Challenges for closed-loop nonlinear model predictive control on legged robots

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MACHINES IN MOTION

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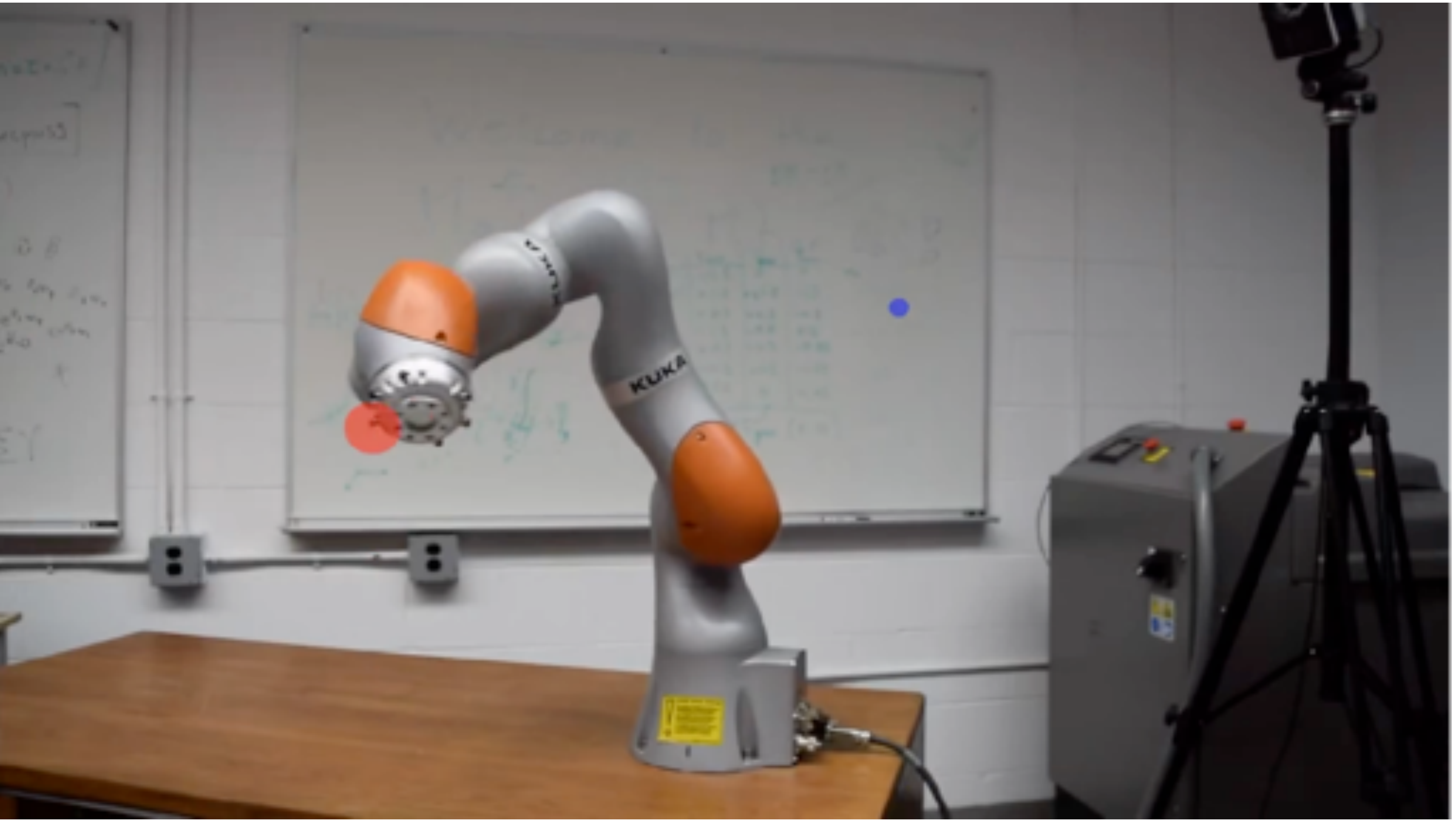
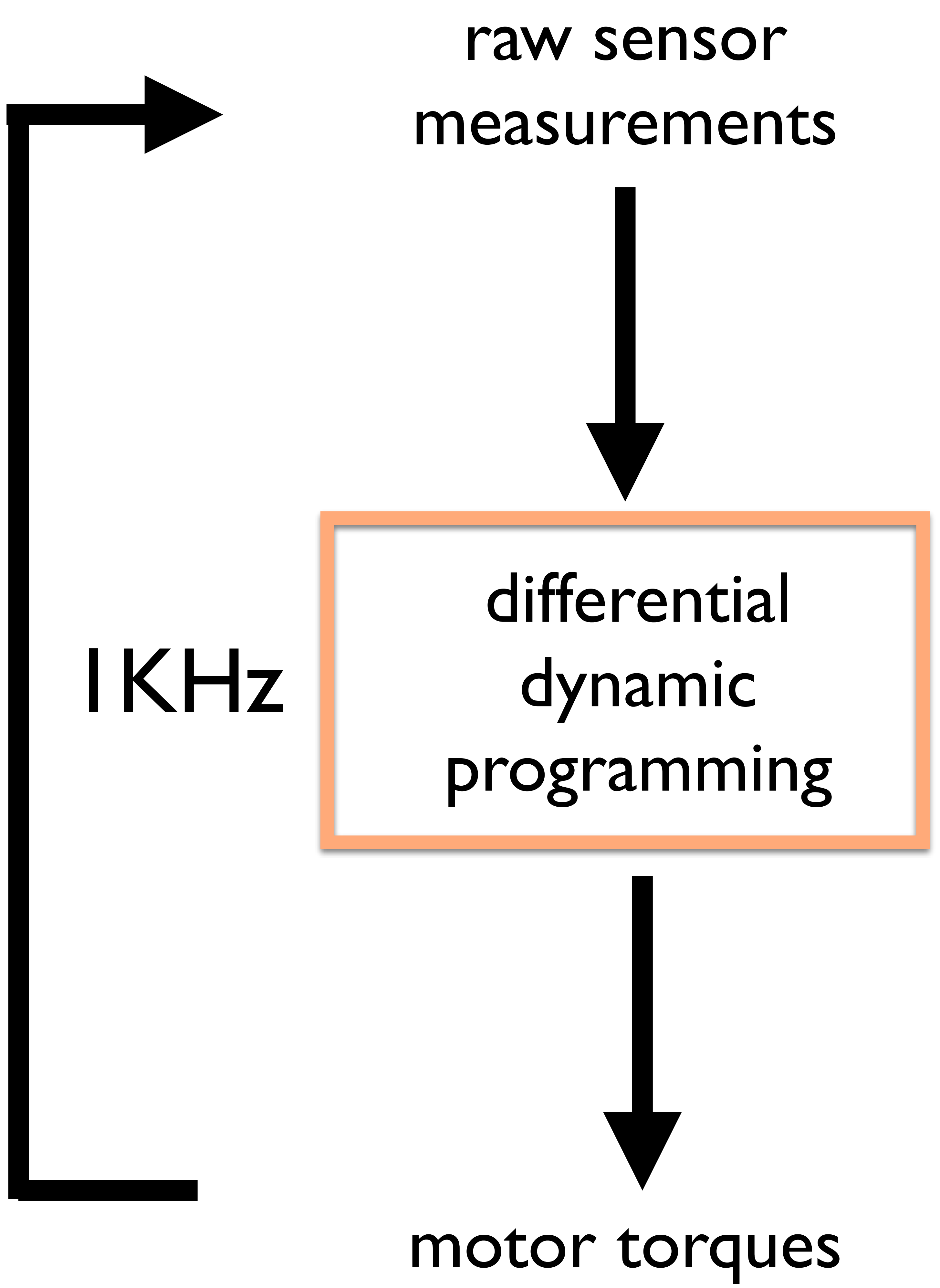
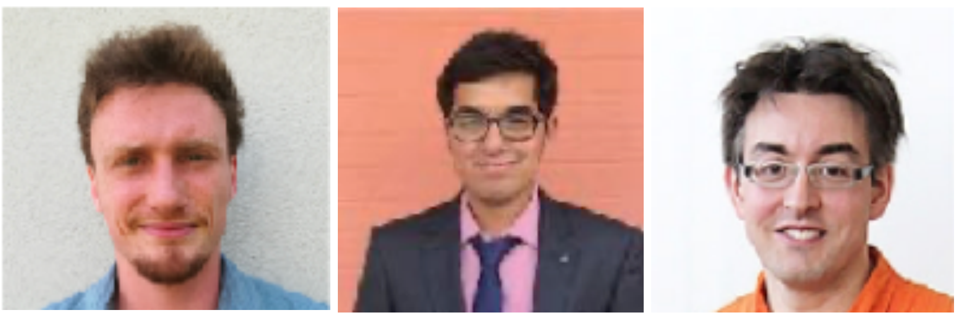
Closed-loop nonlinear model predictive control





$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{h}(\mathbf{q}, \dot{\mathbf{q}}) = \boldsymbol{\tau}$$



[Kleff et al. ICRA 2021]

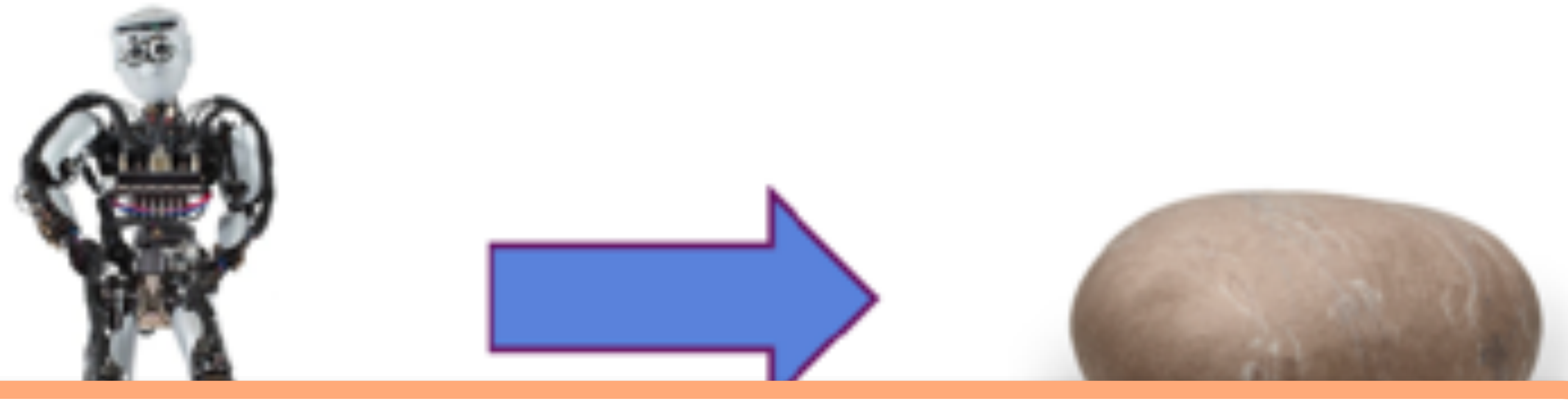
crocoddyl
Contact Robot Optimal Control by Differential Dynamic Library

Nonlinear whole-body MPC for legged robots

unactuated dynamics = evolution of momentum

$$m\dot{\mathbf{r}} = \mathbf{h}_{\text{linear}}$$

$$\dot{\mathbf{h}} = \Big[\quad M\mathbf{g} + \textstyle\sum_e \mathbf{f}_e \quad \Big]$$



equ

Decomposition of optimal control problem

I optimization of momentum + contact forces

II kinematics optimization

equivalent to a manipulator

any combination of motions and contact forces will satisfy actuated dynamics (ignoring actuation limits)

[Herzog et al., Humanoids 2015,IROS 2016]

centroidal dynamics optimization

$$\min_{\substack{\mathbf{F}_c,\ \mathbf{x}_{CoM} \\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM}}} \sum_t \phi_F(\mathbf{F}_c) + \phi_x(\mathbf{x}_{CoM},\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM})$$

subject to

$$m\ddot{\mathbf{x}}_{CoM} = m\mathbf{g} + \sum_c \mathbf{F}_c$$

$$\dot{\mathbf{L}}_{CoM} = \sum_c (\mathbf{r}_c - \mathbf{x}_{CoM}) \times \mathbf{F}_c$$

$$\mathbf{F}_c \in \text{friction cones}$$

$$(\mathbf{x}_{CoM},\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM}) \in \text{Box Constraints}$$


[Meduri et al., arxiv.org/abs/2201.07601, T-RO in press]

centroidal dynamics optimization

$$\min_{\substack{\mathbf{F}_c,\ \mathbf{x}_{CoM} \\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM}}} \sum_t \phi_F(\mathbf{F}_c) + \phi_x(\mathbf{x}_{CoM},\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM})$$

Separable cost

forces vs. positions/momentum

subject to

$$m\ddot{\mathbf{x}}_{CoM} = m\mathbf{g} + \sum_c \mathbf{F}_c$$

$$\dot{\mathbf{L}}_{CoM} = \sum_c (\mathbf{r}_c - \mathbf{x}_{CoM}) \times \mathbf{F}_c$$

Equality constraints are bi-linear

$$\mathbf{F}_c \in \text{friction cones}$$

$$(\mathbf{x}_{CoM},\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM}) \in \text{Box Constraints}$$

Inequality constraints are easy to project (indicator functions)

[Meduri et al., arxiv.org/abs/2201.07601, T-RO in press]

$$\min_{\mathbf{F}_c,\ \mathbf{x}_{CoM},\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM}} \sum_t \phi_F(\mathbf{F}_c) + \phi_x(\mathbf{x}_{CoM},\ \dot{\mathbf{x}}_{CoM},\ \mathbf{L}_{CoM})$$

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ADMM for centroidal dynamics

1) solve force problem (positions are fixed)
=> simple QP

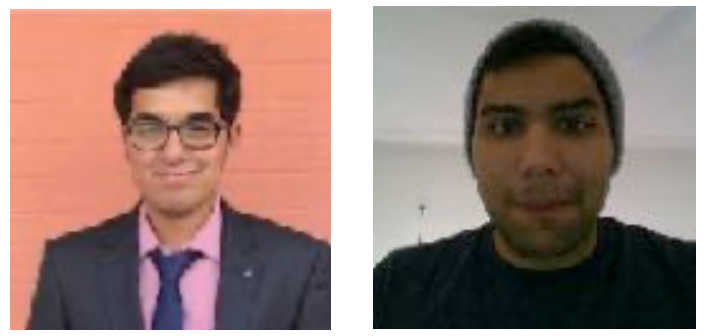
2) solve position problem (forces are fixed)
=> simple QP

3) Dual variables update
(linear analytic formula)

=> iterate until convergence
(early termination for MPC)

FISTA for QP solver (Fast Iterative Shrinkage Thresholding Algorithm)

- Nesterov accelerated gradient descent + projection operators for constraints
- First order method (only gradients) with second order convergence guarantees
- Easy to implement



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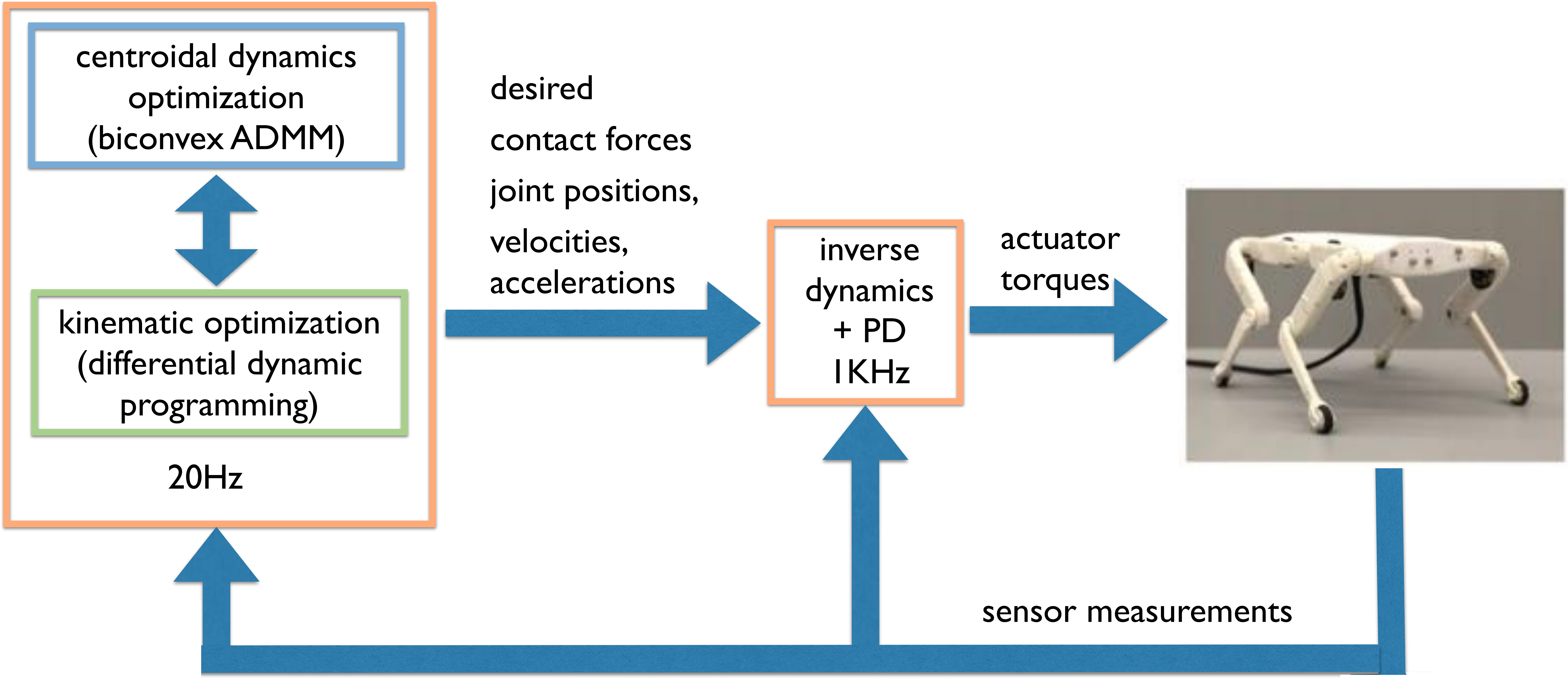
Closed-loop nonlinear model predictive control



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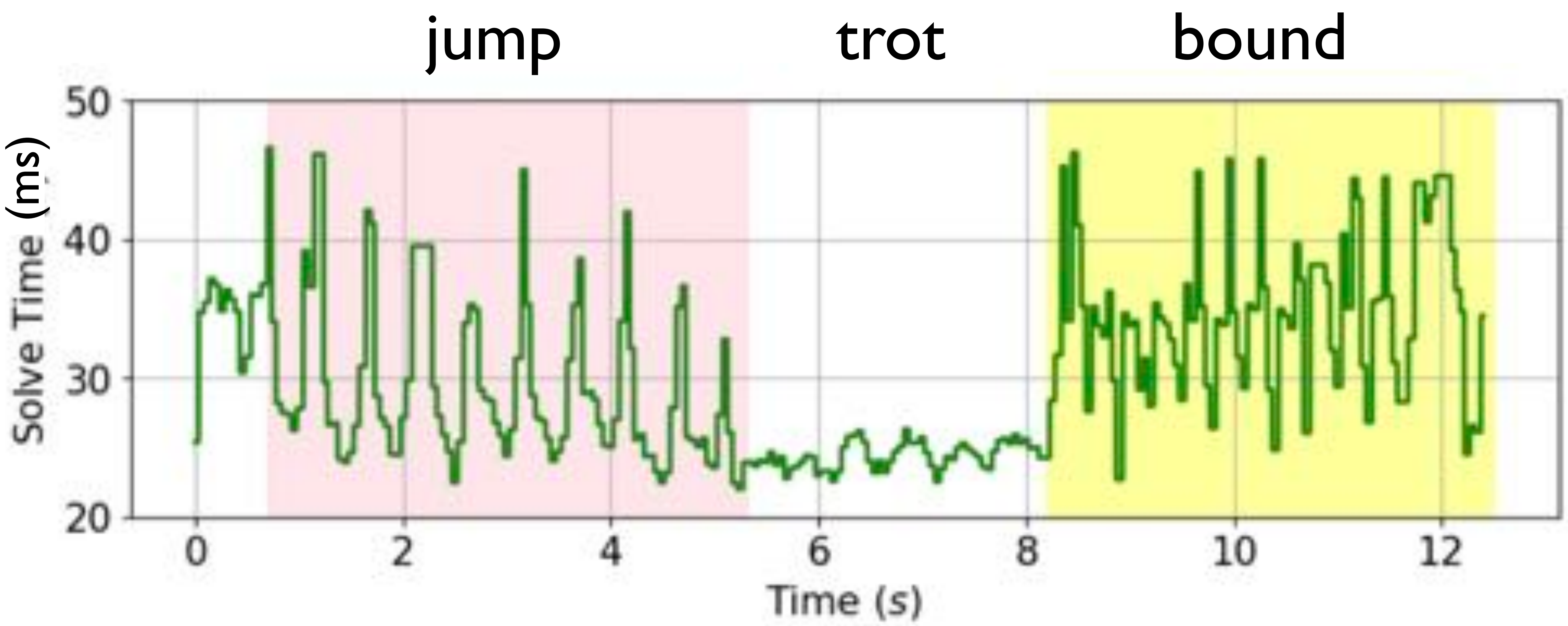
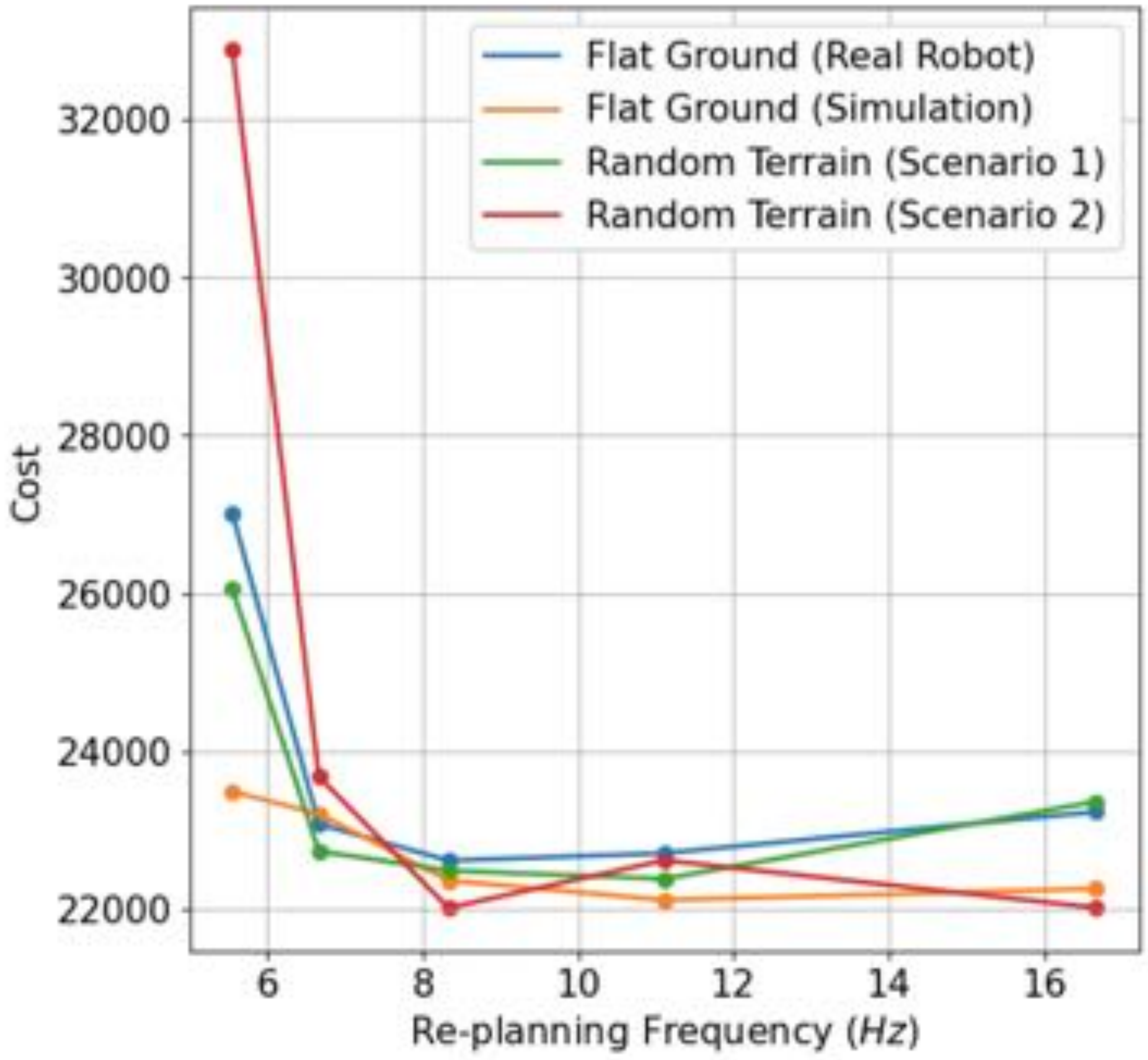
Solve times (whole-body) during gait transitions



# of collocation points 10 (jump/trot) and 12 (bound)

[Meduri et al., arxiv.org/abs/2201.07601, T-RO in press]

Do we need to close a faster MPC loop?



Measured cost as a function of re-planning frequency on 3 different terrains + real robot

Agreement real robot and simulation

>10Hz not much is gained

[Meduri et al., arxiv.org/abs/2201.07601, T-RO in press]

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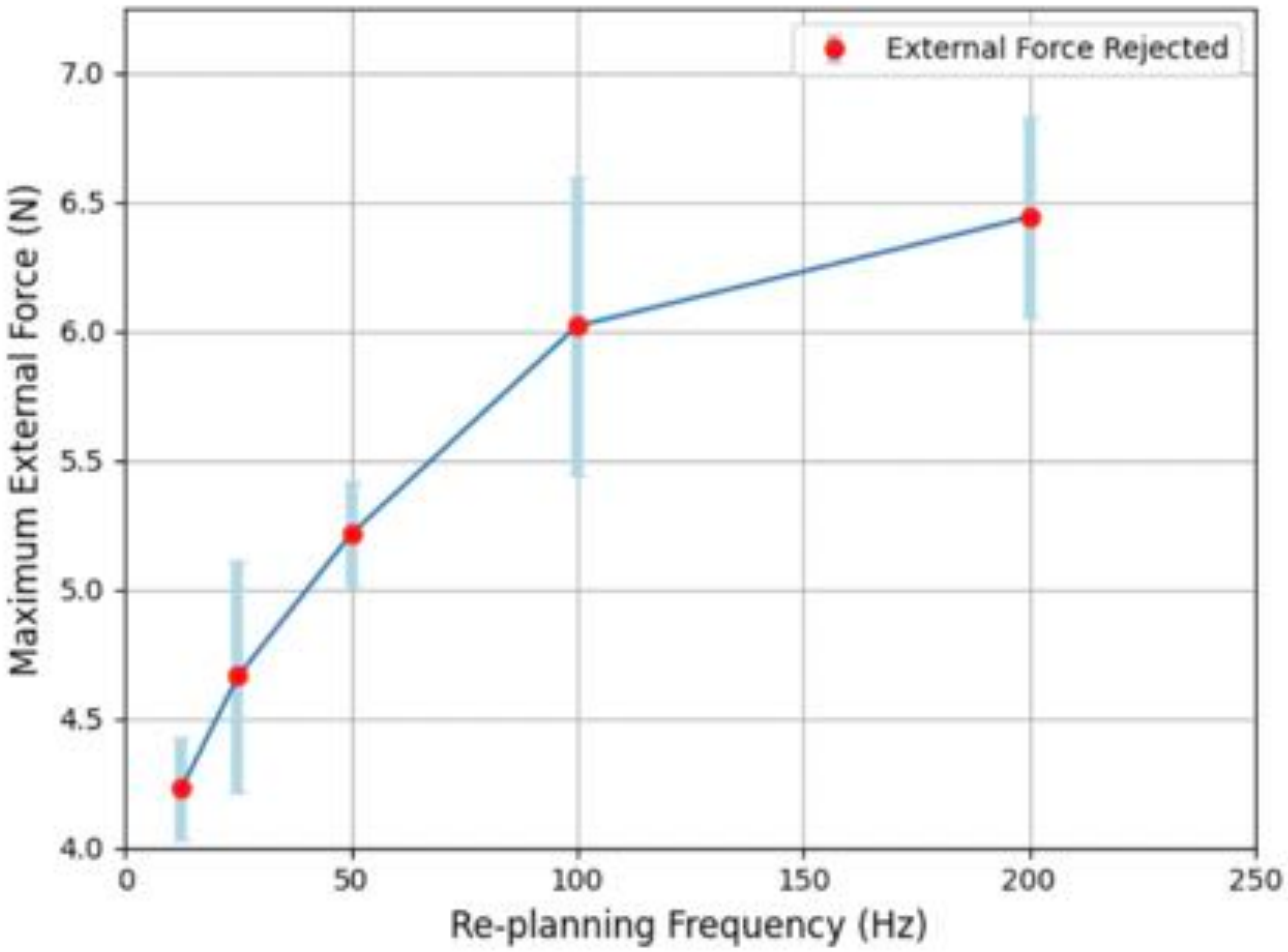


Maximum external force rejected as a function of re-planning frequency (simulation only)

Maximum disturbance rejection increases with MPC frequency


[Meduri et al., arxiv.org/abs/2201.07601, T-RO in press]

Closed-loop nonlinear model predictive control

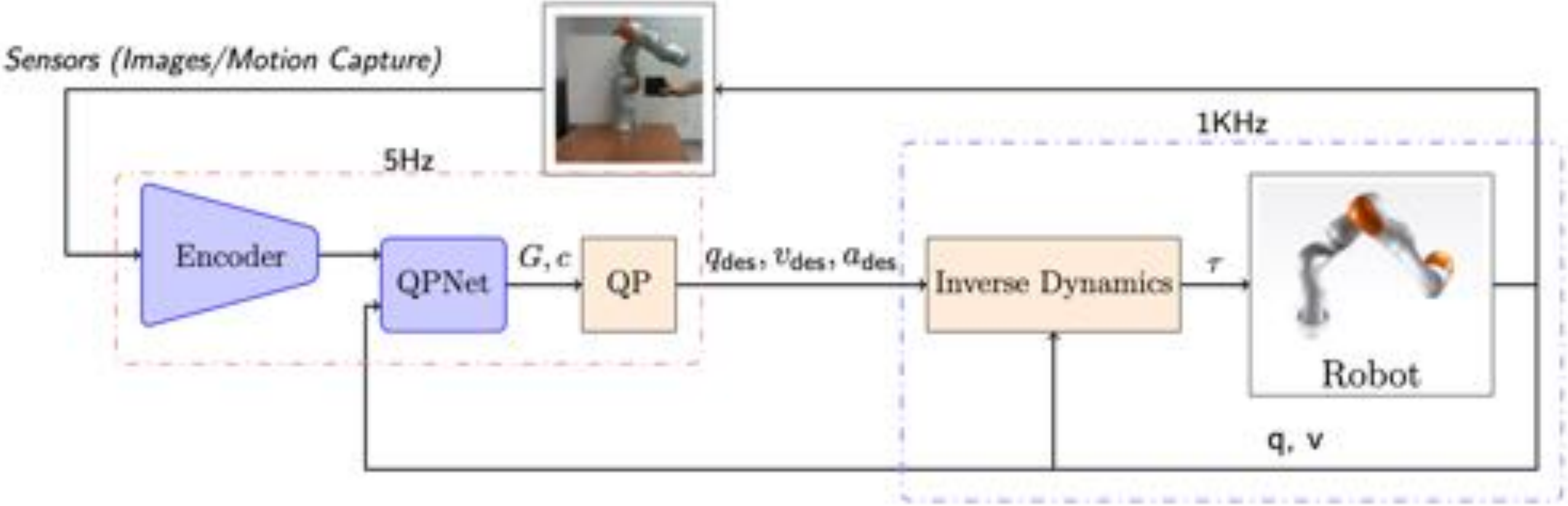
- Efficient solver for whole-body MPC
- Closed-loop MPC leads to very robust behaviors (easy to transfer to the robot)
- First-order methods are very exciting

Problems

- solve times are still high / requires a lot of online compute
- no online contact / gait adaptation
- high barrier to entry => need to write your own solver

Learning to reduce optimizer complexity

Learning cost functions mapping sensors to OC problems

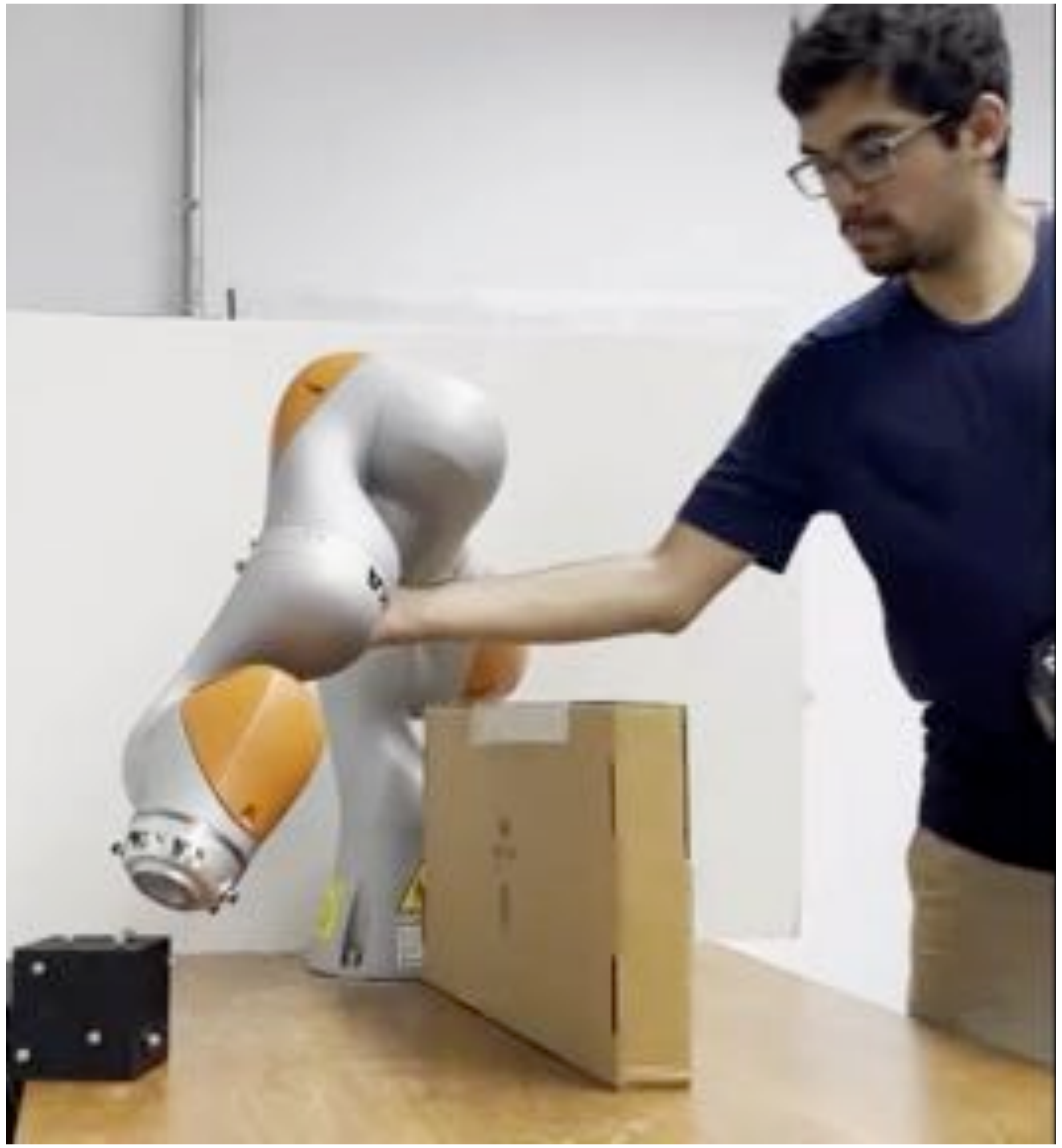


Move all the complexity in the cost function

Cost function NN => adapted sensor-driven quadratic cost at each control cycle

At each MPC cycle => simple QP with constraints

[Meduri et al.,https://arxiv.org/abs/2209.09451]



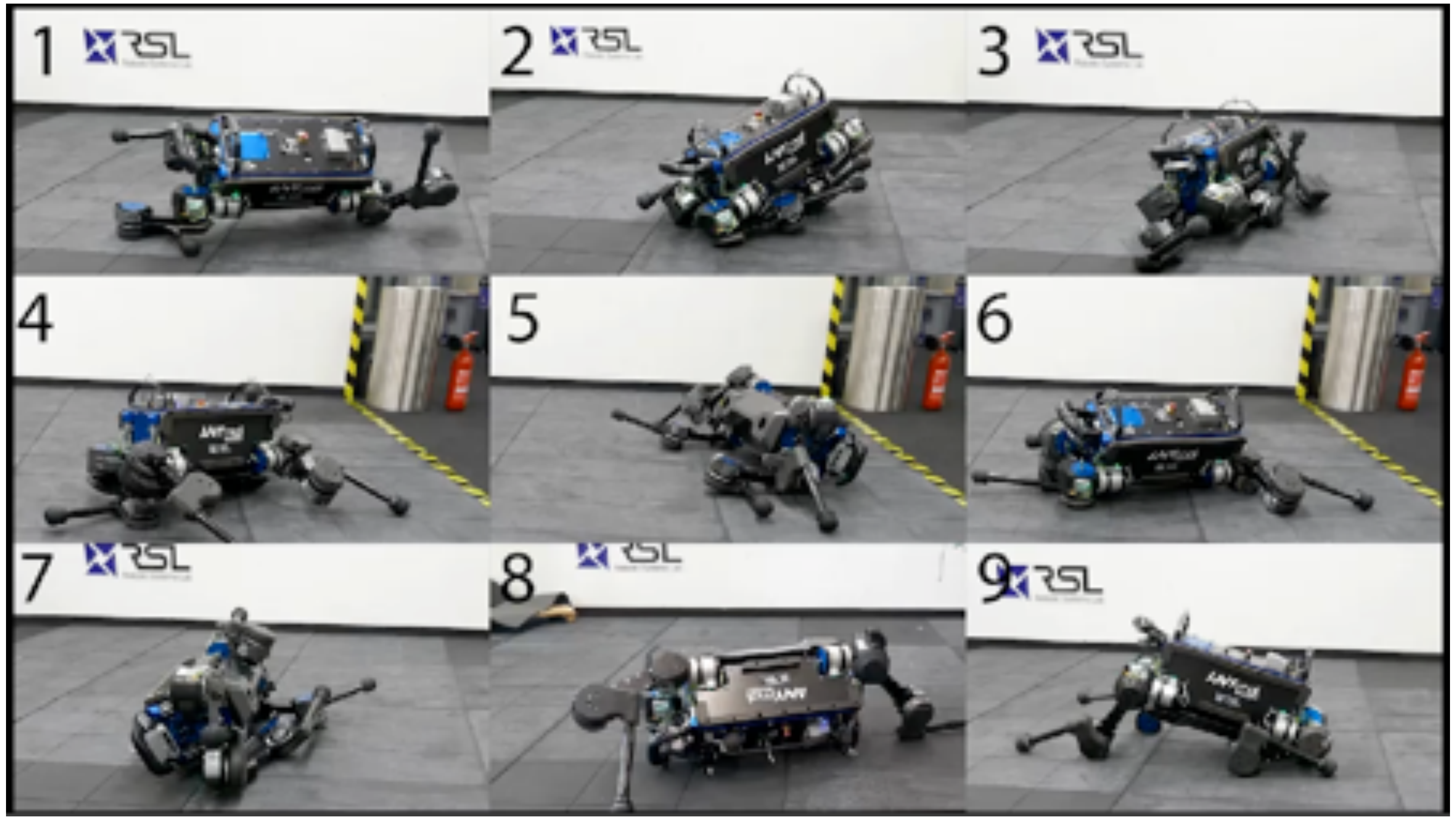
Only a QP solved at each control cycle yet can avoid obstacles

Cost includes vision + position/velocity sensing



[Meduri et al., https://arxiv.org/abs/2209.09451]

But is this the way to go…?



[Hwangbo et al. 2019]

[Huang et al. 2022]

Direct policy learning with RL has had impressive successes

Perception is naturally included
low barrier to entry (simple algorithms)

Closed-loop nonlinear model predictive control

- Efficient solver for whole-body MPC
- Closed-loop MPC leads to very robust behaviors (easy to transfer to the robot)
- First-order methods are very exciting
- Learning costs / value function help lower complexity / include perception

Still many remaining issues:

- high barrier to entry for traj. opt. / MPC
- perception is often ignored
- where do we go from here? how do we relate to RL recent successes?

https://github.com/machines-in-motion

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