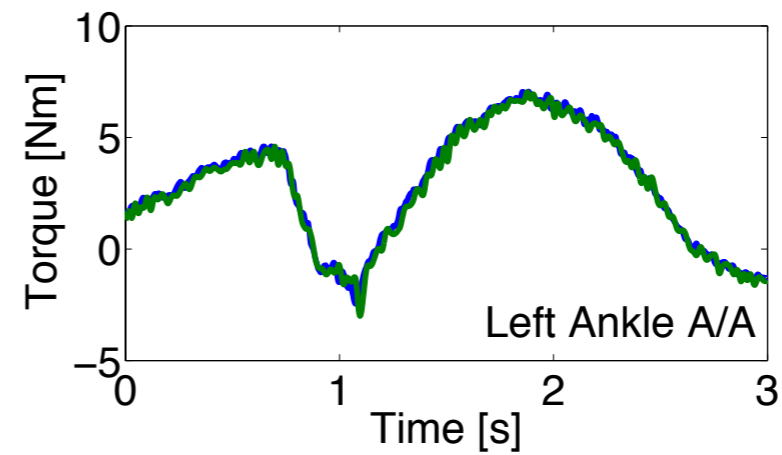
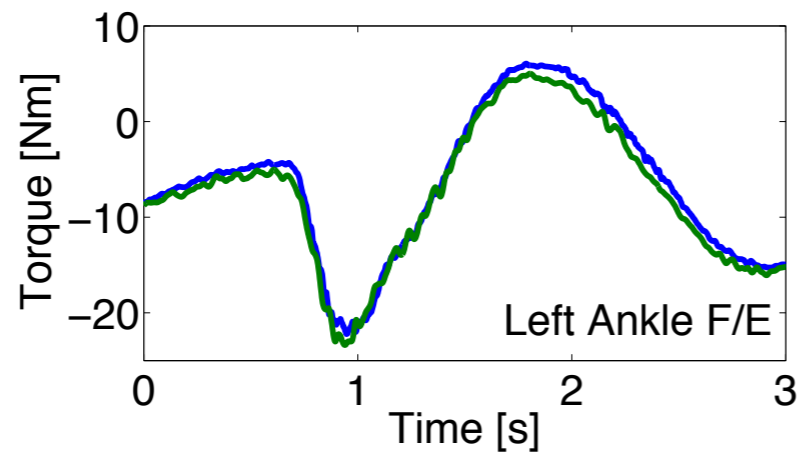
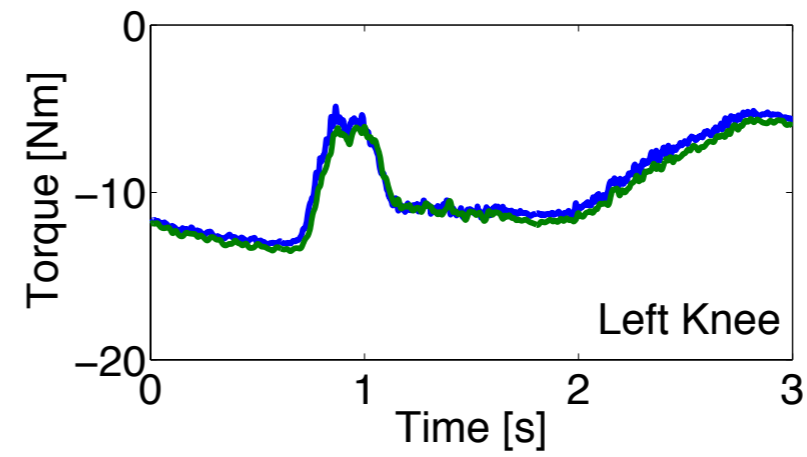
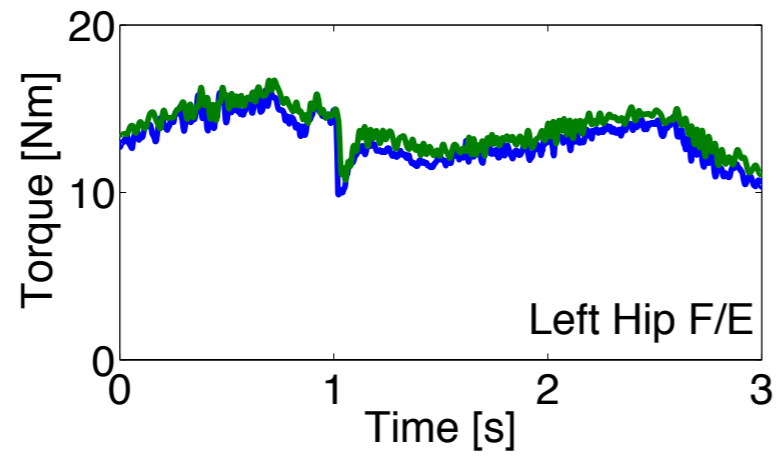
Torque tracking performance

[Boaventura et al. 2012]



Tracking a 15Hz sine torque profile (5Nm amplitude)

Torque tracking performance



Control of hydraulics

- Painful to tune controllers for each DOF
- Control performance not so good for ankles
(velocity compensation gain really depends on position)
- Now: looking into automatic tuning / learning control
(current work by S.Trimpe)

Inverse dynamics for legged robots

[Righetti et al., IJRR 2013]

QR decomposition of constraint Jacobian

[Mistry et al. 2010]

$$\mathbf{J}_c^T = [\mathbf{Q}_c \ \mathbf{Q}_u] \begin{bmatrix} \mathbf{R} \\ \mathbf{0} \end{bmatrix}$$

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

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Equations of motion:

$$\mathbf{Q}_u^T (\mathbf{M}\ddot{\mathbf{q}}_d + \mathbf{h}) = \mathbf{Q}_u^T \mathbf{S}^T \boldsymbol{\tau}$$

Dynamic consistency

$$\boldsymbol{\lambda} = \mathbf{R}^{-1} \mathbf{Q}_c^T (\mathbf{M}\ddot{\mathbf{q}}_d + \mathbf{h} - \mathbf{S}^T \boldsymbol{\tau})$$

Contact force as a
function of actuation

Optimal distribution of contacts

[Righetti et al. 2012]

$$\arg \min_{\boldsymbol{\tau}, \boldsymbol{\lambda}} \frac{1}{2} \boldsymbol{\tau}^T \mathbf{W}_{\boldsymbol{\tau}} \boldsymbol{\tau} + \mathbf{b}_{\boldsymbol{\tau}}^T \boldsymbol{\tau} + \frac{1}{2} \boldsymbol{\lambda}^T \mathbf{W}_{\boldsymbol{\lambda}} \boldsymbol{\lambda} + \mathbf{b}_{\boldsymbol{\lambda}}^T \boldsymbol{\lambda}$$

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Torque constraints

Contact forces constraints

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$$\arg \min_{\tau, \lambda} \frac{1}{2} \tau^T \mathbf{W}_\tau \tau + \mathbf{b}_\tau^T \tau + \frac{1}{2} \lambda^T \mathbf{W}_\lambda \lambda + \mathbf{b}_\lambda^T \lambda$$

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$$\mathbf{C}_\tau \tau \leq \mathbf{d}_\tau$$

~~$$\mathbf{C}_\lambda \lambda \leq \mathbf{d}_\lambda$$~~

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Torque constraints

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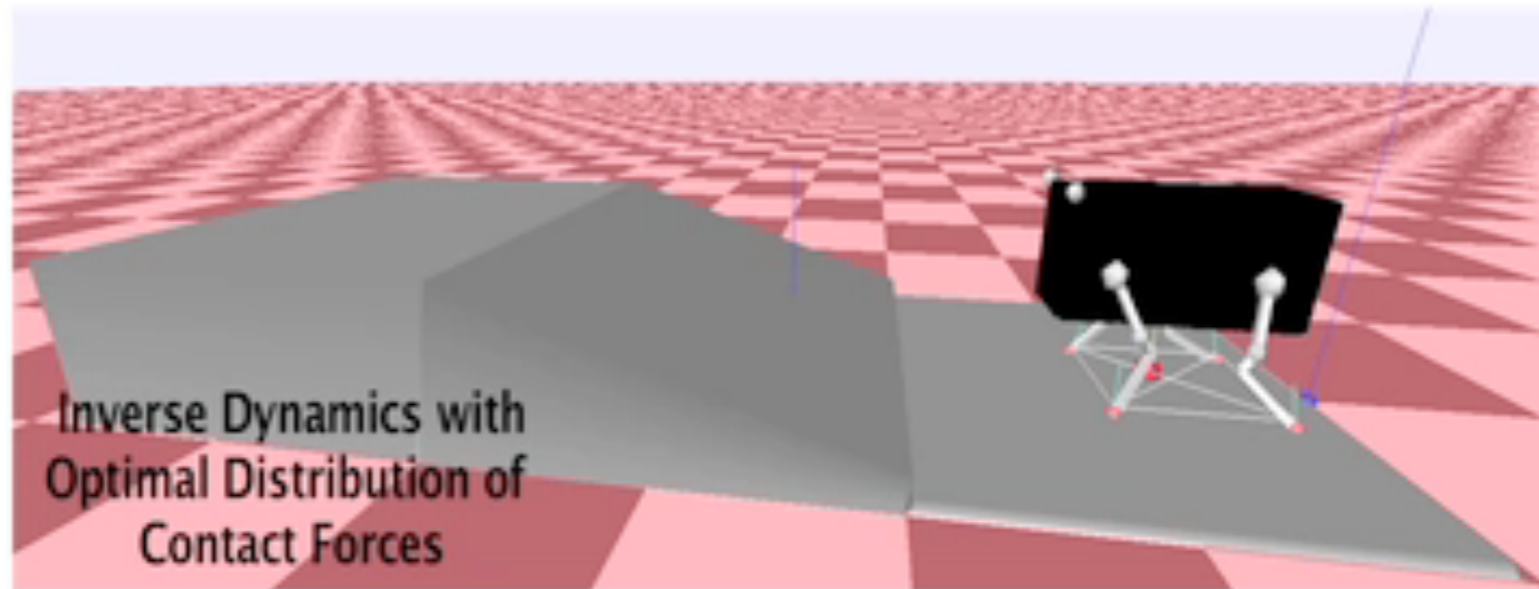
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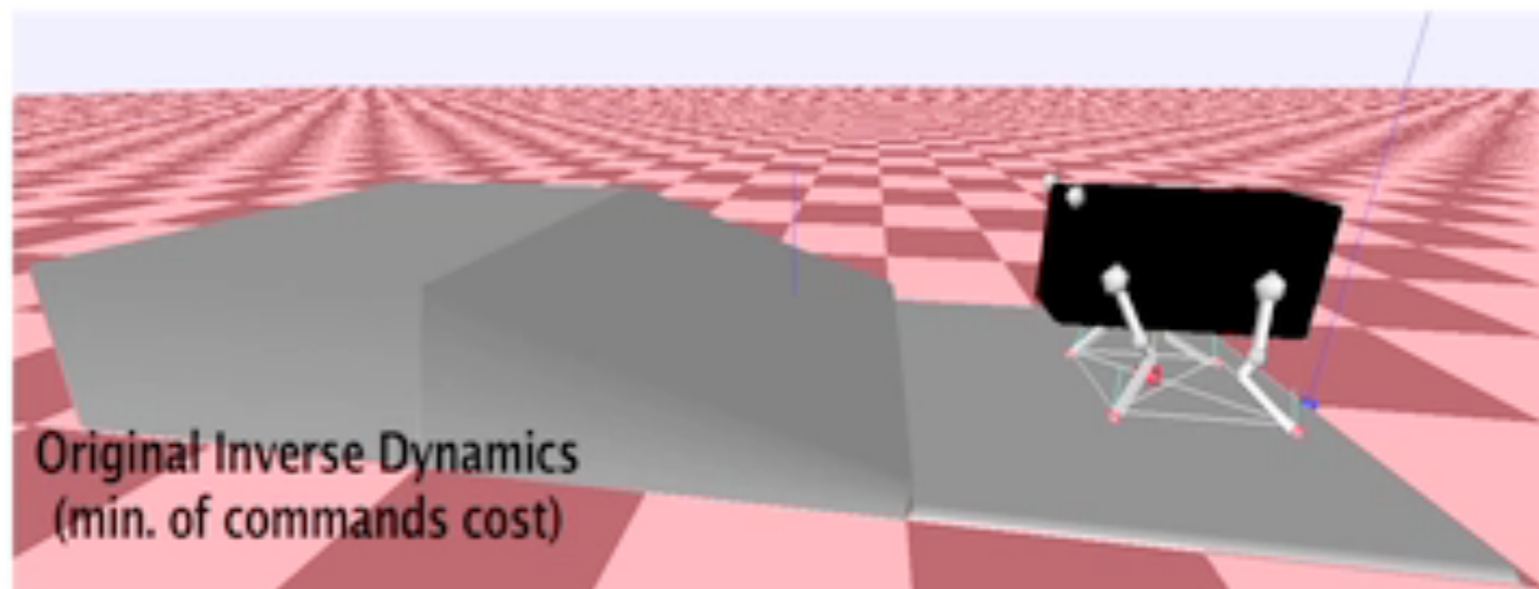
Contact forces constraints

- QP depends only on torques
- No need of an explicit representation of contact forces
- Problem with constant size - no matter the number of contacts

Optimal distribution of contact forces



Climbing a 0.25 radians slope with low friction (coefficient of static friction = 0.4)



Inverse dynamics for legged robots

[Righetti et al., IJRR 2013]
[Mistry et al., 2010]

- Inverse dynamics (joint acceleration) and operational space (task space accelerations) control
- Torque redundancy to optimize contact forces
- Computationally fast (1 KHz control loop)
- Robust to model uncertainties / better with system identification (no need to compute inertia matrix)

Related Work

- **Passivity-based: exploit quasi-static assumption** [Hyon et al, 2007][Ott et al, 2011]
 - + robustness due to passivity; no need for precise dynamics model
 - assumptions are potentially limiting for dynamic motions
- **Control with full Dynamical Model** [Stephens et al, 2010][Hutter et al, 2012][Righetti et al, 2013]
 - + theoretically well suited for dynamic motions
 - requires model and efficient implementation

Motivation

define desired closed-loop
dynamics

e.g. $\mathbf{J}_x \ddot{\mathbf{q}} = PD(\mathbf{x}_{des}, \dot{\mathbf{x}}_{des})$ (1)

- Typical use of the presented framework:
 - define desired closed-loop dynamics
 - pick one $\ddot{\mathbf{q}}^*$ (out of many) that satisfies Eq (1)

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exploit redundancy to optimize cost on torques or forces

$$\begin{array}{ll} \min_{\boldsymbol{\tau}, \boldsymbol{\lambda}} & \boldsymbol{\lambda}^T \mathbf{W} \boldsymbol{\lambda} \\ \text{s.t.} & \mathbf{M} \ddot{\mathbf{q}}_d + \mathbf{h} = \mathbf{S}^T \boldsymbol{\tau} + \mathbf{J}^T \boldsymbol{\lambda} \\ & \boldsymbol{\tau}_{min} \leq \boldsymbol{\tau} \leq \boldsymbol{\tau}_{max} \end{array}$$

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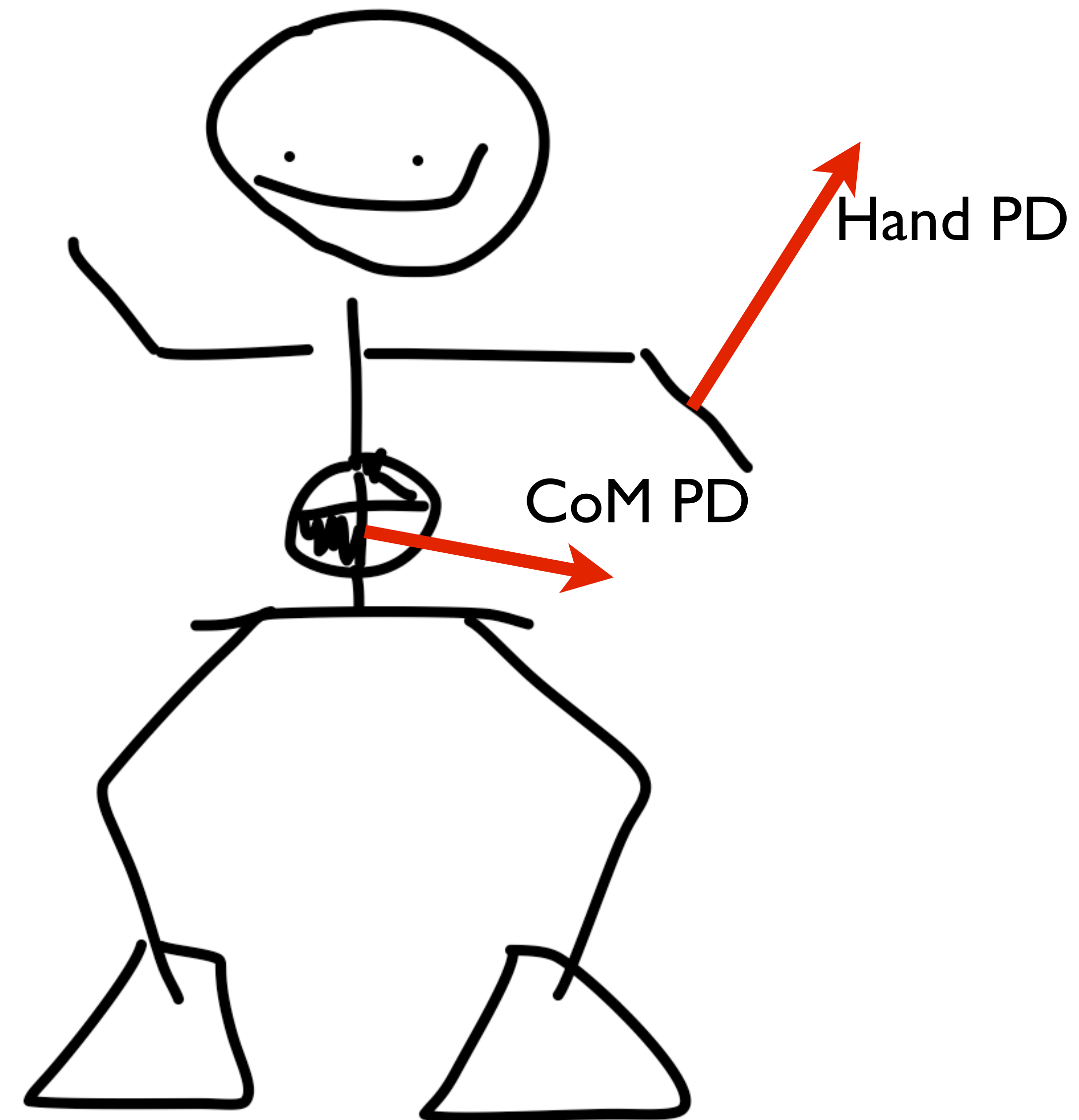


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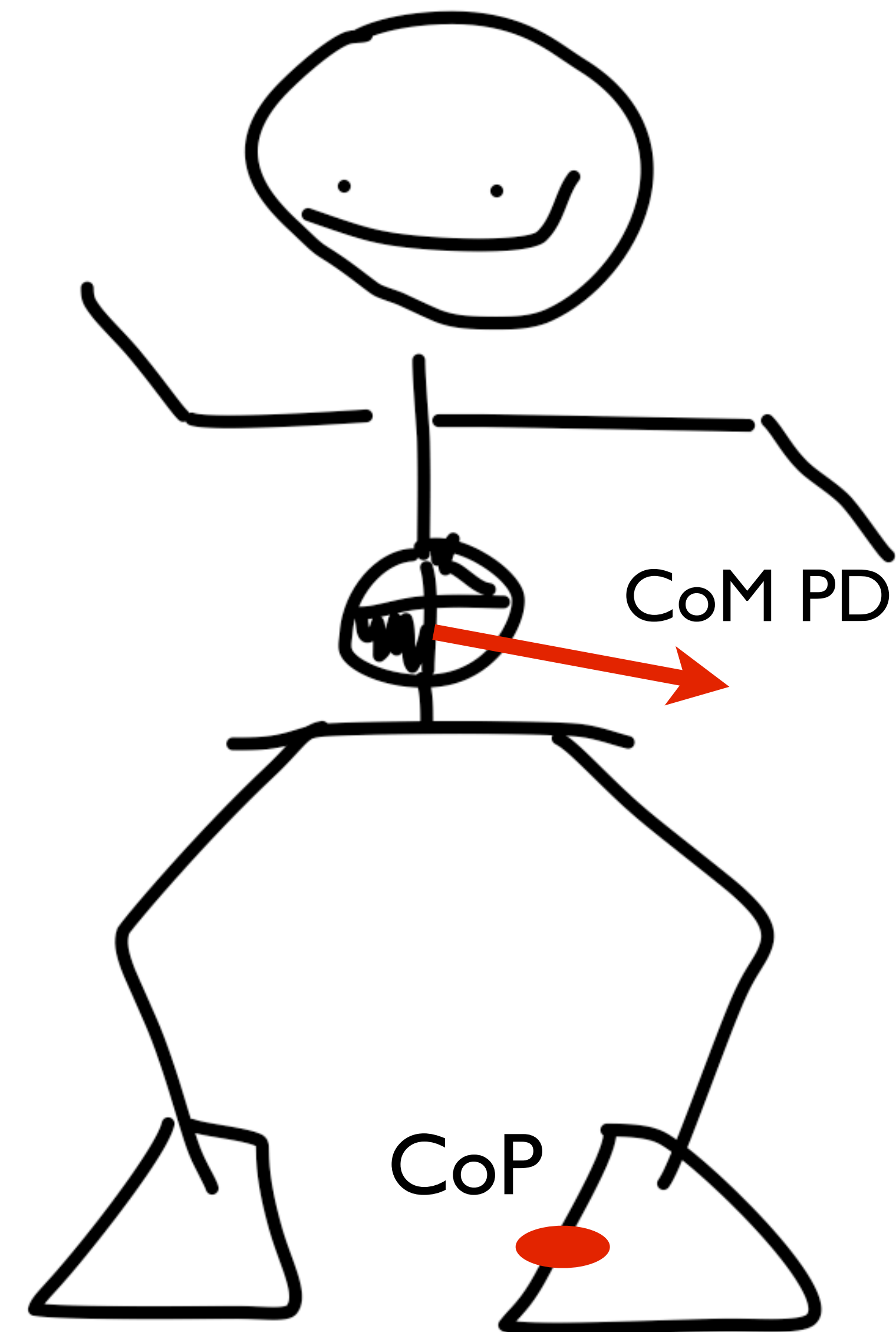
- Typical use of the presented framework:
 - define desired closed-loop dynamics
 - pick one $\ddot{\mathbf{q}}^*$ (out of many) that satisfies Eq (1)
 - optimize over space of redundant torques and forces
- Potentially suboptimal or even infeasible by ignoring all other solutions to Eq (1)
- In addition it is useful to be able to express hierarchies on inequalities

Hierarchies



- We want
 - the CoM to have PD behavior
 - the hand as well
- what if both cannot be satisfied?
- => weighting might help

Hierarchies



- We want
 - the CoM to have PD behavior
 - the hand as well
 - what if both cannot be satisfied?
 - \Rightarrow weighting might help
-
- We want
 - the CoM to have PD behavior
 - CoP to reside inside support polygon
 - if CoP constr. violated \Rightarrow kinematics constraint wrong
 - \Rightarrow hierarchies

Related Work

- cascades of QPs: recursively solve a QP without violating optimality of previous QPs [de Lasa,2010, Mansard, 2012]
- generalize pseudo-inverse approaches: allow inequality constraints
- have not been implemented in a feedback-loop on a robot before
- requires efficient implementation to run on torque controlled robot
- how well does it perform under model-uncertainty, noisy velocity measures and realistic base-state estimation?

Cascades of QPs

[deLasa et. al., 2010]

$$\mathbf{y} = \begin{bmatrix} \ddot{\mathbf{q}} \\ \boldsymbol{\tau} \\ \boldsymbol{\lambda} \end{bmatrix}$$

$$\mathbf{W}_1(\mathbf{B}_1\mathbf{y} + \mathbf{b}_1) = \mathbf{w}_1$$

Cascades of QPs

[deLasa et. al., 2010]

$$\text{QP I: } \min_{\mathbf{y}, \mathbf{v}_1, \mathbf{w}_1} \|\mathbf{v}_1\|^2 + \|\mathbf{w}_1\|^2$$
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$\mathbf{y} = \begin{bmatrix} \ddot{\mathbf{q}} \\ \tau \\ \lambda \end{bmatrix}$

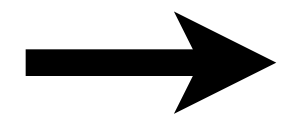
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substitute w

$$\min_{\mathbf{y}, \mathbf{v}_1} \|\mathbf{v}_1\|^2 + \|\mathbf{W}_1(\mathbf{B}_1\mathbf{y} + \mathbf{b}_1)\|^2$$
$$\text{s.t. } \mathbf{V}_1(\mathbf{A}_1\mathbf{y} + \mathbf{a}_1) \leq \mathbf{v}_1$$



find optimizer
 $\mathbf{y}_1^*, \mathbf{v}_1^*$

Cascades of QPs

[deLasa et. al., 2010]

$$\begin{array}{ccc}
 \text{QP I: } \min_{\mathbf{y}, \mathbf{v}_1, \mathbf{w}_1} \|\mathbf{v}_1\|^2 + \|\mathbf{w}_1\|^2 & & \min_{\mathbf{y}, \mathbf{v}_1} \|\mathbf{v}_1\|^2 + \|\mathbf{W}_1(\mathbf{B}_1\mathbf{y} + \mathbf{b}_1)\|^2 \\
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 & \text{substitute w} & \\
 & & \mathbf{W}_1(\mathbf{B}_1\mathbf{y} + \mathbf{b}_1) = \mathbf{w}_1
 \end{array}$$

All optimal solutions:

$$\mathbf{y} = \mathbf{y}_1^* + \mathbf{Z}_1 \mathbf{u}_2,$$

$$\mathbf{V}_1(\mathbf{A}_1\mathbf{y} + \mathbf{a}_1) - \mathbf{v}_1^* \leq 0$$

\longrightarrow
find optimizer
 $\mathbf{y}_1^*, \mathbf{v}_1^*$

\mathbf{Z}_i surjective map onto $\bigcap_{j=1}^i \text{Nullspace}(\mathbf{W}_j \mathbf{B}_j)$

Cascades of QPs

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substitute w

All optimal solutions:

$$\begin{array}{ccc}
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Cascades of QPs

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QP 2:
$$\min_{\mathbf{u}_2, \mathbf{v}_2} \|\mathbf{v}_2\|^2 + \|\mathbf{W}_2(\mathbf{B}_2\mathbf{y} + \mathbf{b}_2)\|^2$$

s.t.
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\longrightarrow
...

\mathbf{Z}_i surjective map onto $\bigcap_{j=1}^i \text{Nullspace}(\mathbf{W}_j\mathbf{B}_j)$

Computation Time

- Solving a cascade of QPs in lms requires an efficient implementation
- QP variables: $n+6 + n + 6*c$ (c = number of constrained endeffectors)
- Highest priority objective:
$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{N}(\mathbf{q}, \dot{\mathbf{q}}) = \boldsymbol{\tau} + \mathbf{J}_c^T \boldsymbol{\lambda}$$
$$\tilde{\mathbf{M}}(\mathbf{q})\ddot{\mathbf{q}} + \tilde{\mathbf{N}}(\mathbf{q}, \dot{\mathbf{q}}) = \tilde{\mathbf{J}}_c^T \boldsymbol{\lambda}$$
- By substituting $\boldsymbol{\tau} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{N}(\mathbf{q}, \dot{\mathbf{q}}) - \mathbf{J}_c^T \boldsymbol{\lambda}$ we save n variables and n constraints!

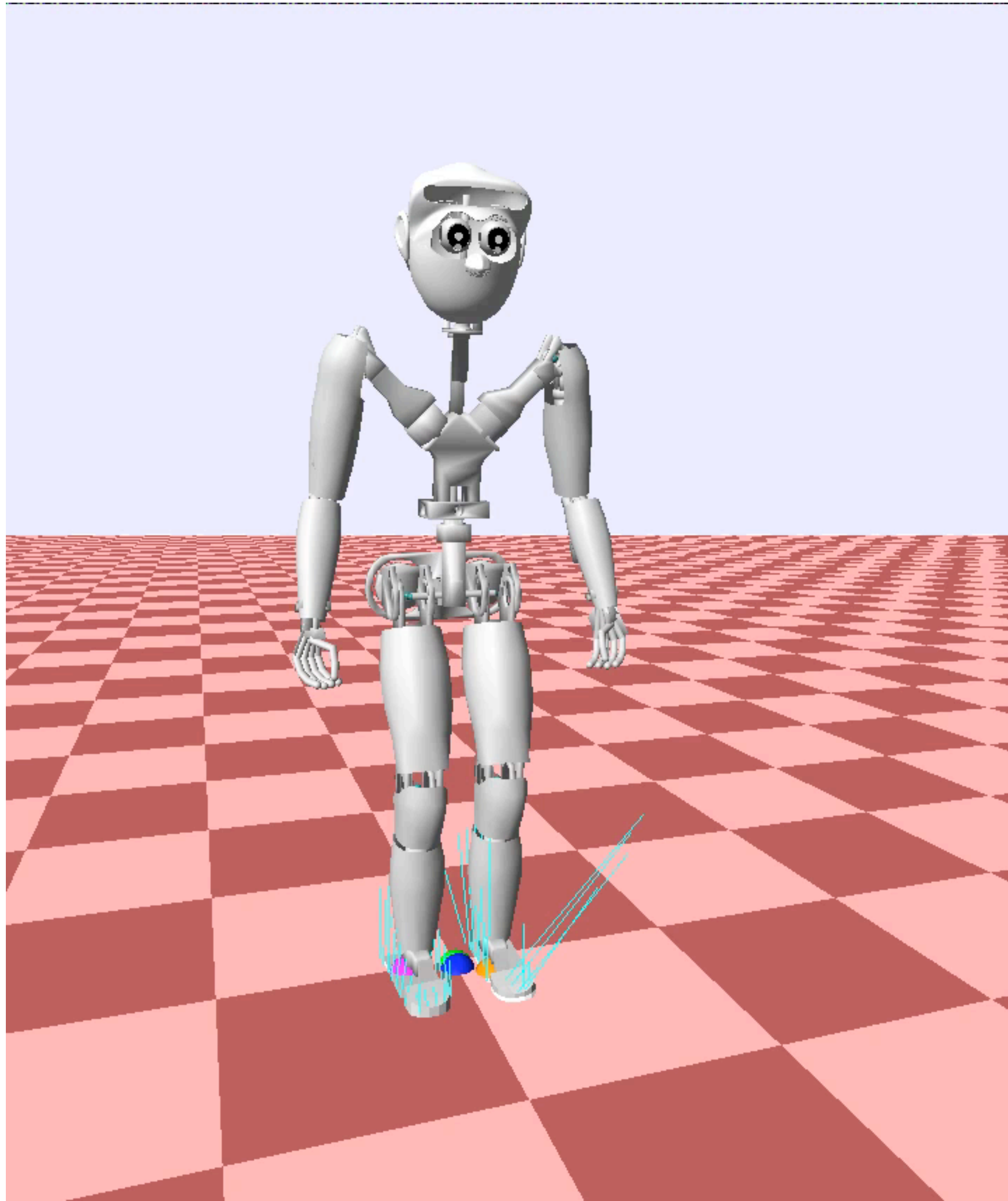
Computation Time

- Solving a cascade of QPs in lms requires an efficient implementation
- QP variables: $n+6 + n + 6*c$ (c = number of constrained endeffectors)
- Highest priority objective: ~~$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{N}(\mathbf{q}, \dot{\mathbf{q}}) = \boldsymbol{\tau} + \mathbf{J}_c^T \boldsymbol{\lambda}$~~
 $\tilde{\mathbf{M}}(\mathbf{q})\ddot{\mathbf{q}} + \tilde{\mathbf{N}}(\mathbf{q}, \dot{\mathbf{q}}) = \tilde{\mathbf{J}}_c^T \boldsymbol{\lambda}$
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- SVD (required for \mathbf{Z}) and solving QP is done in parallel \Rightarrow SVD comes for free

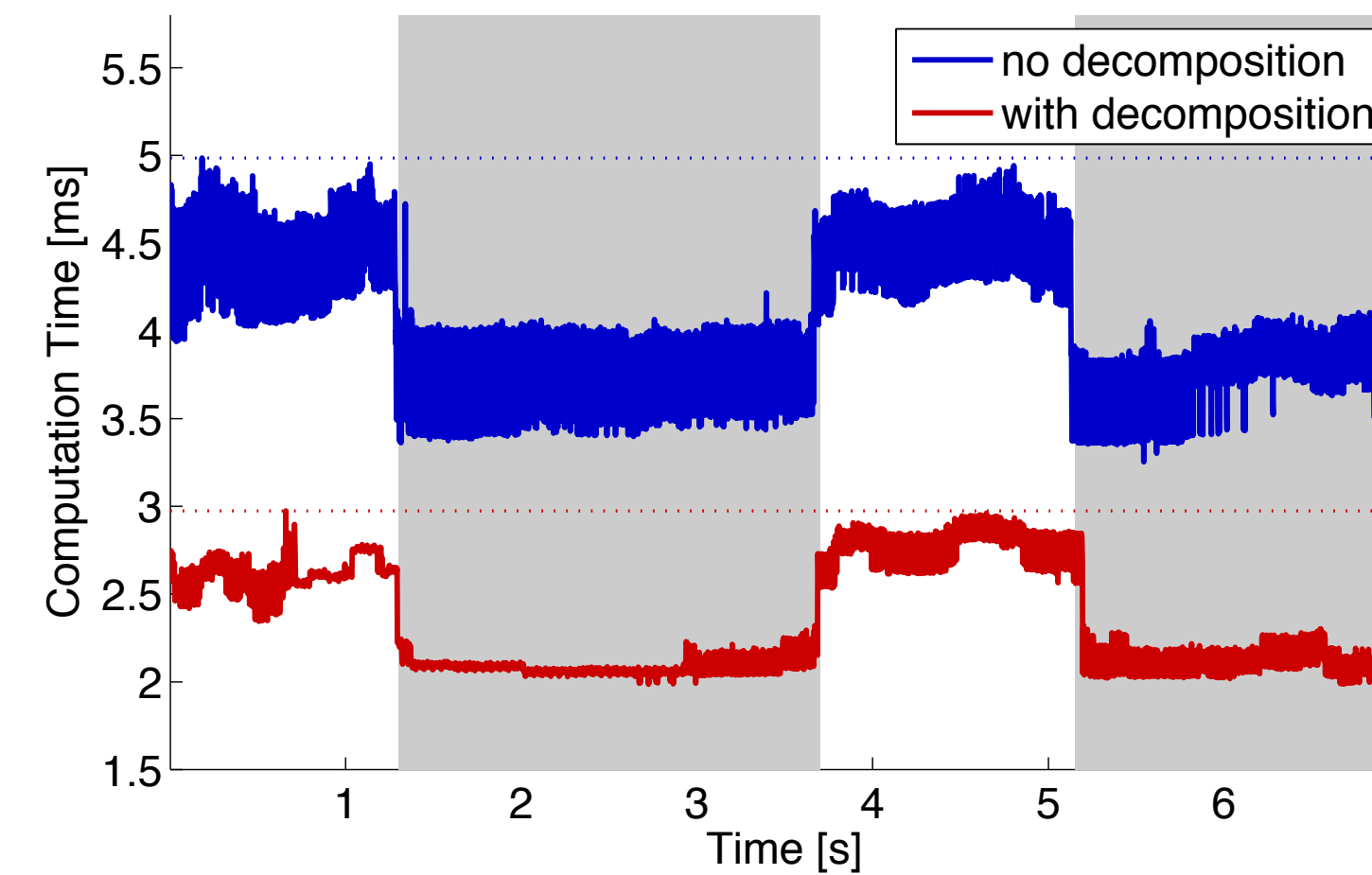
Computation Time

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- SVD (required for \mathbf{Z}) and solving QP is done in parallel \Rightarrow SVD comes for free
- first hierarchie is always EoM and torque constraints \Rightarrow no QP needs to be solved

Speedup



Priority	Nr. of eq(uality) and ineq(uality) constraints	Constraint/Task
1	25 eq	Eq. (12) (not required for simplified problem)
2	6 eq 2 × 25 ineq $c \times 6$ eq $c \times 4$ ineq $c \times 4$ ineq 2 × 25 ineq	Newton Euler Eq. (13) torque limits kinematic contact constraint CoPs reside in sup. polygons GRFs reside in friction cones joint acceleration limits
3	3 eq $(2 - c) \times 6$	PD control on CoM PD control on swing foot
4	$25 + 6$ eq	PD control on posture
5	$c \times 6$ eq	regularizer on GRFs
DoFs: 25		max. time: 5 ms / 3 ms



Momentum Control

$$\mathbf{H}_G(\mathbf{q})\dot{\mathbf{q}} = \mathbf{m} \quad [\text{Orin, \& Goswami 2008}]$$

$$\dot{\mathbf{m}}_{ref} = \mathbf{P} \begin{bmatrix} M(\mathbf{x}_{cog,des} - \mathbf{x}_{cog}) \\ \mathbf{0} \end{bmatrix} + \mathbf{D}(\mathbf{m}_{des} - \mathbf{m}) + \dot{\mathbf{m}}_{des}$$

$$\begin{aligned} \dot{\mathbf{m}} &= \mathbf{H}_G\ddot{\mathbf{q}} + \dot{\mathbf{H}}_G\dot{\mathbf{q}} \\ &= \begin{bmatrix} \mathbf{I}_{3 \times 3} & \mathbf{0}_{3 \times 3} & \cdots \\ [\mathbf{x}_{cog} - \mathbf{x}_i]_{\times} & \mathbf{I}_{3 \times 3} & \cdots \end{bmatrix} \boldsymbol{\lambda} + \begin{bmatrix} M\mathbf{g} \\ \mathbf{0} \end{bmatrix} \end{aligned}$$

No meaningful integral of angular momentum (orientation)

choice of ang. mom. for motions is non-intuitive. putting it in nullspace of motion generates undesirable behavior

requires deriving H numerically => can suffer from noise

Momentum-based Balance Control

Priority	Nr. of eq(uality) and ineq(uality) constraints	Constraint/Task
1	6 eq 2 × 14 ineq 2 × 6 eq 2 × 4 ineq 2 × 4 ineq 2 × 14 ineq	Newton Euler Eq. (13) torque limits kinematic contact constraint CoPs reside in sup. polygons GRFs reside in friction cones joint acceleration limits
2	6 eq 14 + 6 eq 2 × 6 eq	PD control on system momentum, Eq. (17) PD control on posture regularizer on GRFs
DoFs: 14		max. time: 0.4 ms

- formulation requires only one QP
- runs solidly below 1ms
- guarantees dynamic constraints; makes no trade-offs

Balancing experiments on a torque-controlled humanoid with hierarchical inverse dynamics

Alexander Herzog⁺, Ludovic Righetti⁺⁺,
Felix Grimmeringer⁺, Peter Pastor^{*}, Stefan Schaal⁺⁺

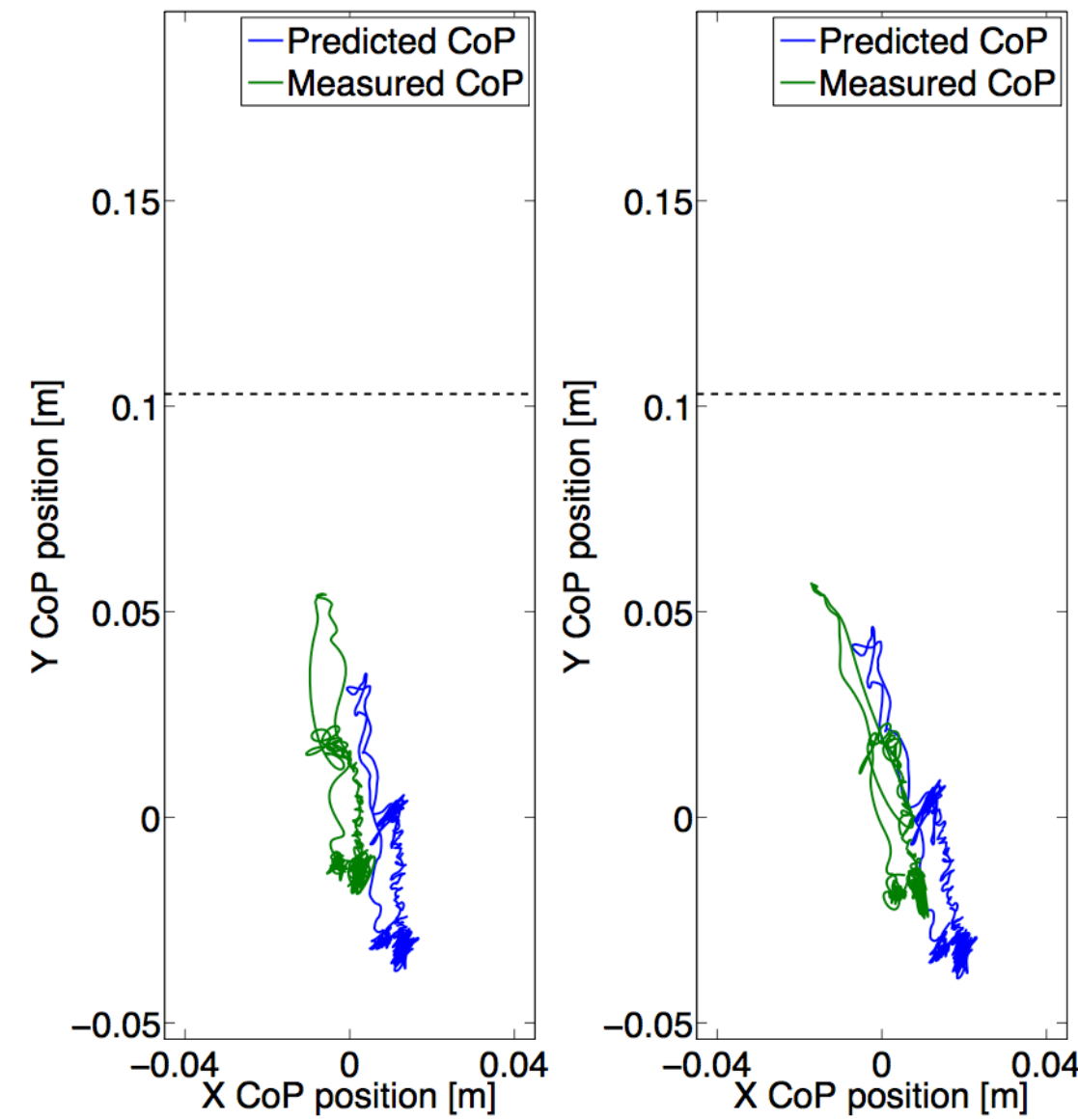
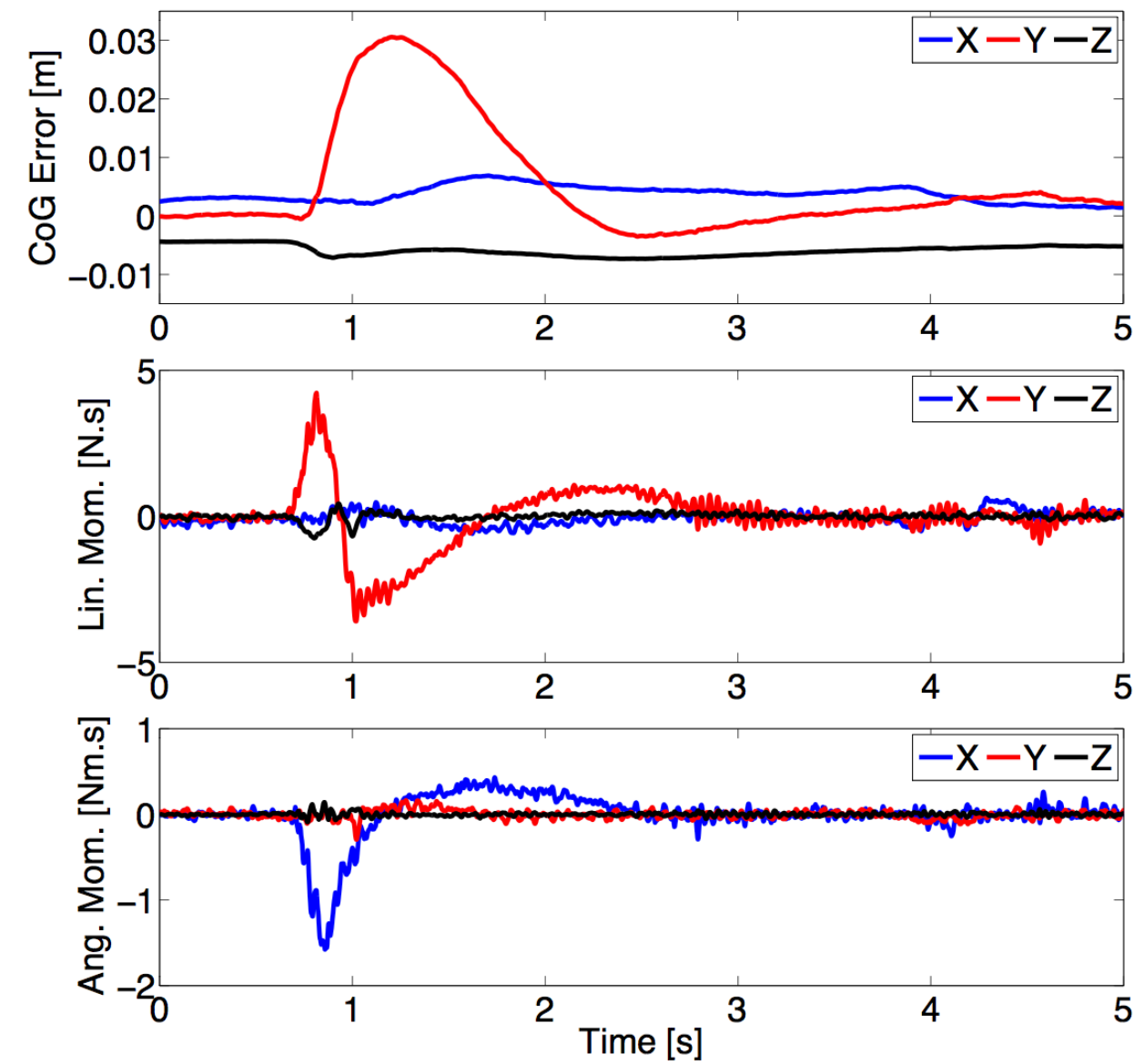


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Max-Planck-Institute for Intelligent Systems



^{*}Computational Learning and Motor Control Lab
University of Southern California

Momentum-based Balance Control



- Recovers CoM position after push
- guarantees admissible CoPs and predicts these reliably

Squatting

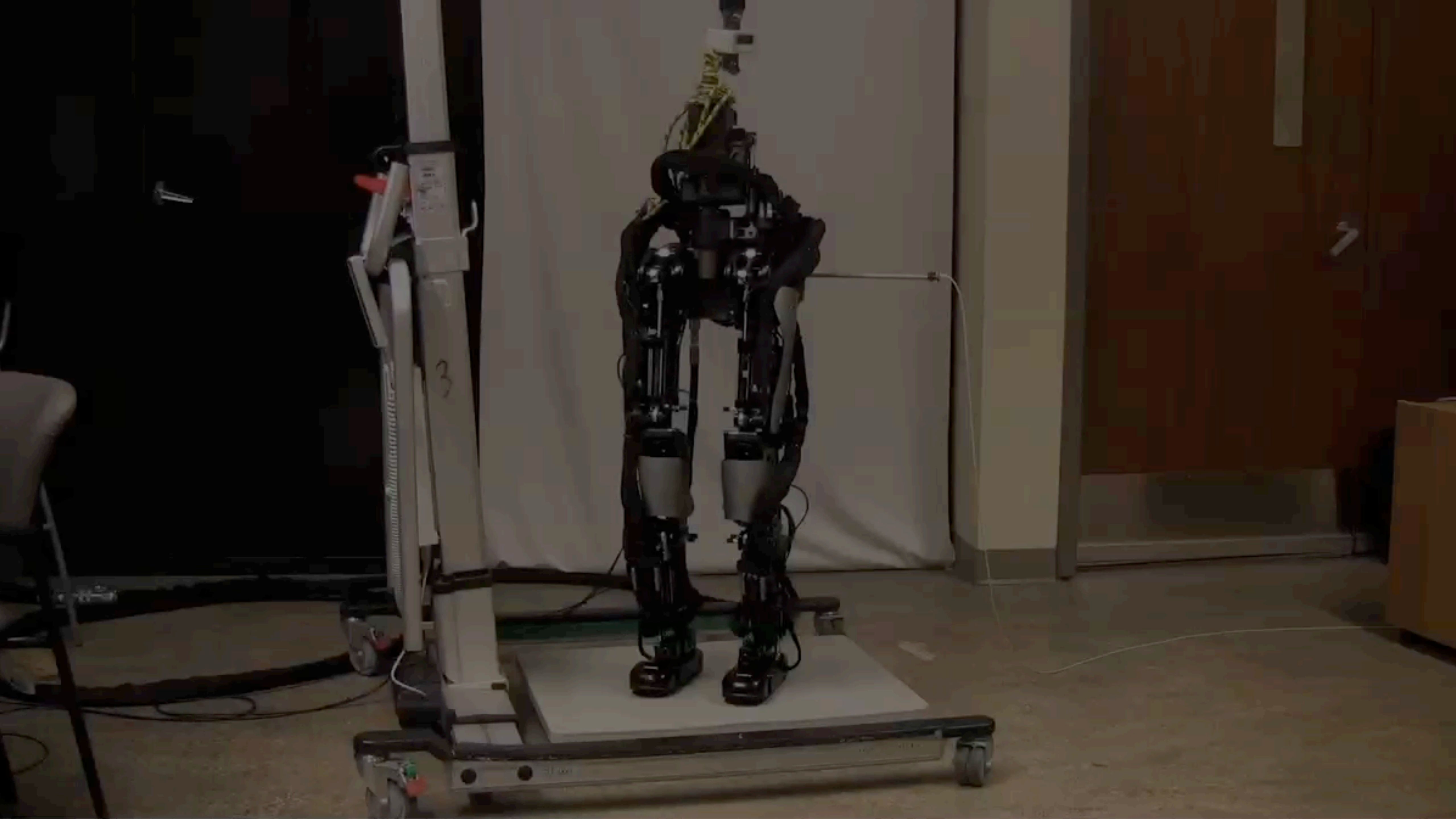
Priority	Nr. of eq(uality) and ineq(uality) constraints	Constraint/Task
1	6 eq	Newton Euler Eq. (13)
	2×14 ineq	torque limits
2	2×6 eq	kinematic contact constraint
	2×4 ineq	CoPs reside in sup. polygons
	2×4 ineq	GRFs reside in friction cones
	2×14 ineq	joint acceleration limits
3	3 eq	PD control on CoG
4	$14 + 6$ eq	PD control on posture
5	2×6 eq	regularizer on GRFs
	DoFs: 14	max. time: 0.9 ms

- prioritize

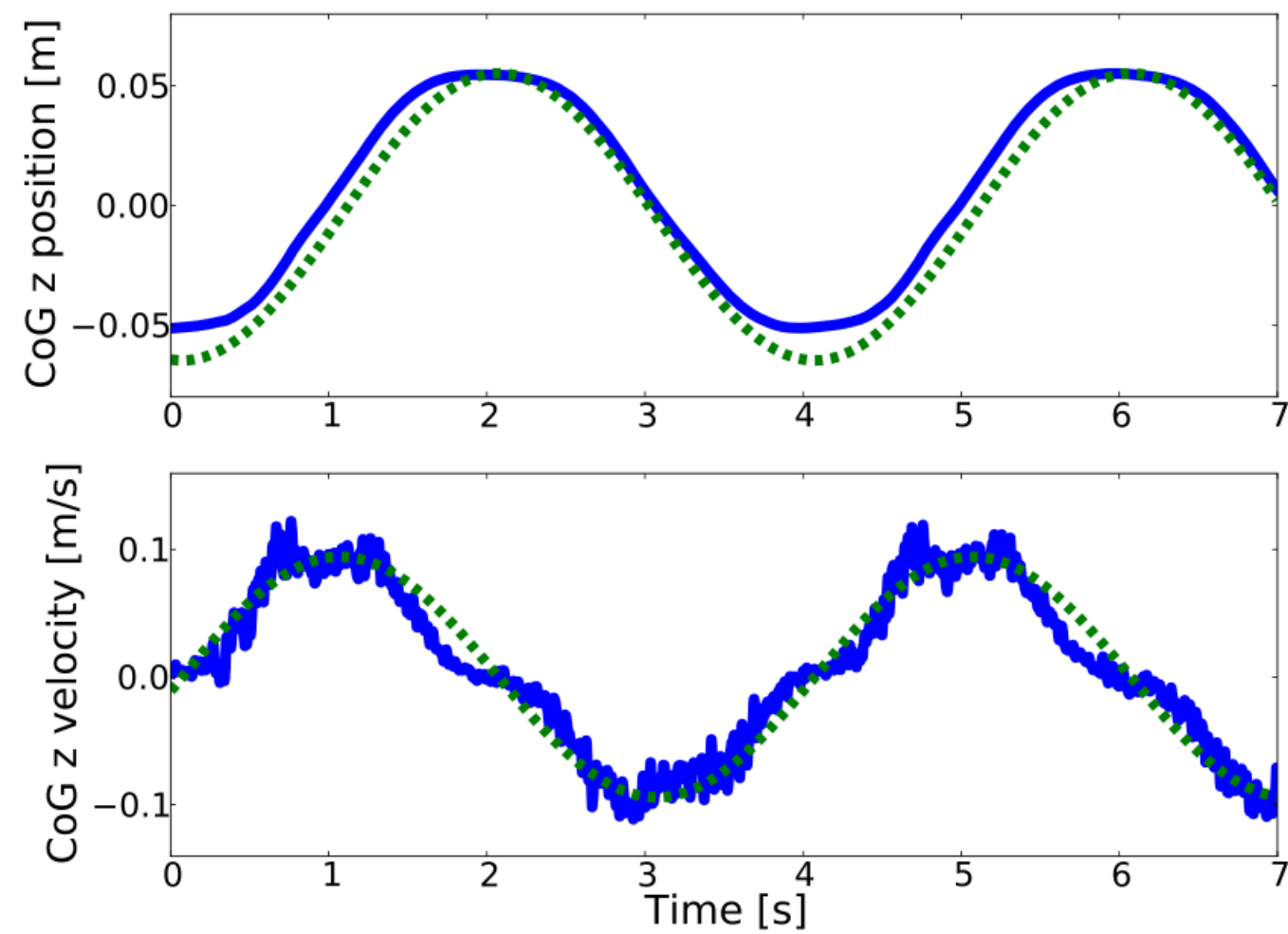
1. dynamic constraints

2. CoM motion tracking

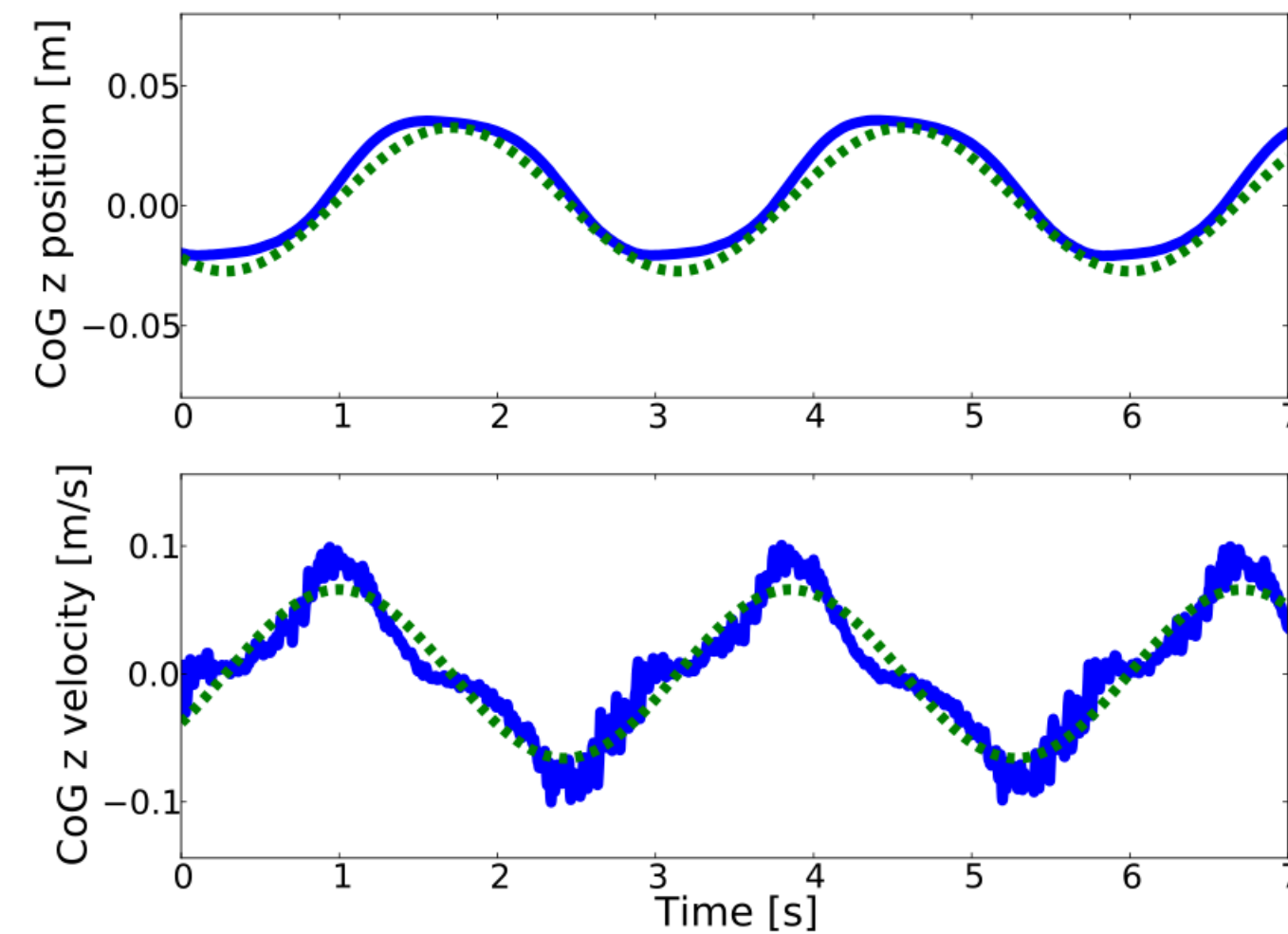
3. redundancy resolution on motion and forces



Squatting



(a) 0.25 Hz high amplitude tracking task



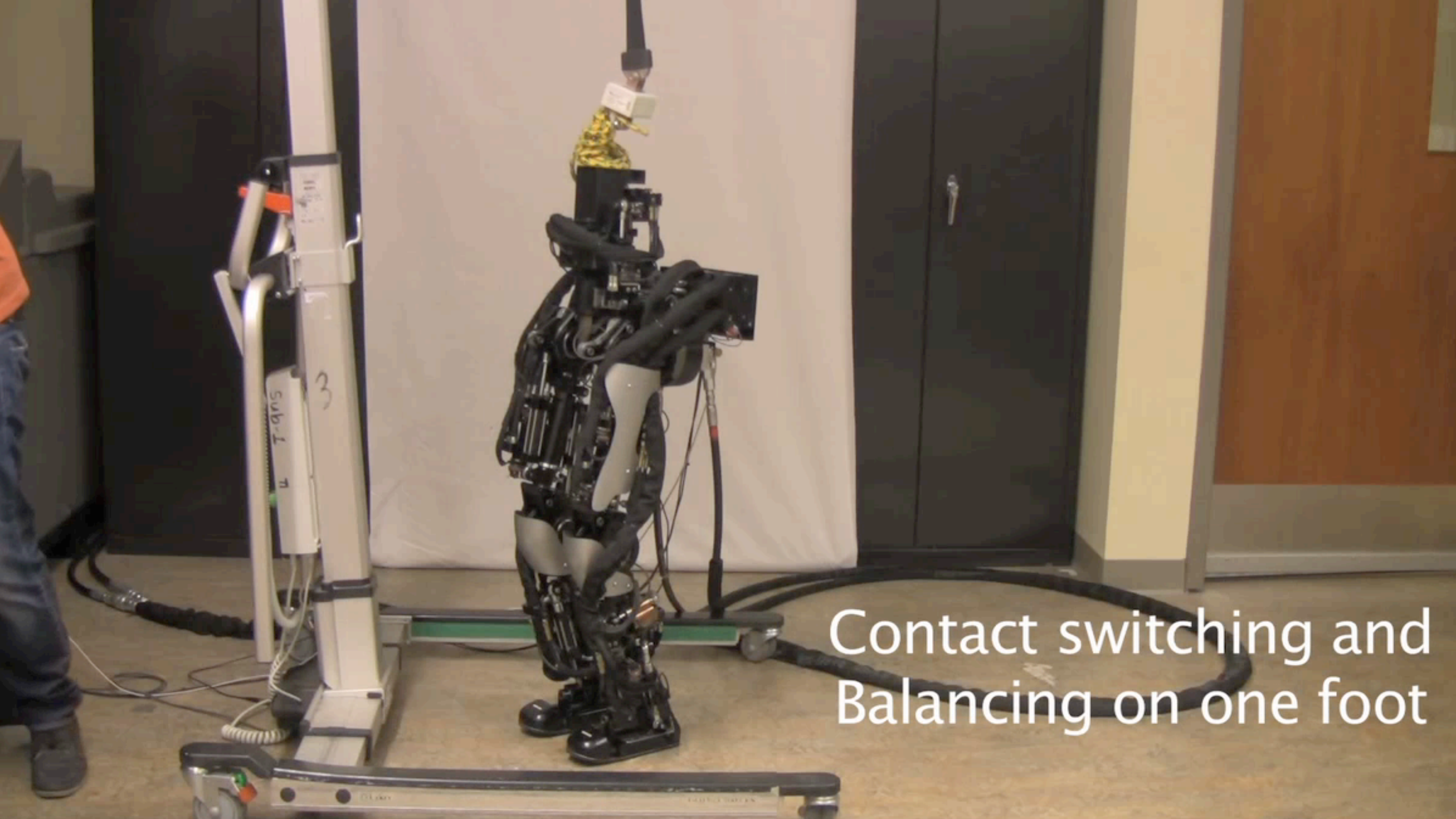
(b) 0.3 Hz low amplitude tracking task

- We can track CoM tasks of different frequencies
- Posture and GRFs are optimized in a lower hierarchy
- allows for balancing up to some extent in face of disturbances
- no ang. mom. control

Balance in Single-Support

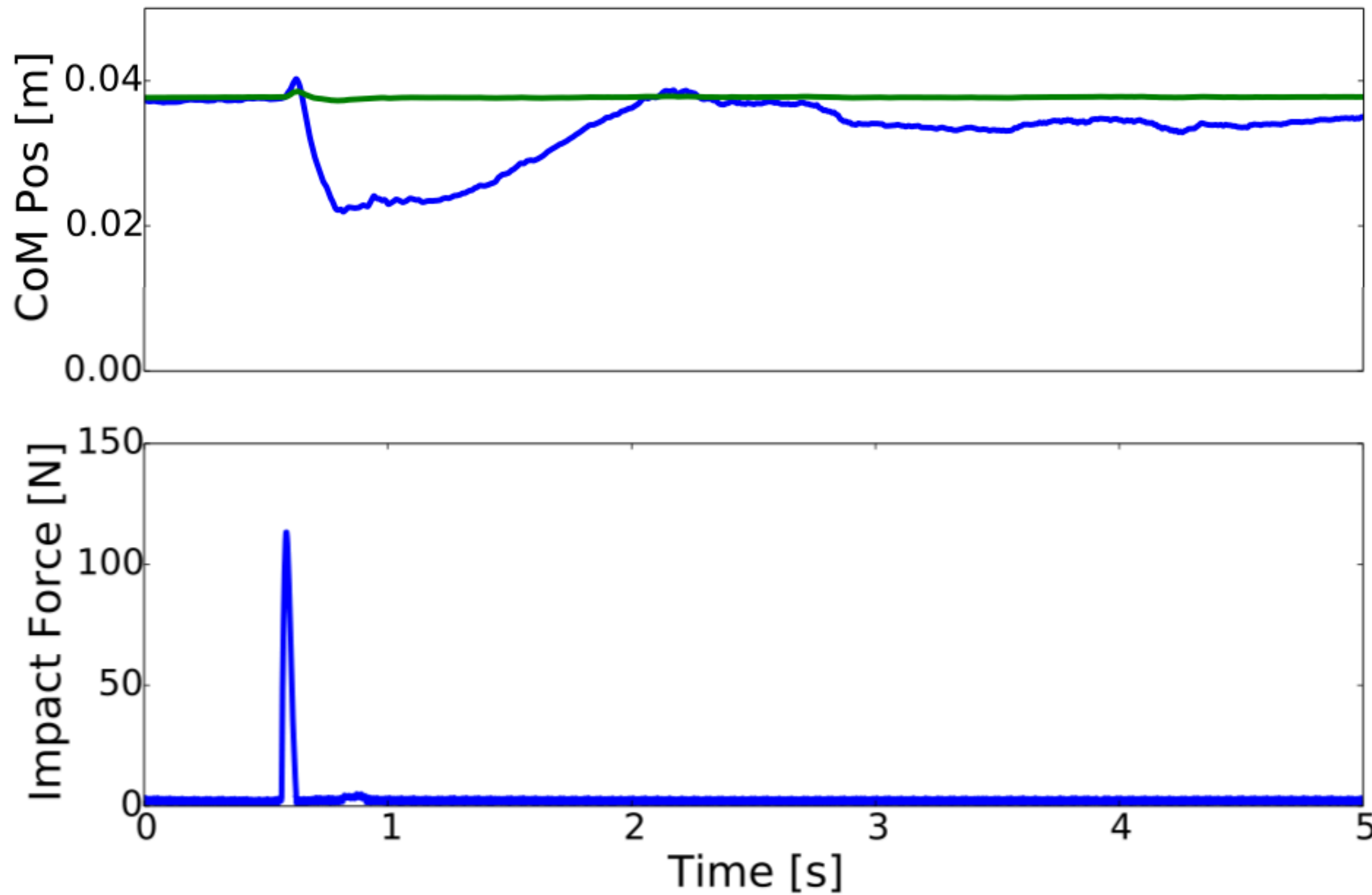
Priority	Nr. of eq(uality) and ineq(uality) constraints	Constraint/Task
1	6 eq	Newton Euler Eq. (13)
	2×14 ineq	torque limits
2	2×4 ineq	CoPs reside in sup. polygons
	2×4 ineq	GRFs reside in friction cones
	2×14 ineq	joint acceleration limits
3	6 eq.	Linear and angular momentum control
	12/6 eq.	kinematic contact constraint
	0/6 eq.	Cartesian foot motion (swing)
	14 eq.	PD control on posture
4	$2 \times 6/1 \times 6$ eq.	regularizer on GRFs
DoFs: 14		max. time: 1.05 ms

- moving on one leg requires contact switches (problematic in hierarchies)
- We put kinematic contact constraints and swing foot task into the same hierarchy to avoid the problem



Contact switching and
Balancing on one foot

Balance in Single-Support



- F/T Sensor attached to stick
- Impulse comparably high to related work* (4.5 to 5.8 Ns)
- transitioning phase for contact switch

*[Ott, 2011]

Notes on Experiments

- We feed forward torques from solver directly. No additional joint control
- Limiting Factors:
 - Naive state estimation
 - dynamic model is obtained from CAD
 - Lag of feasible trajectories => Slacks due to inconsistency with EoM => closed-loop dynamics not achieved

Notes on Experiments

- Solver Formulation:
 - slacks help analyzing conflicts in control
 - the more hierarchies the less intuitive the behavior
 - unclear what des ang. mom. should be when moving
- theoretically QP cascades generate smooth trajectories, when problem changes smoothly, but the slopes can be very high if many inequality constraints become active
- bad velocity readings
- so far no really dynamic motions => are quasi-static approaches sufficient?

Conclusion

- cascades of QPs can be used to express desired closed loop dynamics in a consistent way
- they can be implemented efficiently on a 14 DoF robot
- they work reliably for balancing and CoM tracking tasks despite model uncertainty, sensor noise and a naive estimation