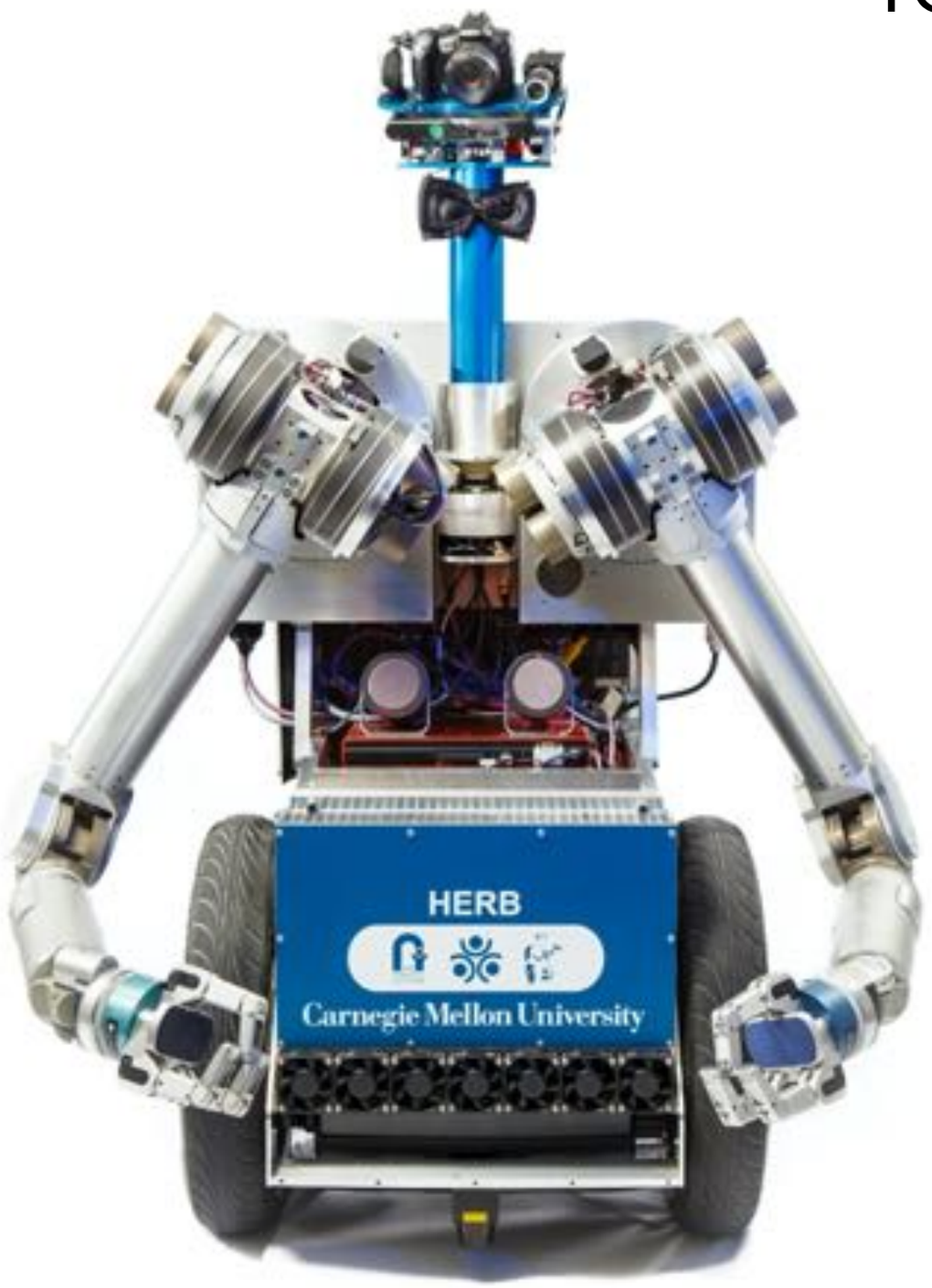
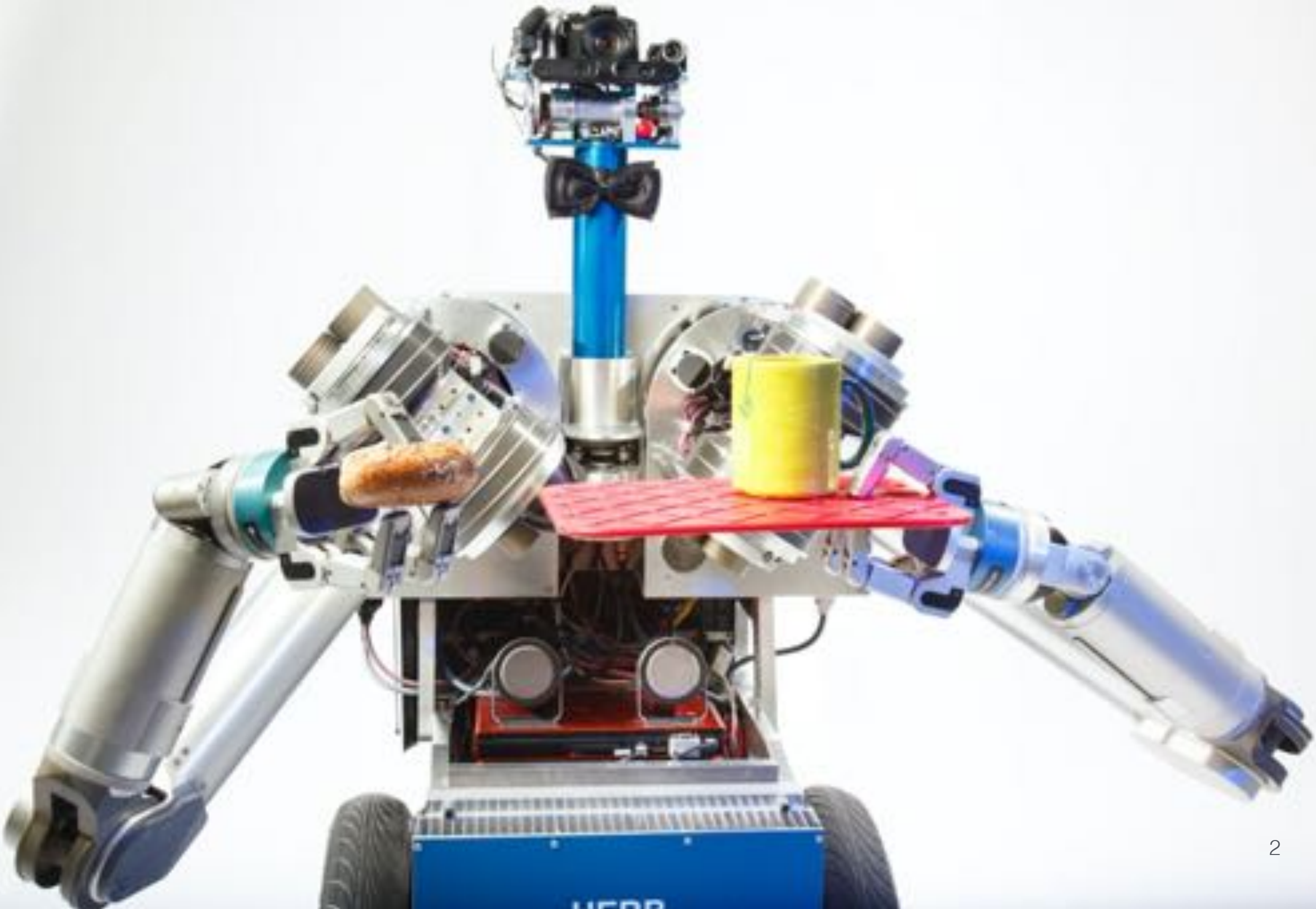


A Bayesian Framework for Robust Manipulation via Contact Sensing

Michael Koval
mkoval@cs.cmu.edu
The Robotics Institute
Carnegie Mellon University



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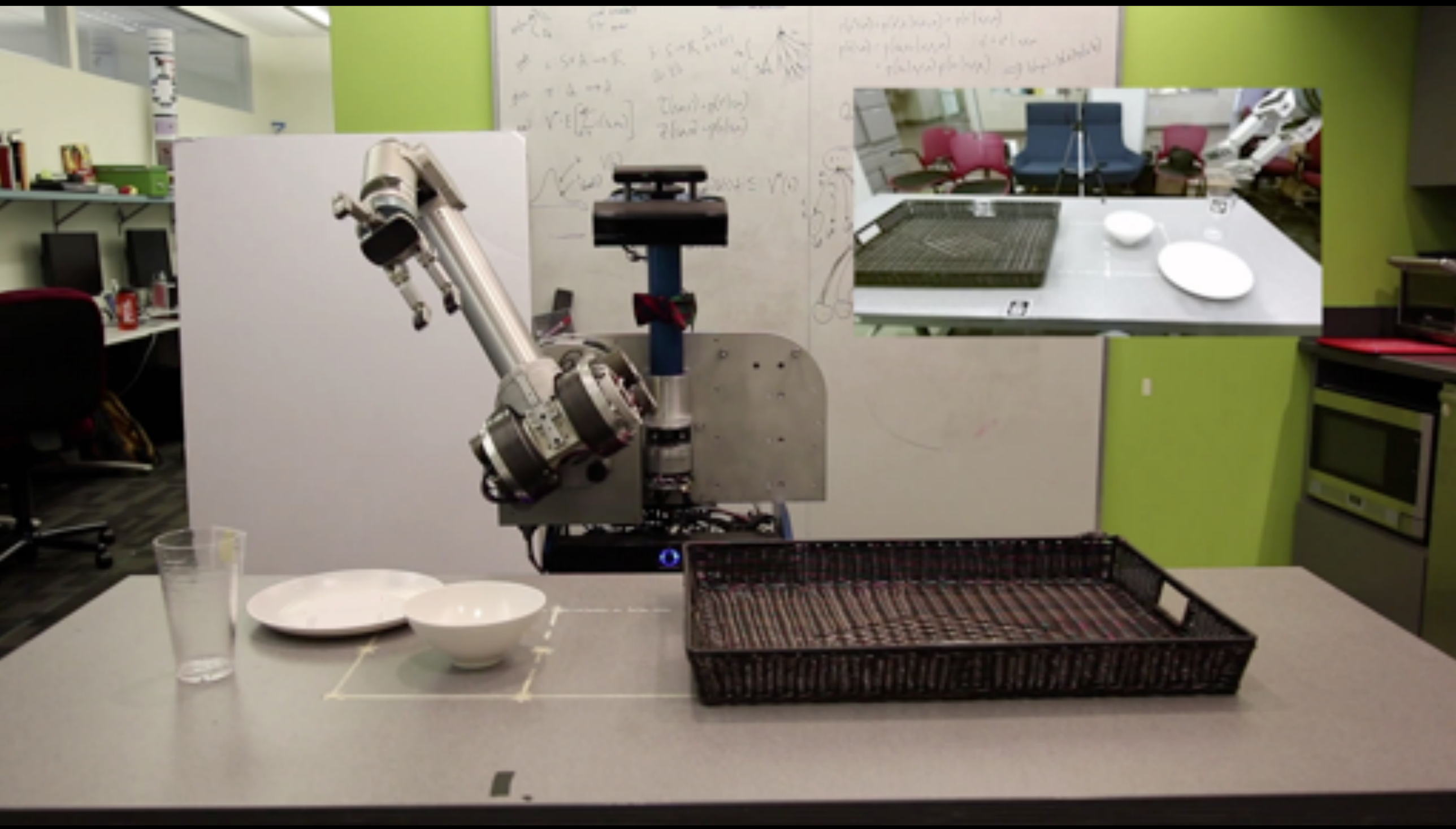
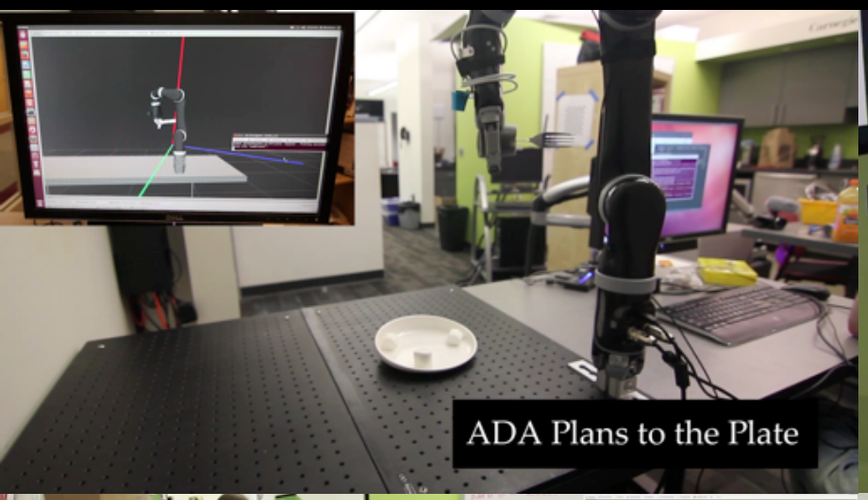
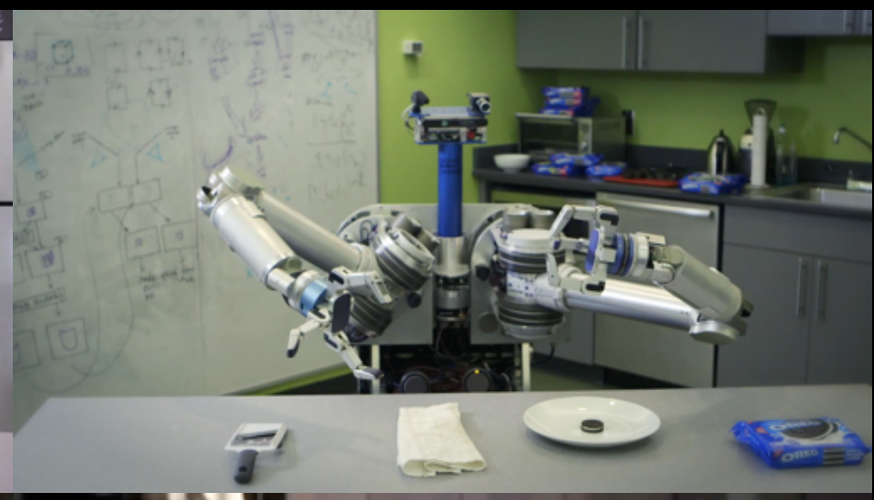
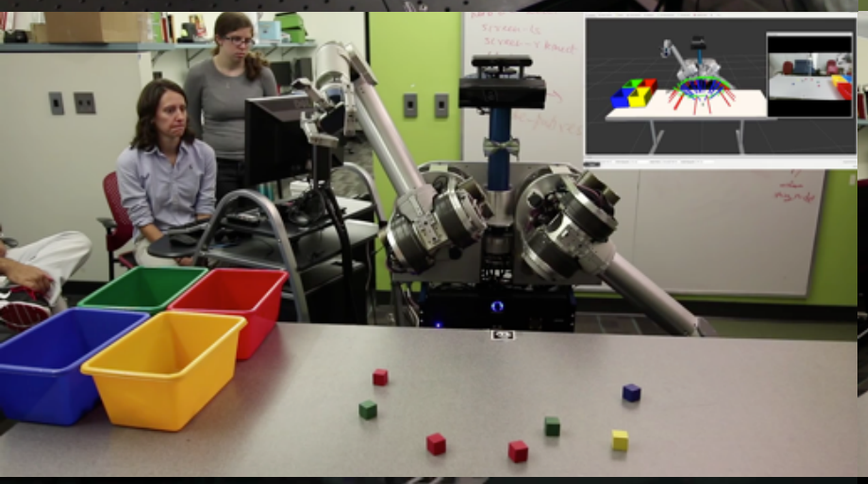


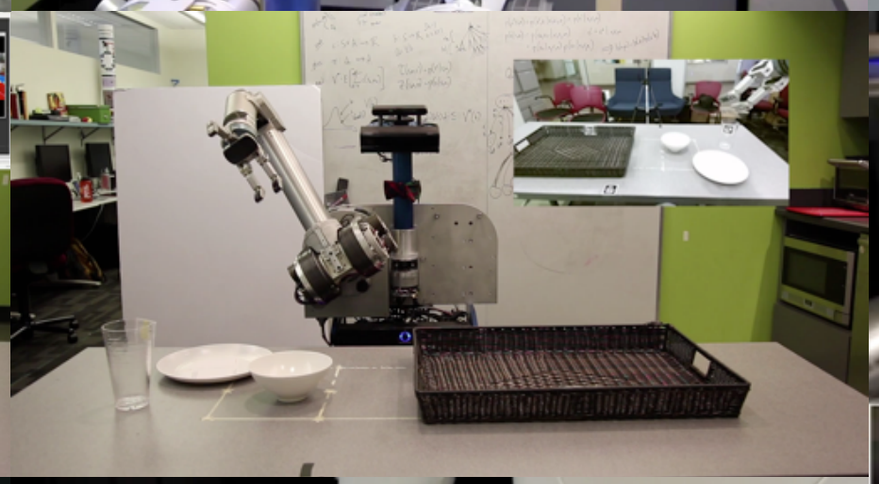
S.S. Srinivasa, A.M. Johnson, M.C. Koval, et al., “Exploiting domain knowledge for multi-step mobile manipulation: architecture, algorithms, and experiments,” ISER, 2016. Under review.

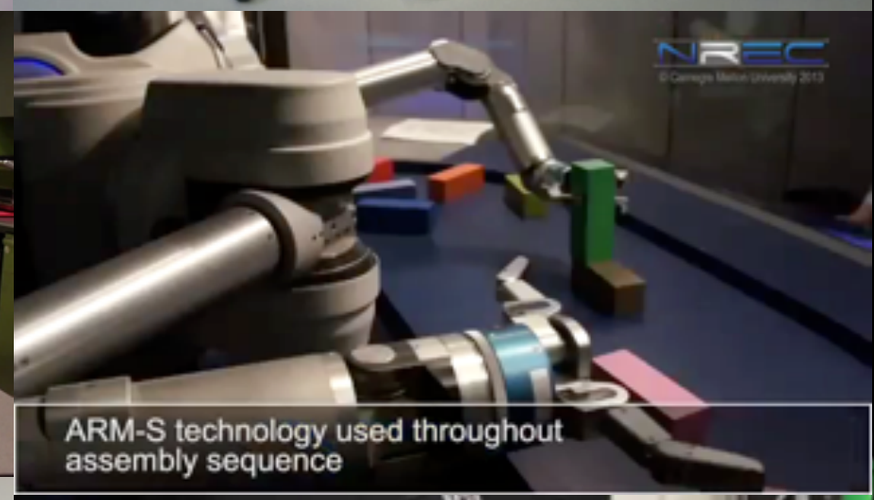

ADA Plans to the Plate

(4×)
Grasp book using force feedback

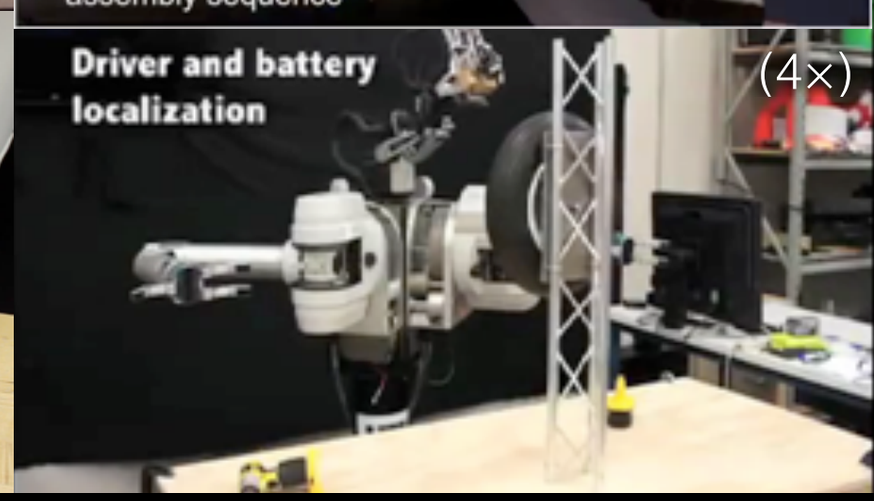




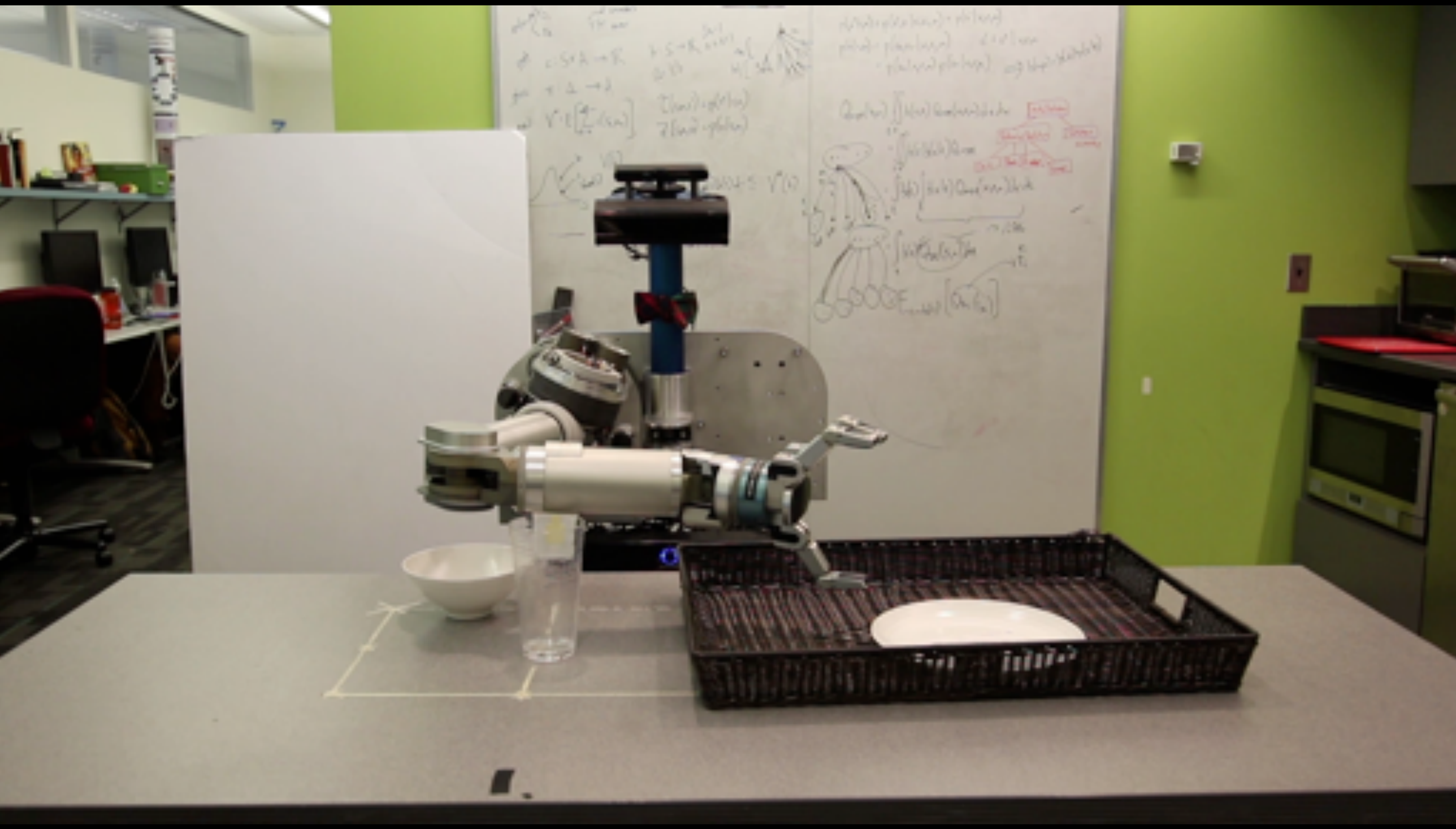



NREC
ARM-S technology used throughout assembly sequence

DARPA Autonomous Robotic Manipulation
NREC Team
PI: Drew Bagnell, Martial Hebert, Nancy Pollard
Team: Moslem Kazemi

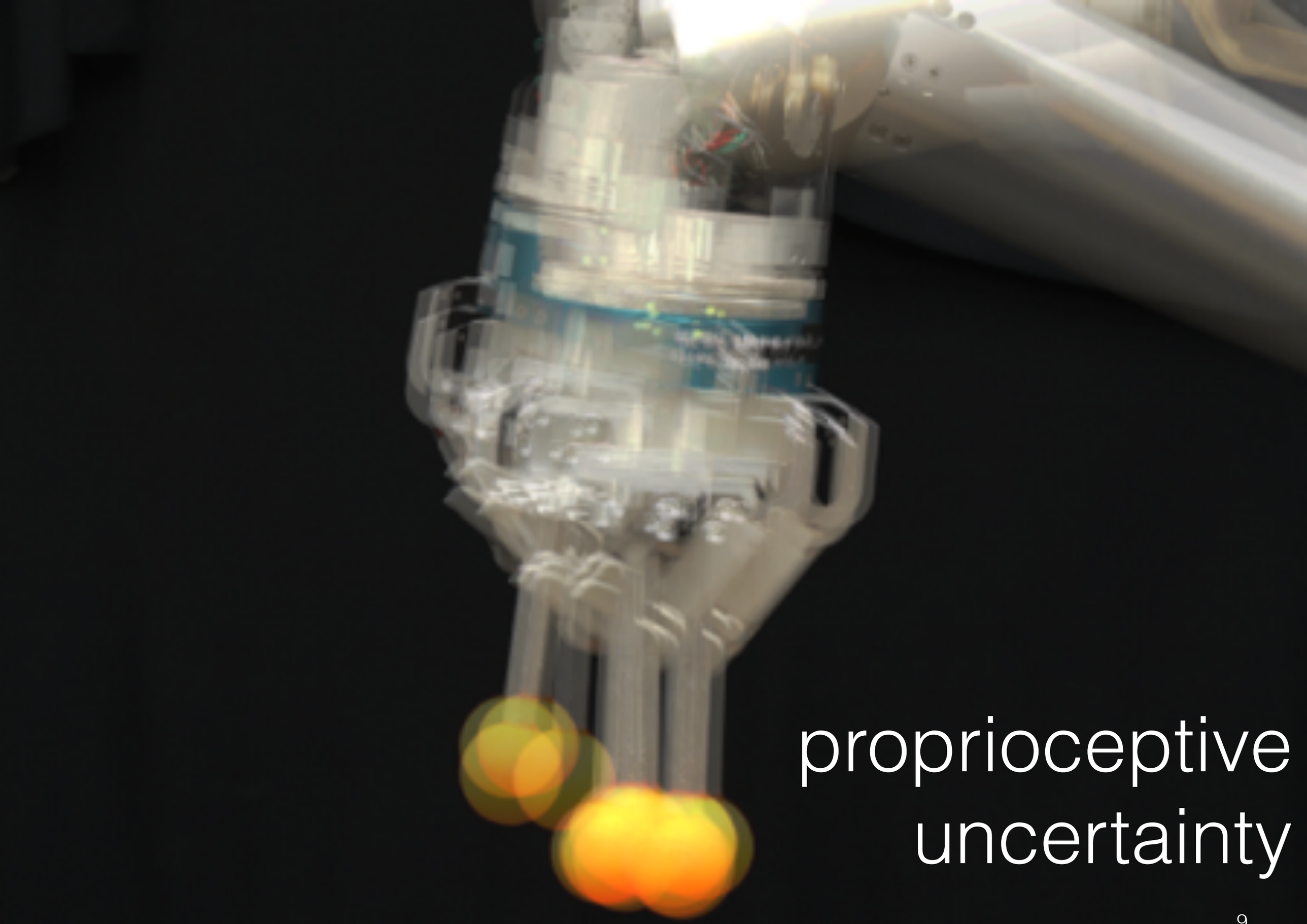

Driver and battery localization
(4×)

By Zen Wave, via Wikimedia Commons. <https://commons.wikimedia.org/wiki/File:FlexLean_Production_Line.jpg>



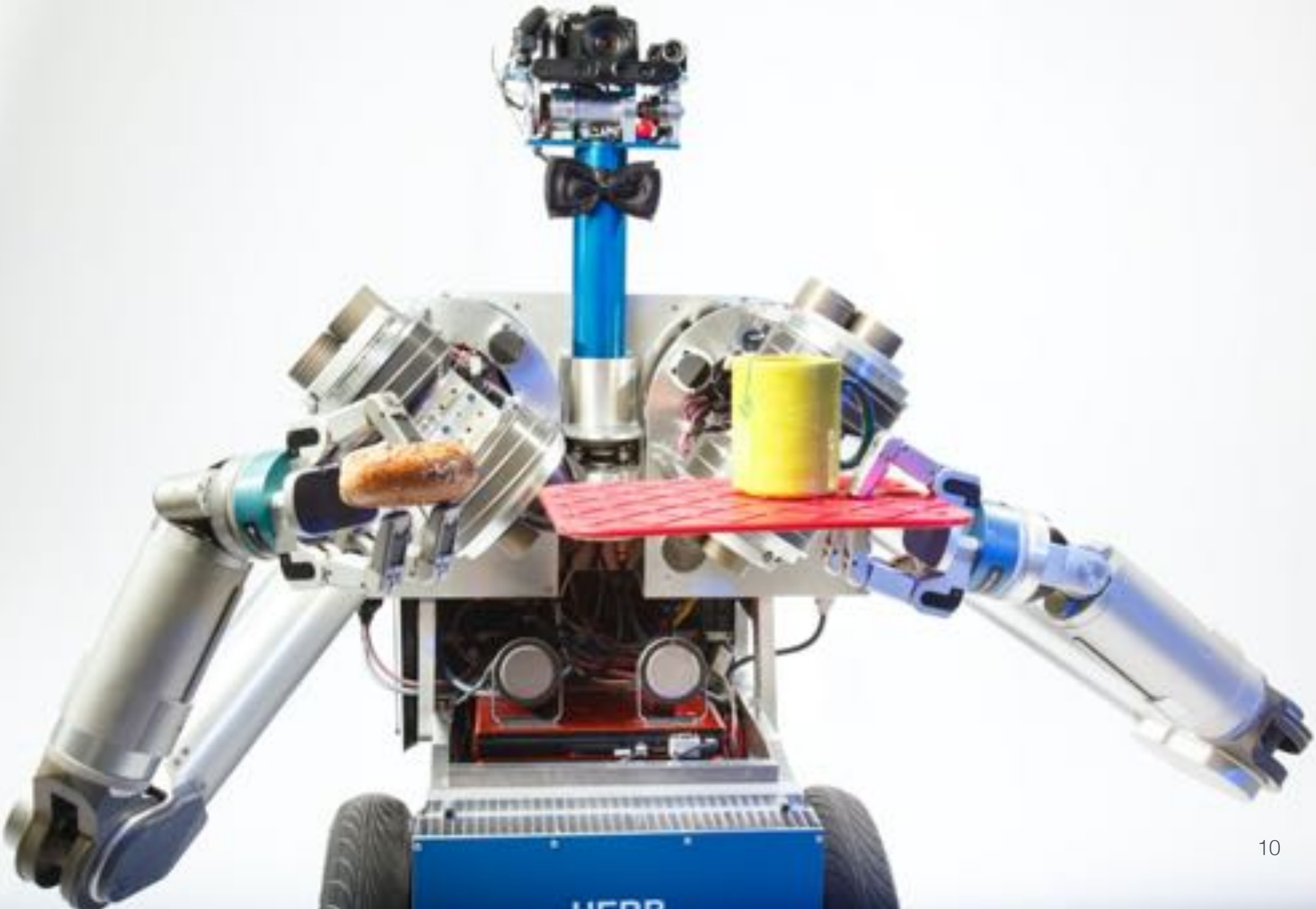
S.S. Srinivasa, A.M. Johnson, M.C. Koval, et al., “Exploiting domain knowledge for multi-step mobile manipulation: architecture, algorithms, and experiments,” ISER, 2016. Under review.

perceptual uncertainty



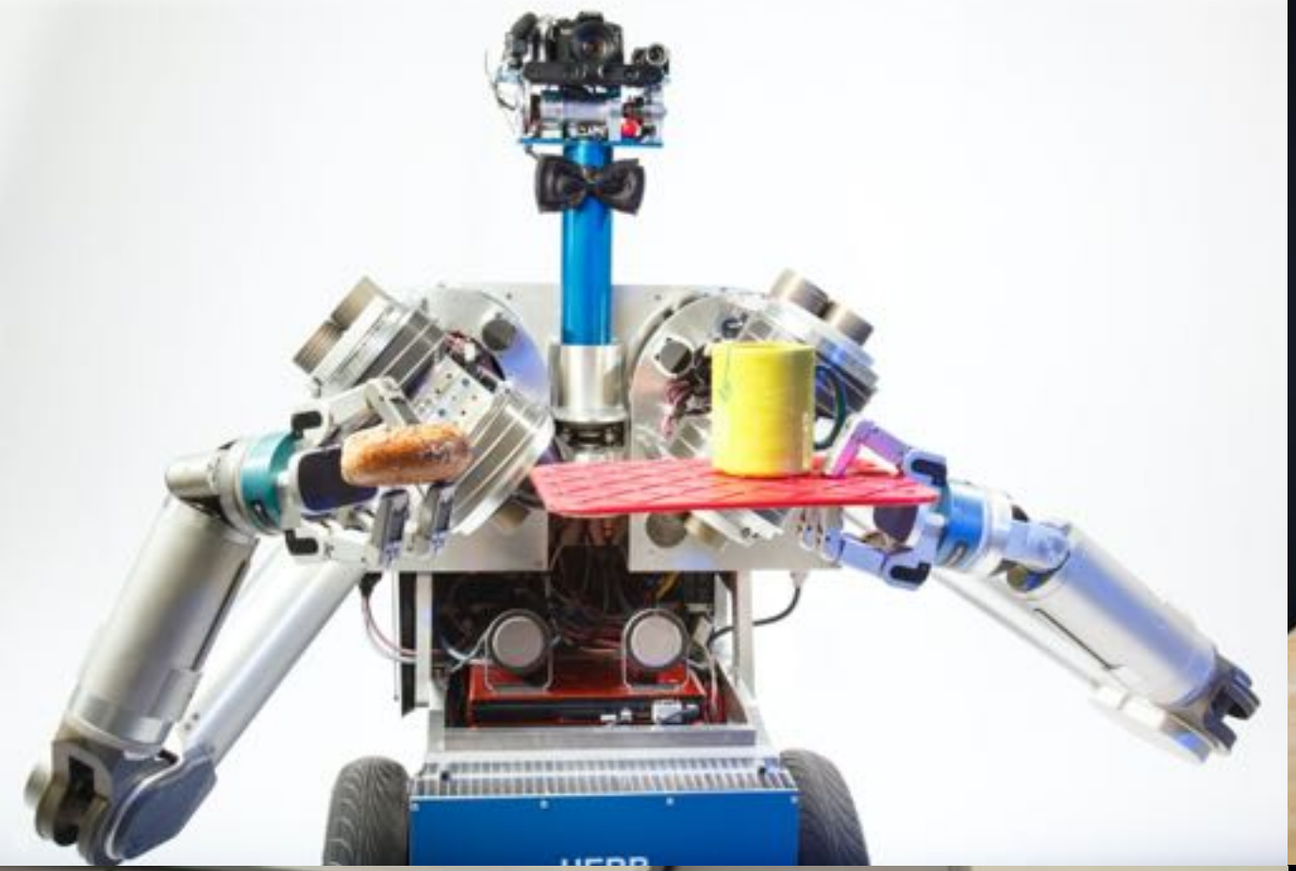
proprioceptive uncertainty

Source: M. Klingensmith, et al. "Closed-loop servoing using real-time markerless arm tracking." ICRA Humanoids Workshop, 2013.



HERB

Personal Robotics Lab

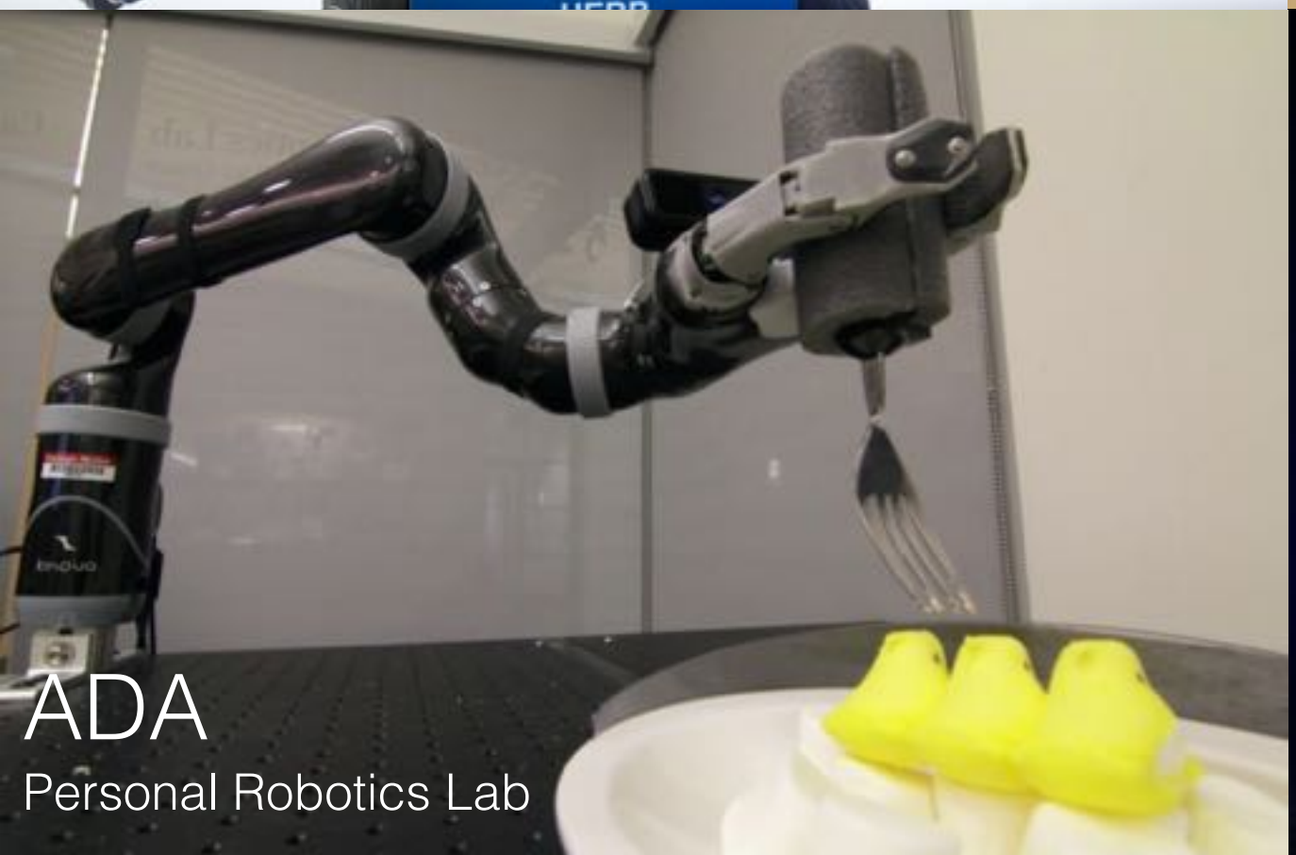


Andy

CMU/NREC

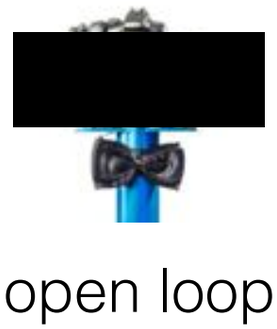
ADA

Personal Robotics Lab



Robonaut 2

NASA/JSC



open loop

tactile feedback

visual feedback

open loop

tactile feedback

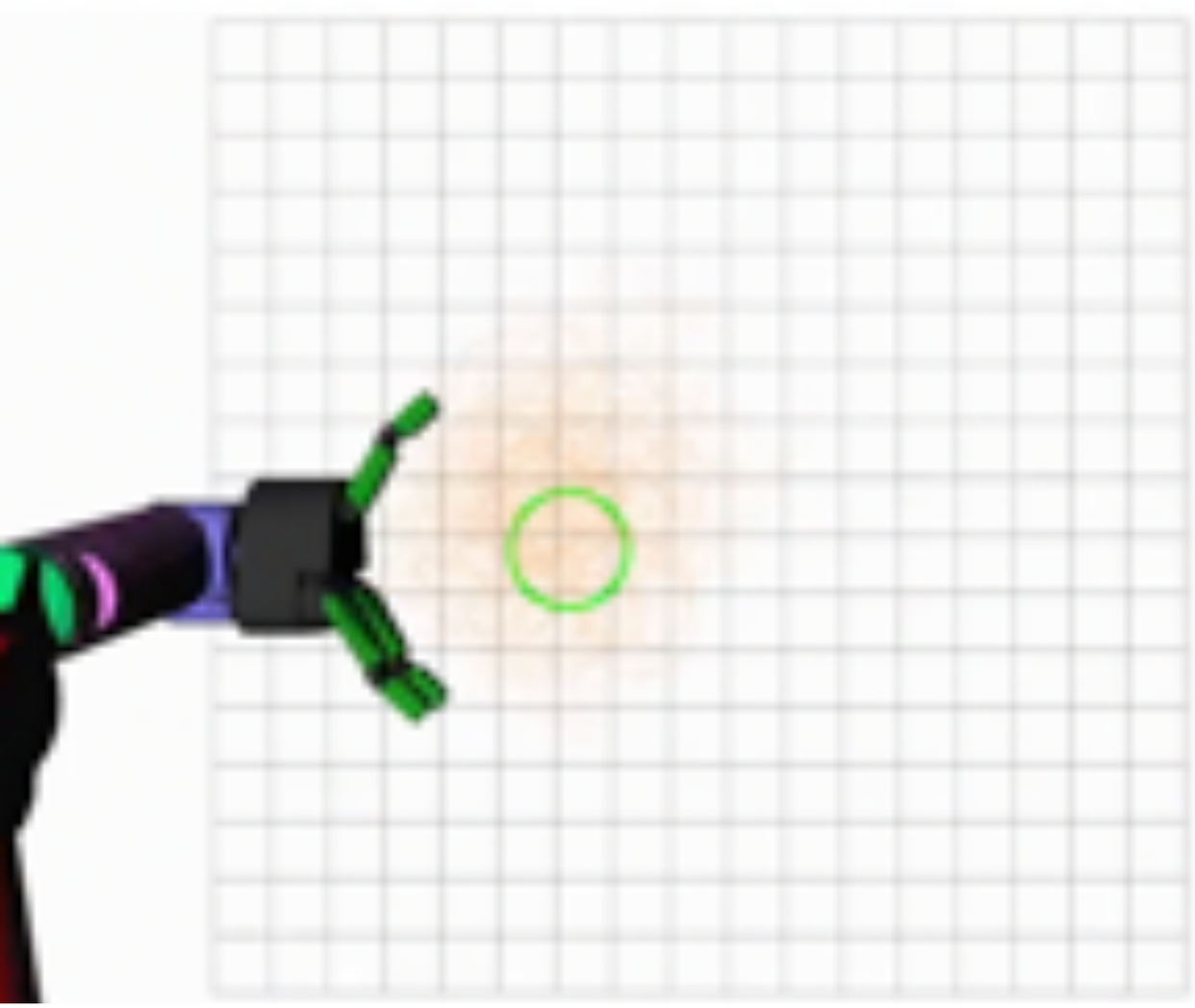
visual feedback

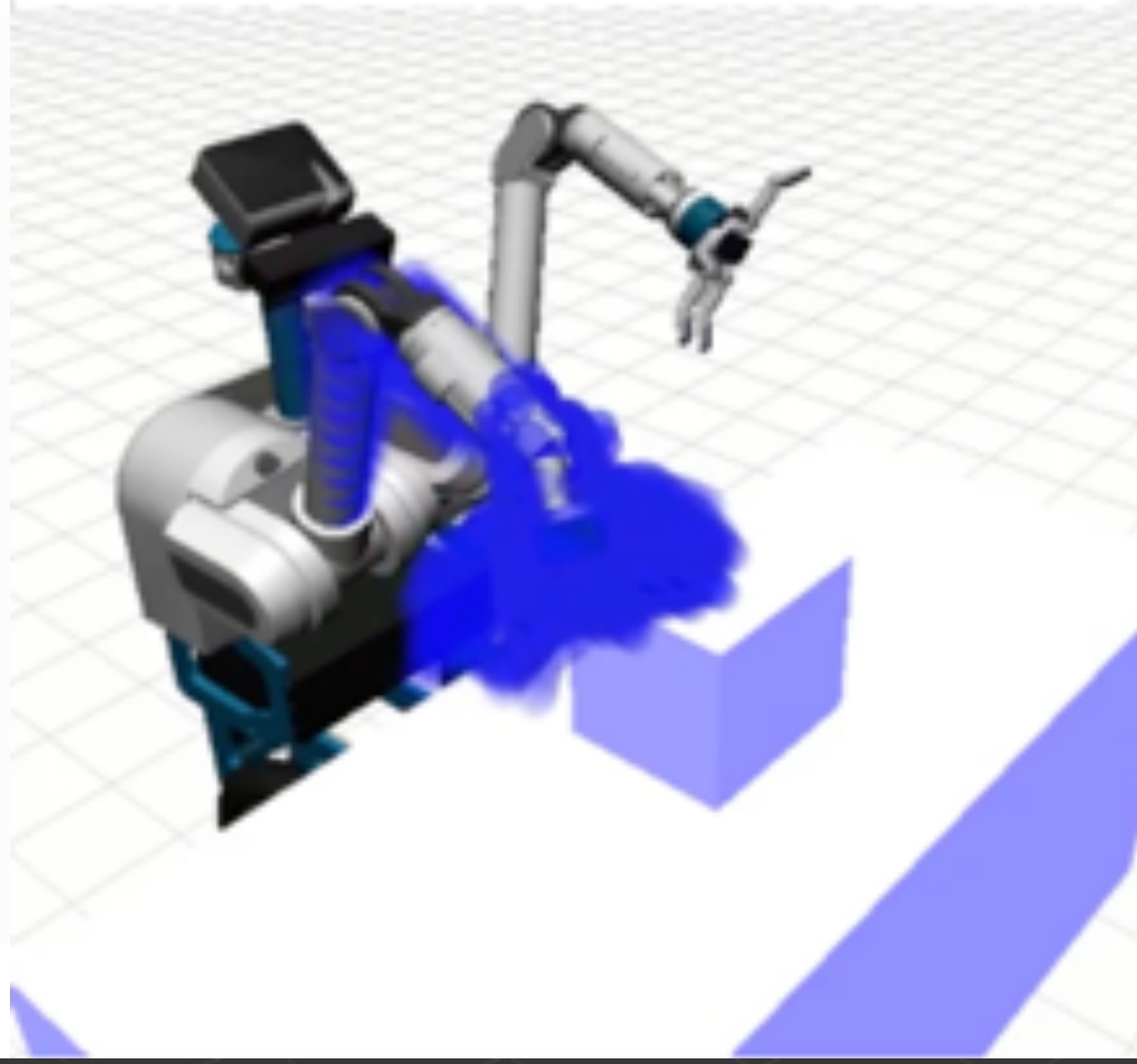
unaffected by
transparency
and specularity

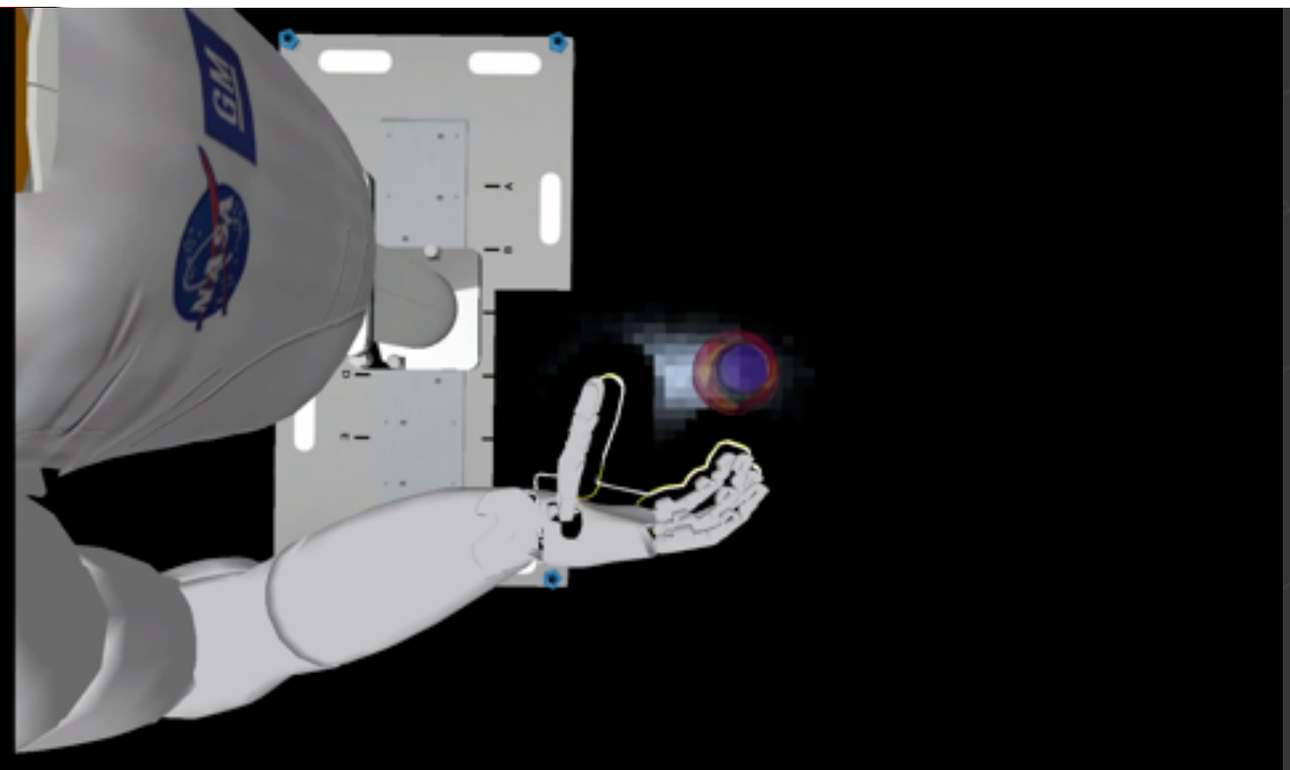
robust to occlusion

Source: http://youtu.be/TU6FKFyVjm0

How can we use contact sensing to reliably manipulate objects under uncertainty?



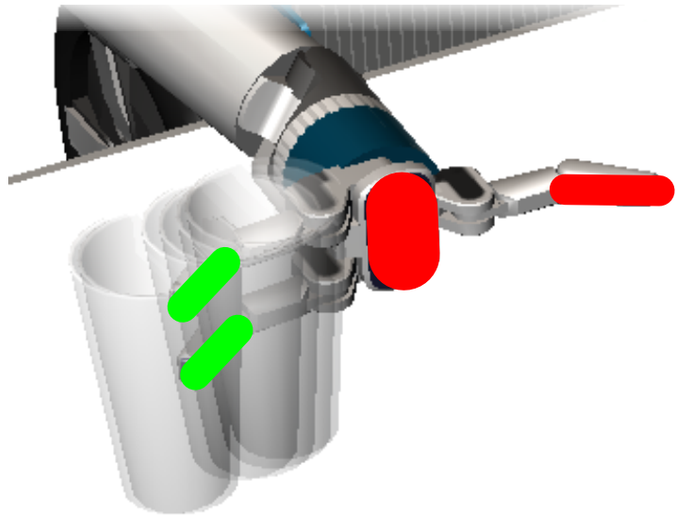




state estimation

belief state

action selection



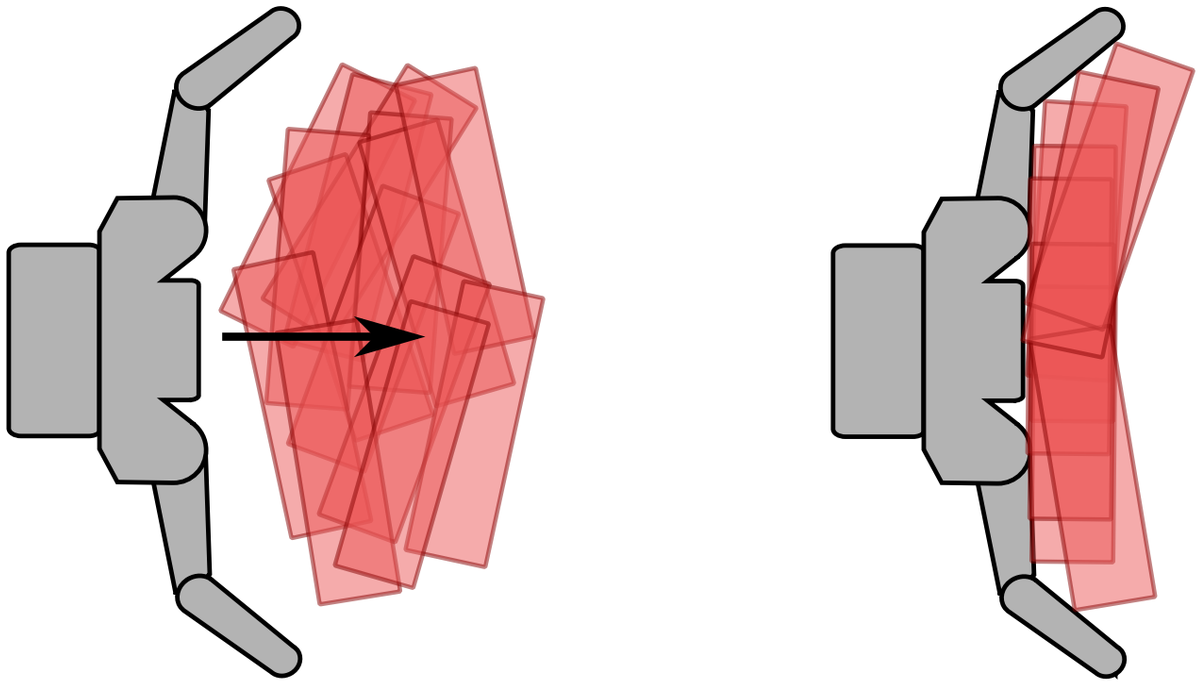
observation

action

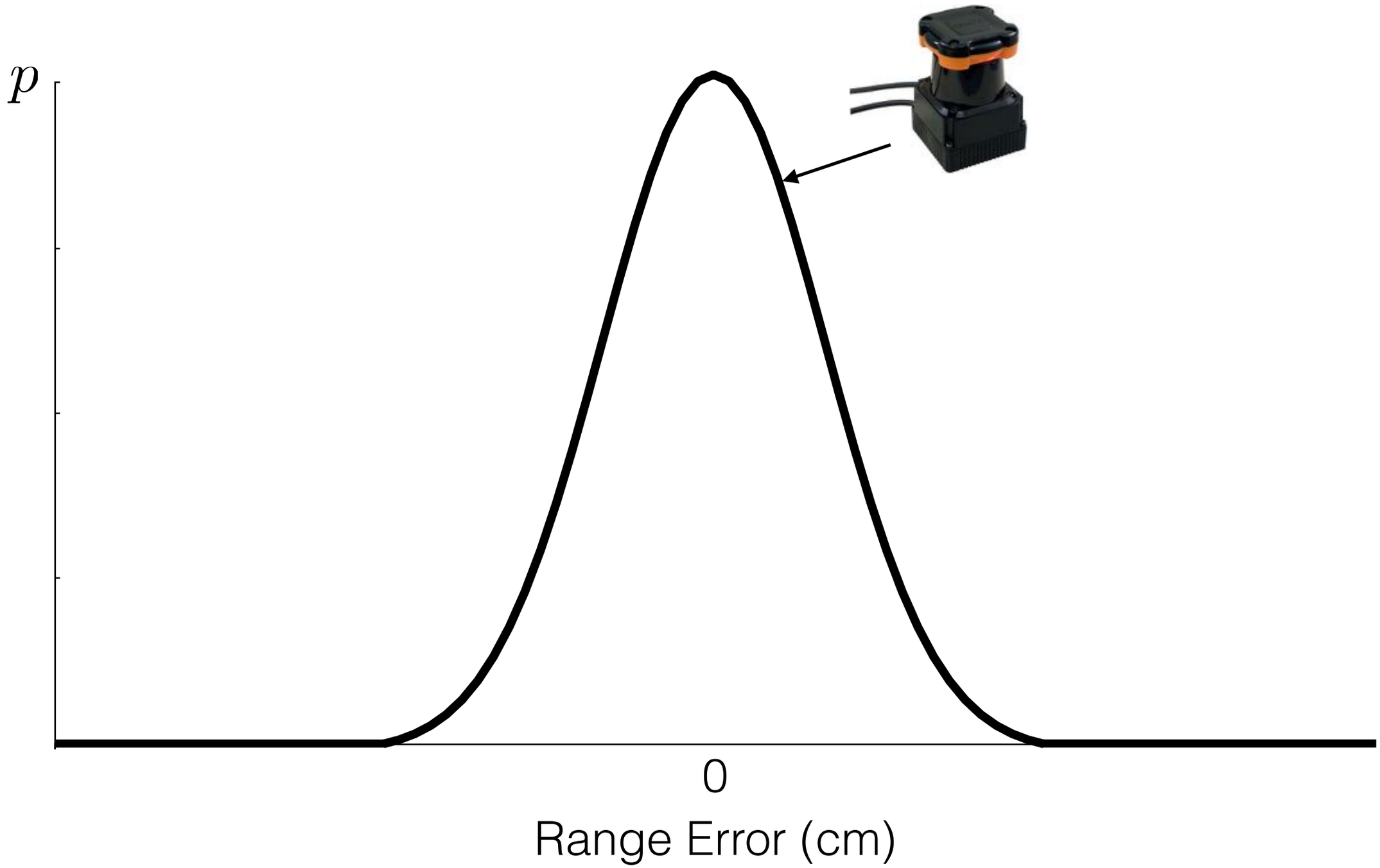
environment

Challenge 1

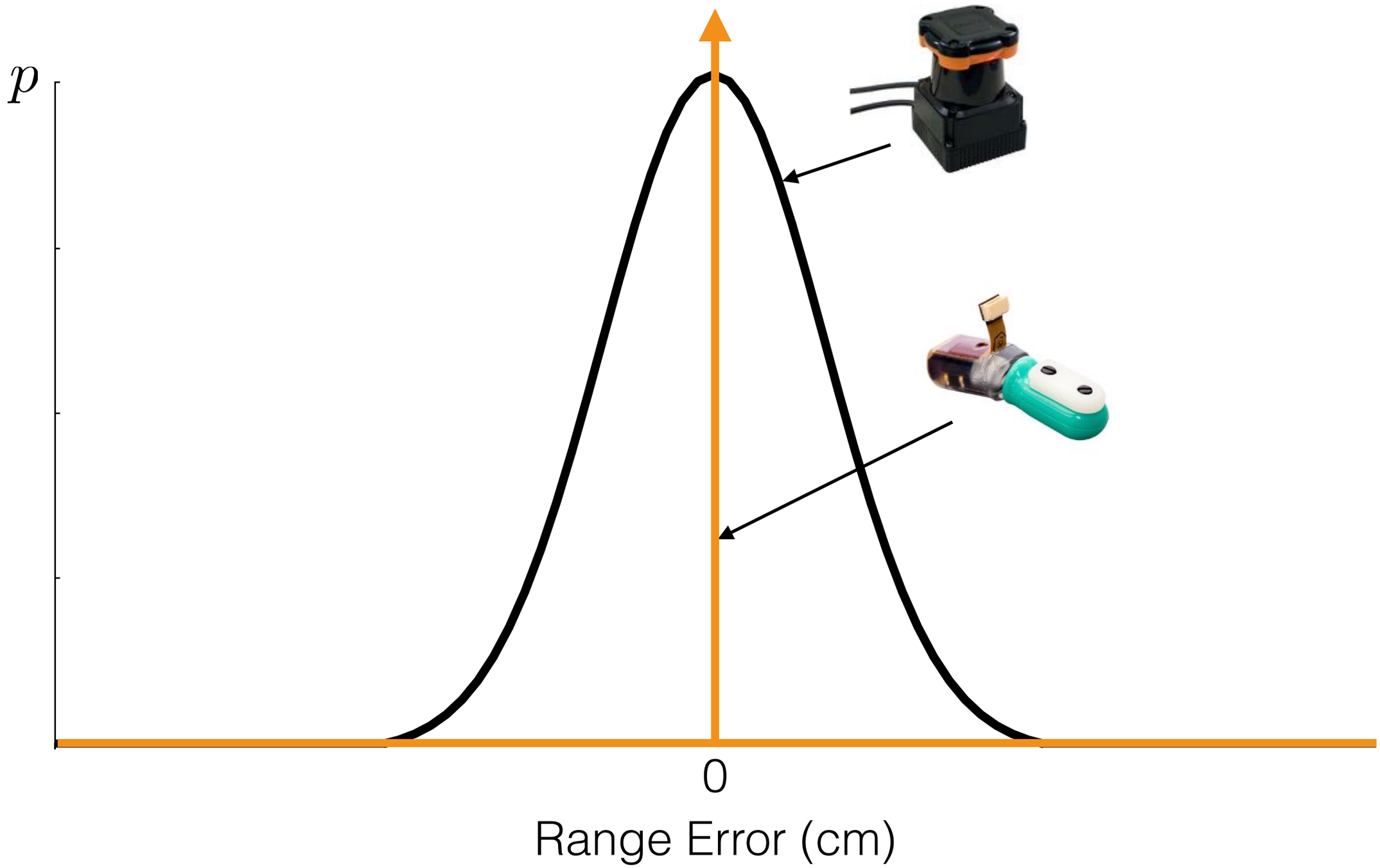
Contact is inherently discontinuous



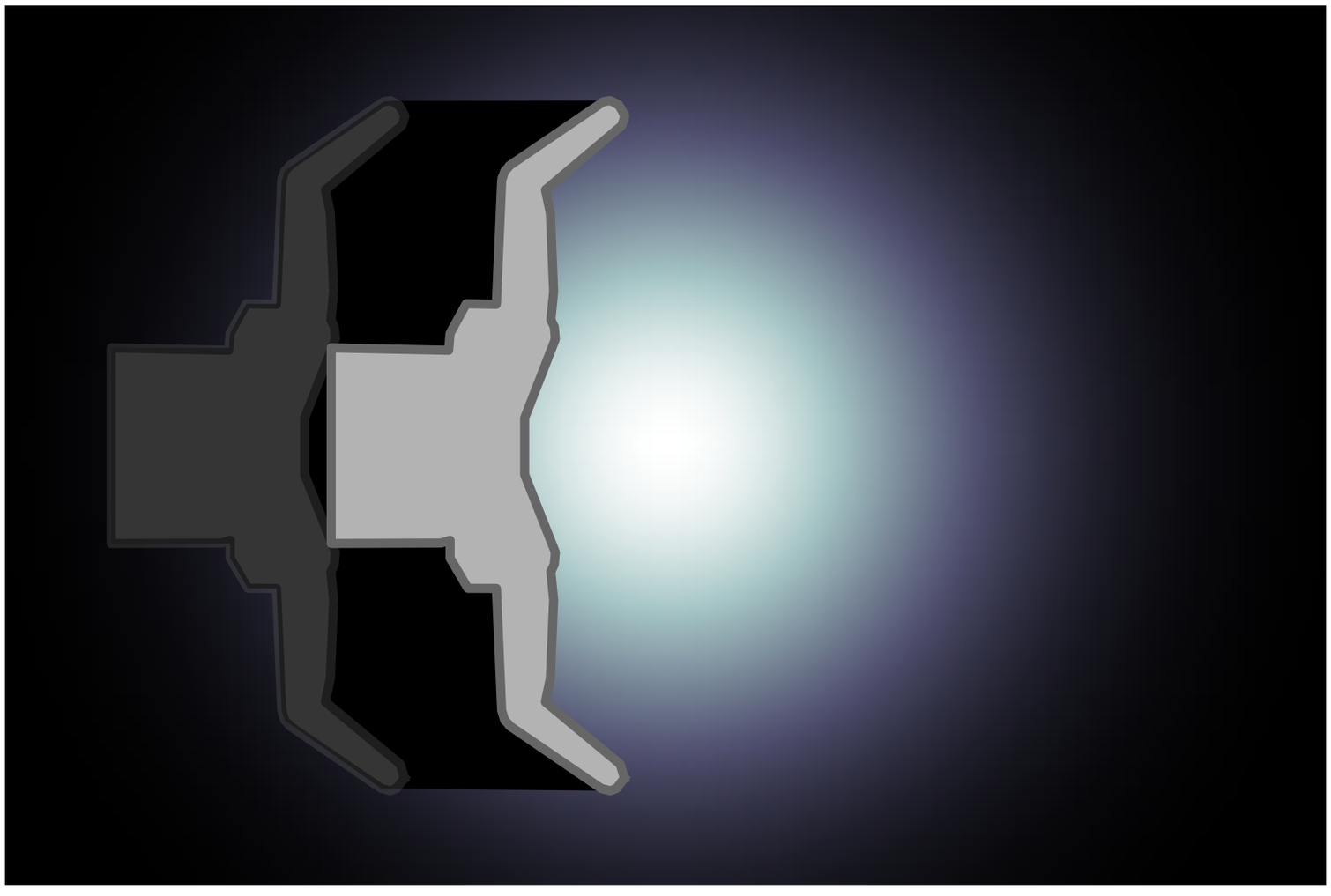
Physics is discontinuous



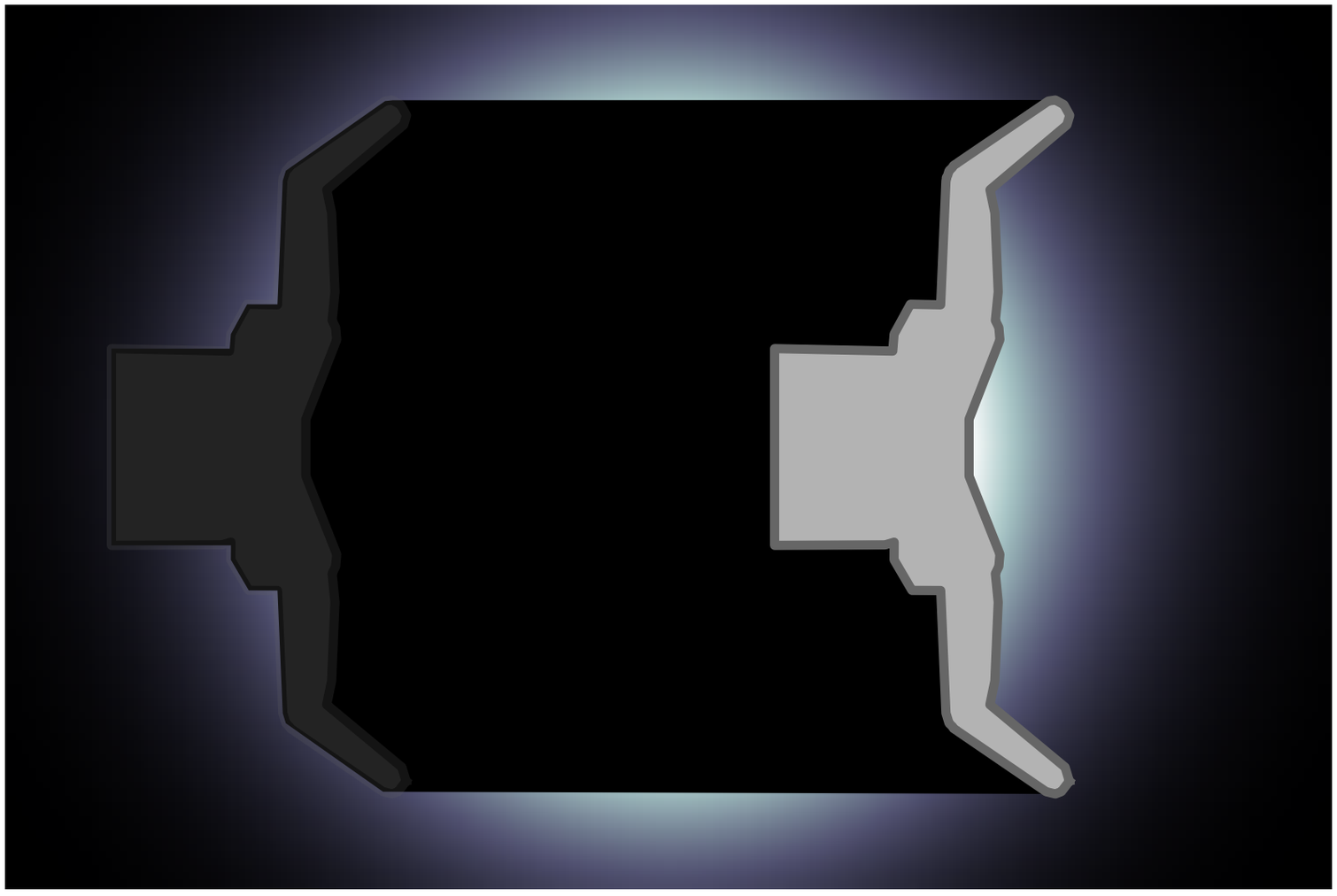
Contact sensing is discontinuous



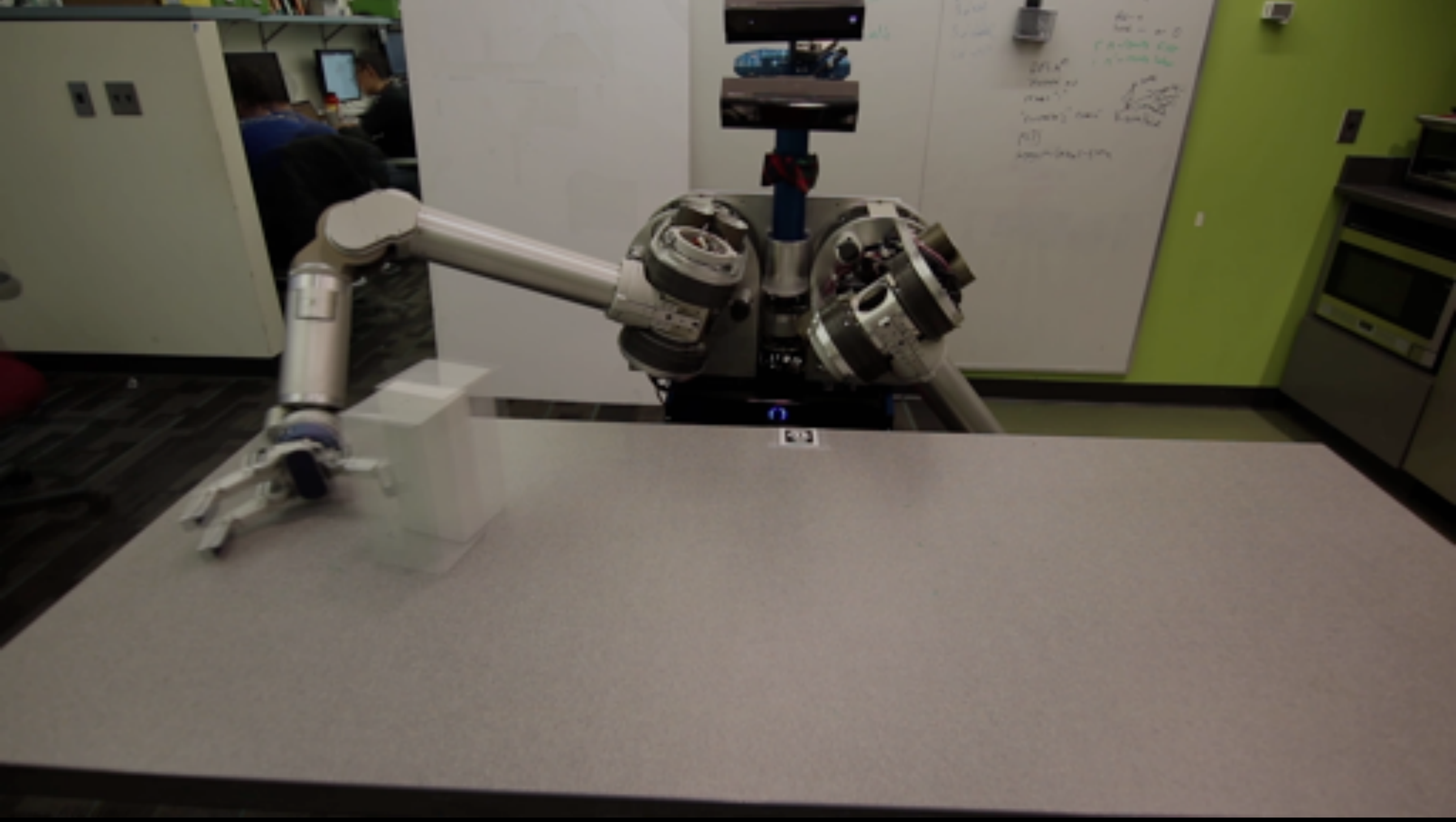
Contact sensing is discontinuous



Belief states are discontinuous



Belief states are discontinuous



Small errors in state can be catastrophic

Source: A.M. Johnson, J.E. King, and S.S. Srinivasa. "Convergent planning." ICRA, 2016. To appear.

Challenge 1

Contact is inherently discontinuous

Challenge 1

Contact is inherently discontinuous

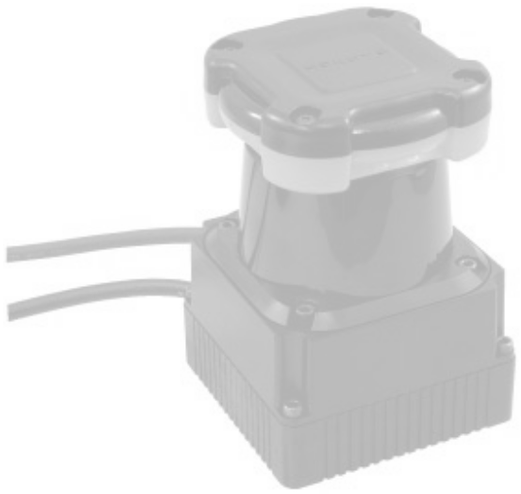
Challenge 2

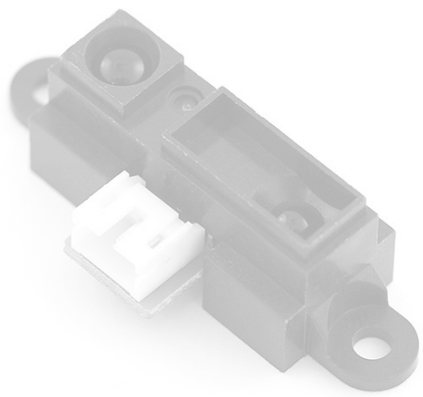
Contact sensors require active sensing

longer range

shorter range

Sensors have different maximum ranges

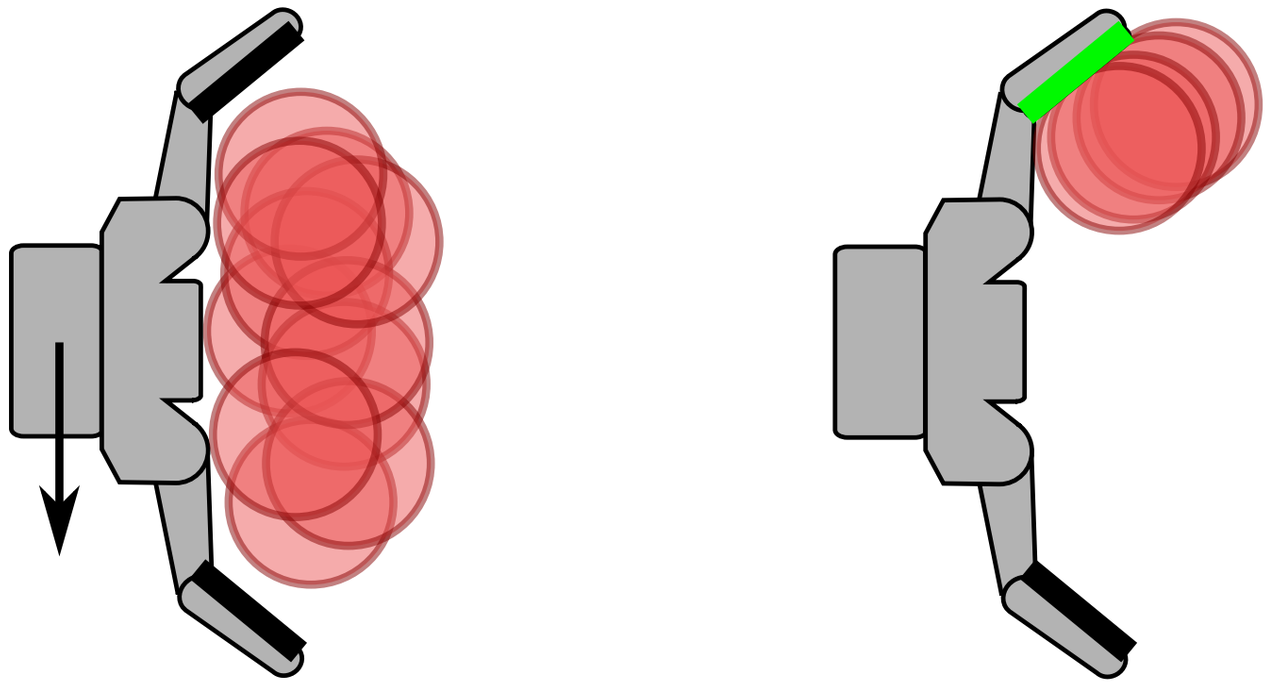




longer range

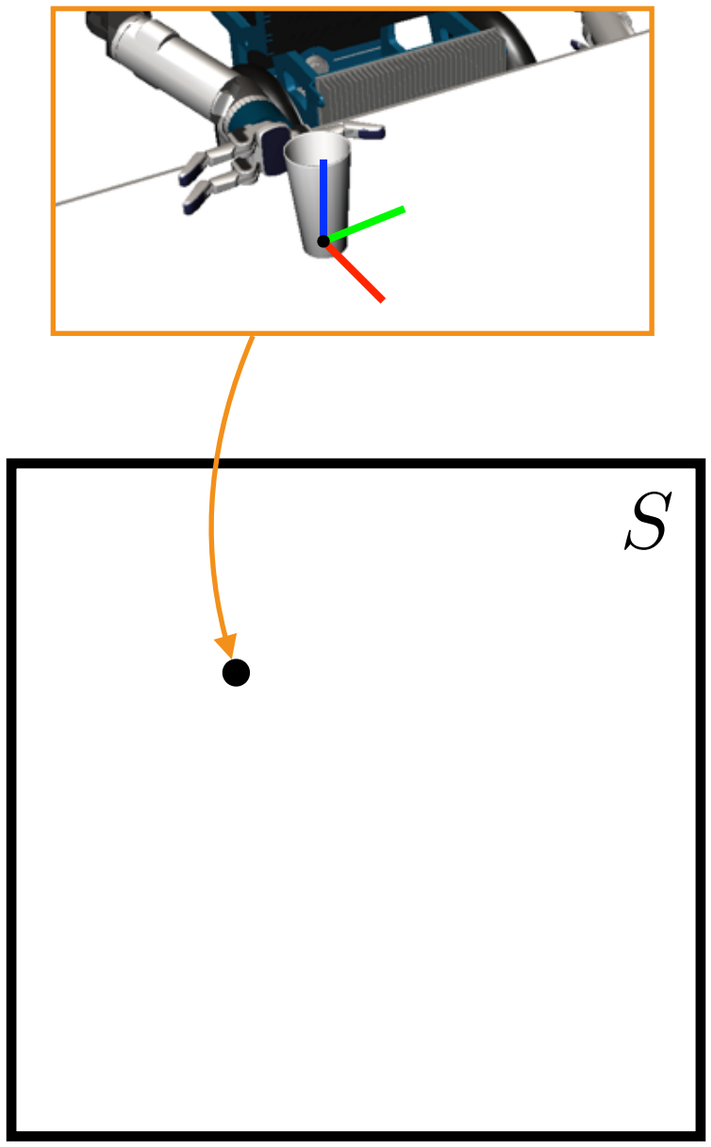
shorter range

Provide rich information only during contact



Contact sensors require active sensing

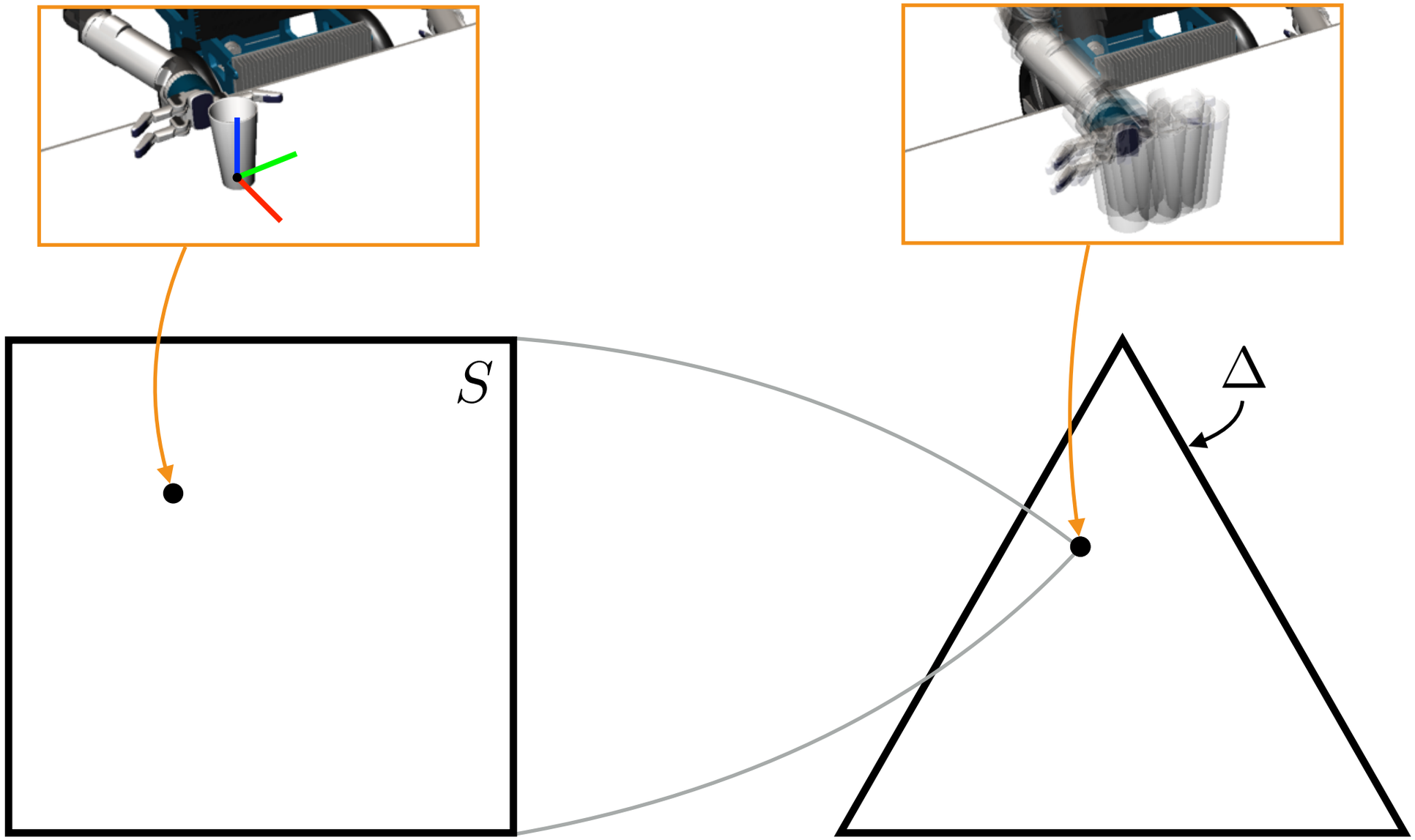
(10×)



state space

$\dim(S) = n$

Active sensing requires planning in belief space



state space

$\dim(S) = n$

belief space

$\dim(\Delta) = \infty$

Active sensing requires planning in belief space

Challenge 1

Contact is inherently discontinuous

Challenge 2

Contact sensors require active sensing

Challenge 1

Contact is inherently discontinuous

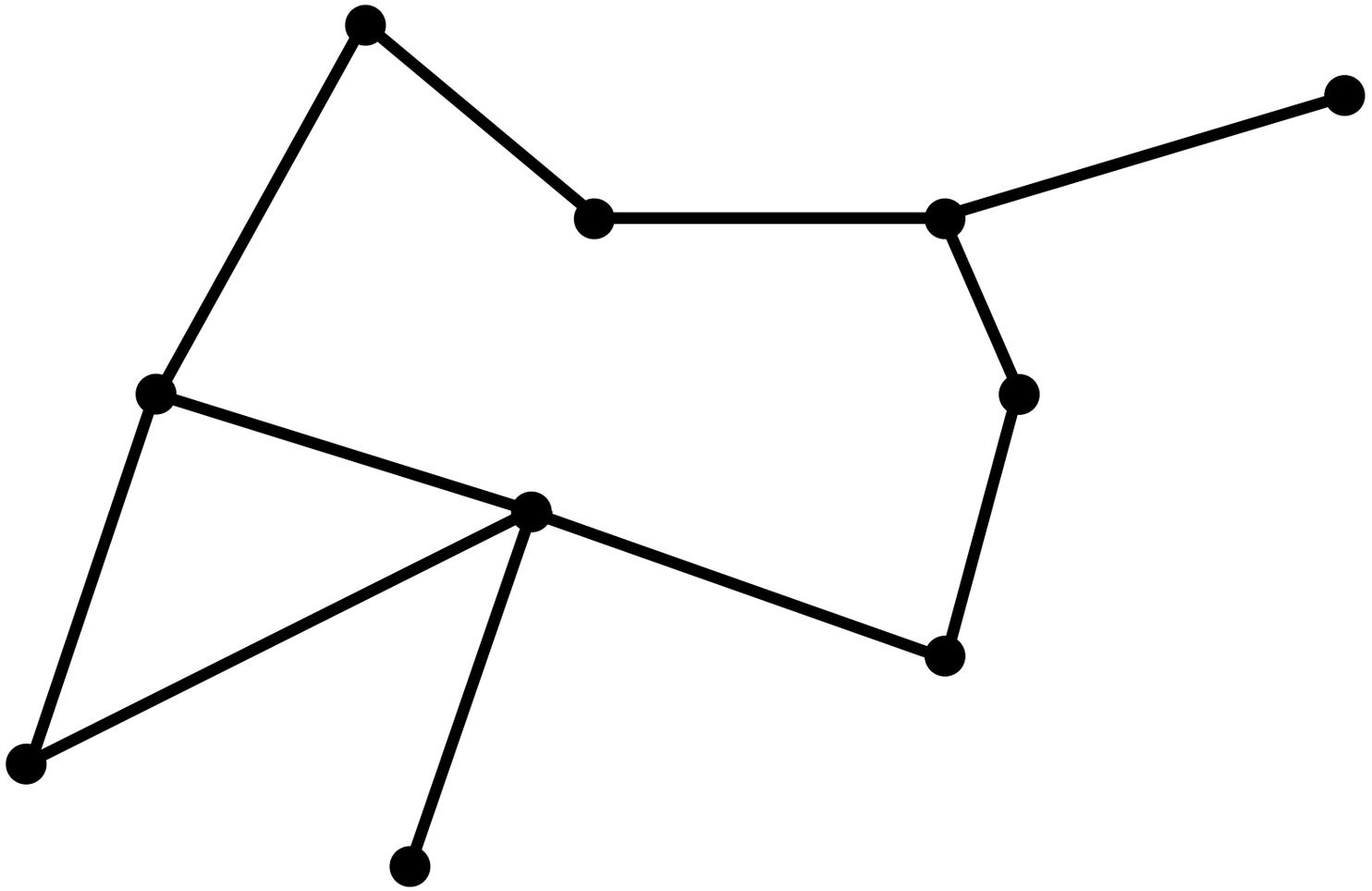
Challenge 2

Contact sensors require active sensing

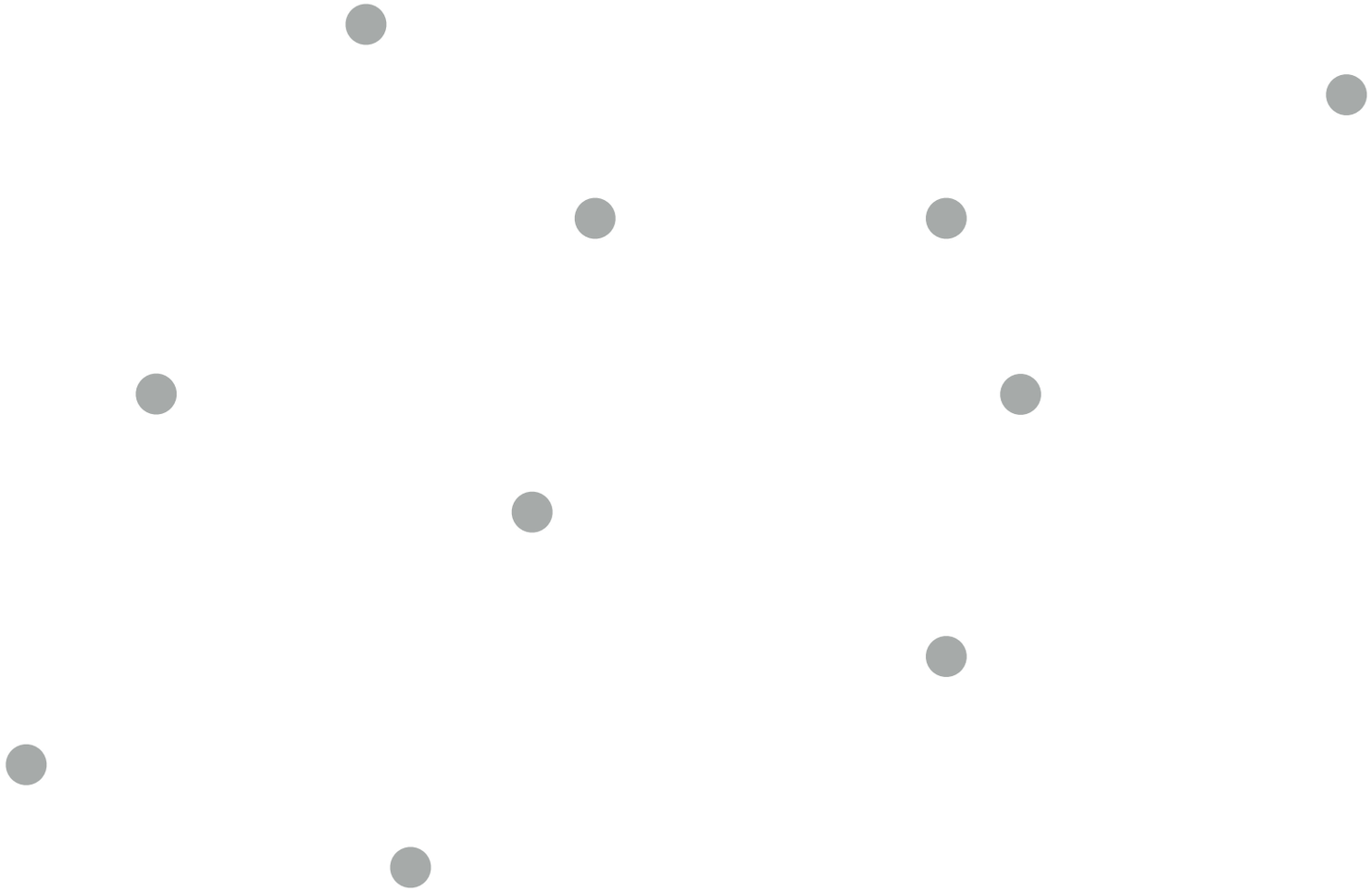
Challenge 3

Manipulation is a physical process

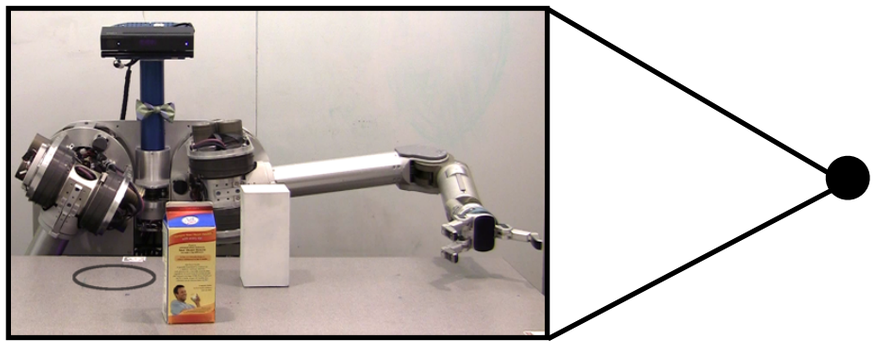
Manipulation planning requires a physics model



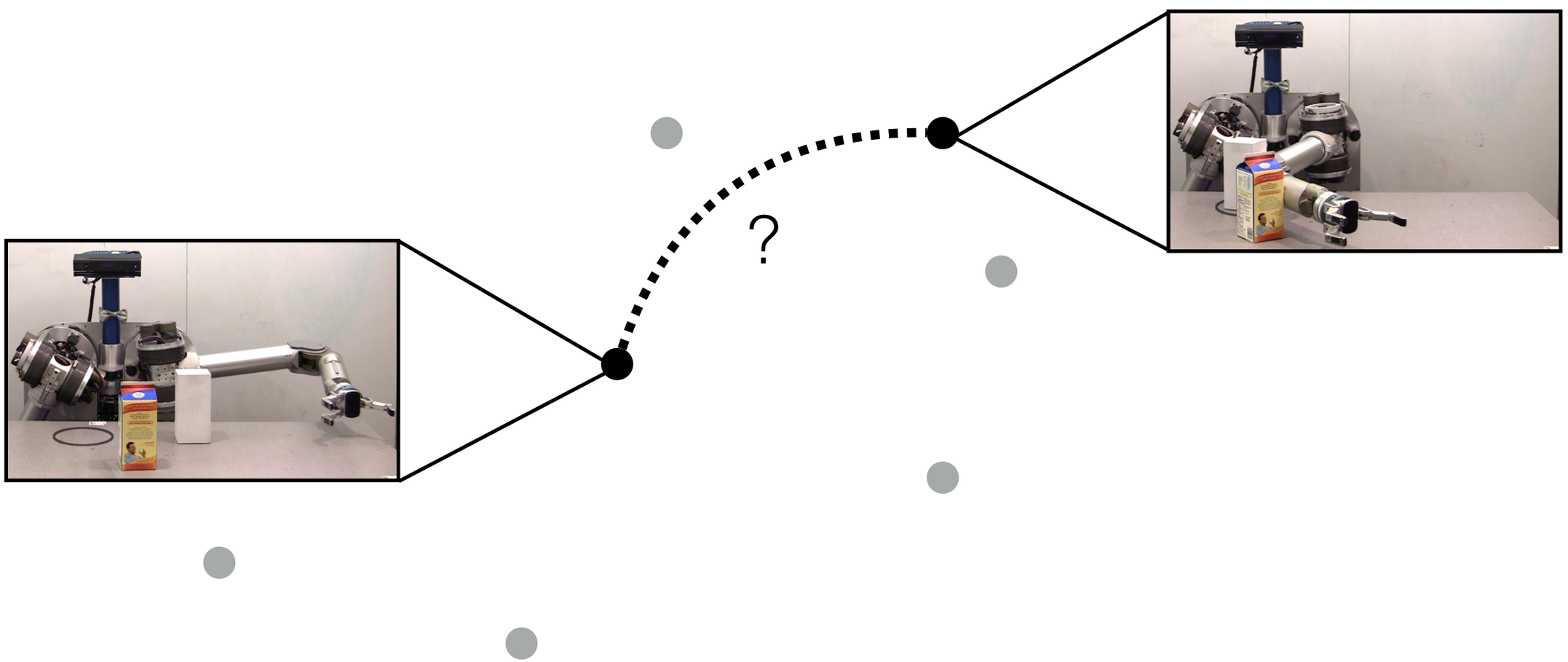
Hard to solve the two-point boundary value problem



Hard to solve the two-point boundary value problem



Hard to solve the two-point boundary value problem



Hard to solve the two-point boundary value problem

Challenge 1

Contact is inherently discontinuous

Challenge 2

Contact sensors require active sensing

Challenge 3

Manipulation is a physical process

Challenge 1

Contact is inherently discontinuous

Challenge 2

Contact sensors require active sensing

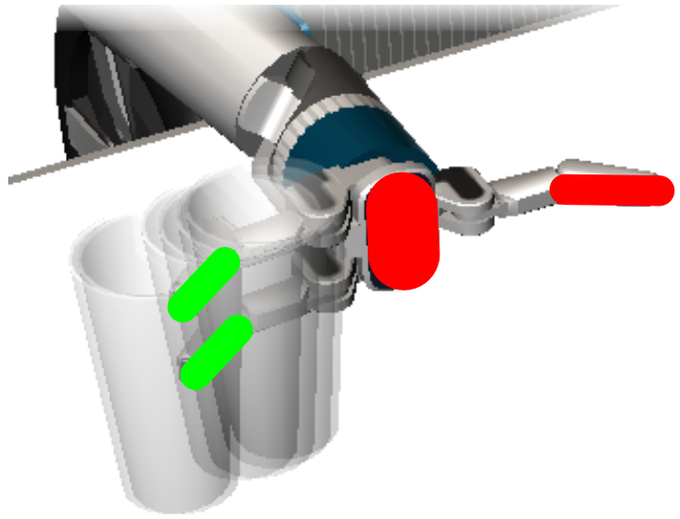
Challenge 3

Manipulation is a physical process

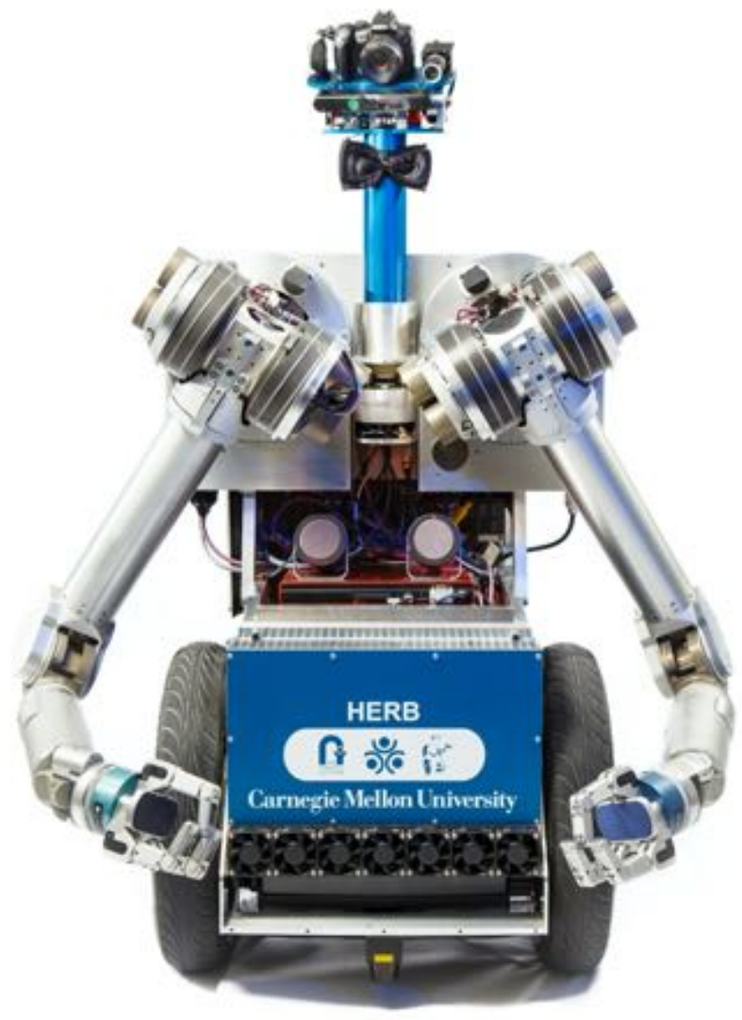
state estimation

belief state

action selection

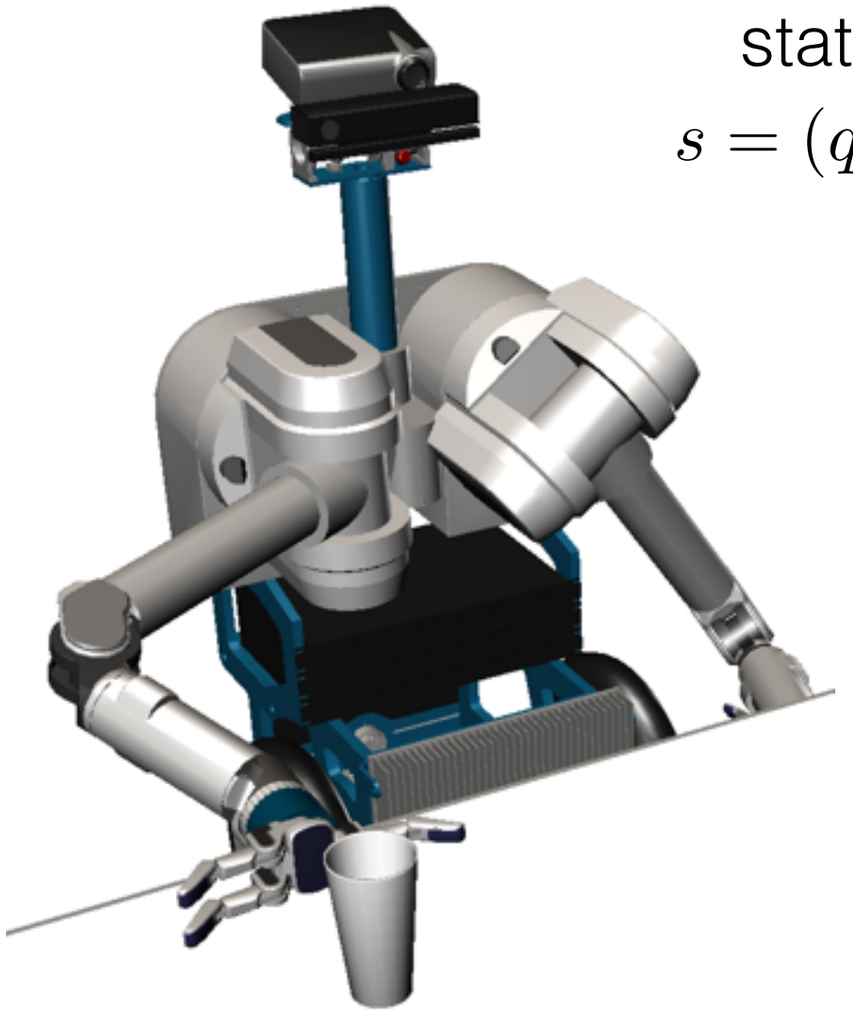


observation



action

environment



state

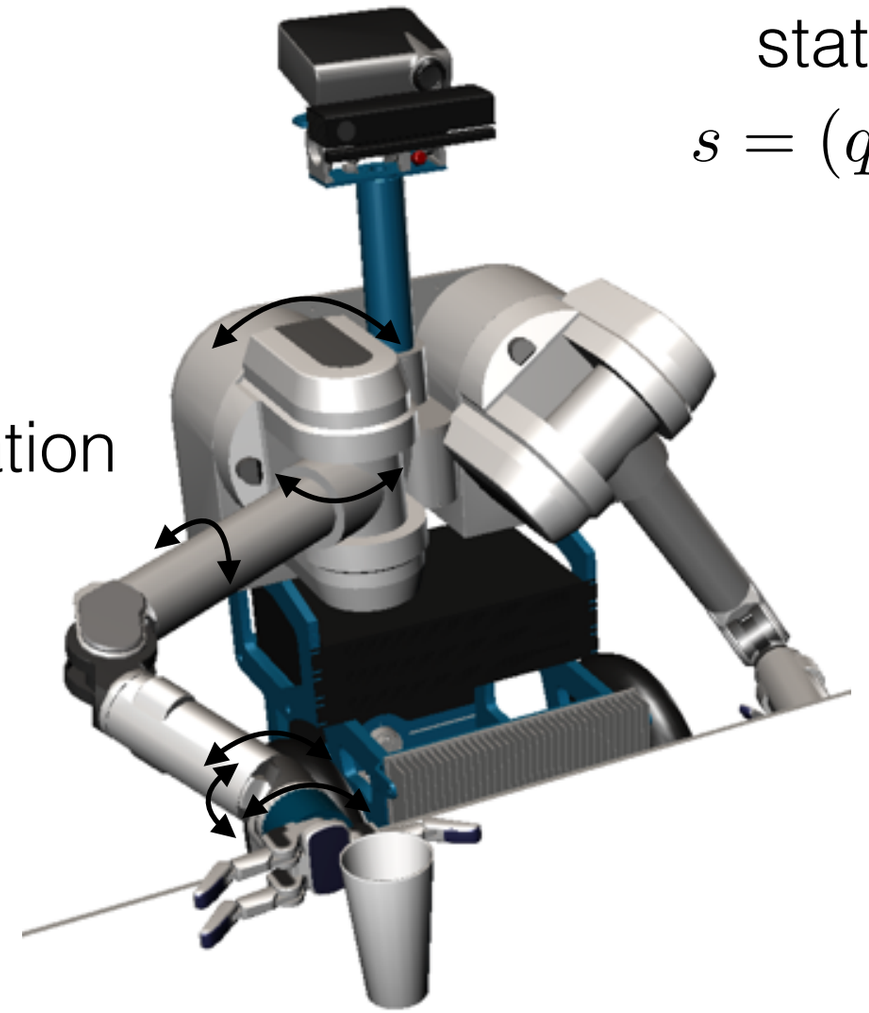
$$s = (q, x)$$

state

$s = (q, x)$

robot configuration

$q \in Q$

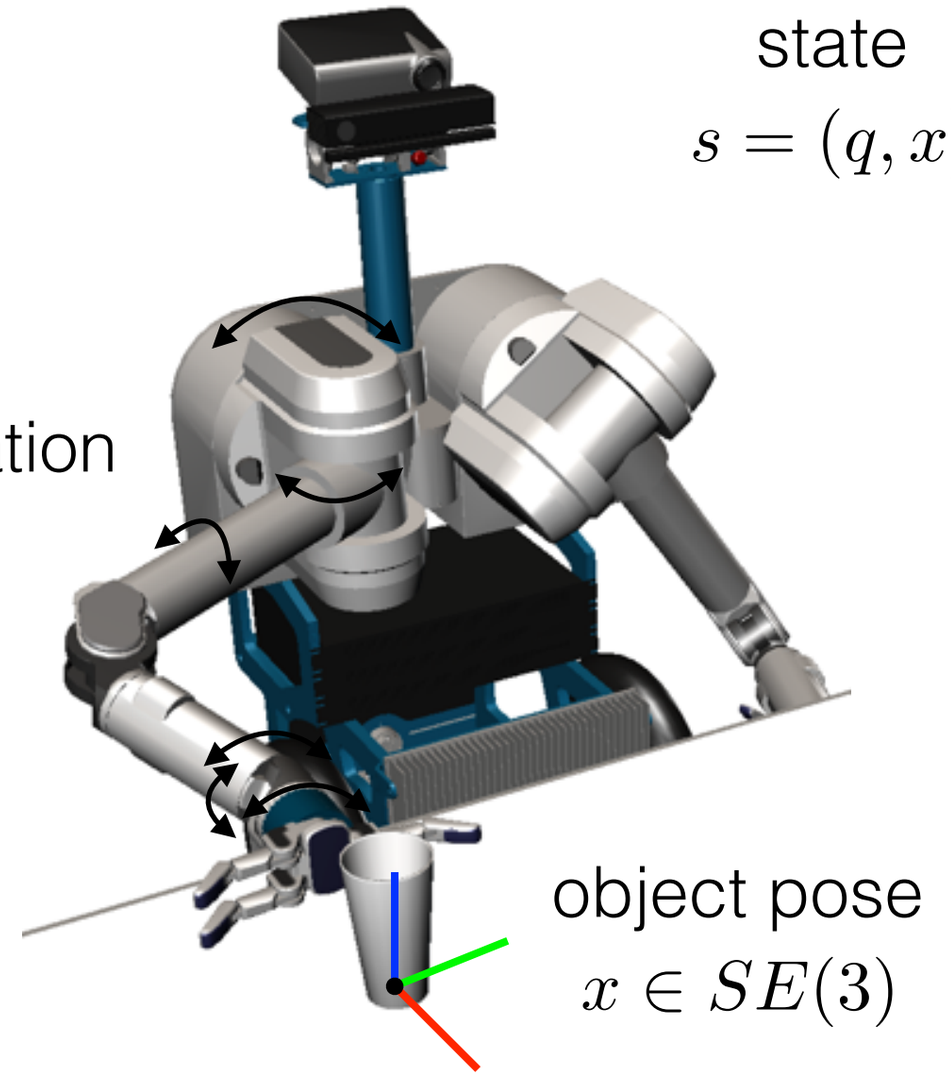


state

$s = (q, x)$

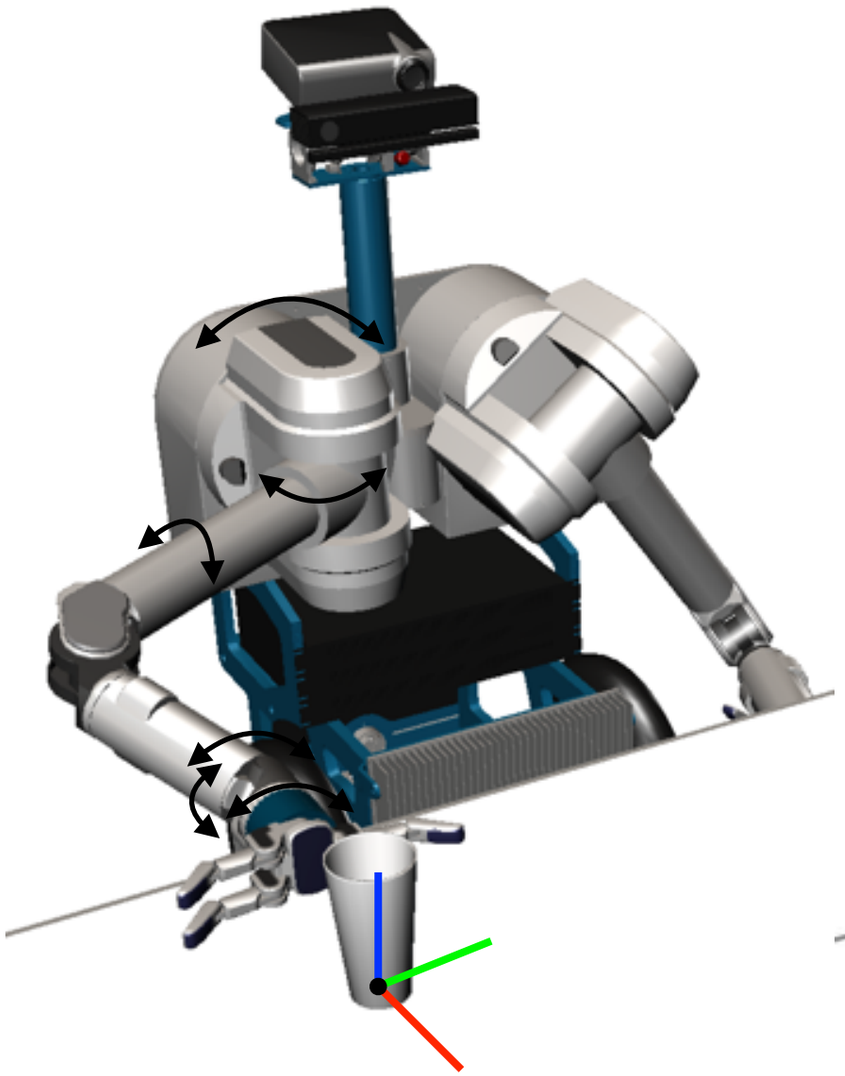
robot configuration

$q \in Q$



object pose

$x \in SE(3)$

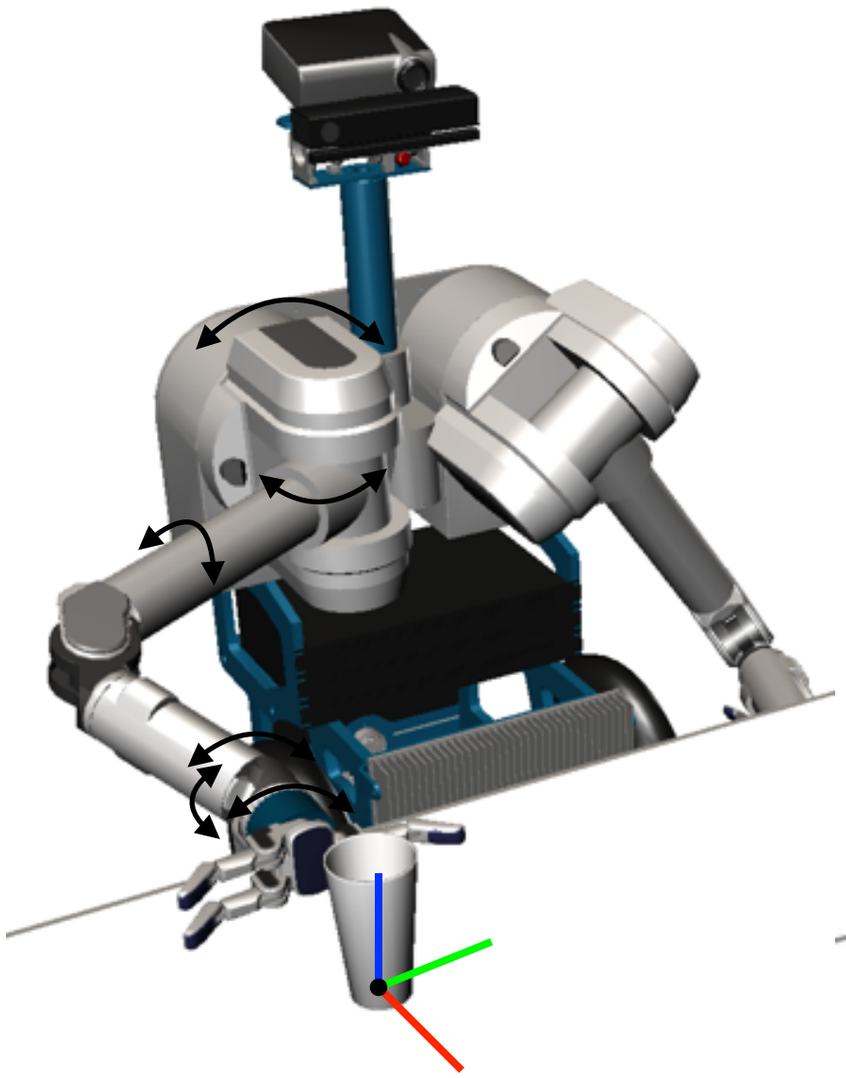


state

$$s = (q, x)$$

action

$$a = (\dot{q}, \Delta t)$$



state

$s = (q, x)$

action

$a = (\dot{q}, \Delta t)$

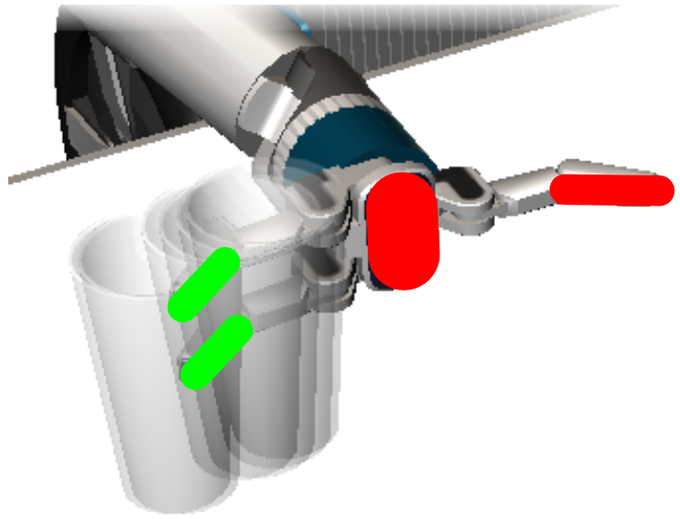
observation

$o = (o_{\mathrm{q}}, o_{\mathrm{c}})$

state estimation

belief state

action selection



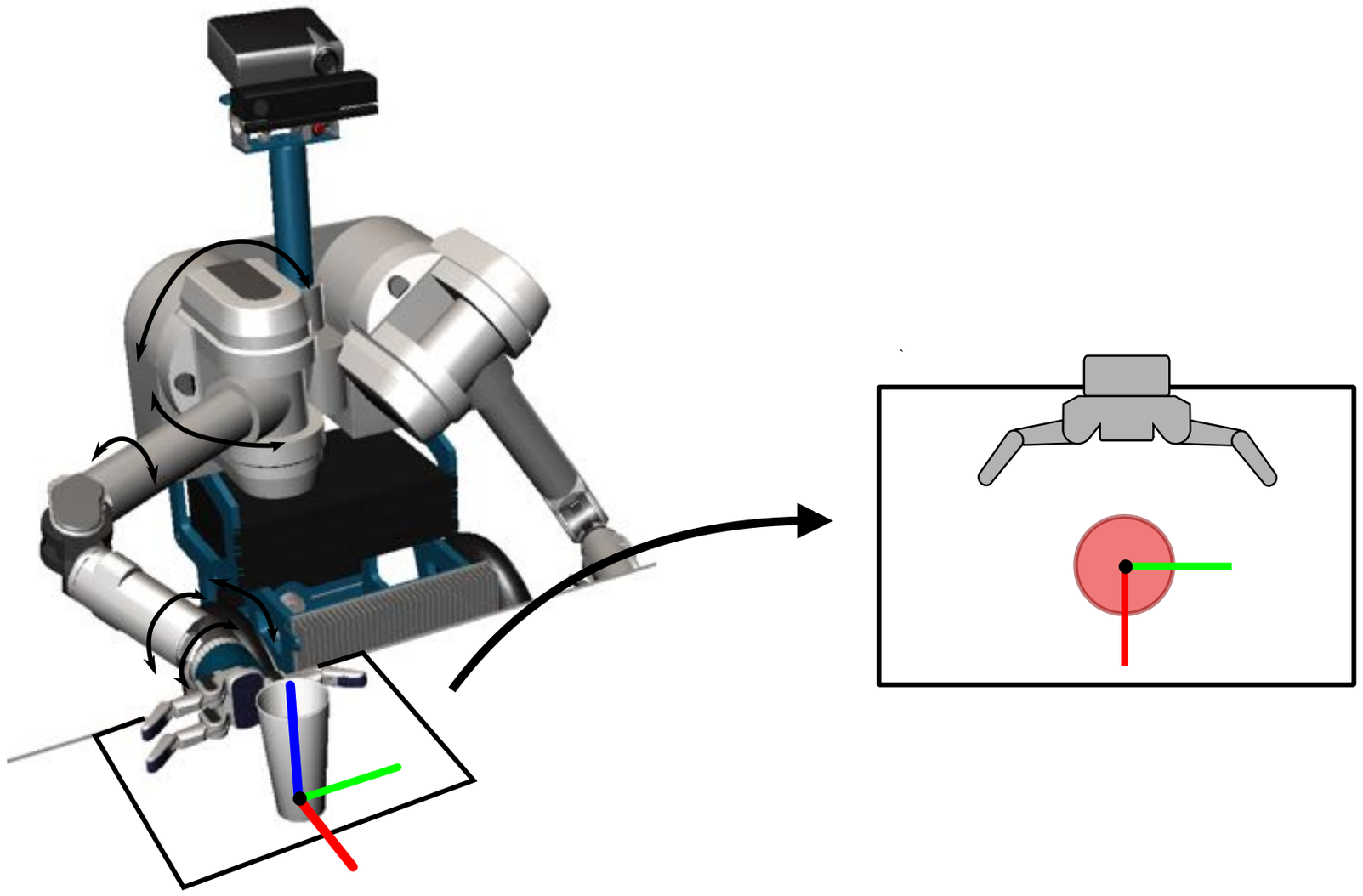
observation

action

environment

Insight 1

Manipulation occurs in a lower-dimensional space



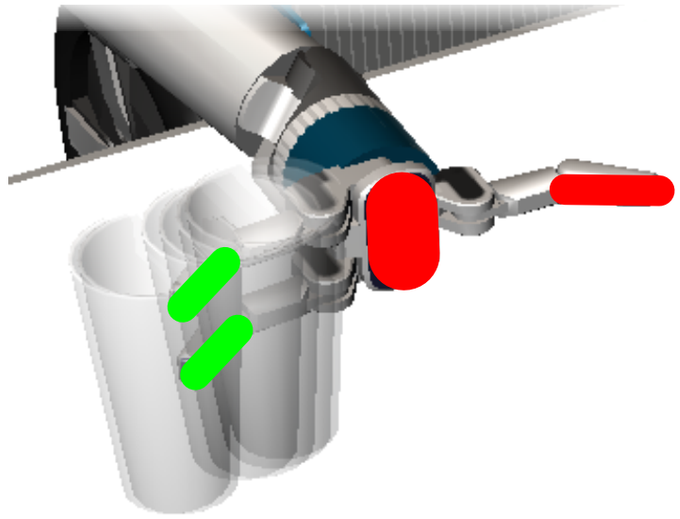
Insight 1

Manipulation occurs in a lower-dimensional space

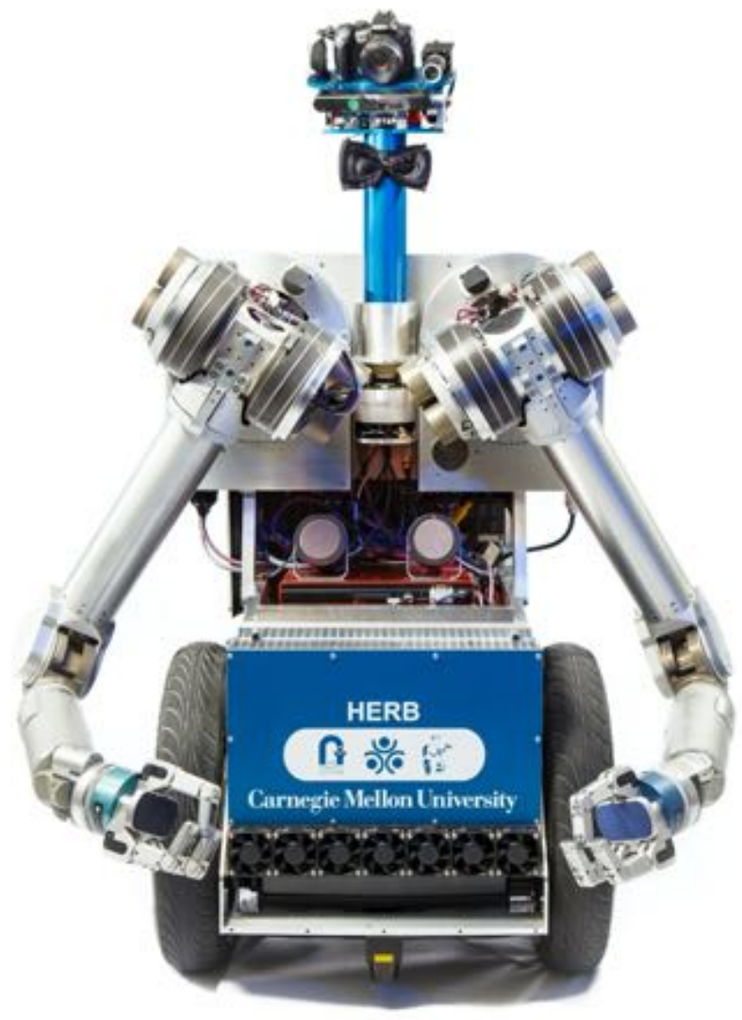
state estimation

belief state

action selection



observation



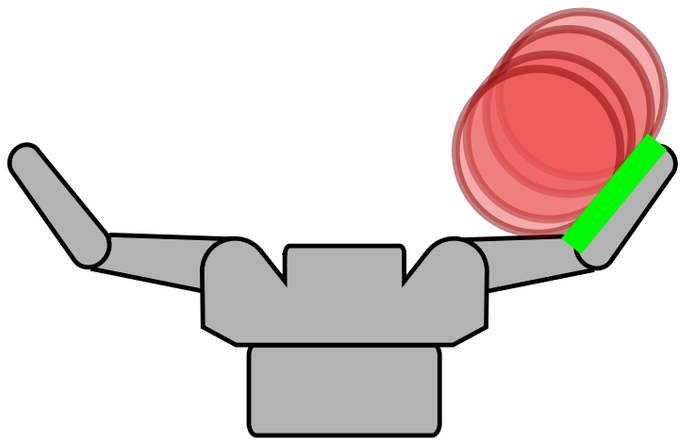
action

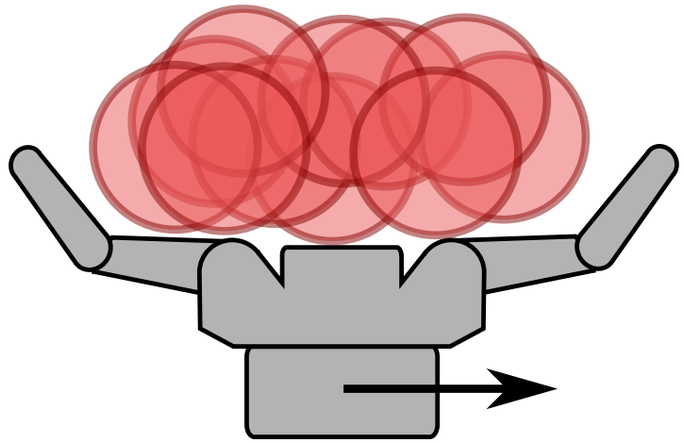
environment

state estimation

belief state

action selection

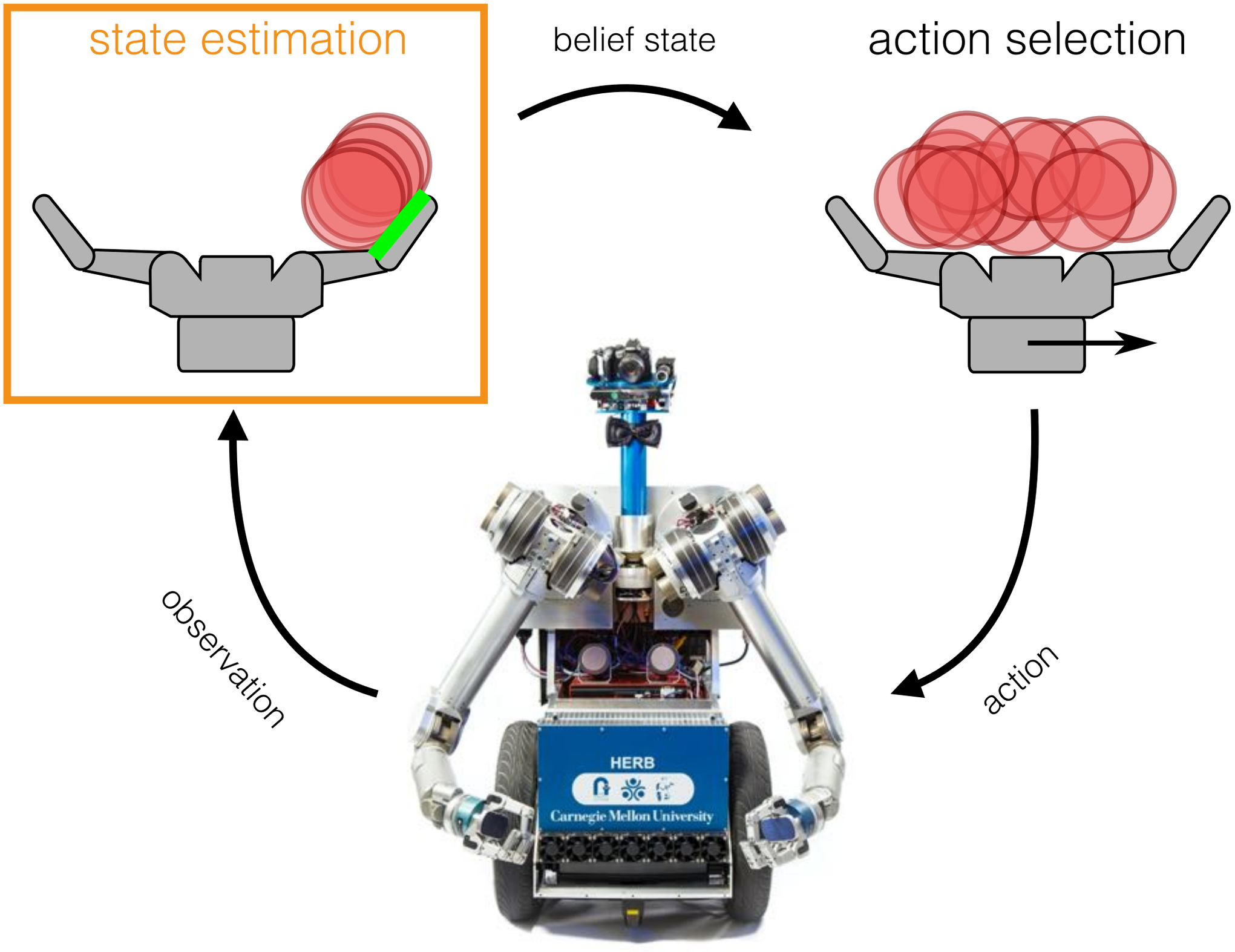


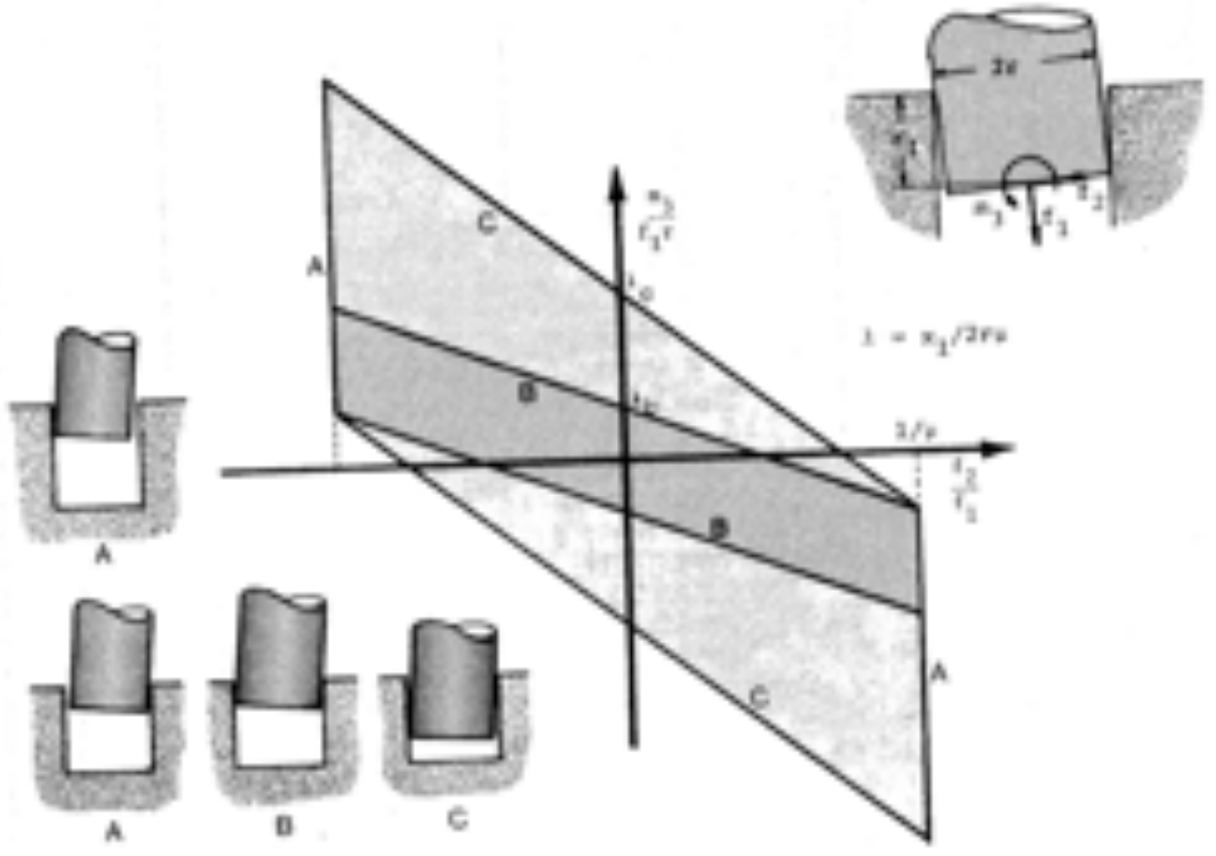


observation

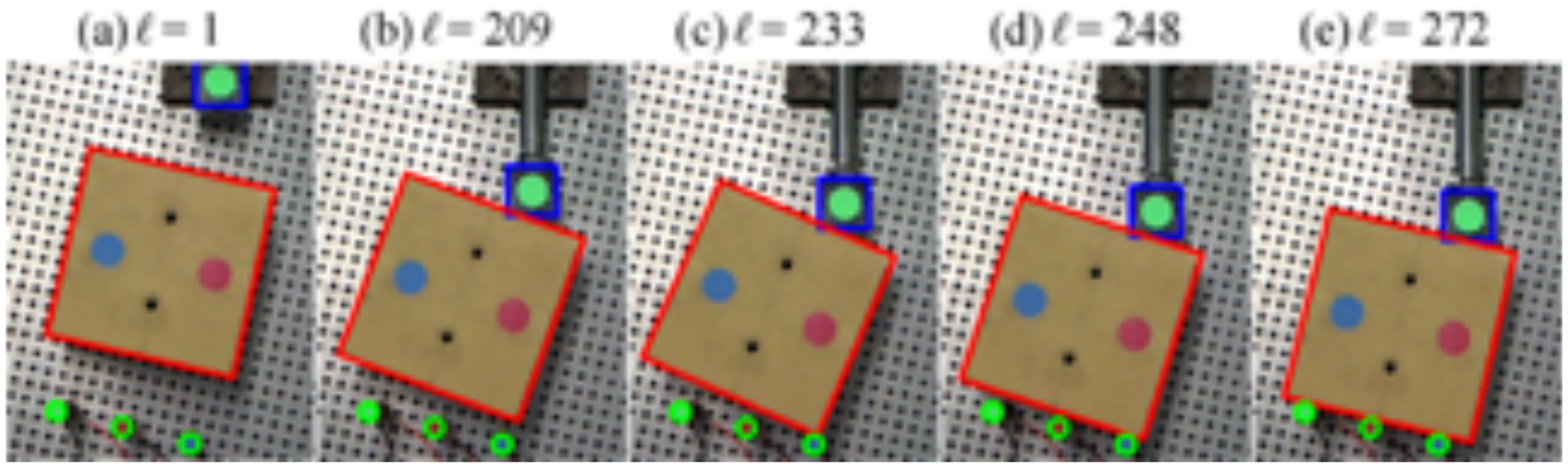
action

environment


state estimation
belief state
action selection
observation
action
HERB
Carnegie Mellon University
environment



S.N. Simunovic. An Information Approach to Parts Mating. PhD thesis, MIT, 1979



L. Zhang and J. Trinkle. “The application of particle filtering to grasping acquisition with visual occlusion and tactile sensing.” IEEE ICRA, 2012.

Experiment 1
(2x)

CPF
n = 250

Experiment 2
(2x)

CPF
n = 250

Experiment 3
(2x)

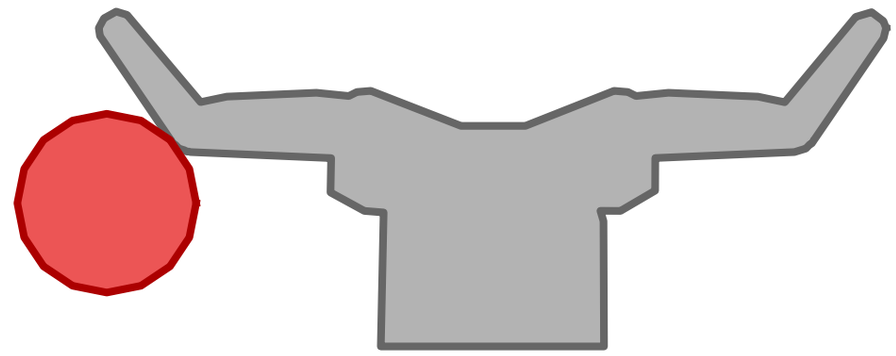
CPF
n = 250

Insight 1

Manipulation occurs in a lower-dimensional space

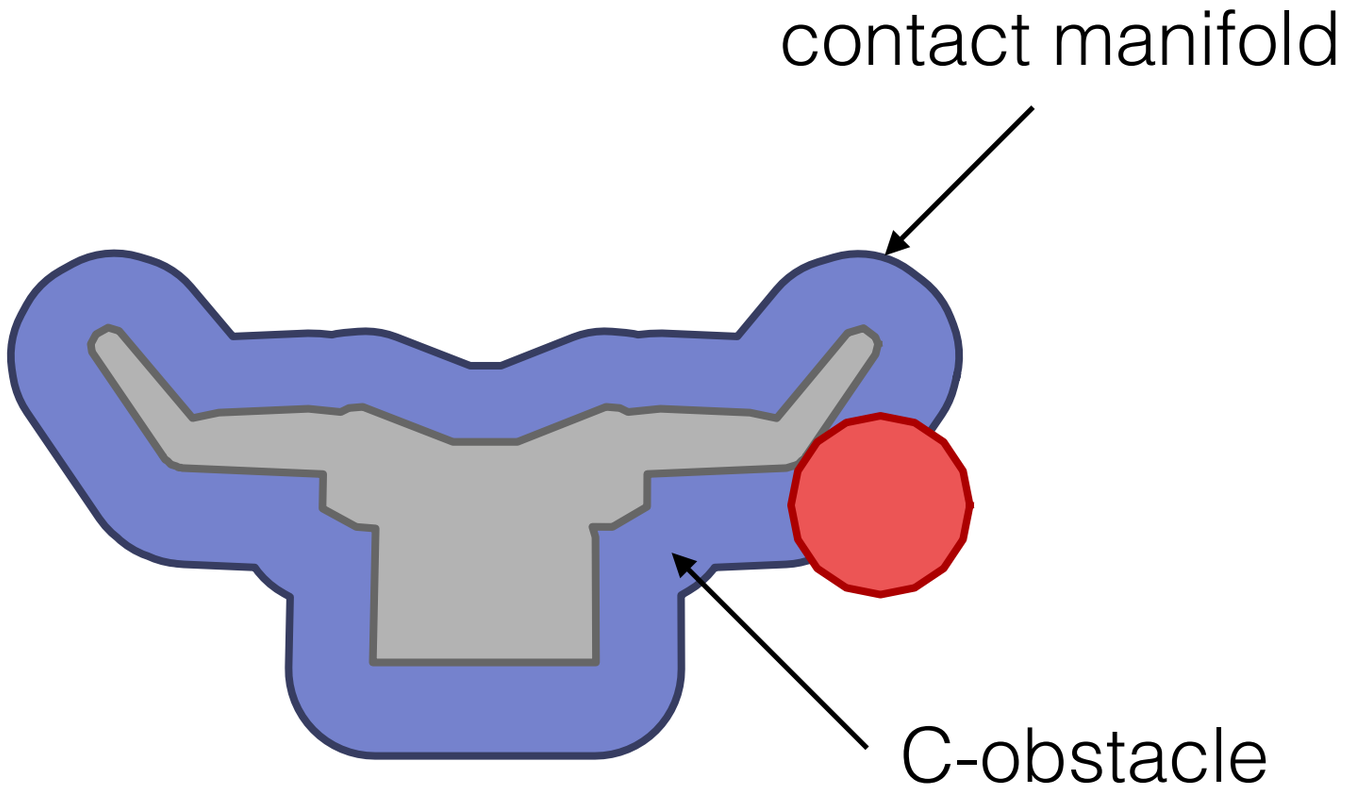
Insight 2

Contact constrains state to a manifold



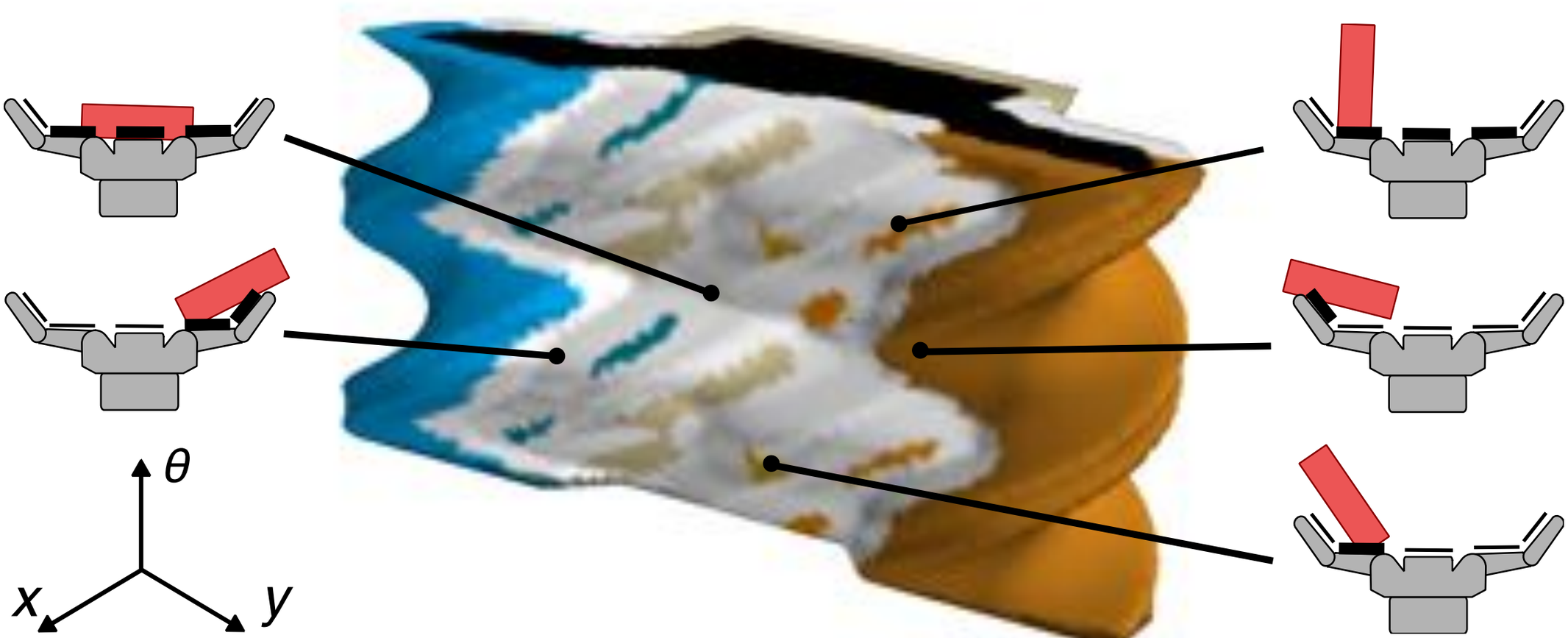
Insight 2

Contact constrains state to a manifold



Insight 2

Contact constrains state to a manifold



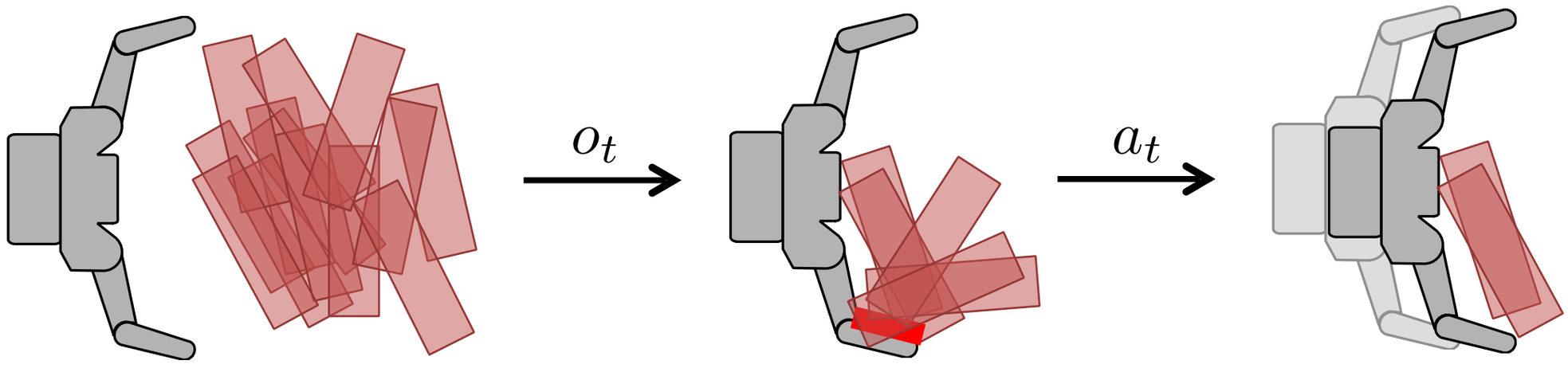
Insight 2

Contact constrains state to a manifold

Dual Proposal Distribution

Reverse the role of the proposal distribution:

1. Sample $s_t^{[i]} \sim \frac{p(o_t|s_t, a_t)}{p(o_t|a_t)}$
2. Weight by $w_t^{[i]} = \int_S p(s_t|s_{t-1}, a_t) b(s_{t-1}) ds_{t-1}$
3. Resample with replacement.



S. Thrun, D. Fox, and W. Burgard. “Monte Carlo localization with mixture proposal distribution” In AAAI. 2000.

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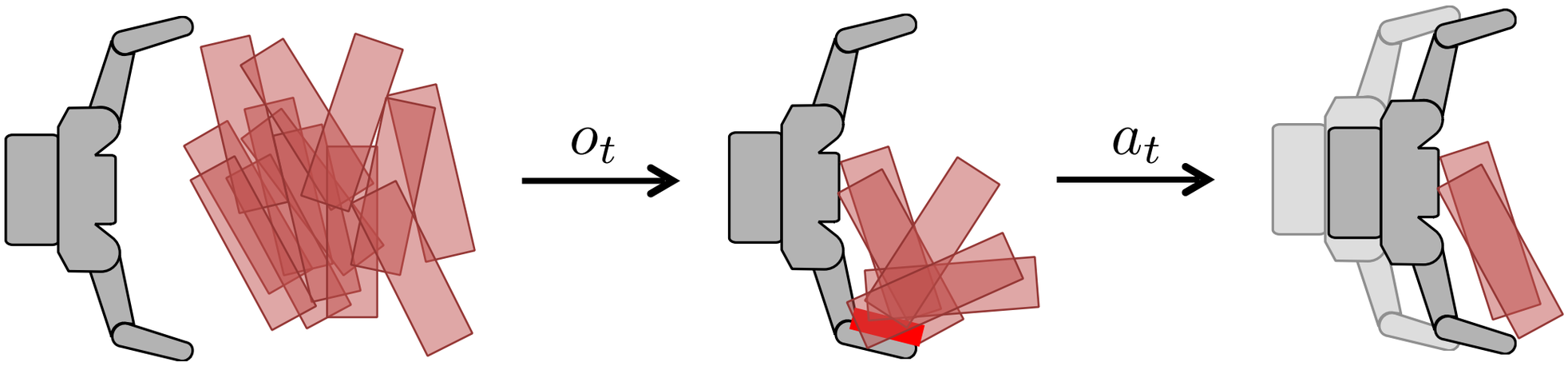
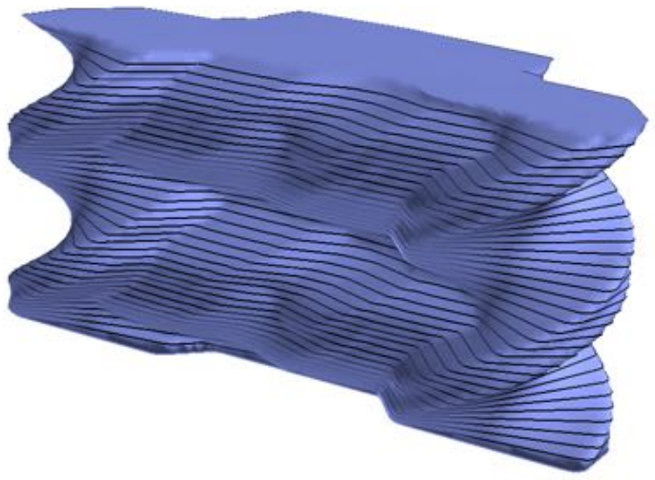
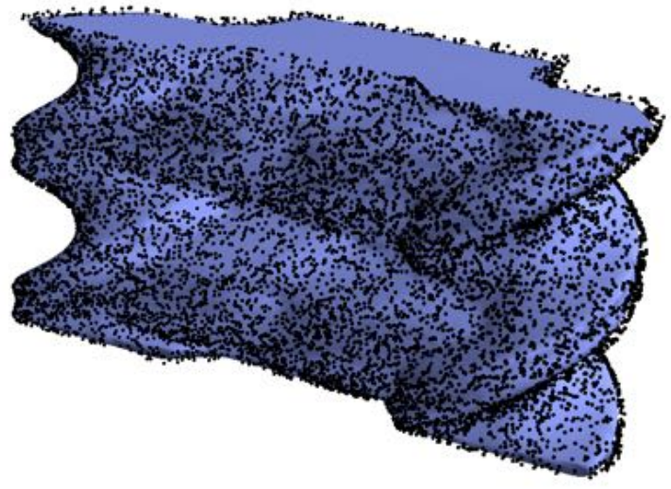


S. Thrun, D. Fox, and W. Burgard. “Monte Carlo localization with mixture proposal distribution” In AAAI. 2000.



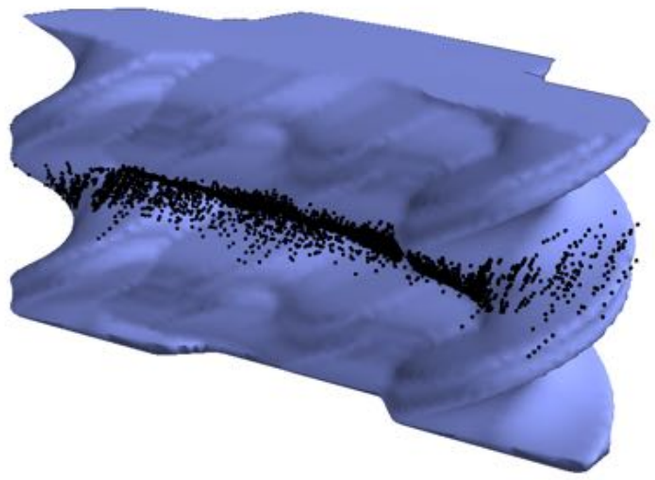
analytic representation

exact Minkowski sums
difficult to implement
only works for polygons



rejection sampled

approximate solution
expensive to compute
task independent



trajectory rollouts

approximate solution
inexpensive to compute
task specific

Explicitly represent the contact manifold

M.C. Koval, M.R. Dogar, N.S. Pollard, and S.S. Srinivasa. “Pose estimation for contact manipulation with manifold particle filters.” IEEE/RJS IROS. 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. "Manifold representations for state estimation in contact manipulation." ISRR, 2013. Invited paper.
M.C. Koval, N.S. Pollard, S.S. Srinivasa. "Pose estimation for planar contact manipulation with manifold particle filters." IJRR, 2015.

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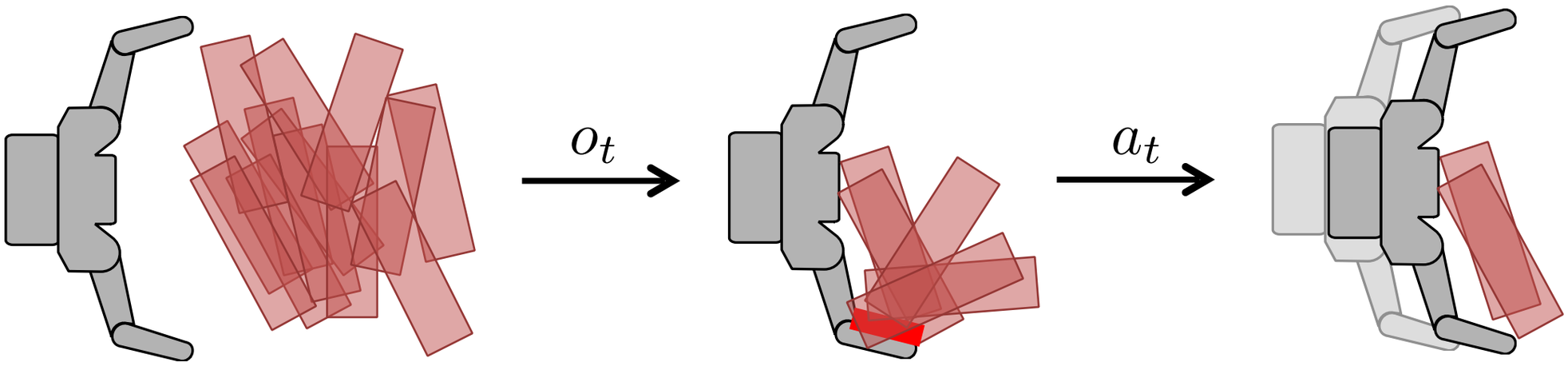
3. Resample with replacement.



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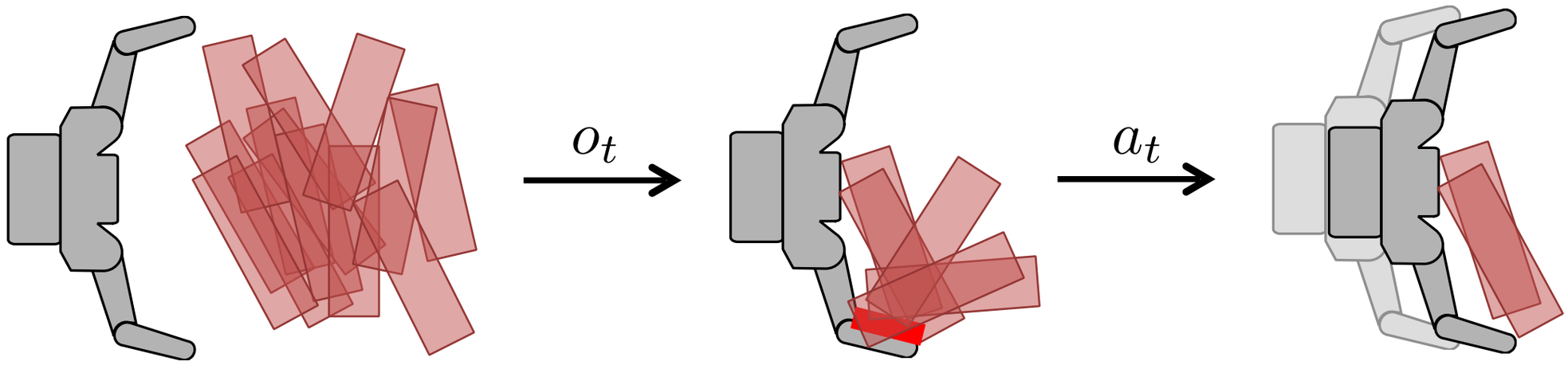

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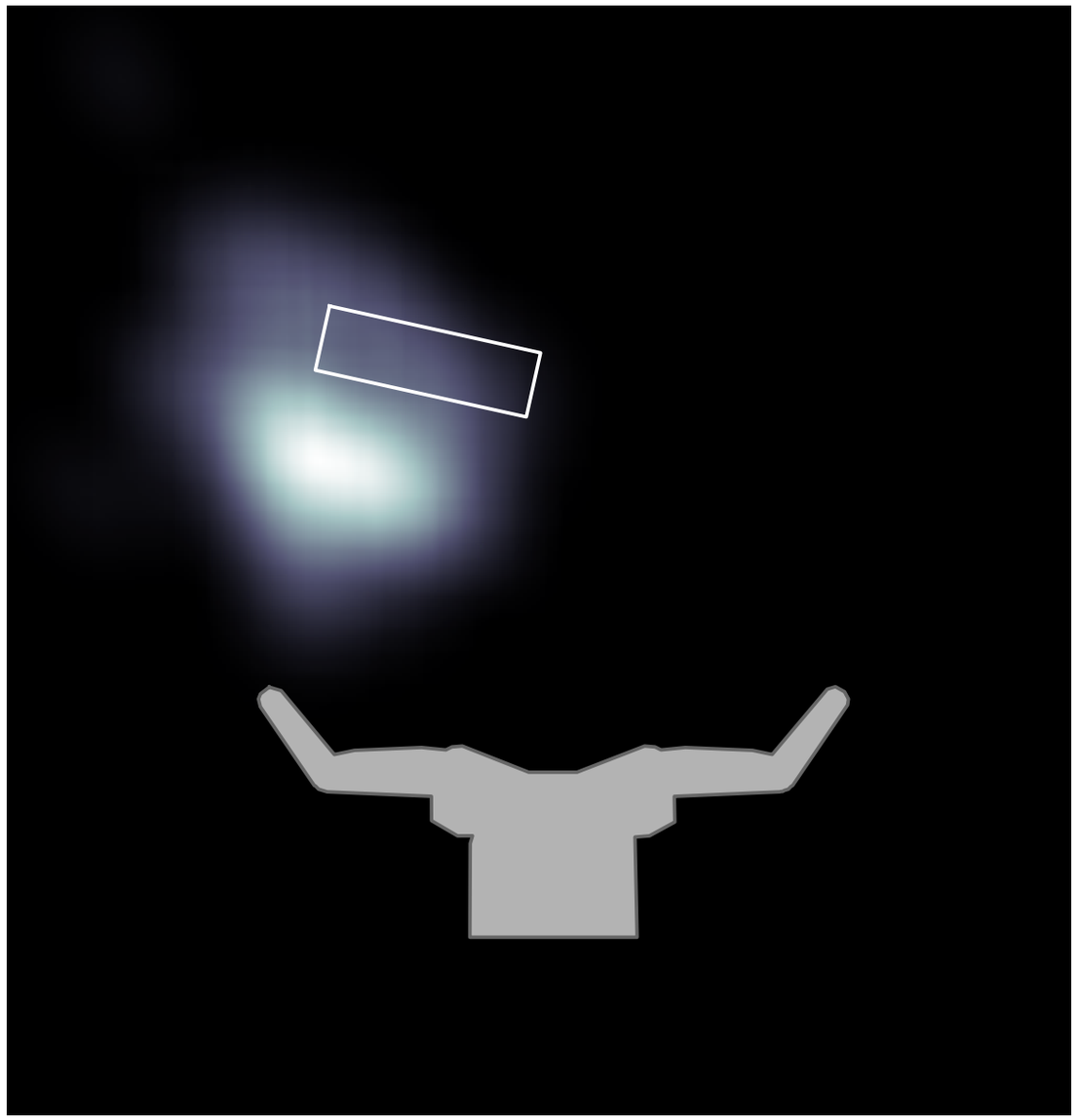


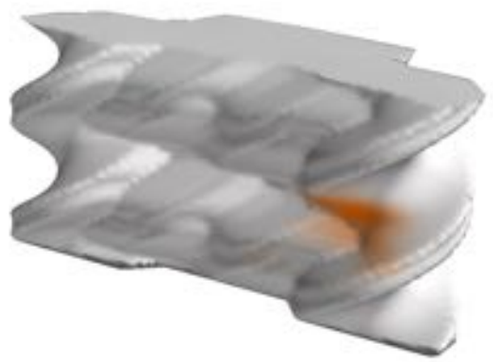
Compute importance weights with density estimation

M.C. Koval, M.R. Dogar, N.S. Pollard, and S.S. Srinivasa. “Pose estimation for contact manipulation with manifold particle filters.” IEEE/RJS IROS. 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. "Manifold representations for state estimation in contact manipulation." ISRR, 2013. Invited paper.
M.C. Koval, N.S. Pollard, S.S. Srinivasa. "Pose estimation for planar contact manipulation with manifold particle filters." IJRR, 2015.

Manifold Particle Filter

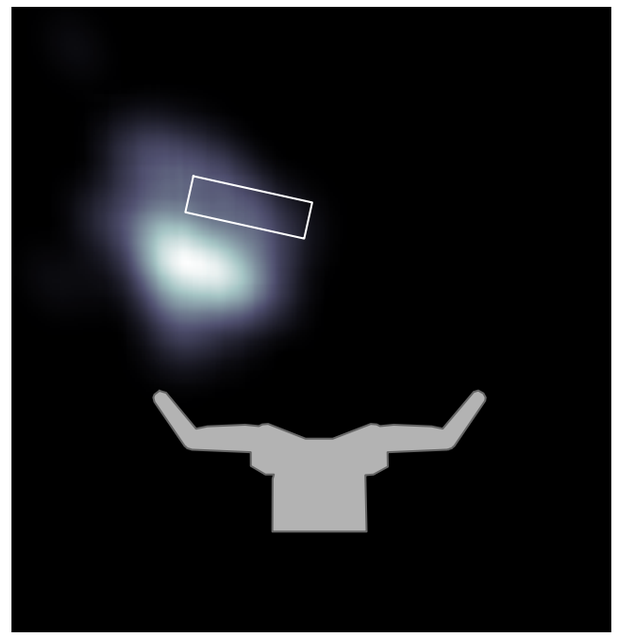
$$b(s_t) = p(M_1)$$

$$\approx p(o_t|s_t, a_t)$$



contact manifold

$$+ p(M_2)$$



free space

Adaptively sample from both distributions

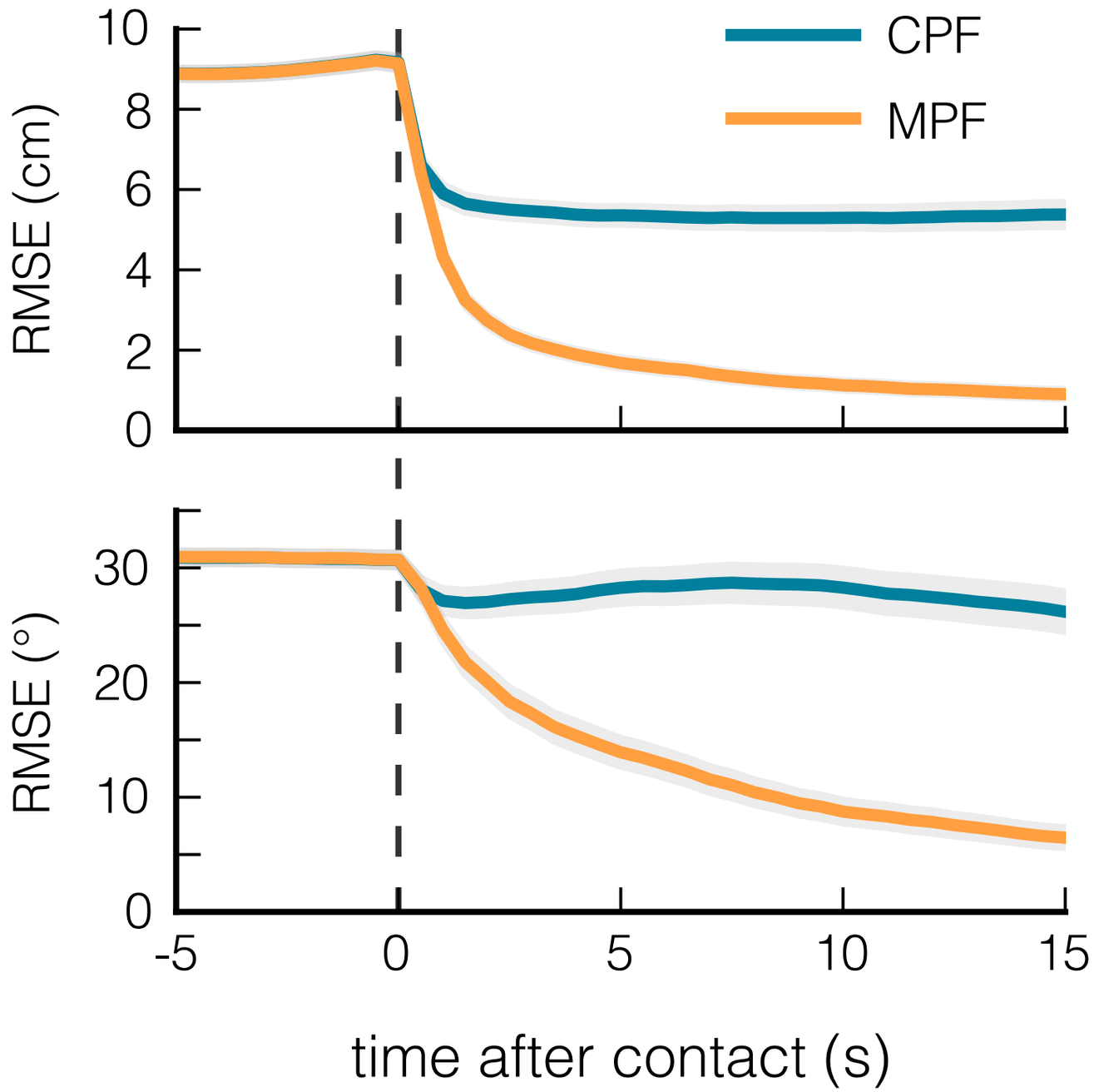
M.C. Koval, M.R. Dogar, N.S. Pollard, and S.S. Srinivasa. “Pose estimation for contact manipulation with manifold particle filters.” IEEE/RJS IROS. 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. "Manifold representations for state estimation in contact manipulation." ISRR, 2013. Invited paper.
M.C. Koval, N.S. Pollard, S.S. Srinivasa. "Pose estimation for planar contact manipulation with manifold particle filters." IJRR, 2015.

Experiment 1
(2x)

CPF
n = 250

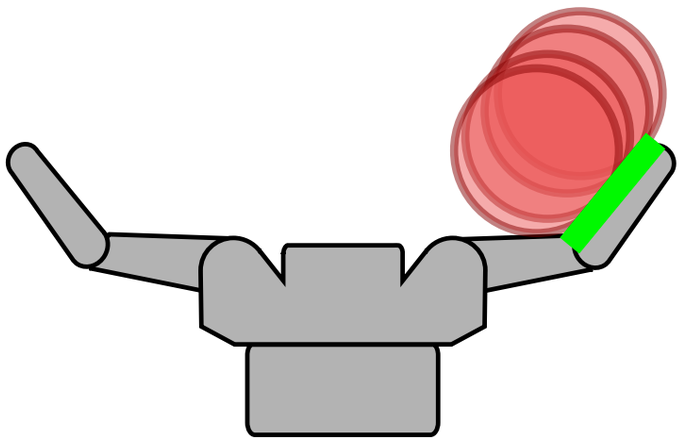
Experiment 1
(2x)

MPF
n = 225, d = 25



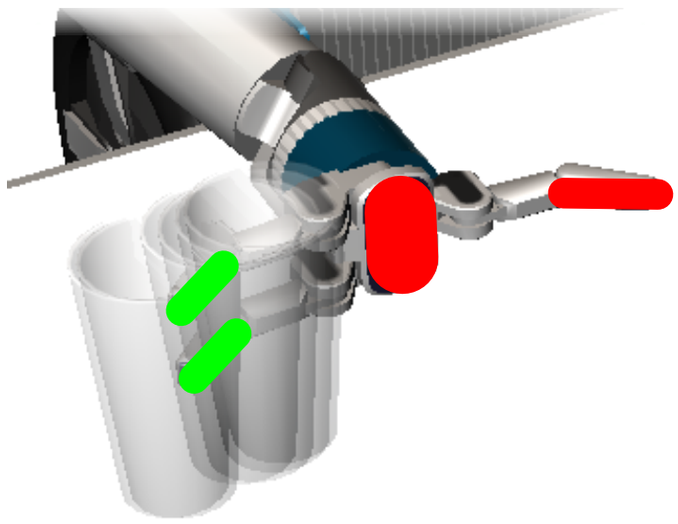
MPF outperforms the CPF after contact

M.C. Koval, M.R. Dogar, N.S. Pollard, and S.S. Srinivasa. “Pose estimation for contact manipulation with manifold particle filters.” IEEE/RJS IROS. 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. "Manifold representations for state estimation in contact manipulation." ISRR, 2013. Invited paper.
M.C. Koval, N.S. Pollard, S.S. Srinivasa. "Pose estimation for planar contact manipulation with manifold particle filters." IJRR, 2015.



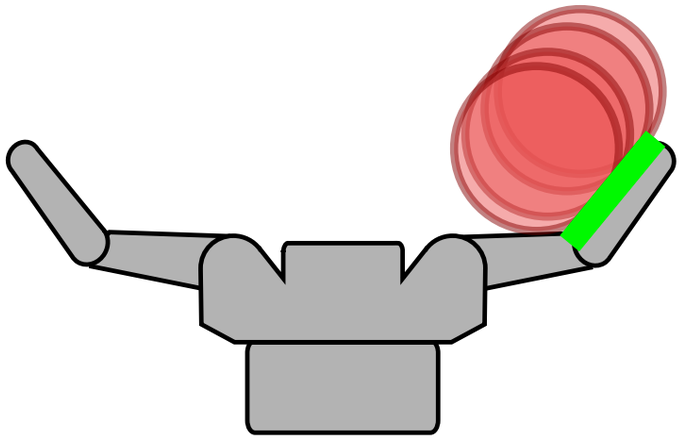
3 DOF C-space

?



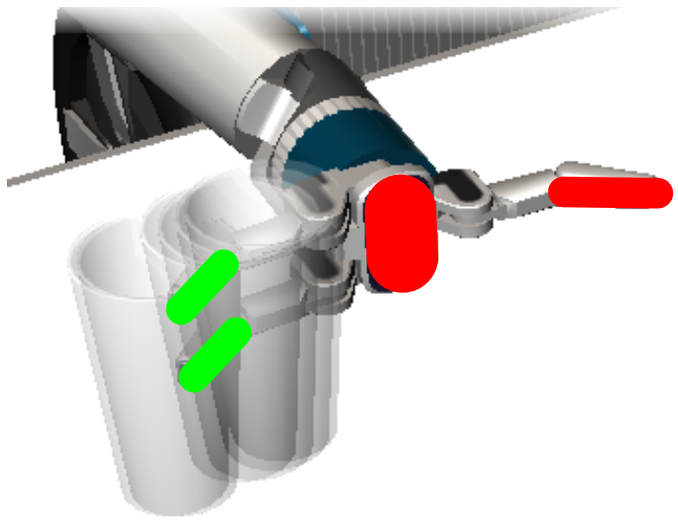
>7 DOF C-space

How can we generalize to a high-DOF C-space?

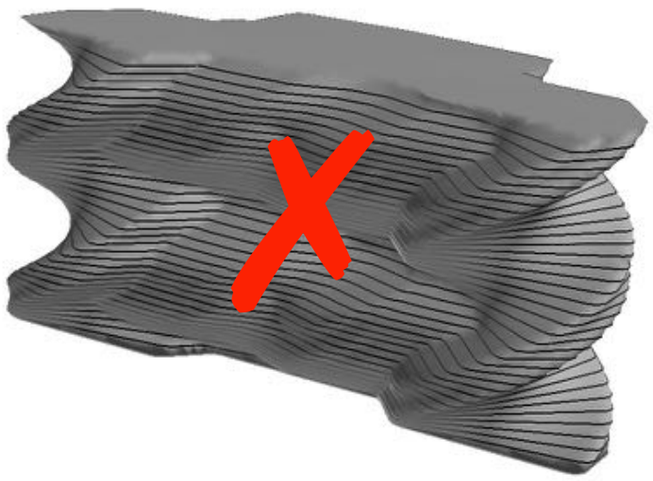


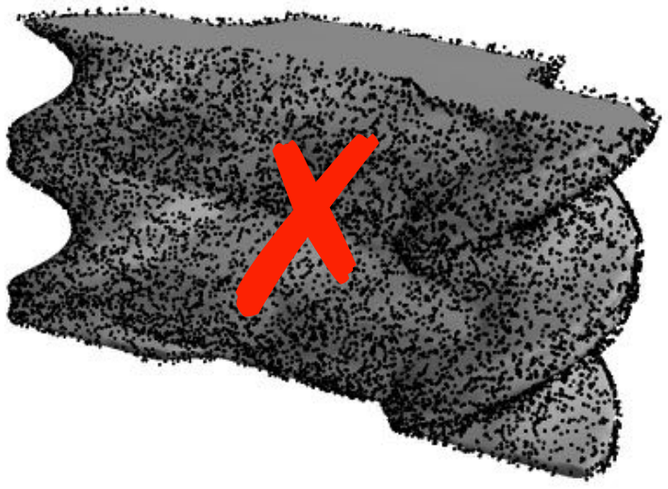
3 DOF C-space

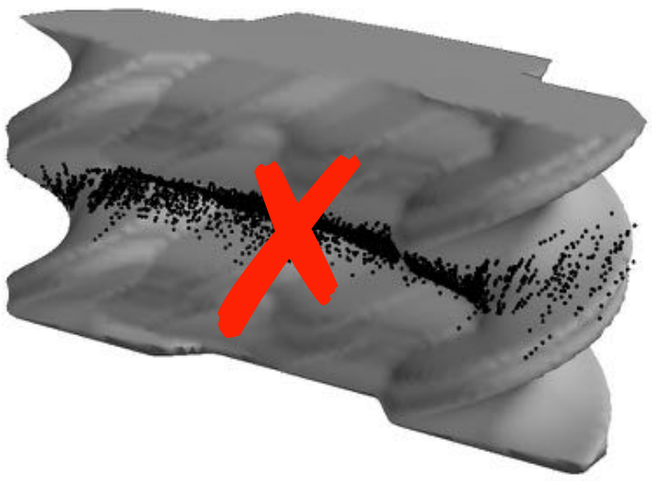
?



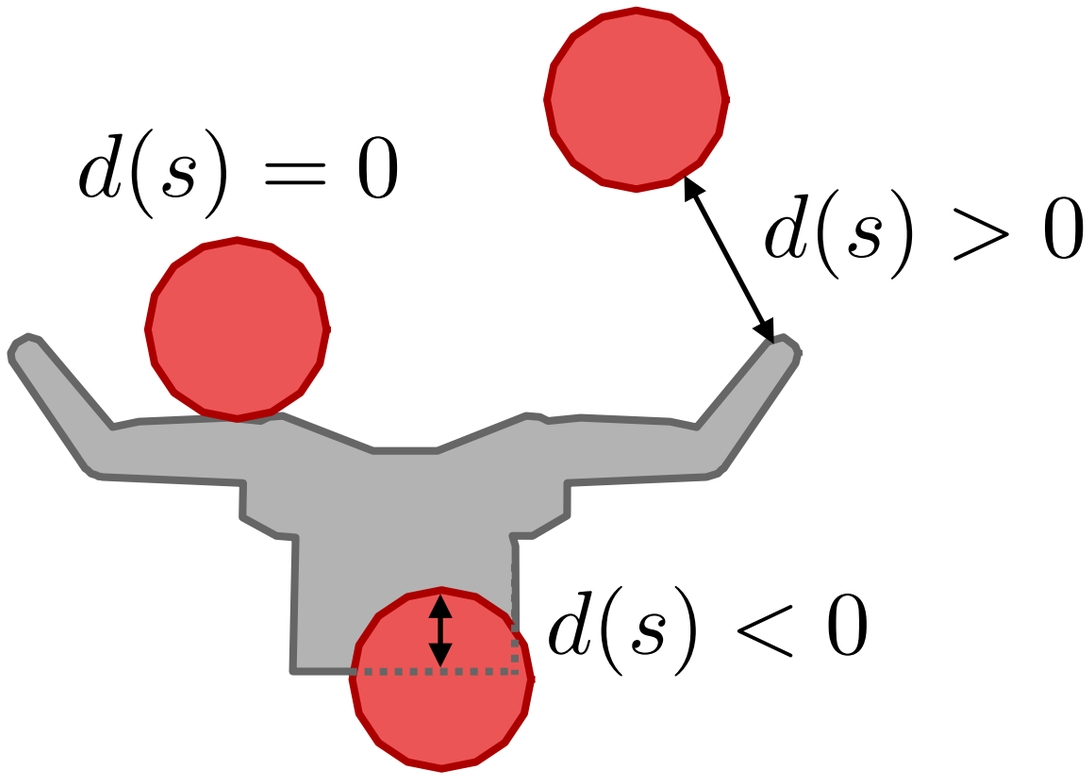
>7 DOF C-space





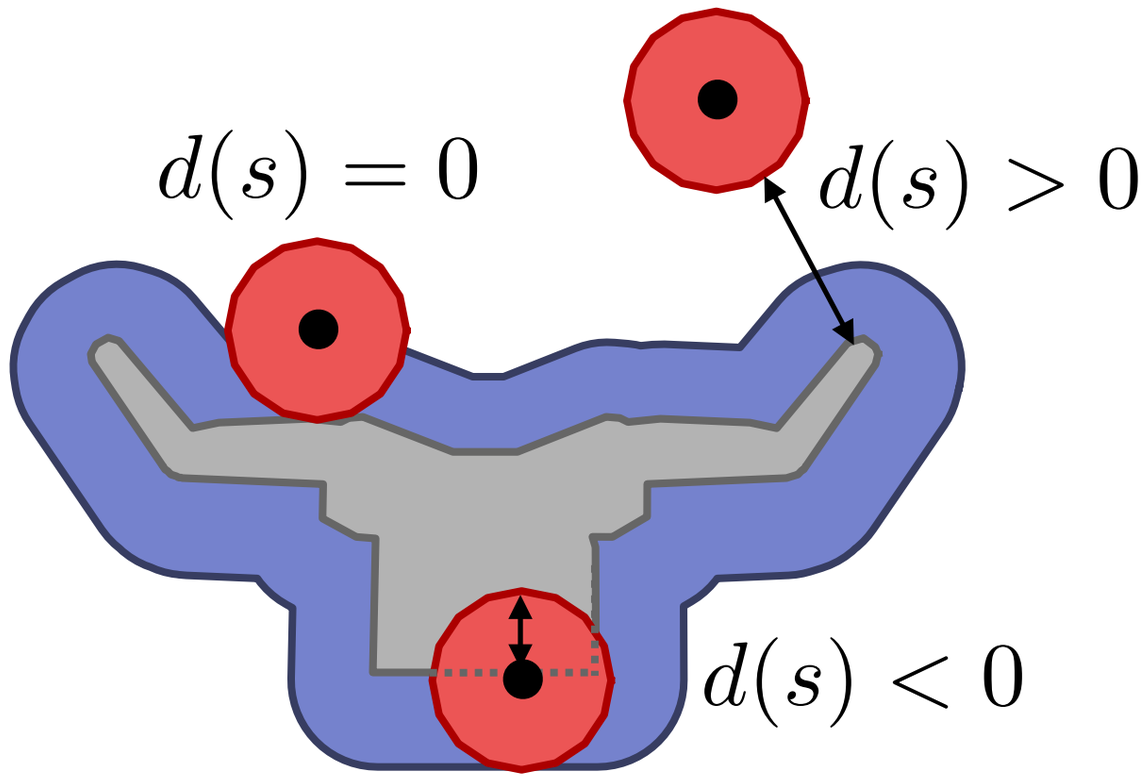


Implicitly represent the contact manifold.



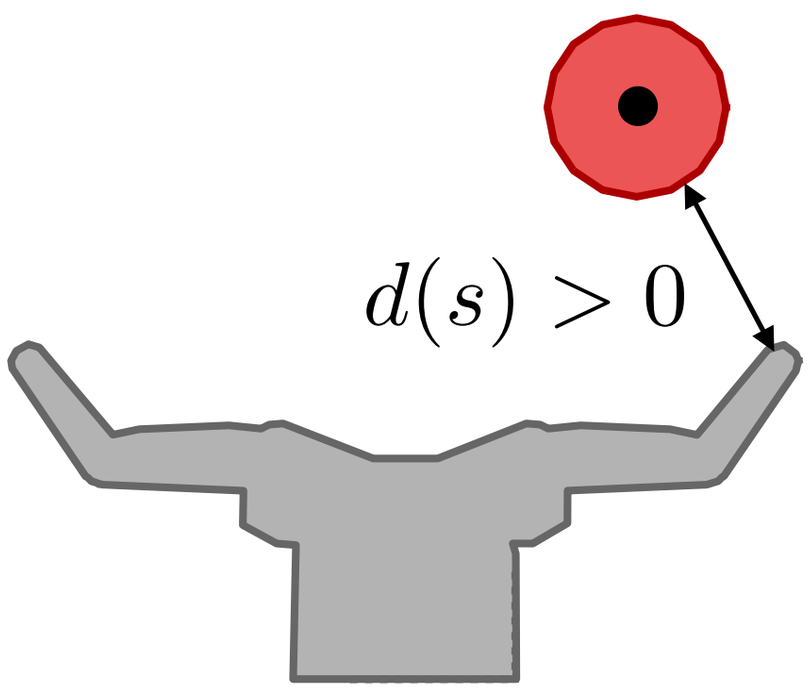
Contact occurs when $d(s) = 0$

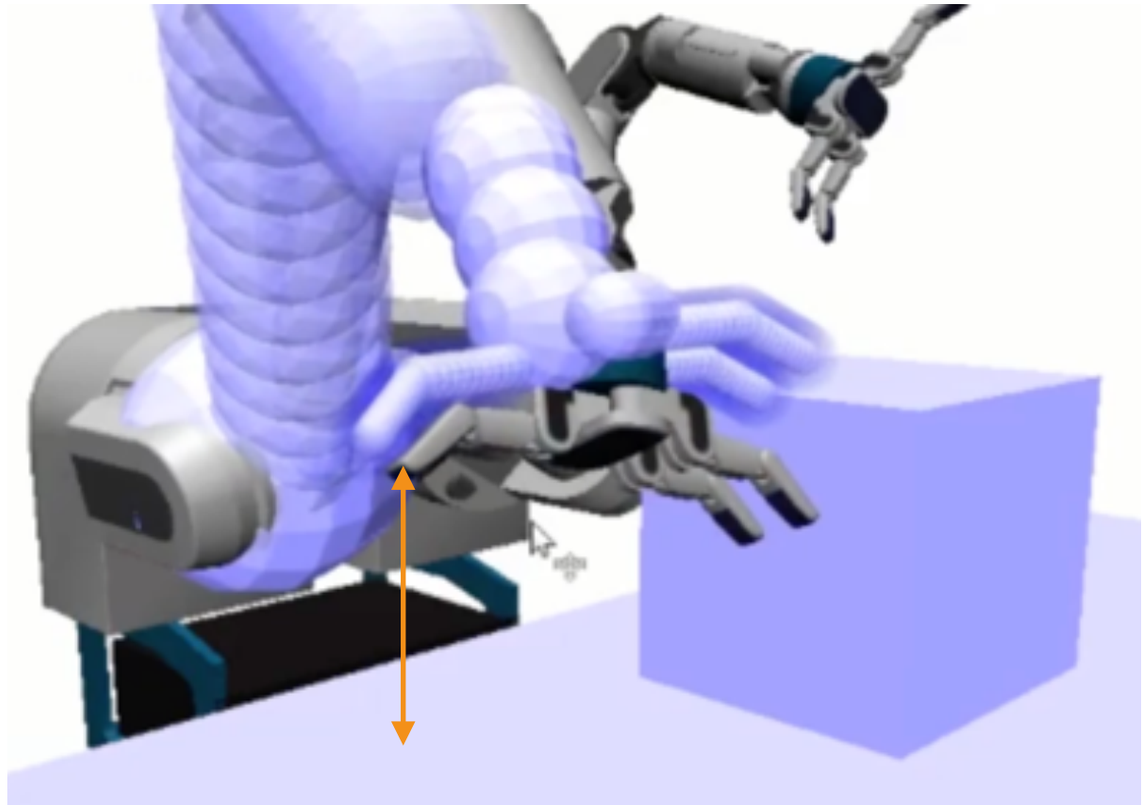
M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



Implicitly define contact manifold as $\{s : d(s) = 0\}$

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.

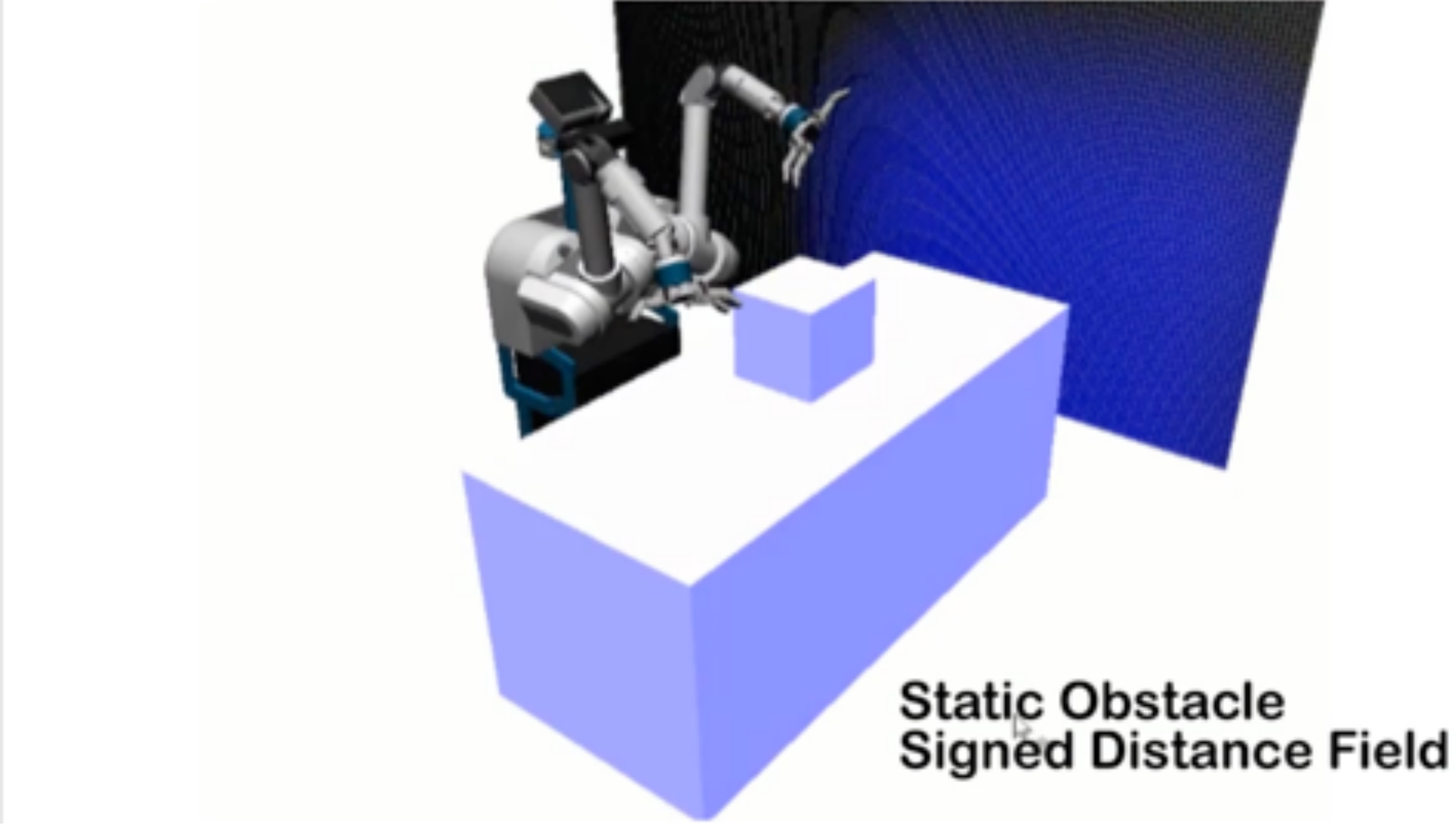




$d(s) > 0$

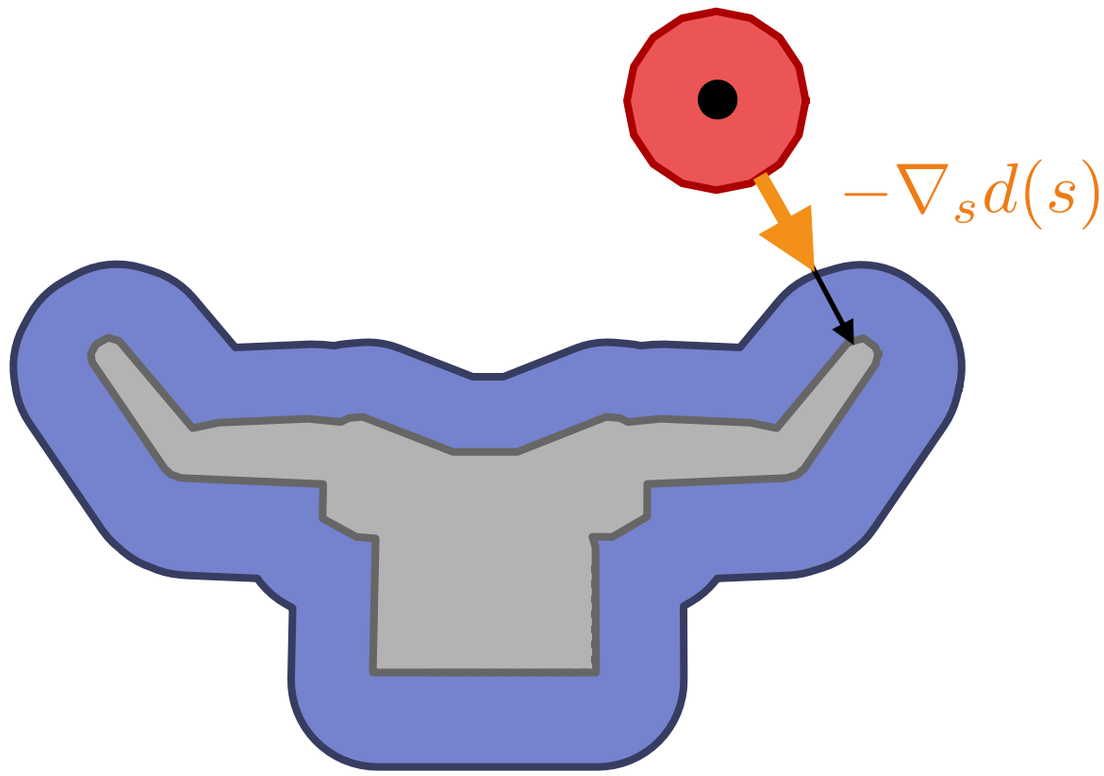
Duality between object pose and robot configuration

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



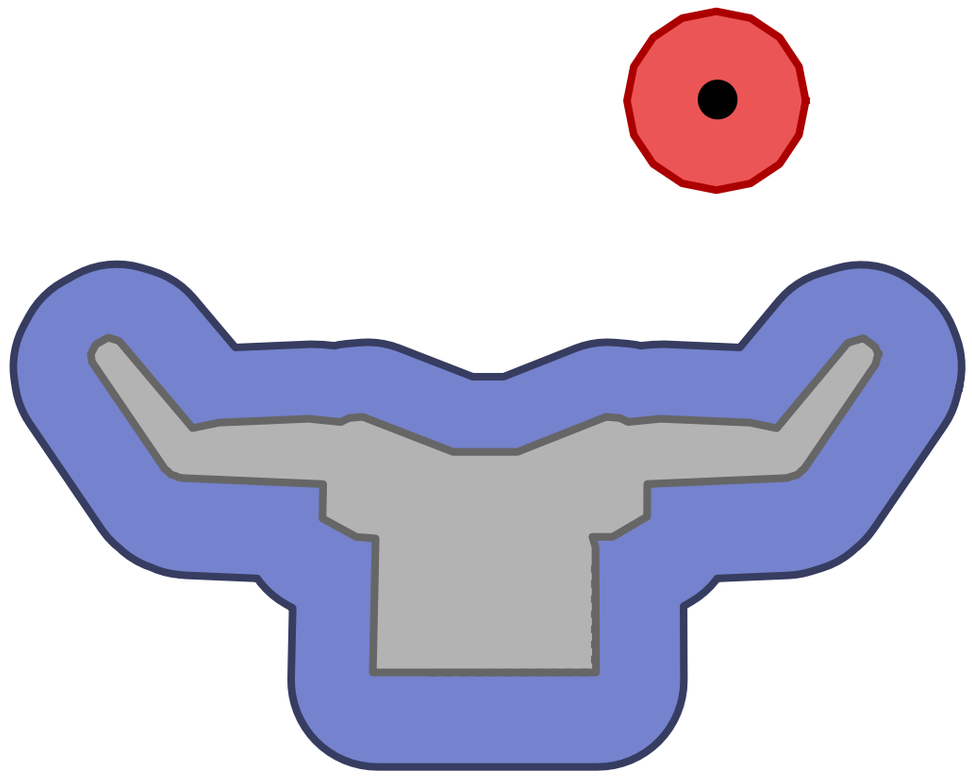
Compute $d(s)$ using a signed distance field

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



Project onto the contact manifold via root finding

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



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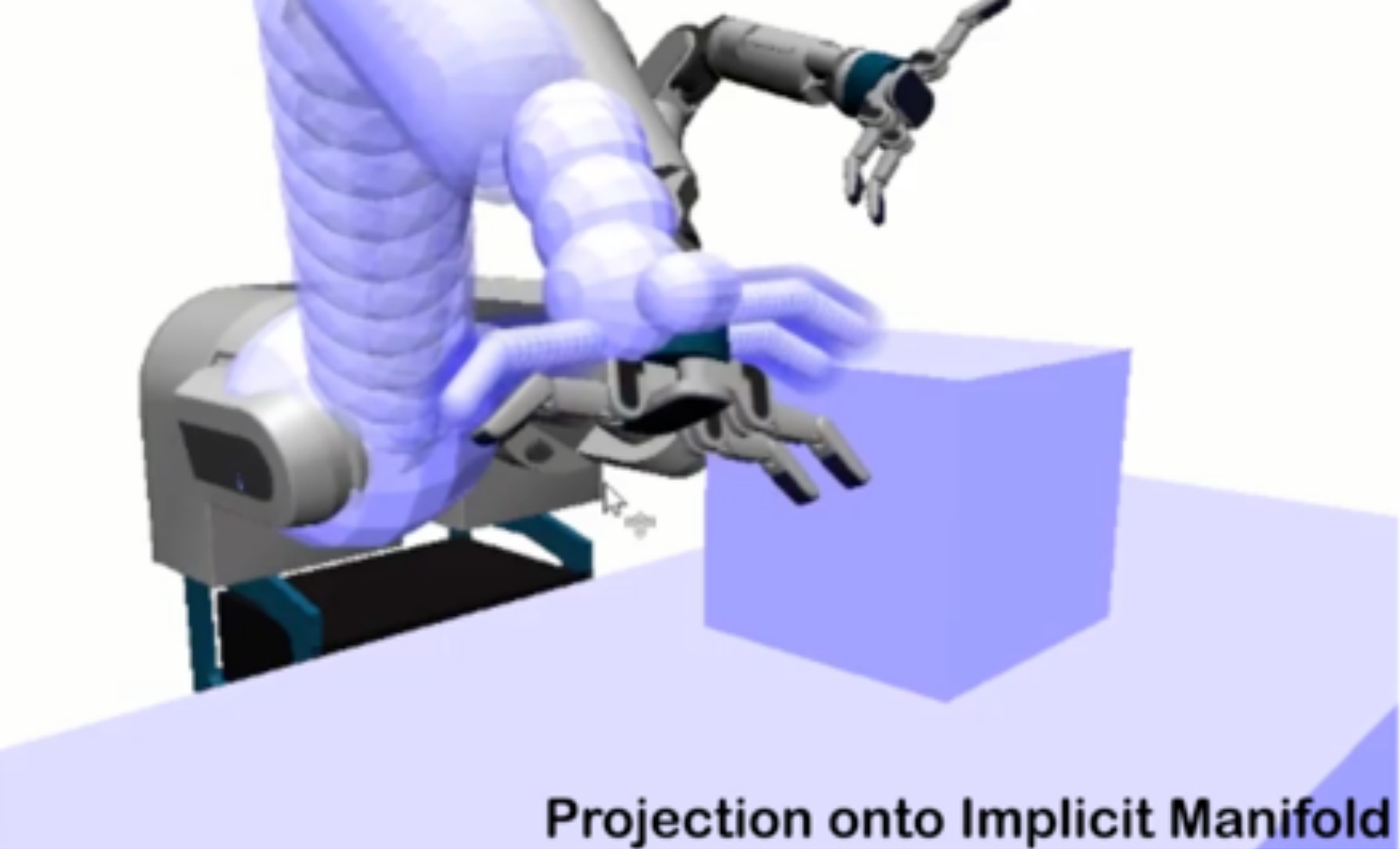
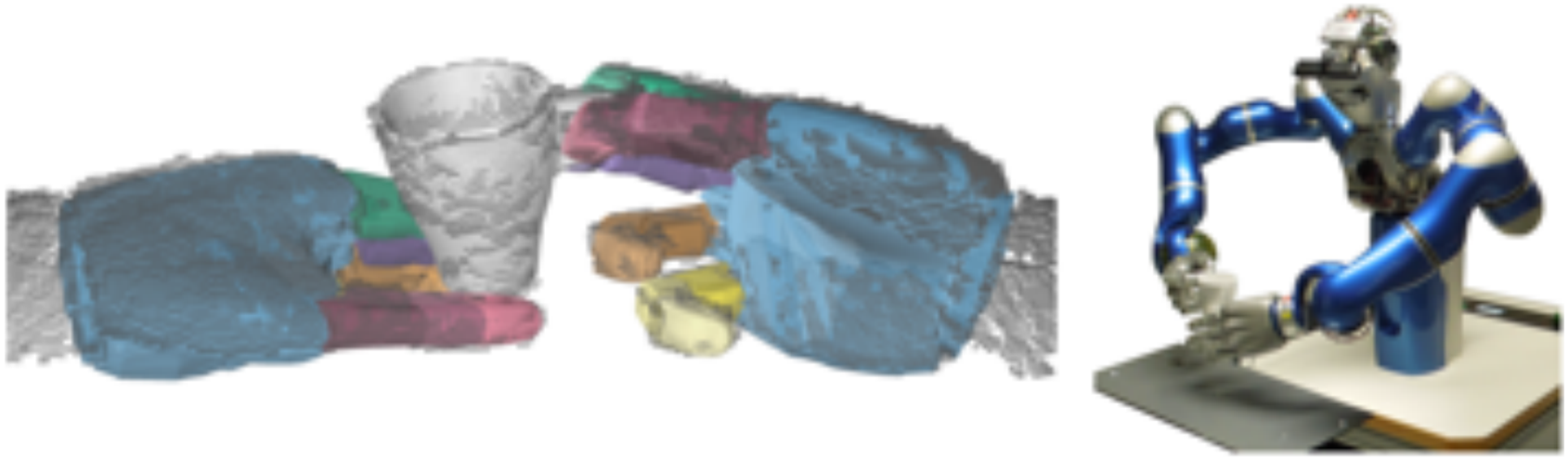
M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.

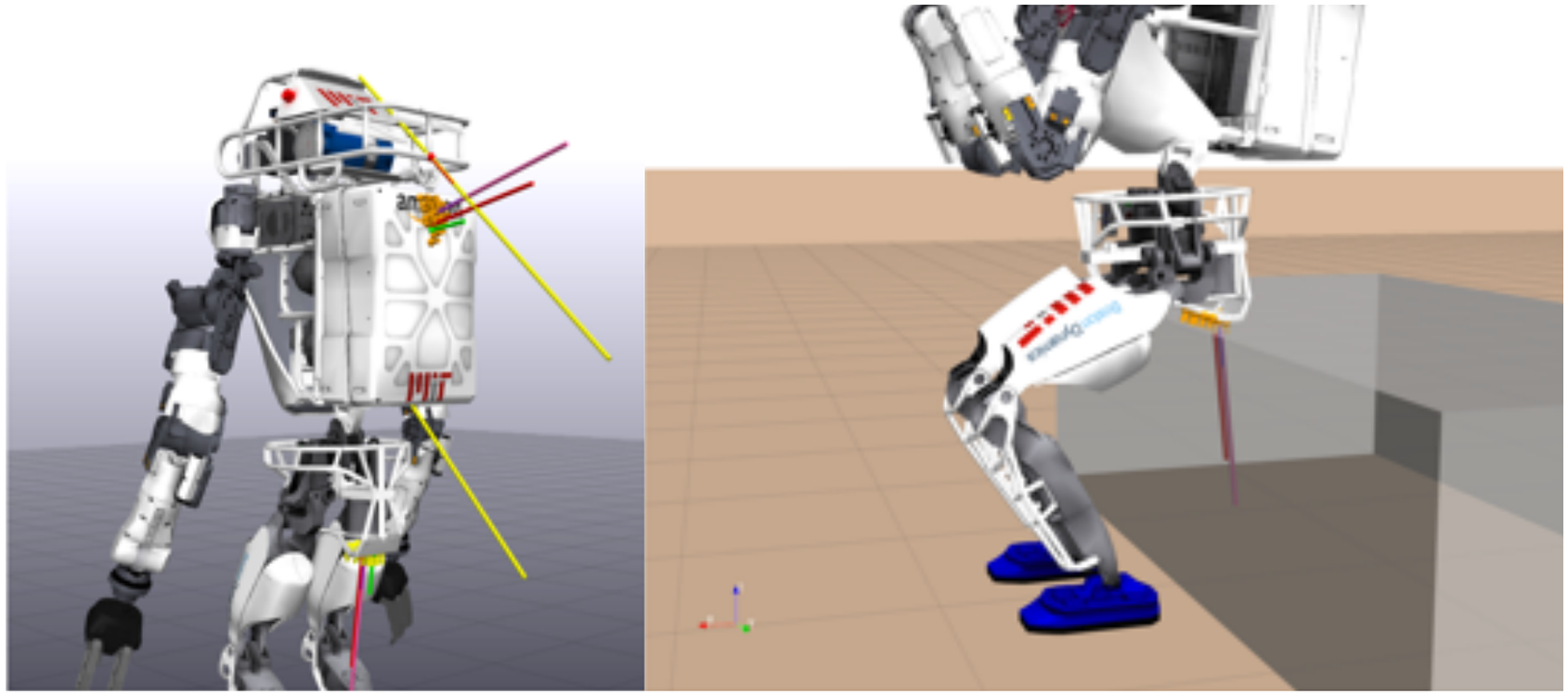


Project using a numeric root finding algorithm

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



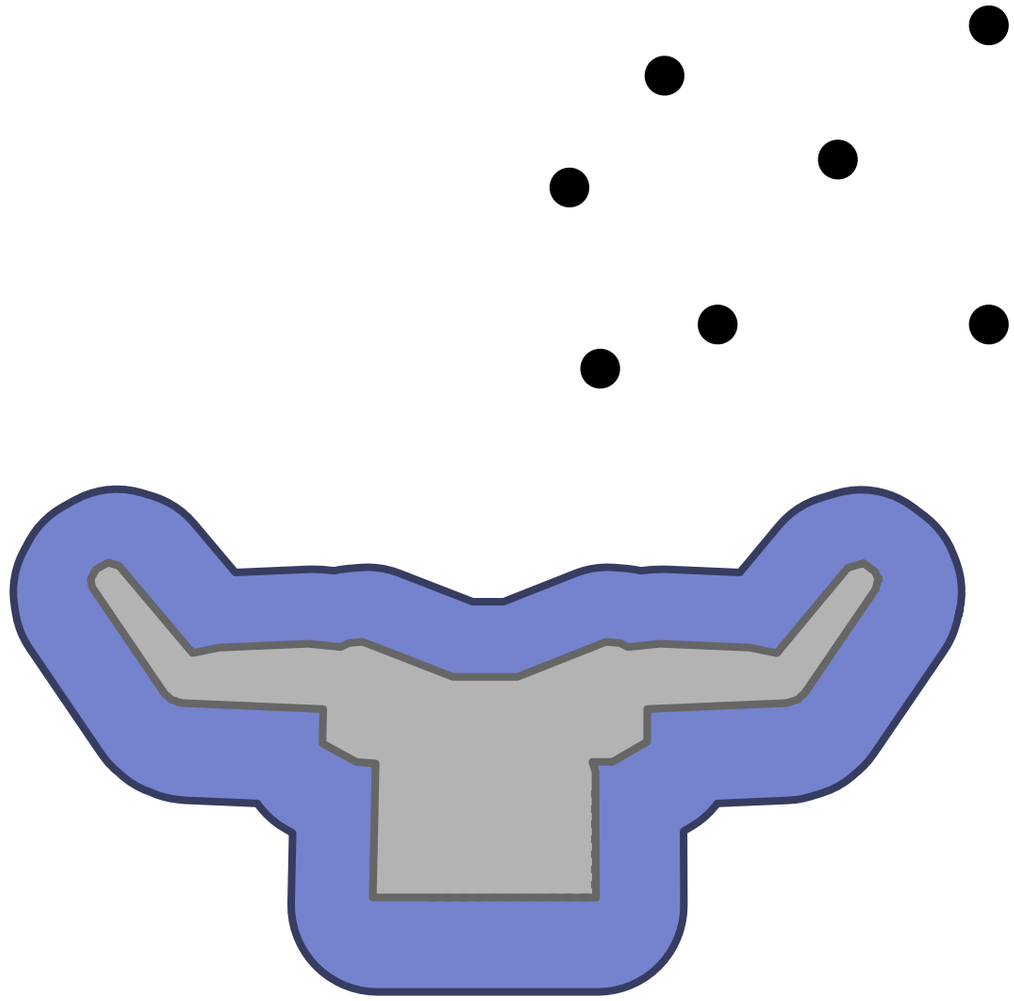
T. Schmidt, et al. “Depth-based tracking with physical constraints for robot manipulation”. ICRA, 2015.



L. Manuelli and R. Tedrake. “Localizing external contact using proprioceptive sensors: The contact particle filter.” Under review.

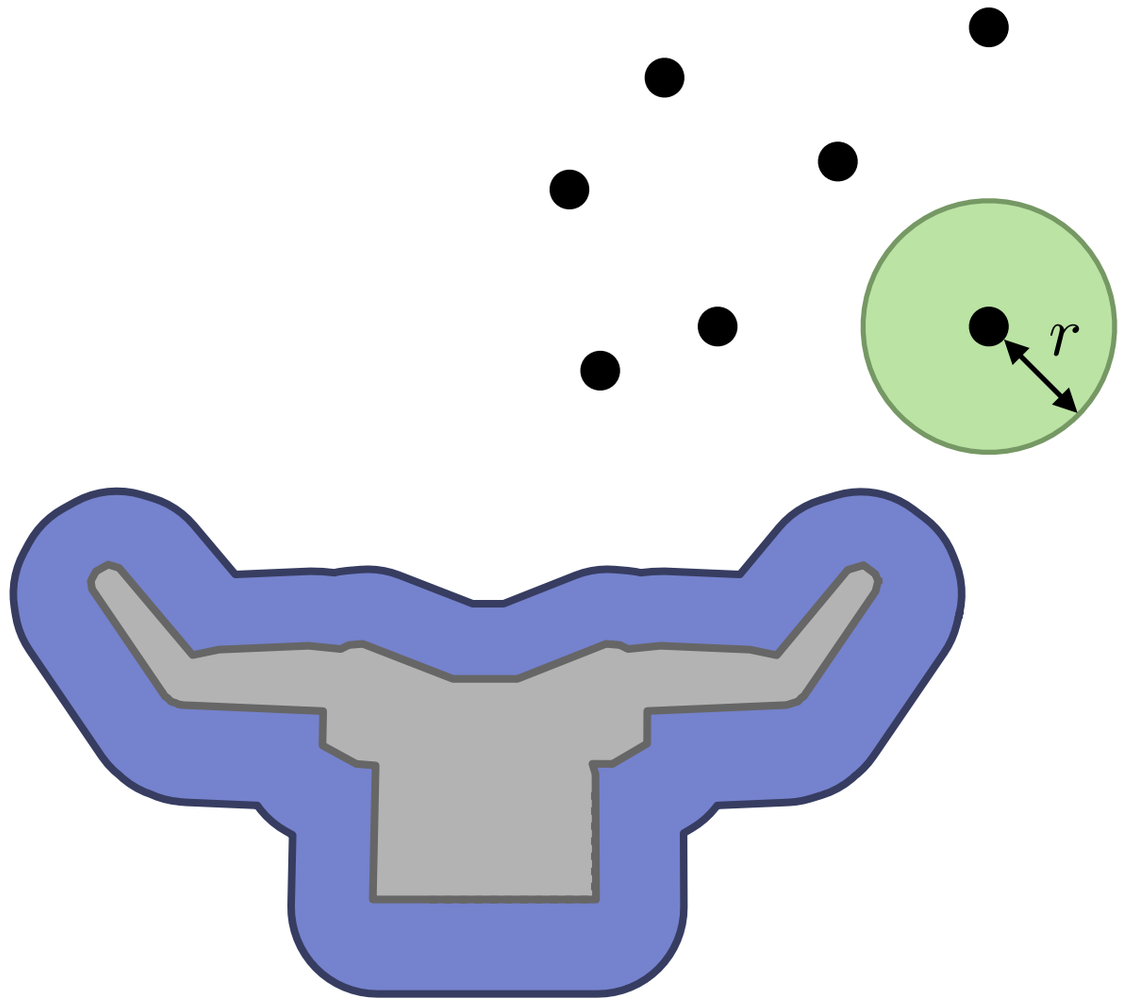
How do we seed the root finder?

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." `arXiv:1604.07224`, 2016.



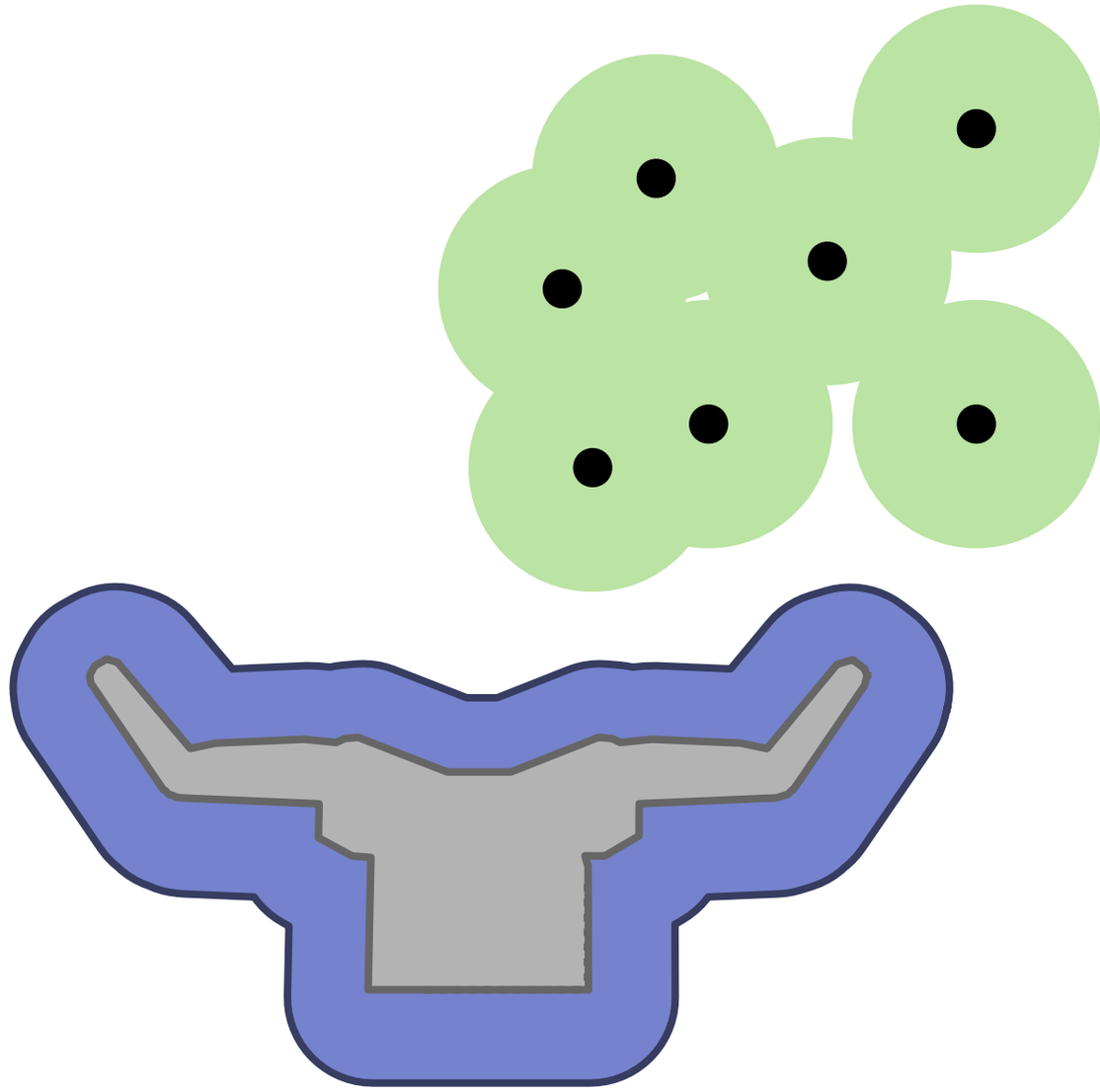
Sample initializations near existing particles

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



Sample initializations near existing particles

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." `arXiv:1604.07224`, 2016.



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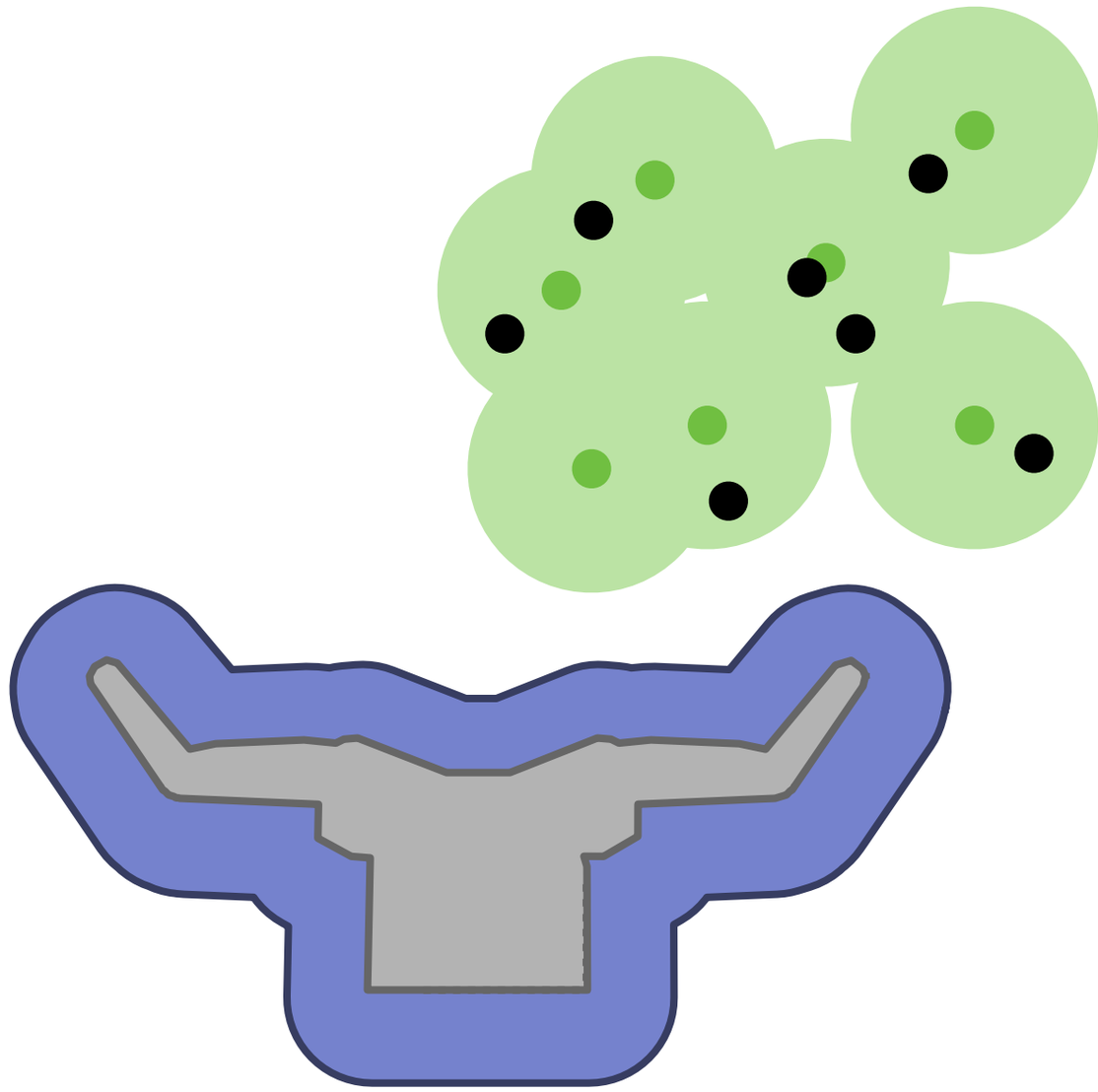

Sample initializations near existing particles

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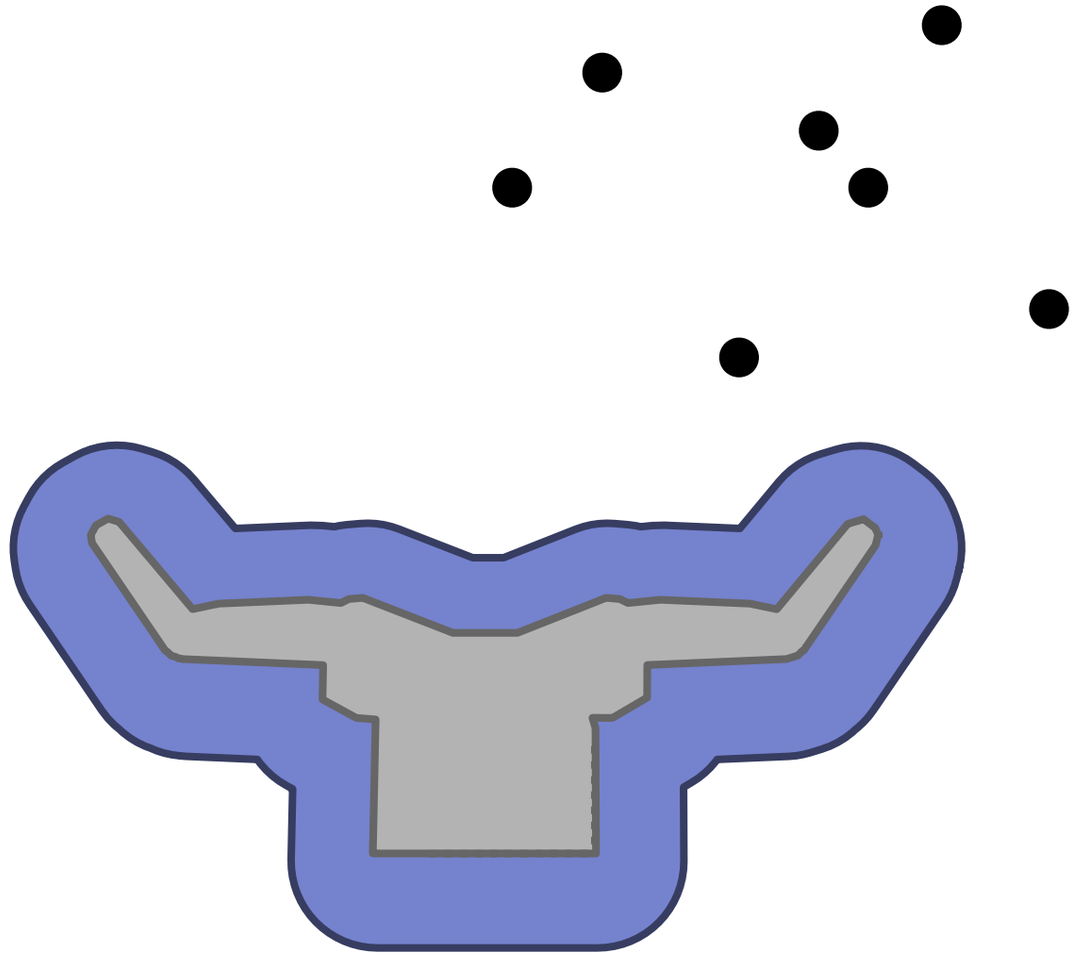
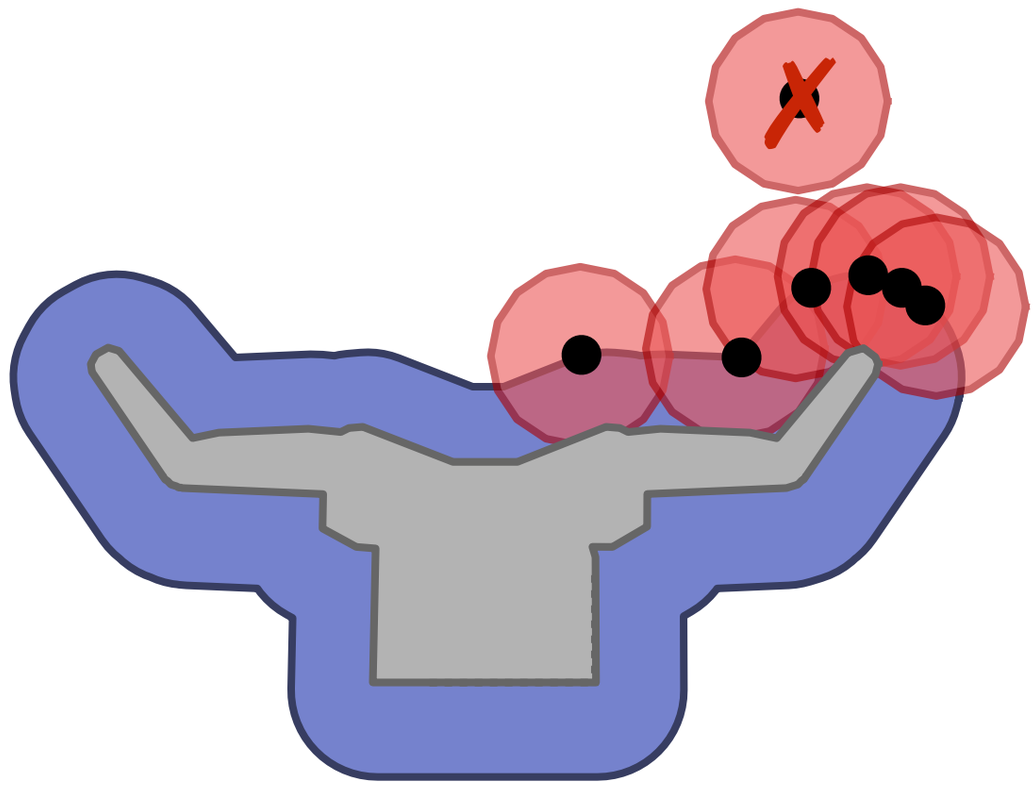


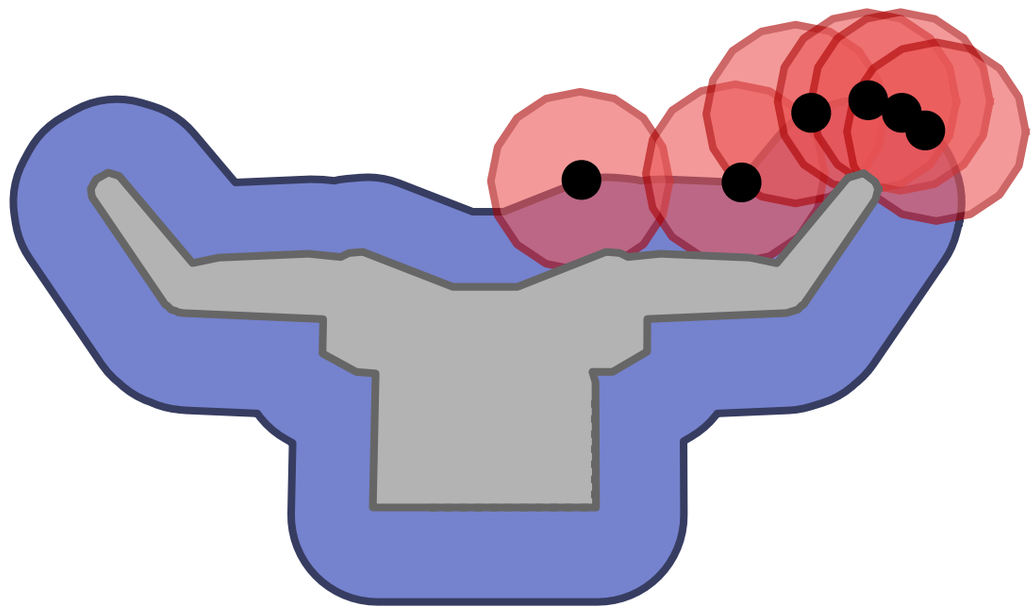
Project each sample onto the contact manifold

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



Reject particles that are stuck in local minima

M. Klingensmith, M.C Koval, S.S. Srinivasa, N.S. Pollard, and M. Kaess. "State estimation on high-dimensional implicit contact manifolds." arXiv:1604.07224, 2016.



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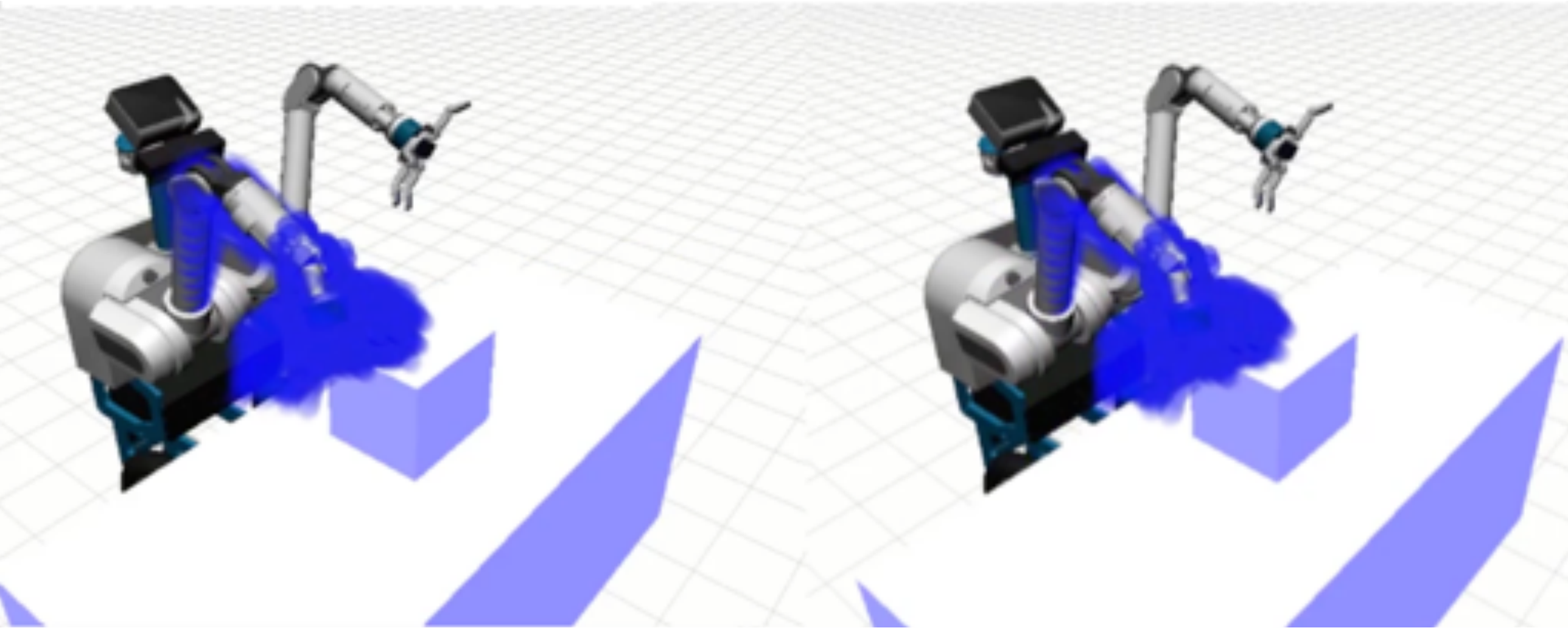
(1×)

red = contact detected, blue = particle



Manifold Particle Filter

Conventional Particle Filter

Implement projection via numerical root finding

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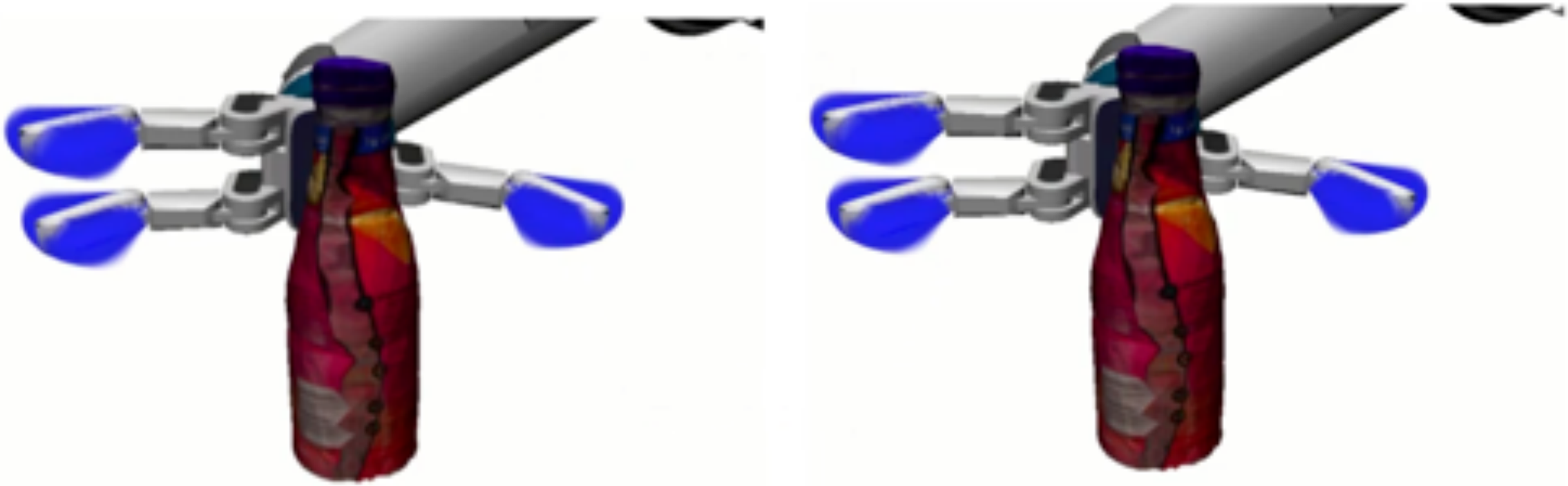

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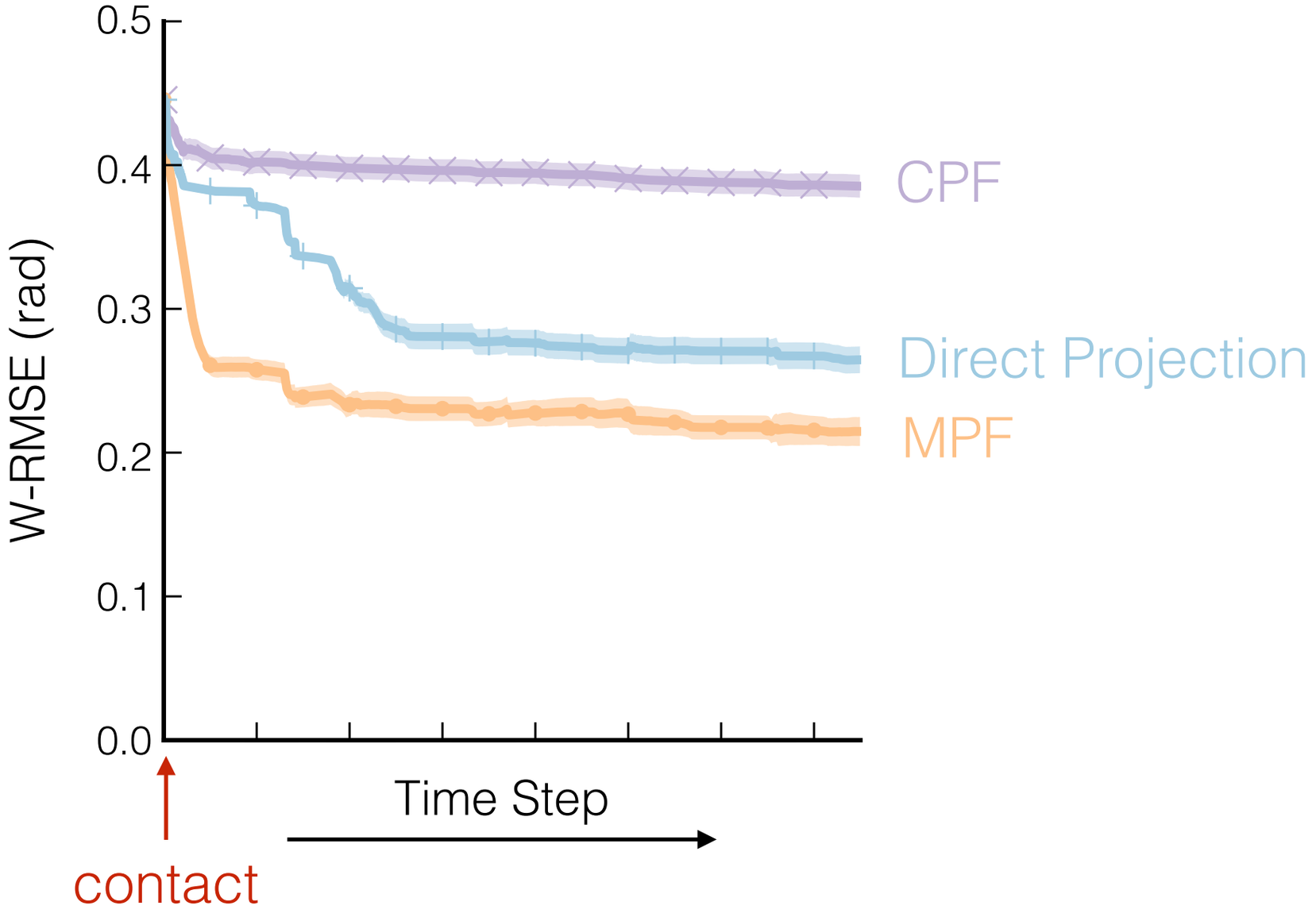

MPF still achieves lower error than the CPF

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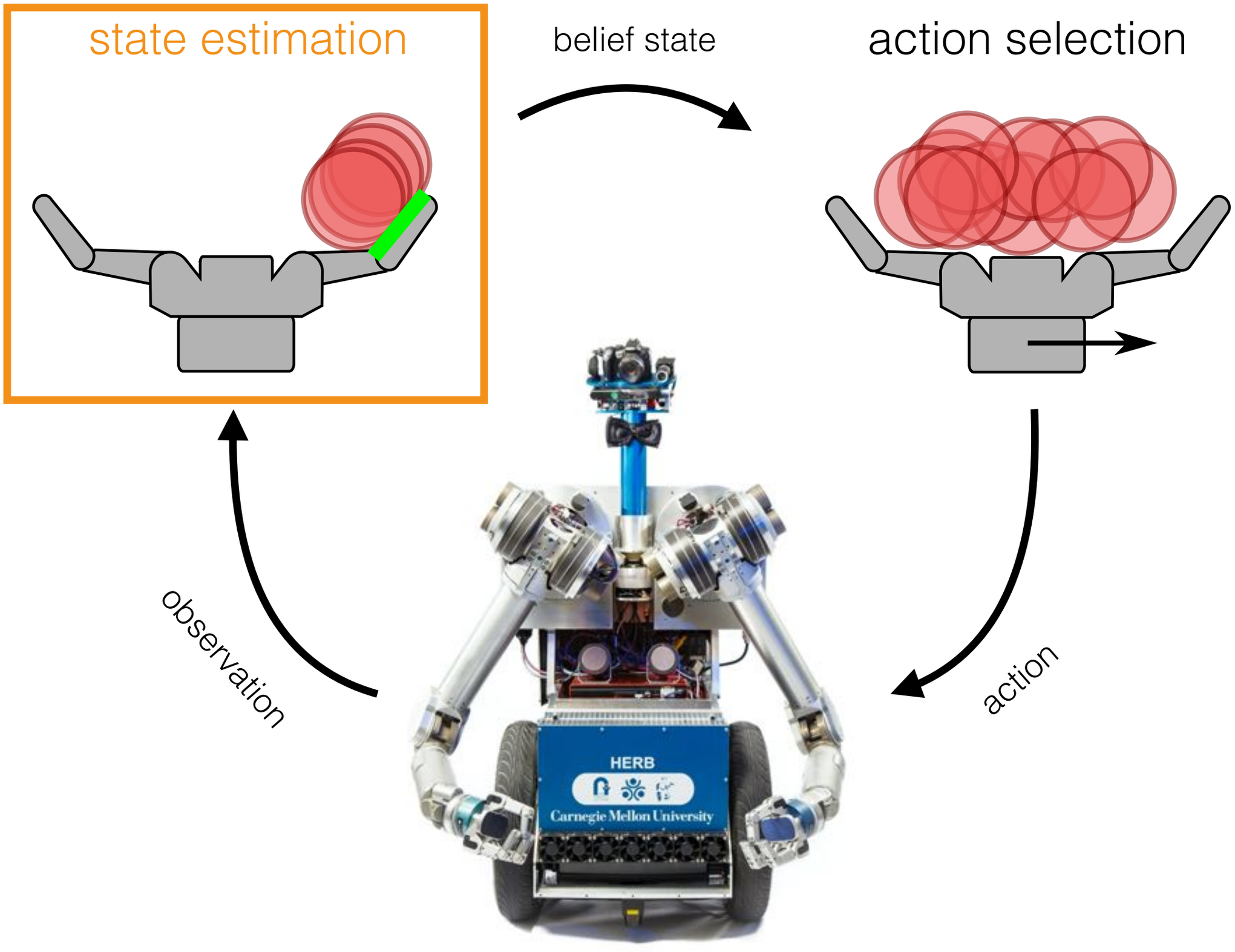
Insight 1

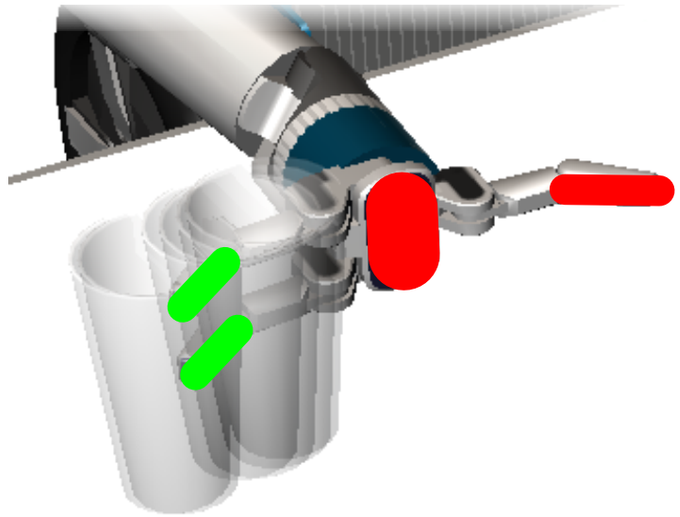
Manipulation occurs in a lower-dimensional space

Insight 2

Contact constrains state to a manifold


state estimation
belief state
action selection
observation
action
HERB
Carnegie Mellon University
environment

state estimation



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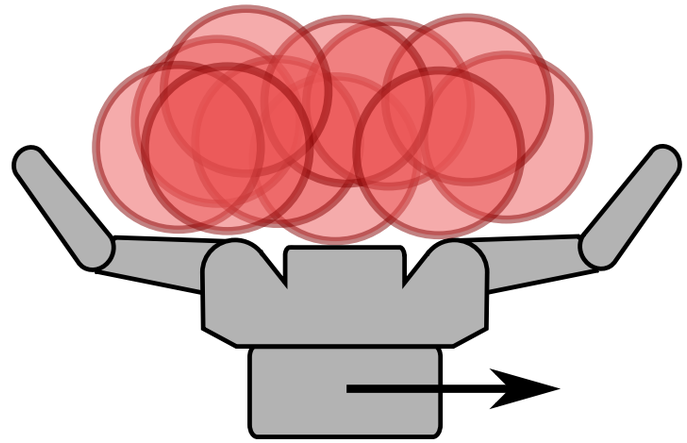

observation

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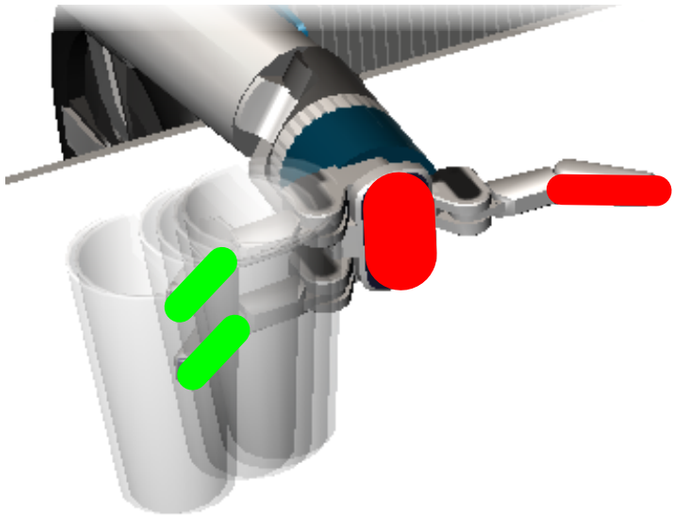

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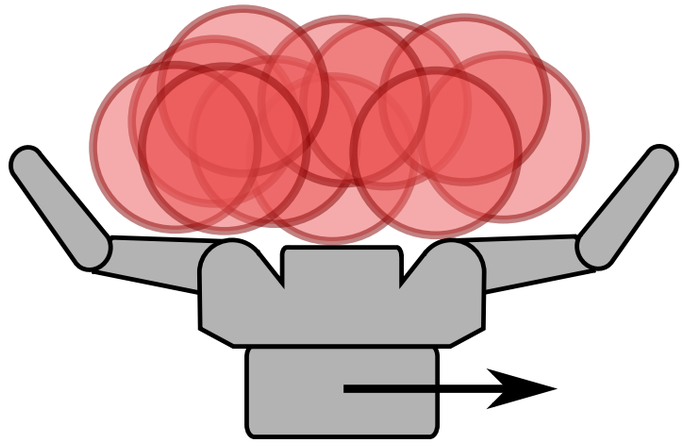
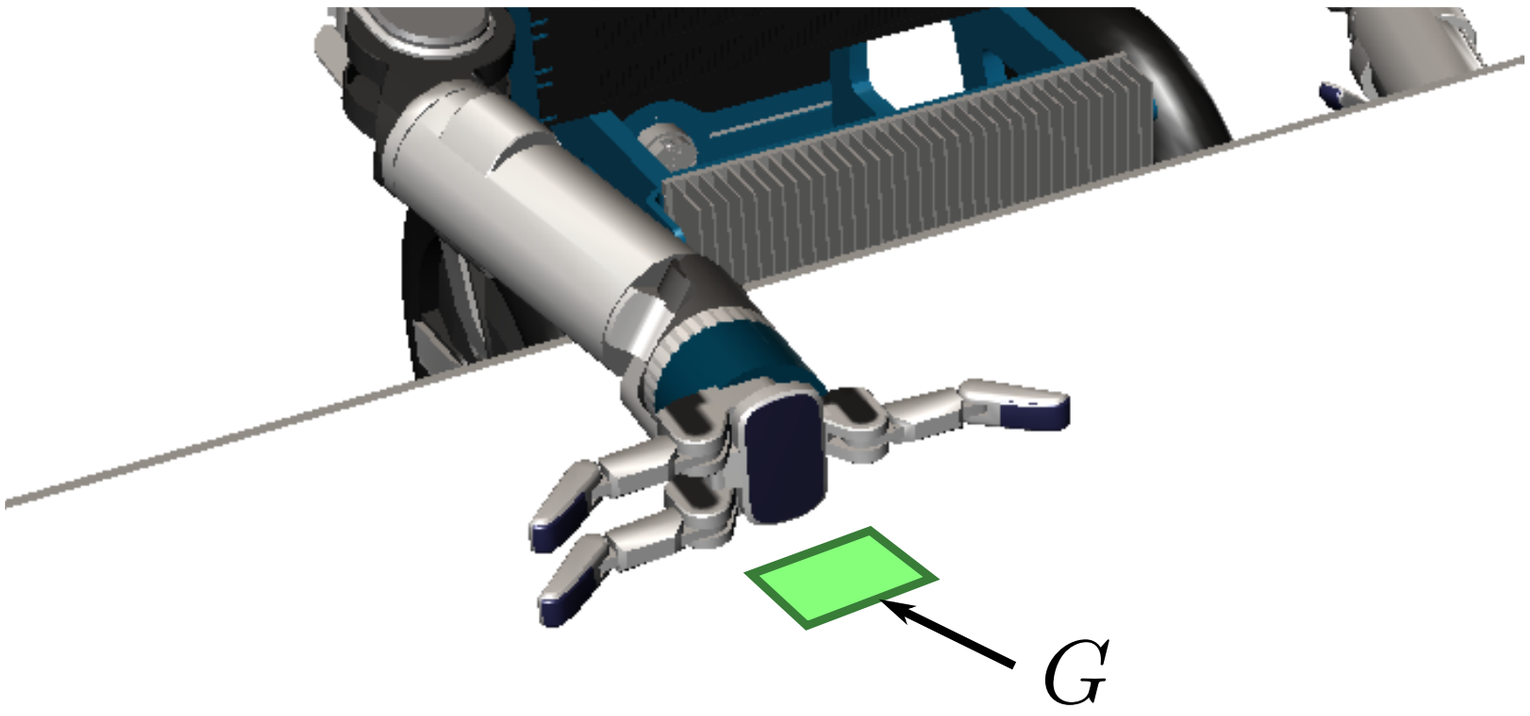


observation

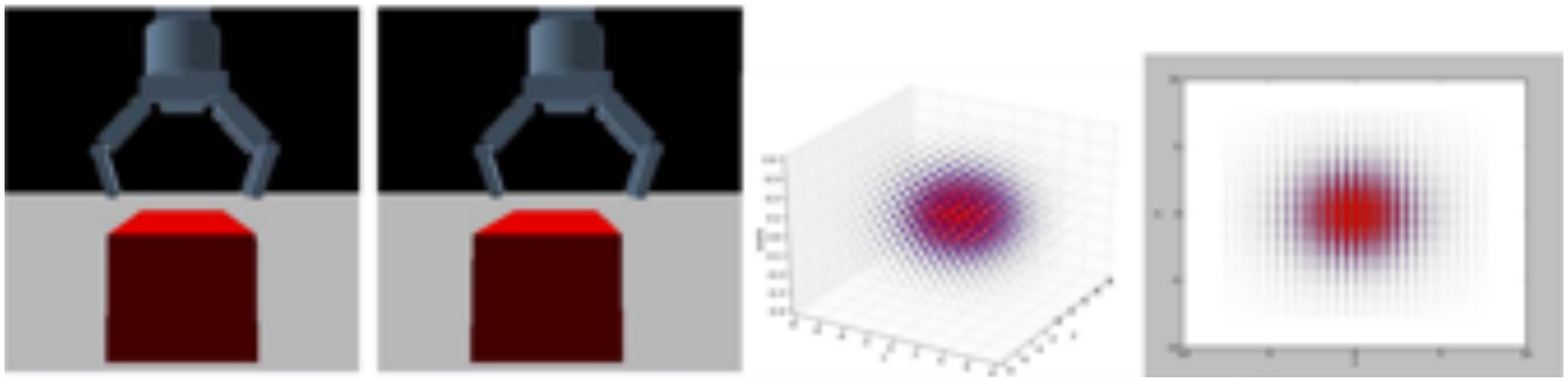
action

environment

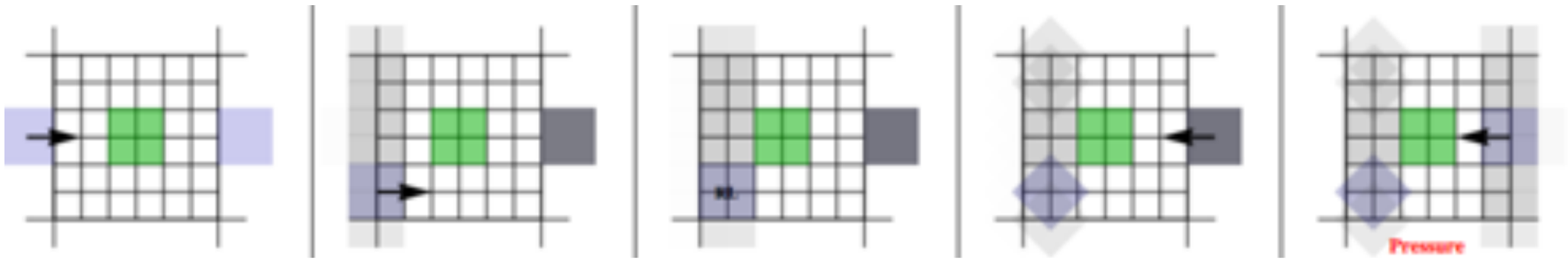
$$R(s,a) = \begin{cases} 0 & : s \in G \\ -\Delta t & : \text{otherwise} \end{cases}$$



Find a policy that maximizes a reward function



K. Hsiao. “Relatively robust grasping.” PhD thesis, MIT, 2009.



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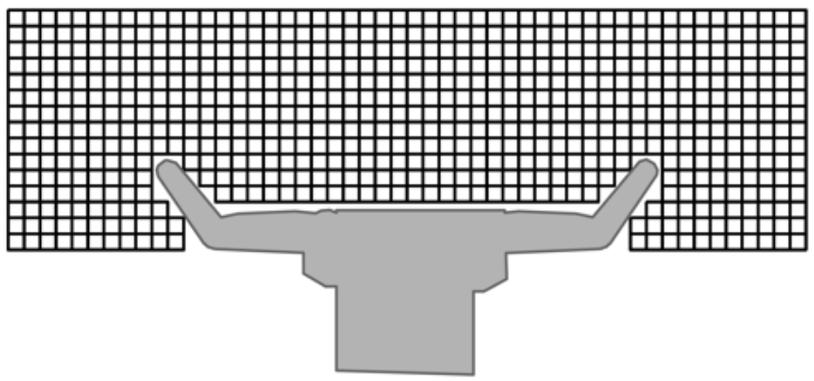
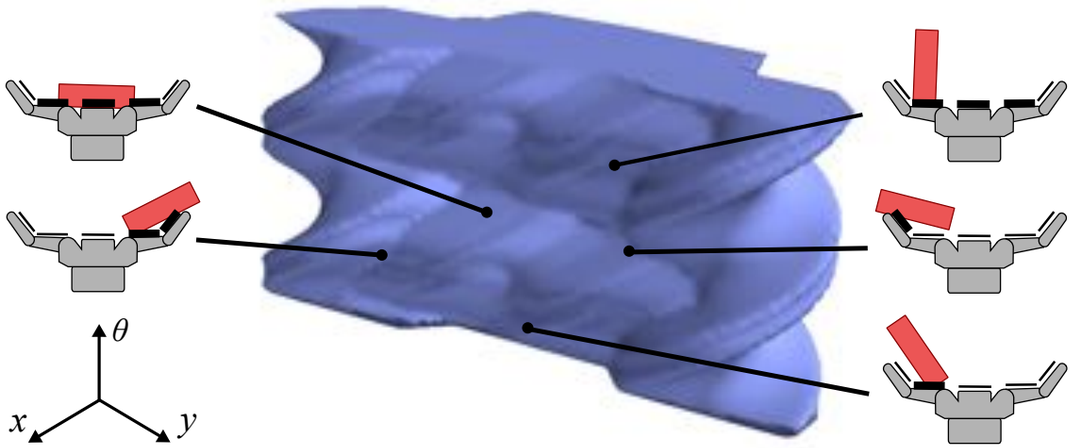


uniform no-contact discretization

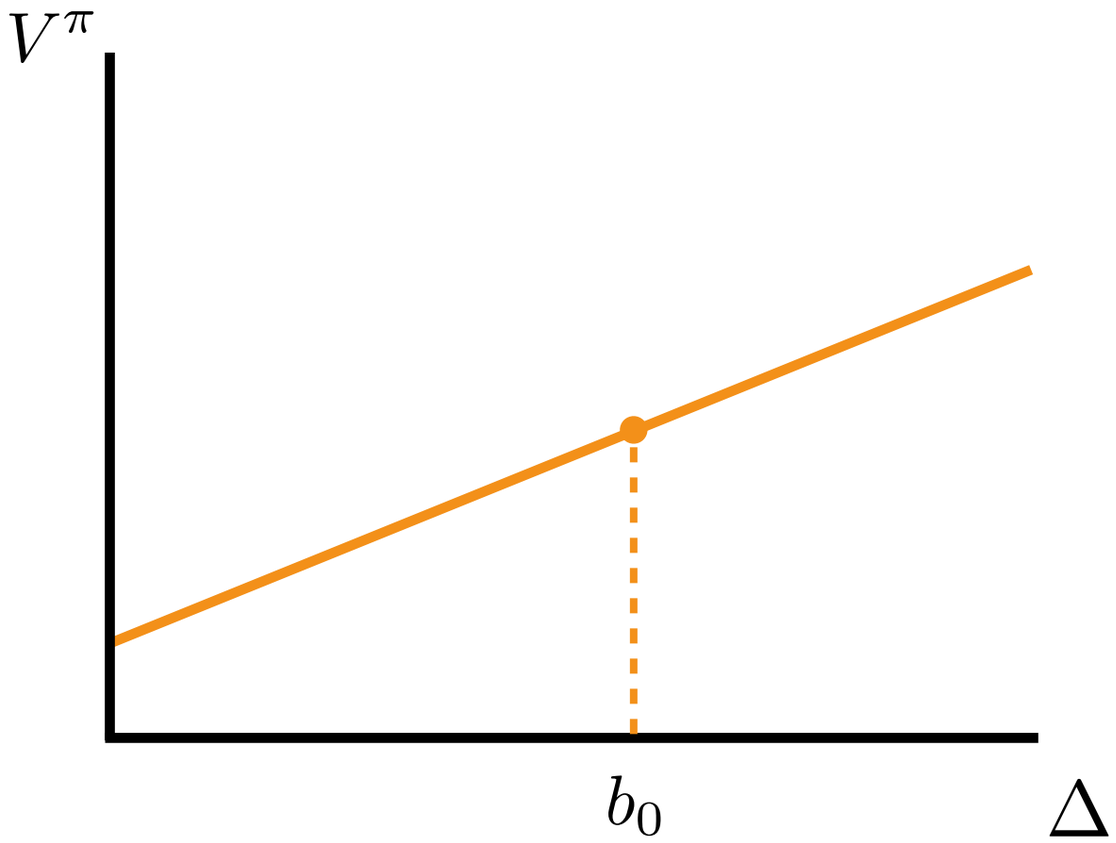
+

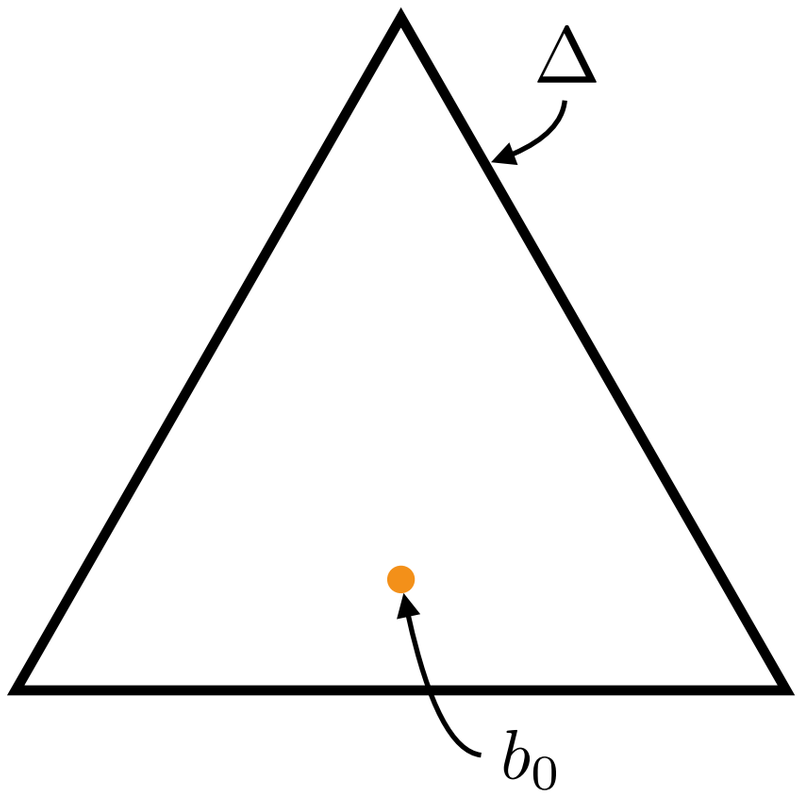


contact manifold discretization

Discretize and solve using an offline POMDP solver

$$V^{\pi} = \sum_{t=1}^{\infty} \gamma^t R(s_t, a_t)$$





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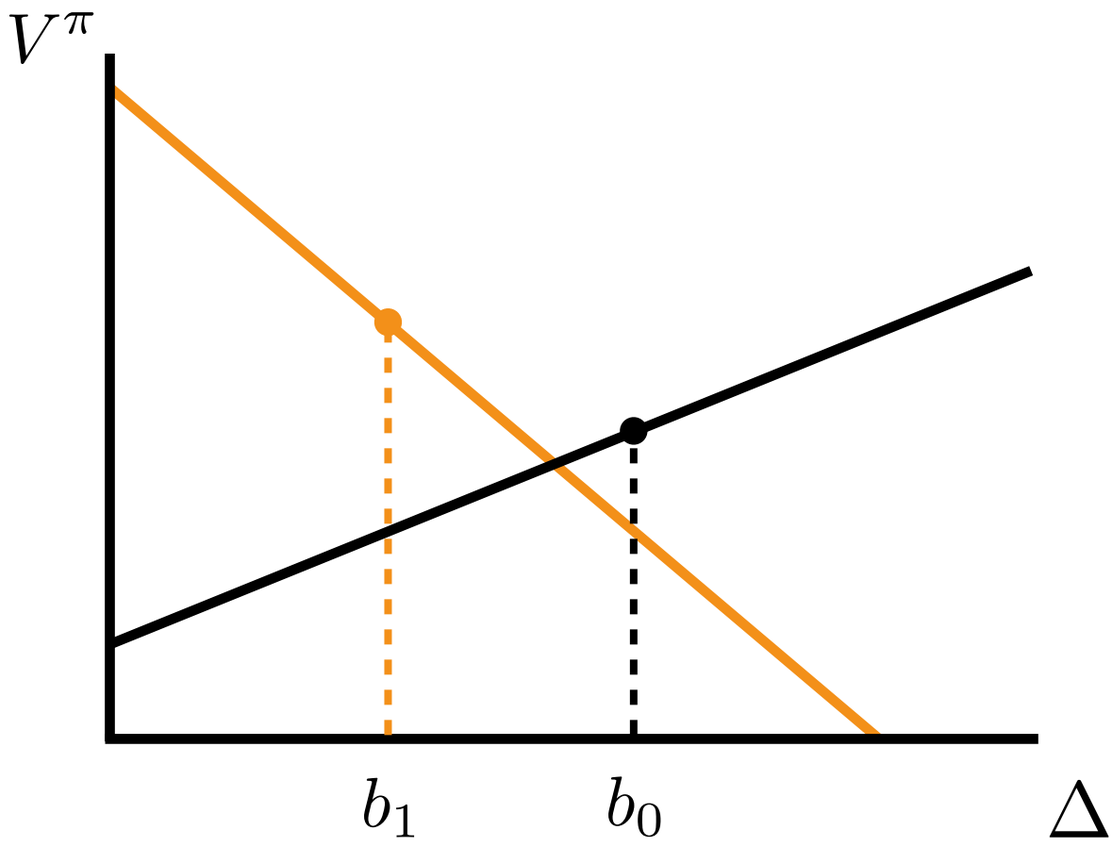

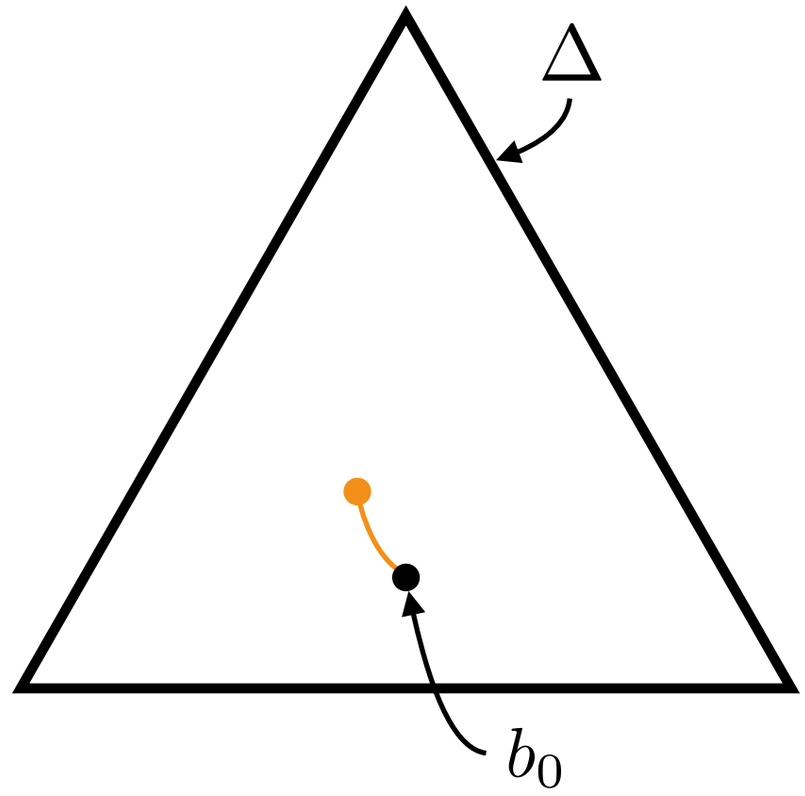

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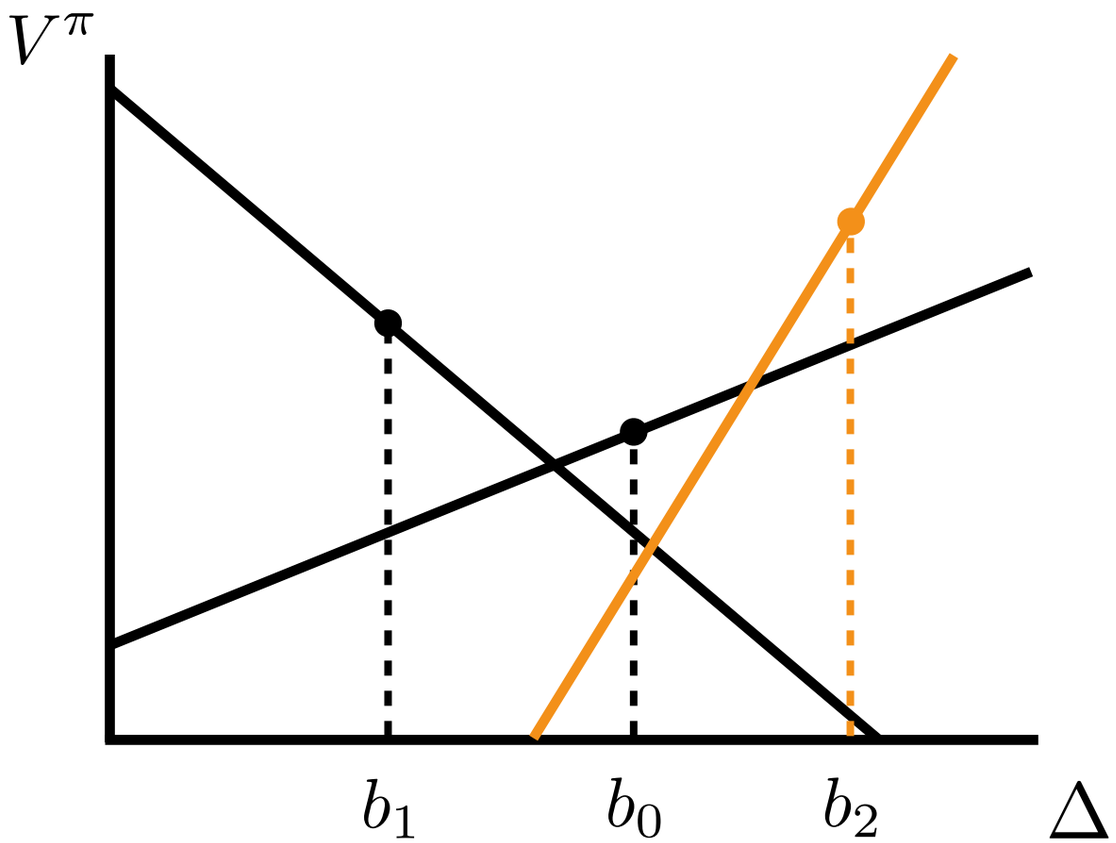

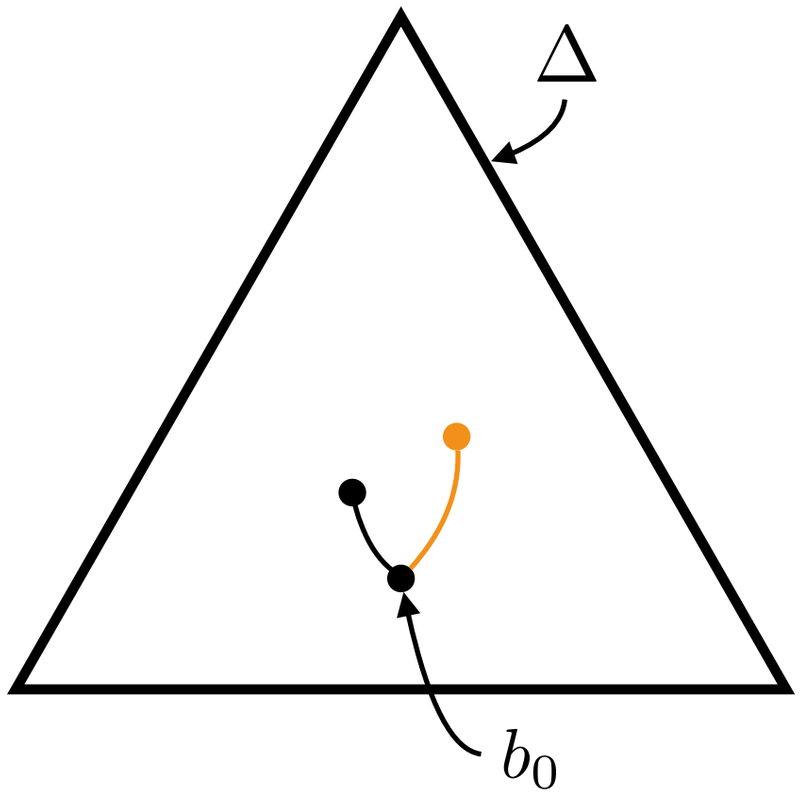

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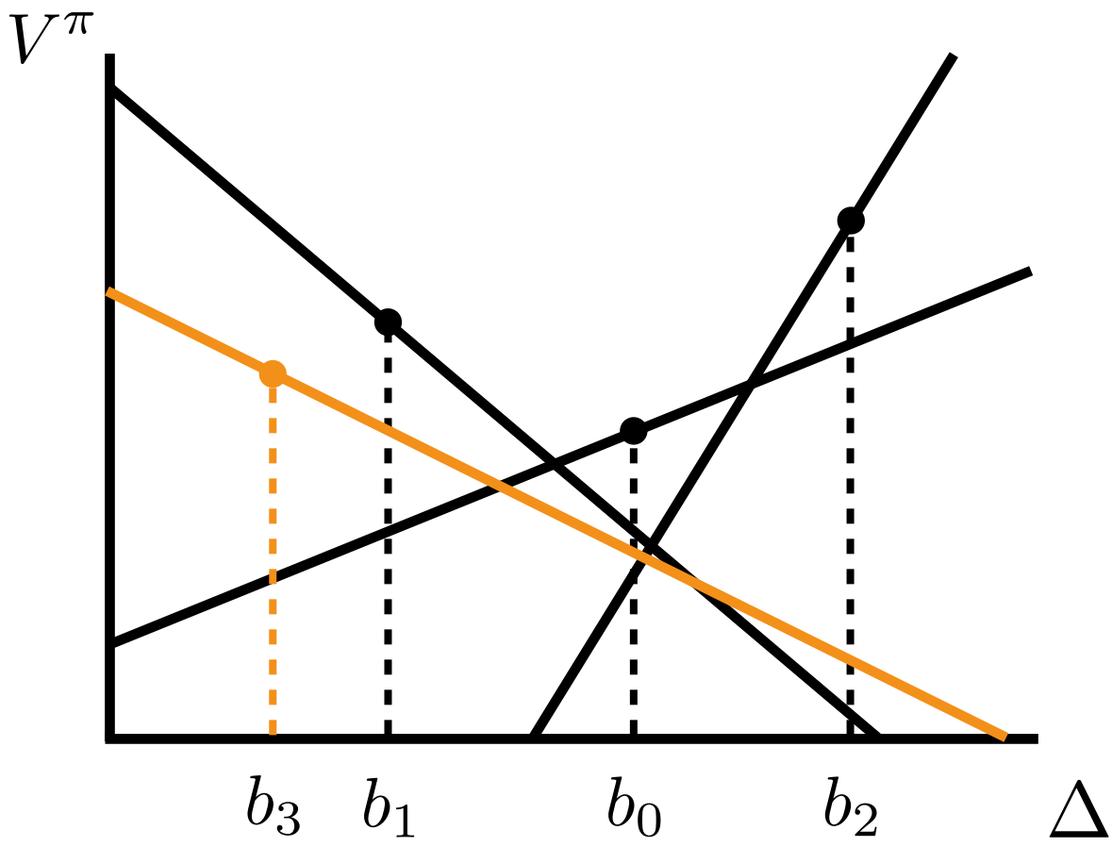

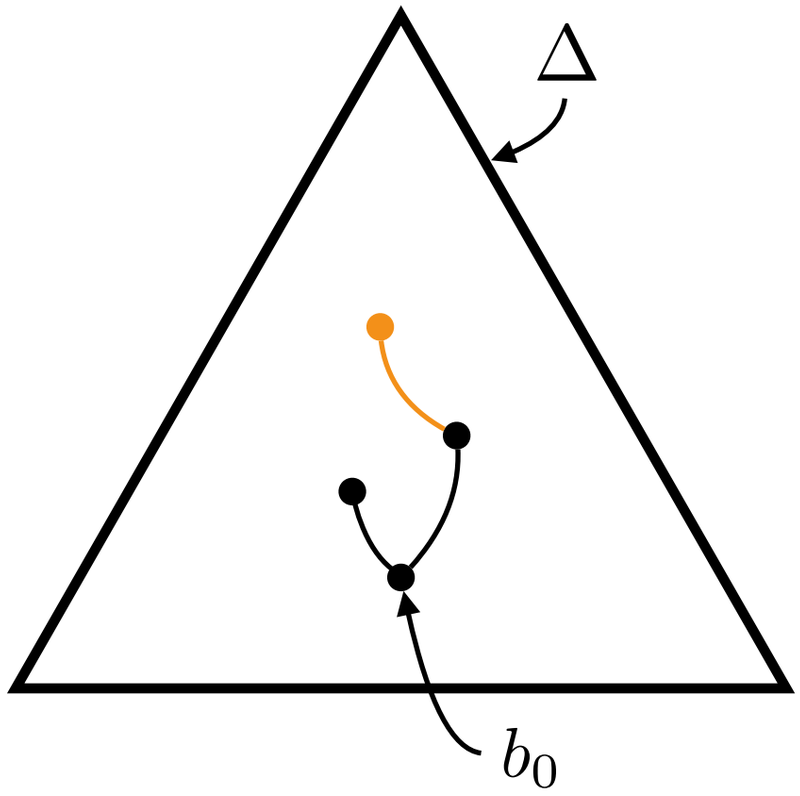

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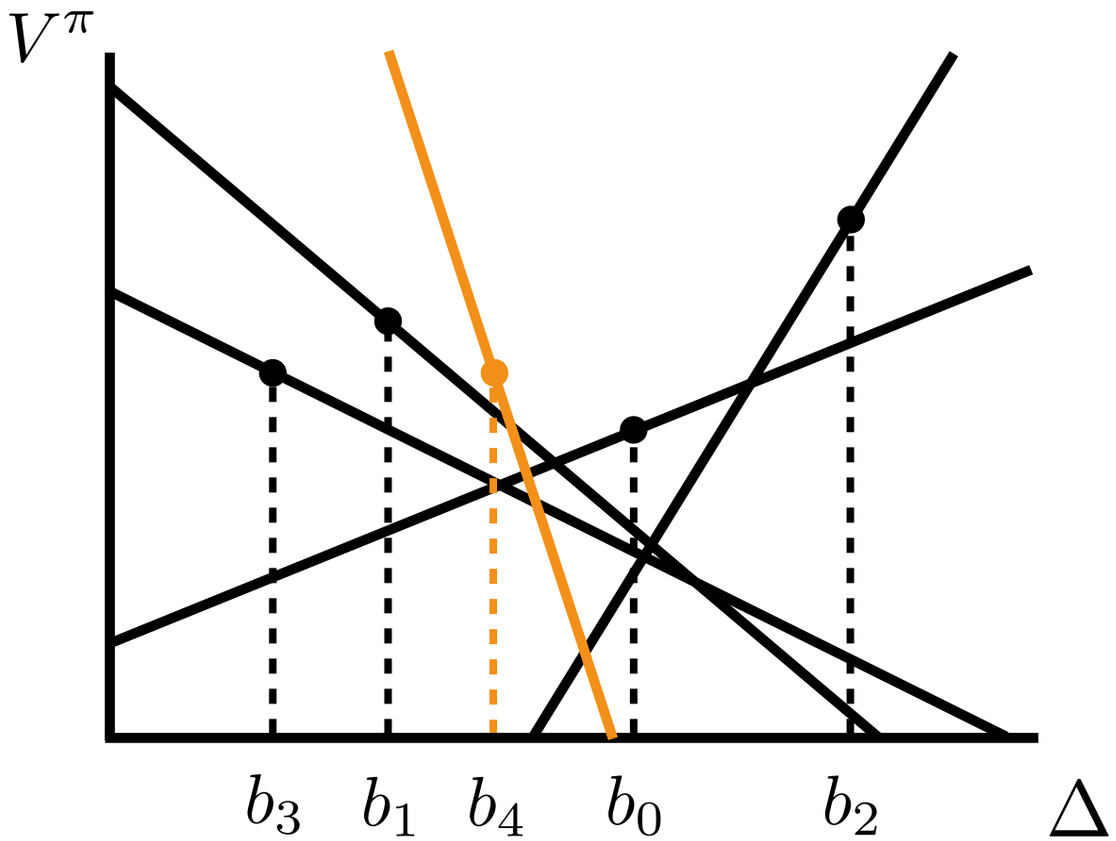

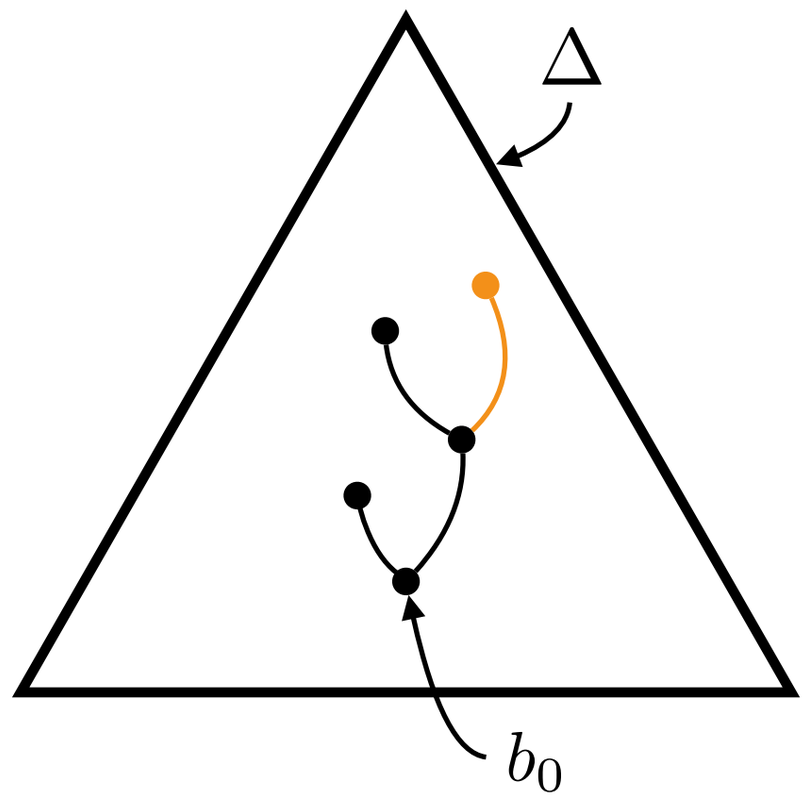

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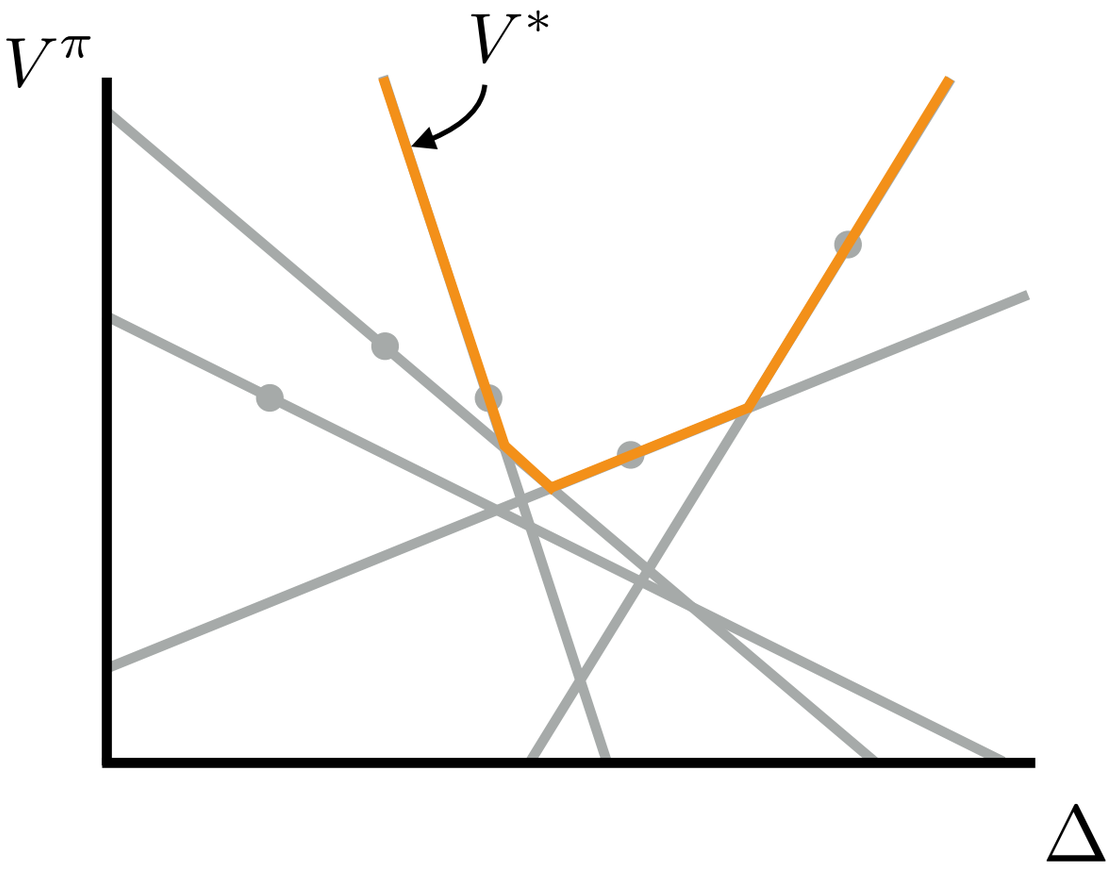
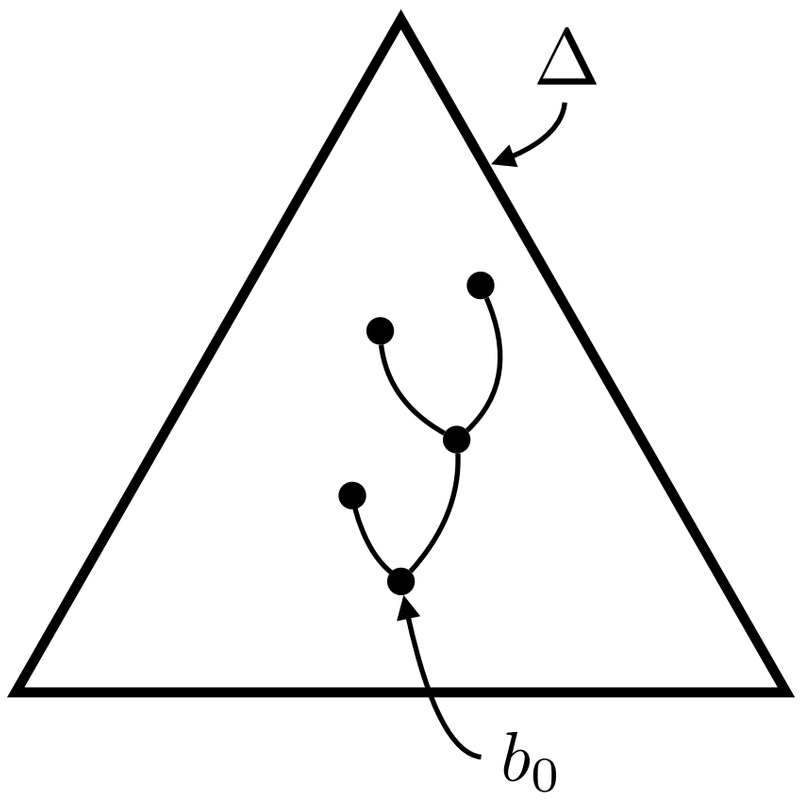
$$\pi^* = \arg\max_\pi V^\pi\left[b(s_0)\right]$$





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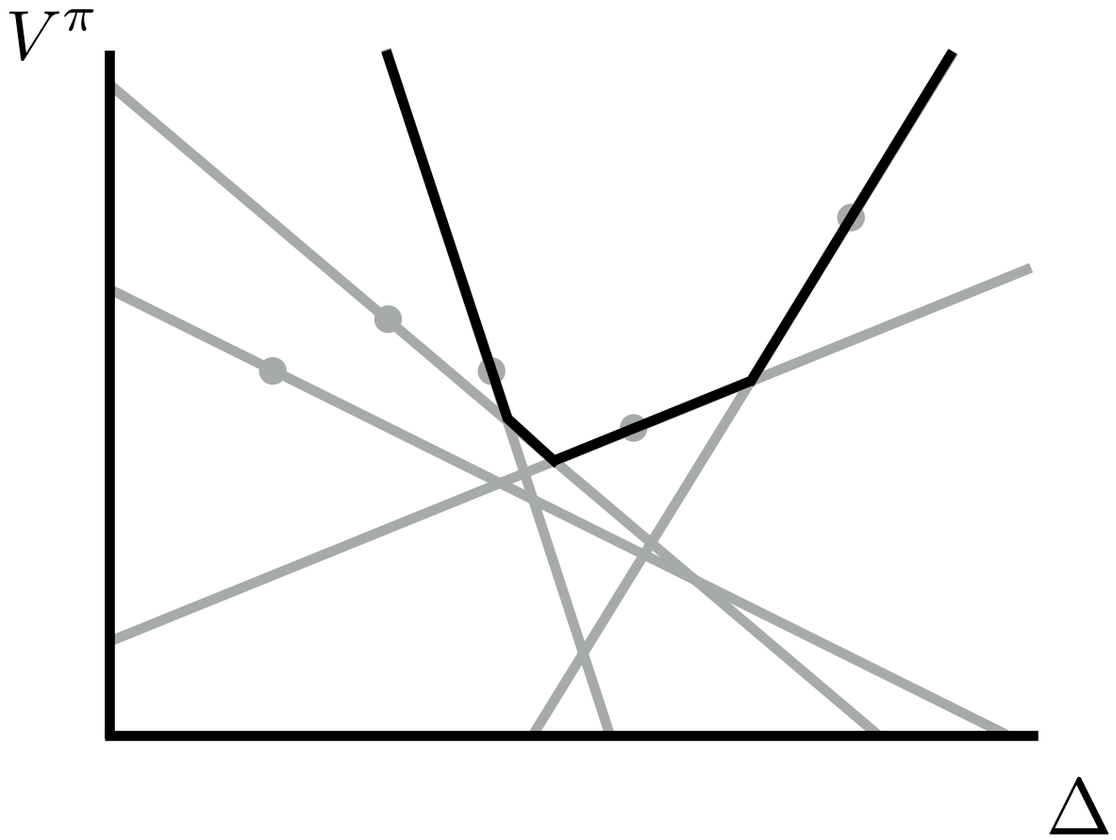
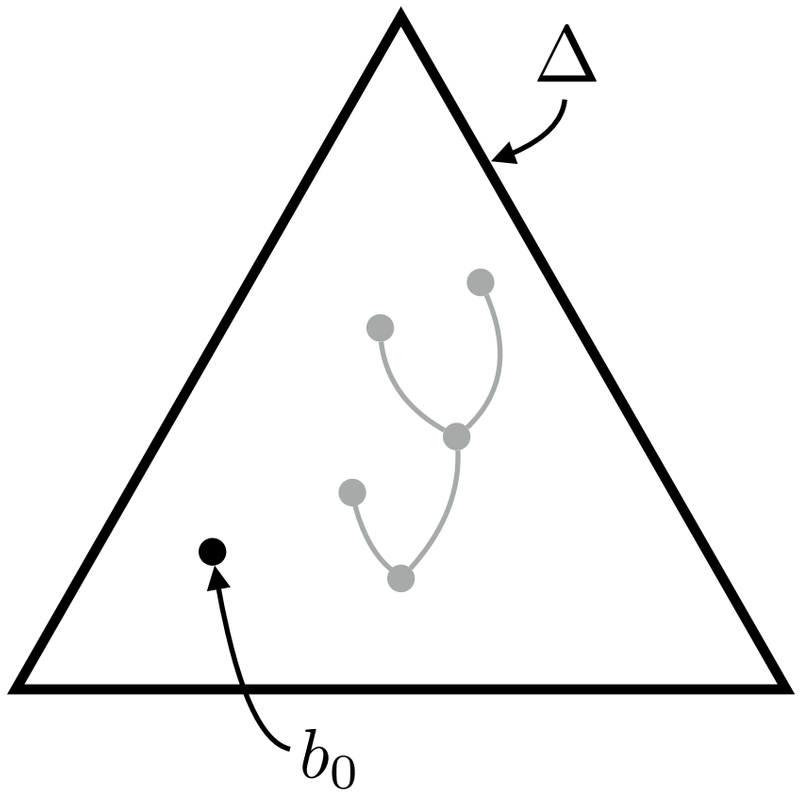
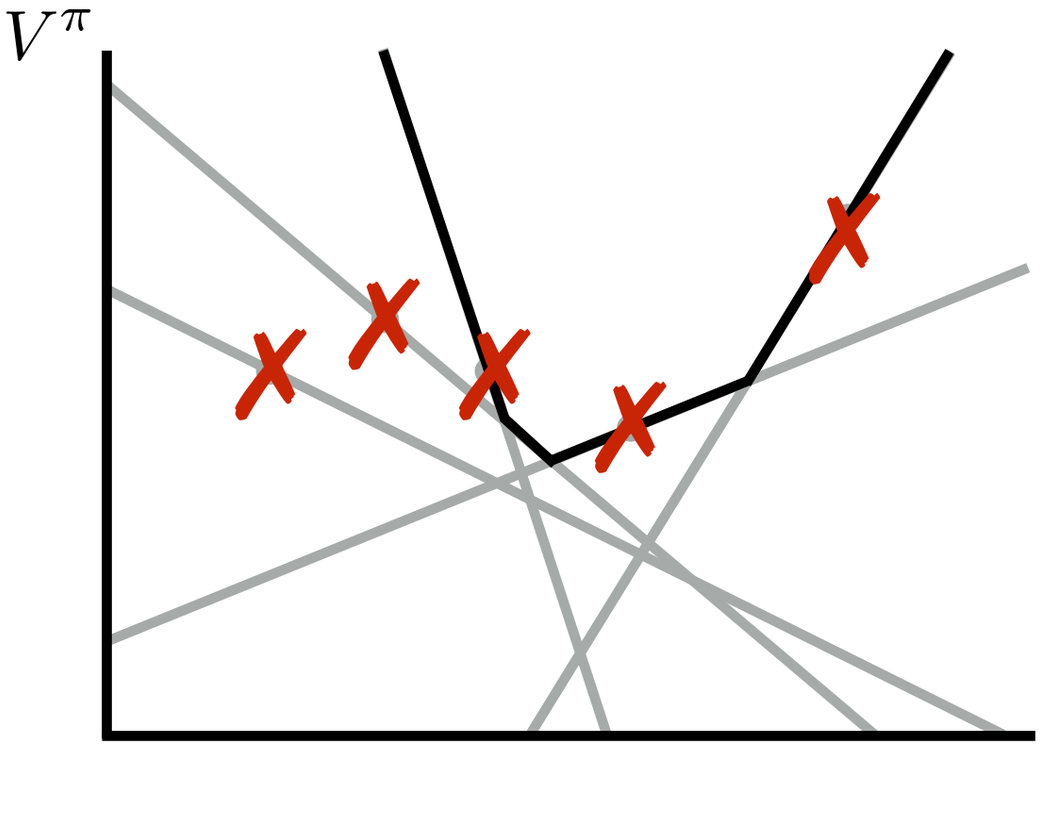
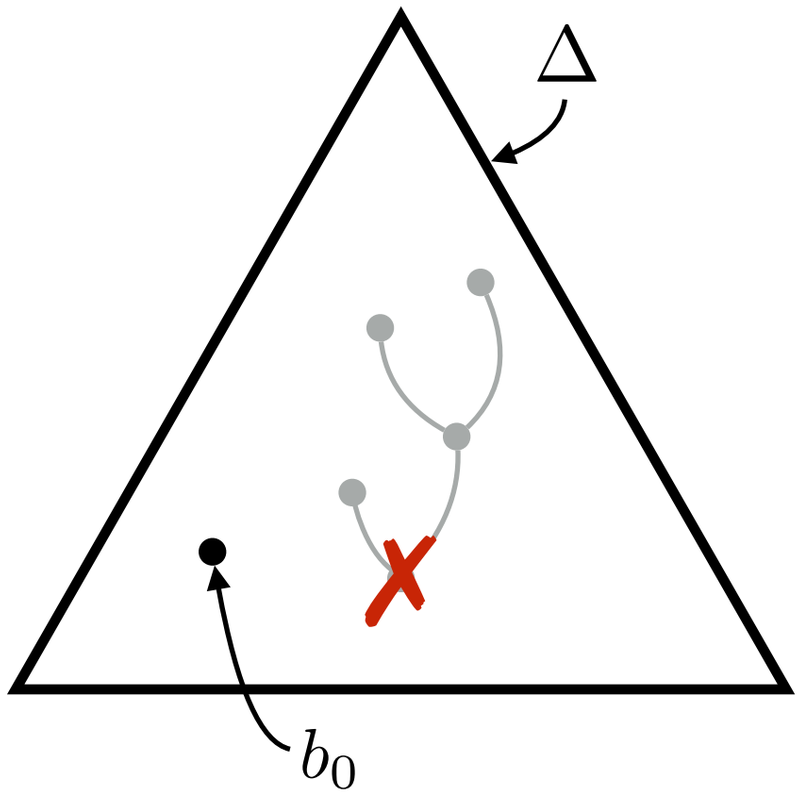




What if we get a new problem instance?





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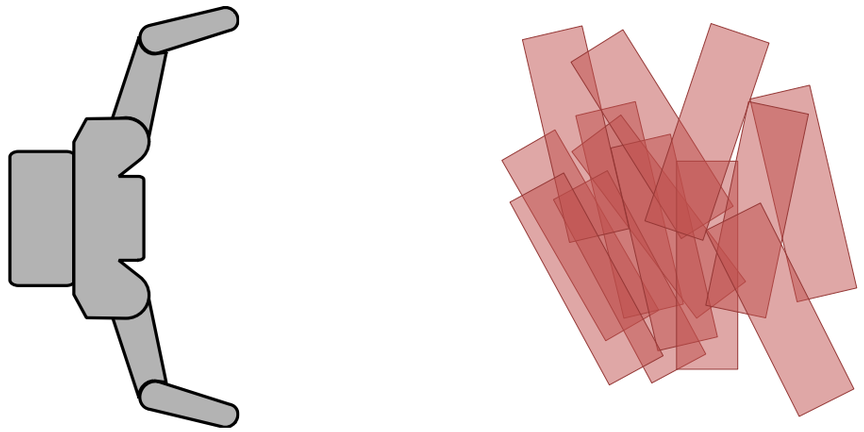
Manipulation occurs in a lower-dimensional space

Insight 2

Contact constrains state to a manifold

Insight 3

Pre-contact search and post-contact policy can be decoupled



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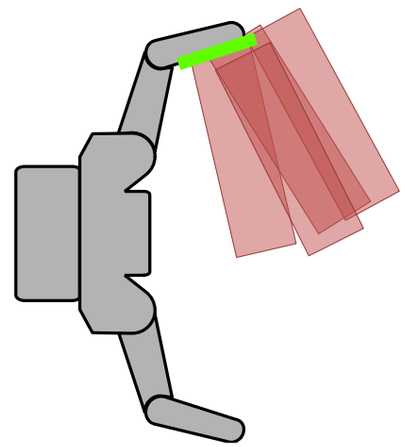

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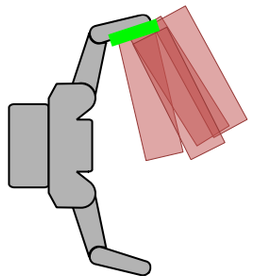

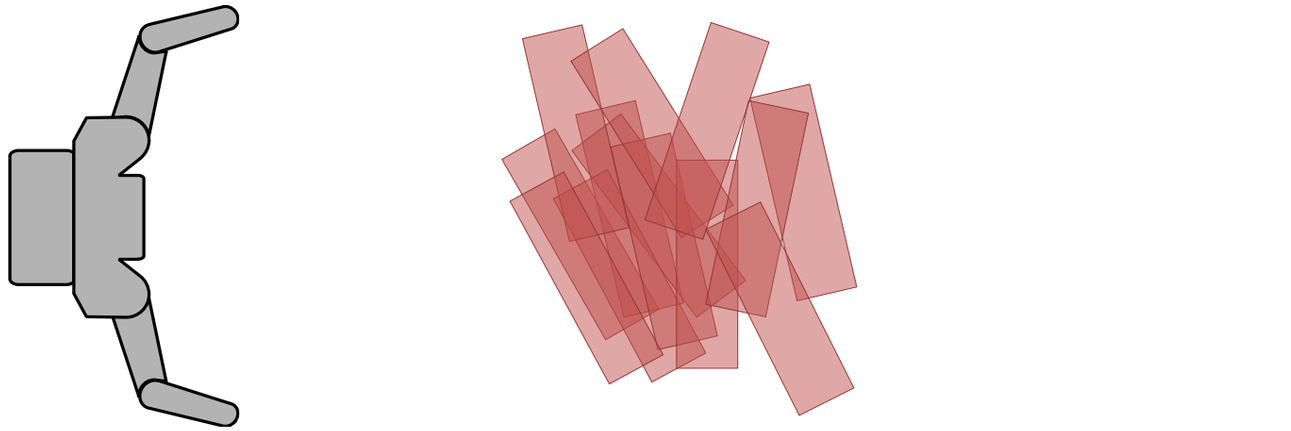

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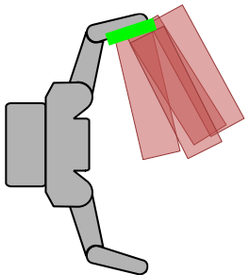

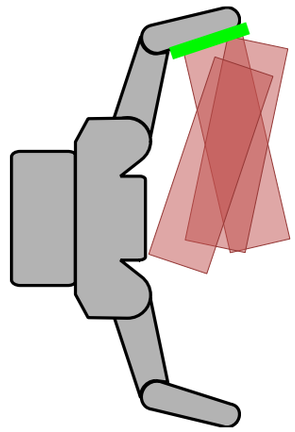

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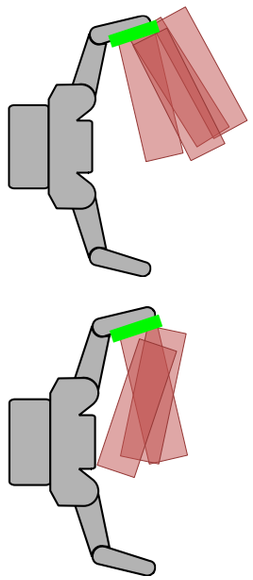

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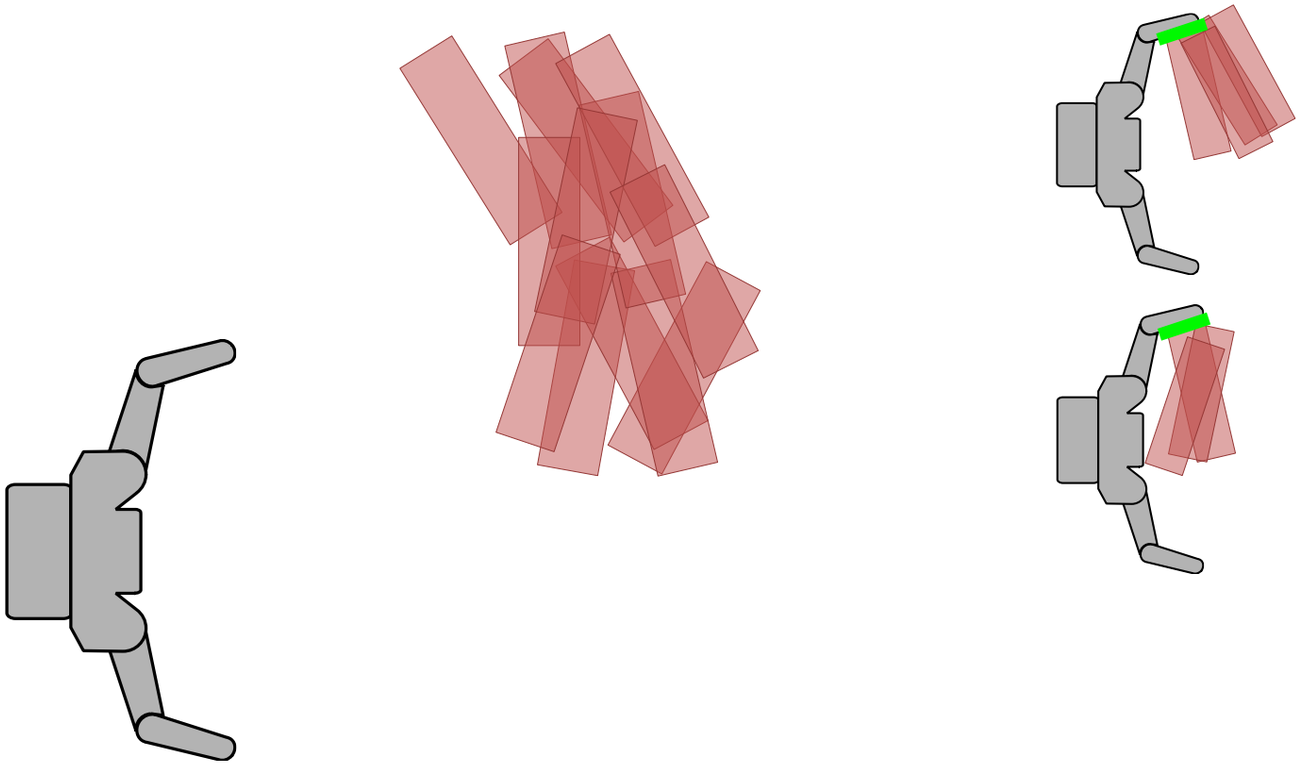

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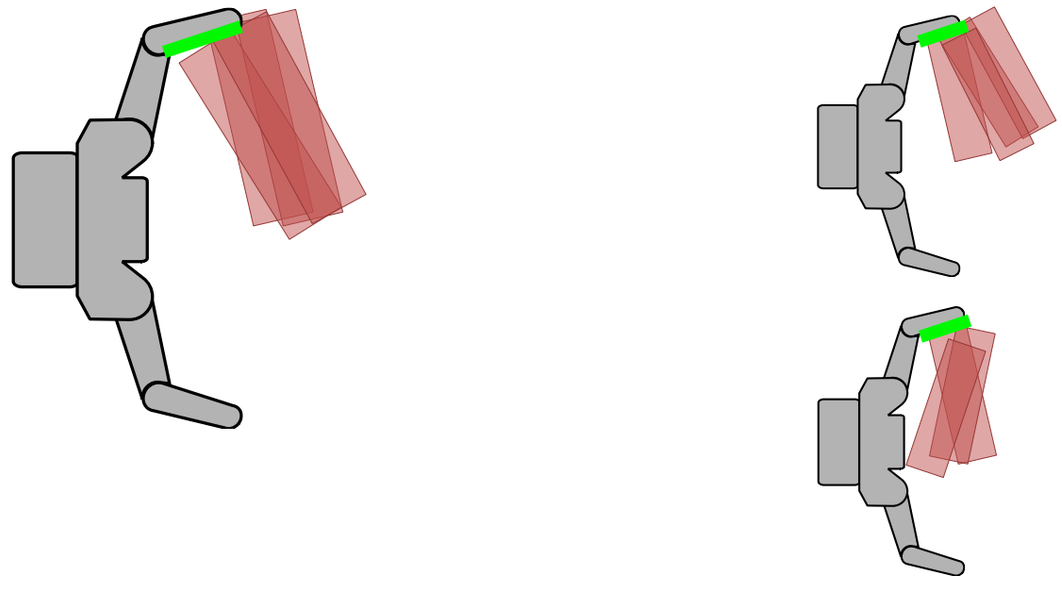

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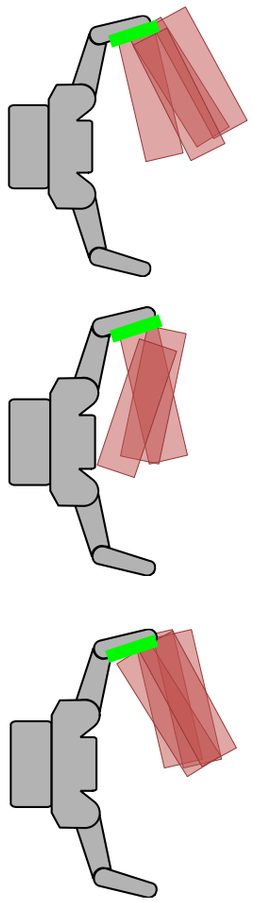

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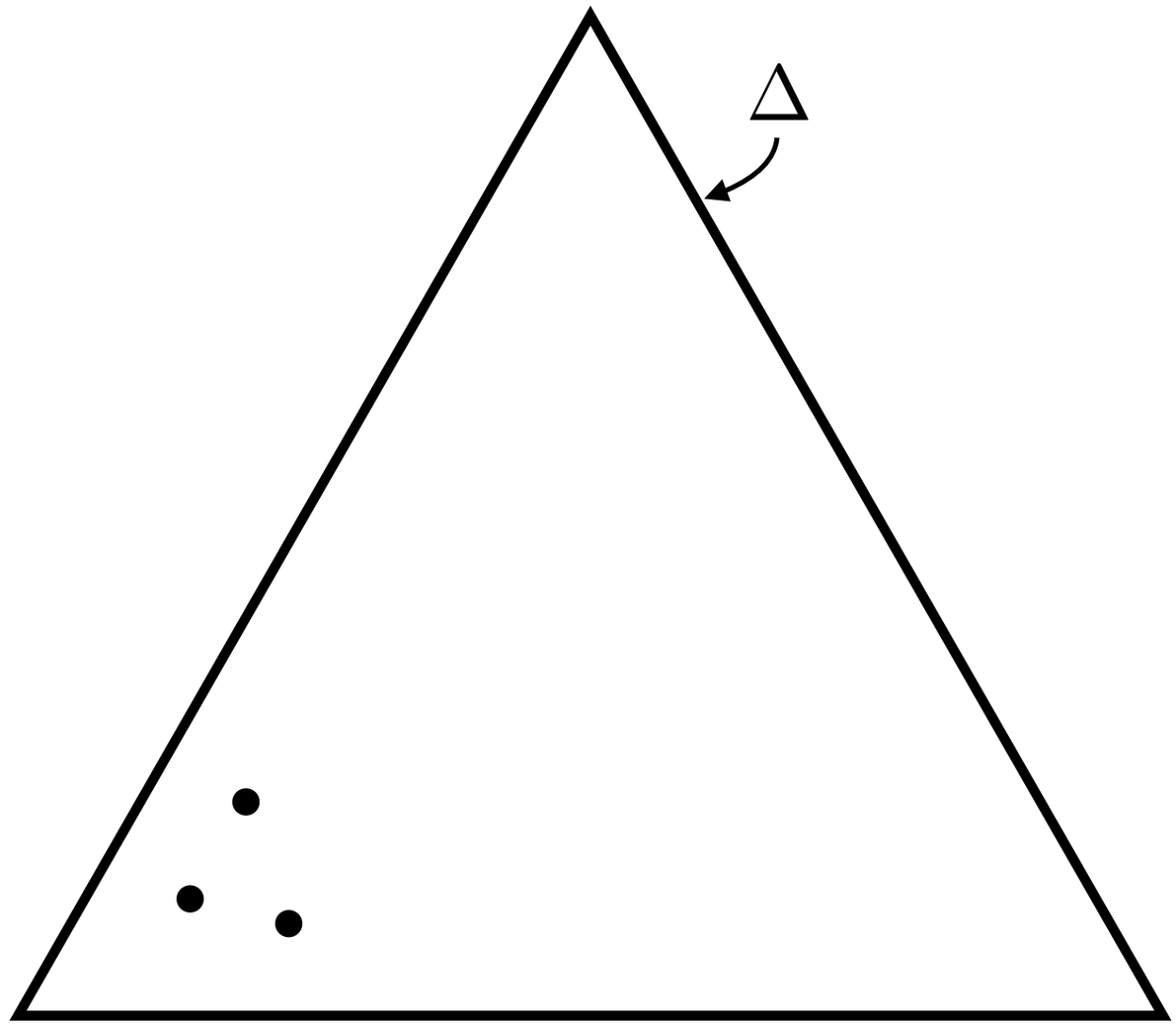

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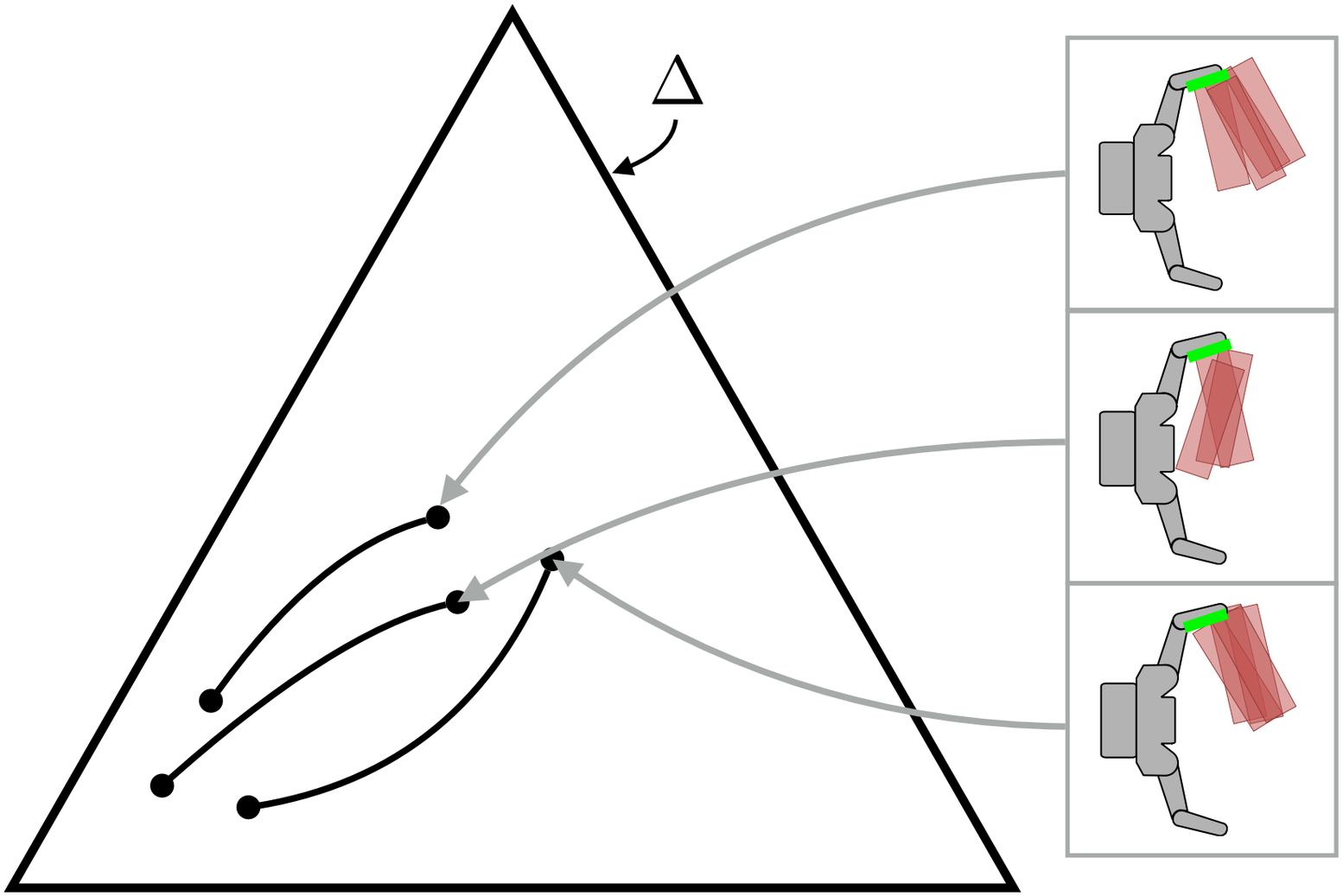

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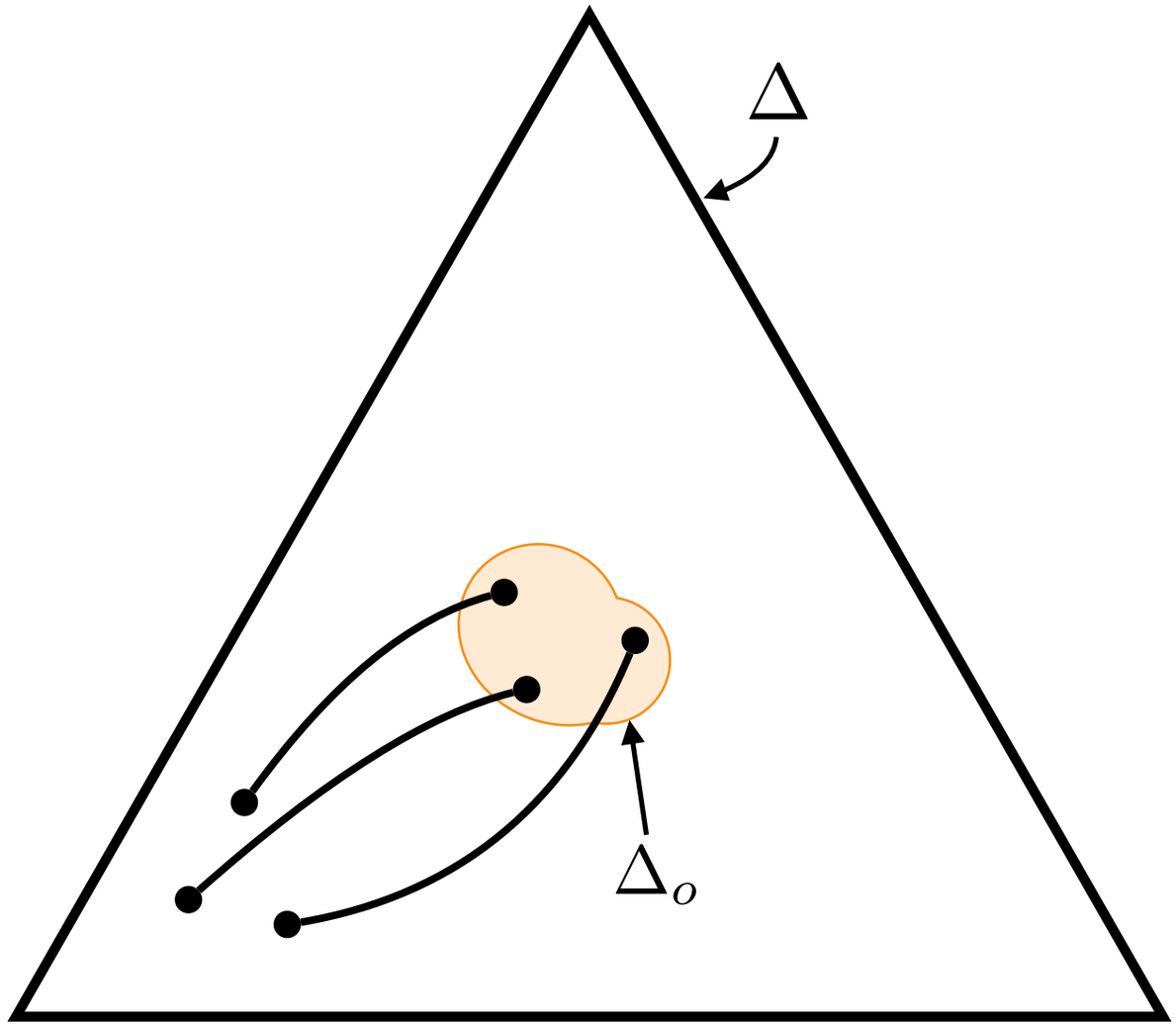

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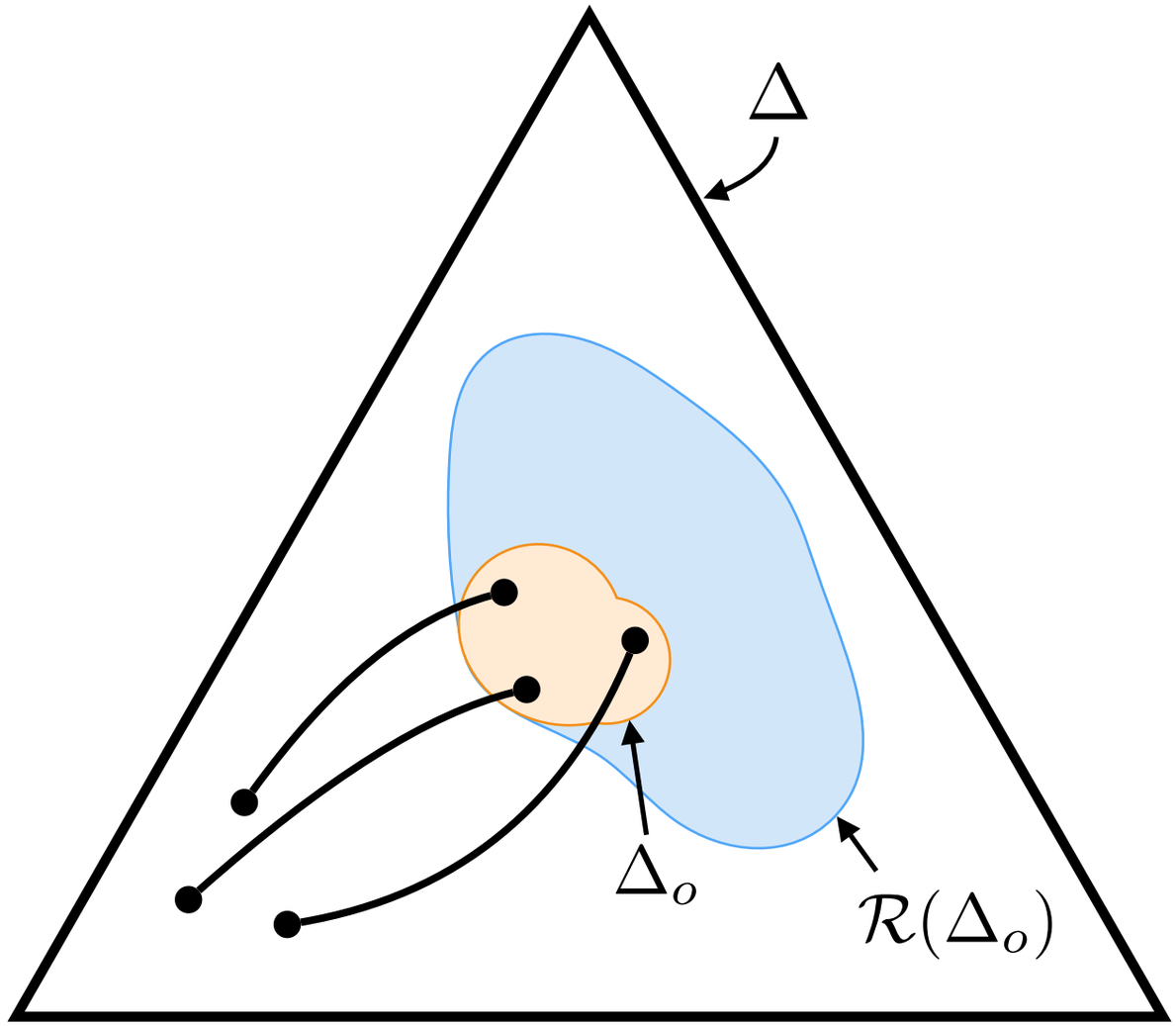

The post-contact belief space is small

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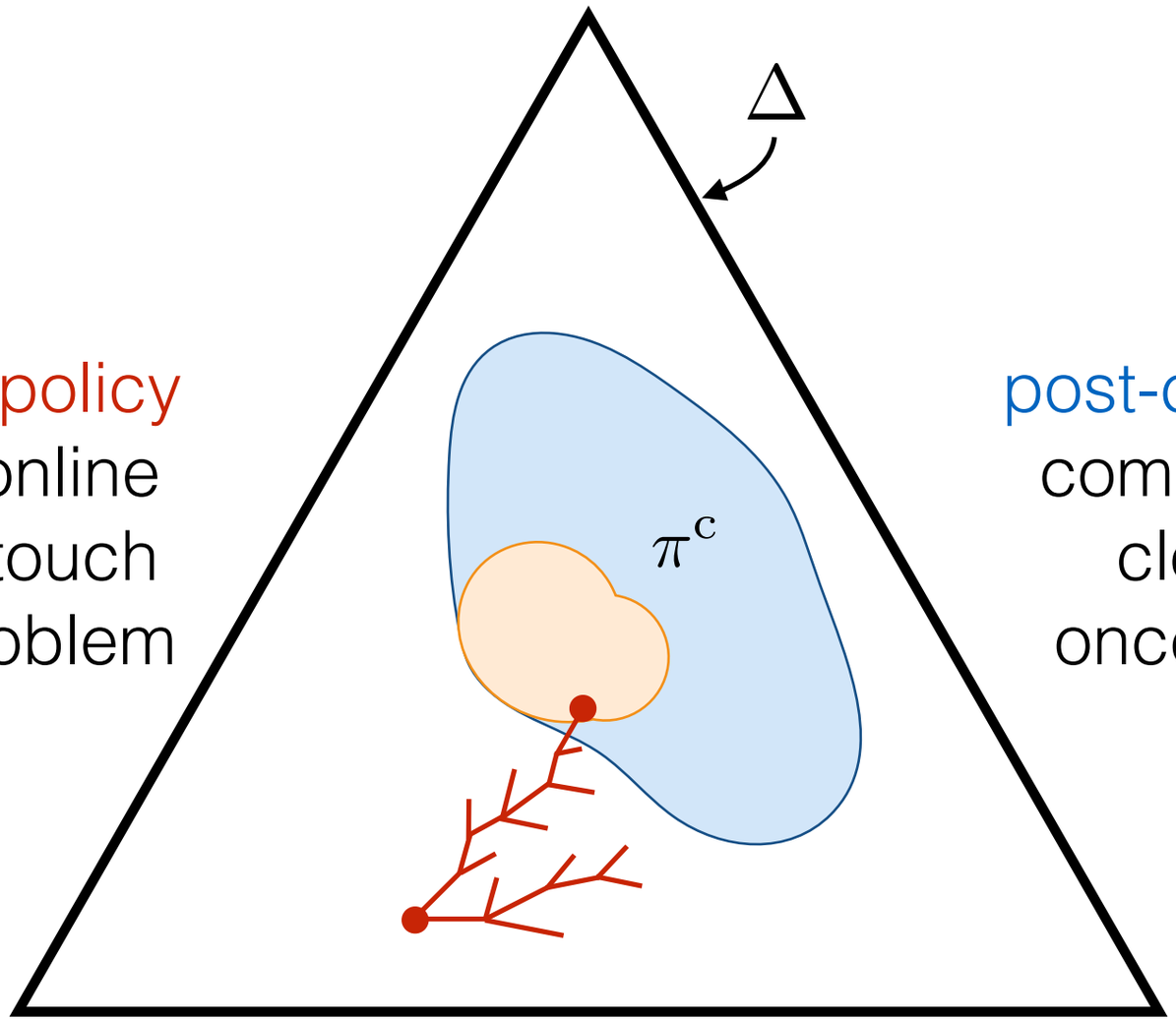
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” IJRR, 2016.

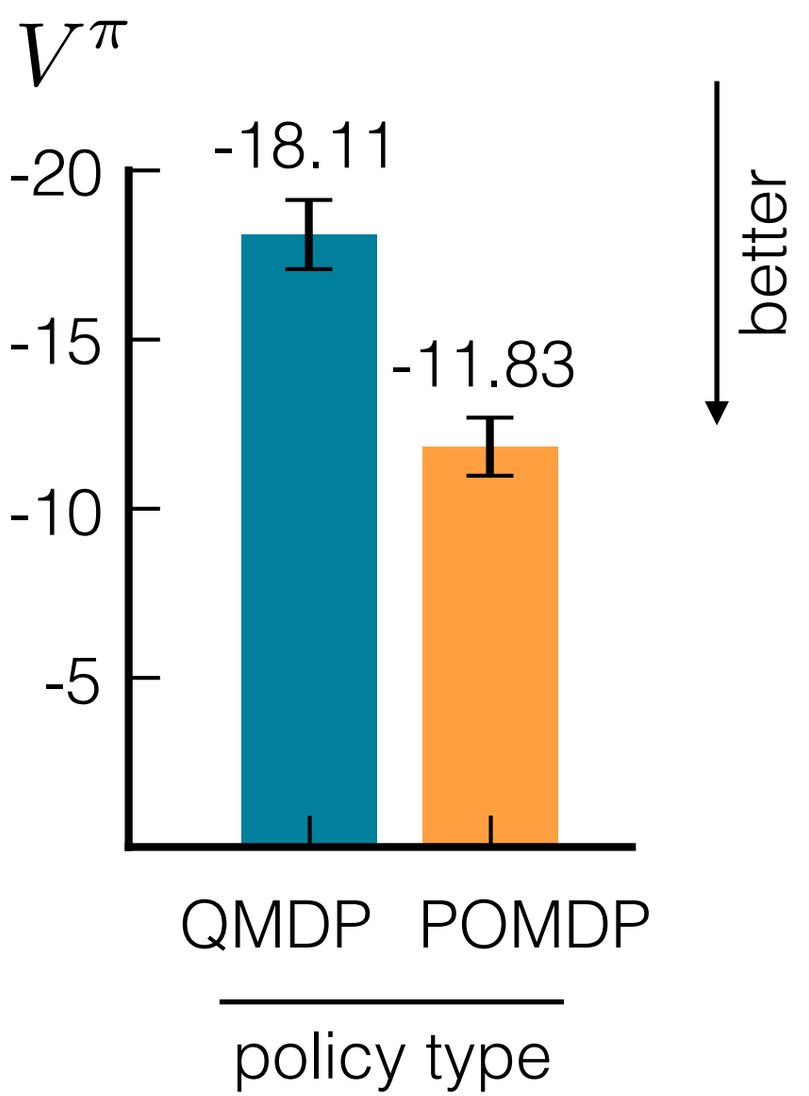
pre-contact policy
computed online
move-until-touch
once per problem



post-contact policy
computed offline
closed-loop
once per object

Decompose into pre- and post-contact policies

M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” RSS, 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” IJRR, 2016.



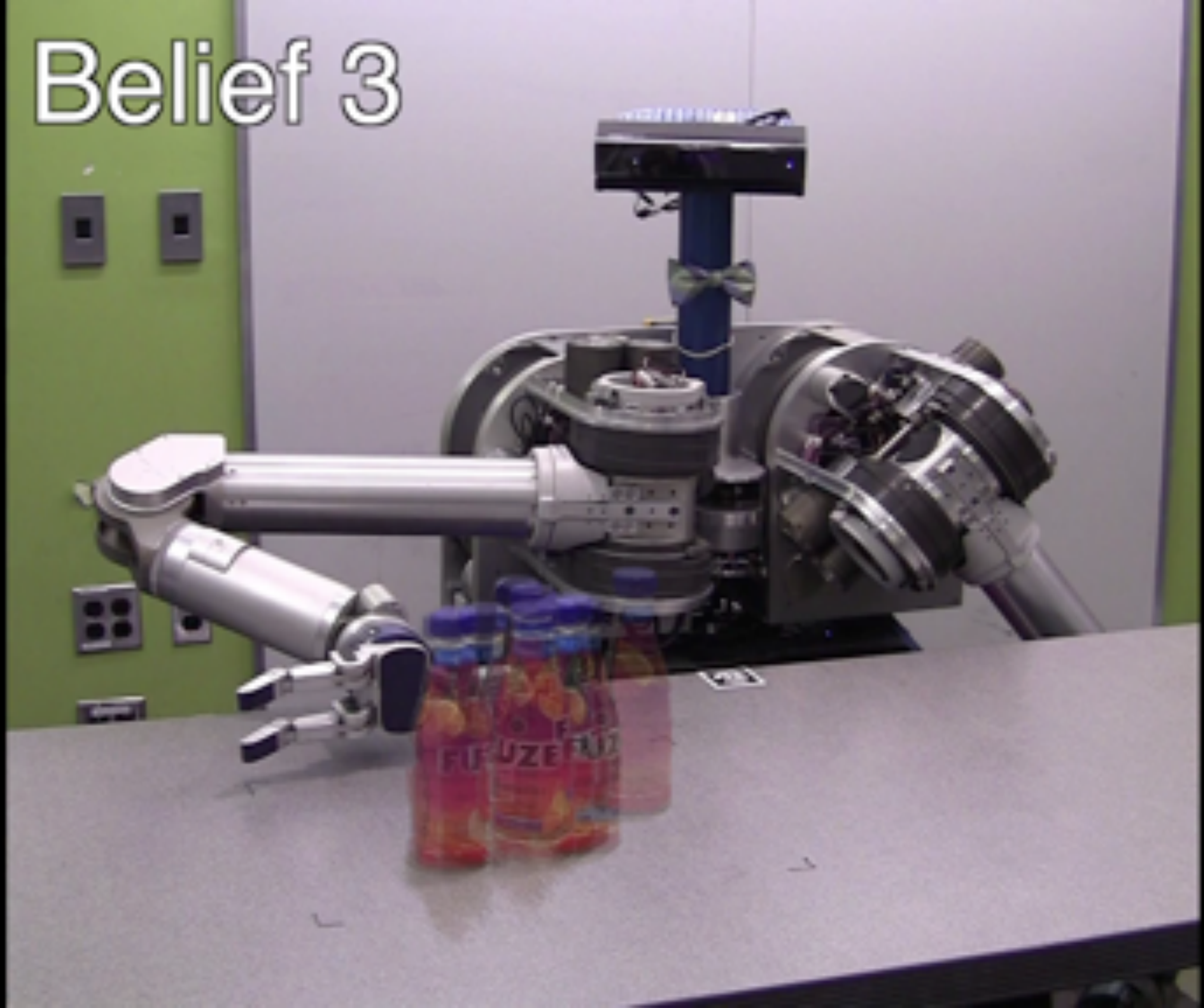
Post-contact policy outperforms a baseline

M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” RSS, 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” IJRR, 2016.

simulation (2×)

M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” RSS, 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” IJRR, 2016.

Belief 3



20/30 QMDP

27/30 POMDP

What about the other three?

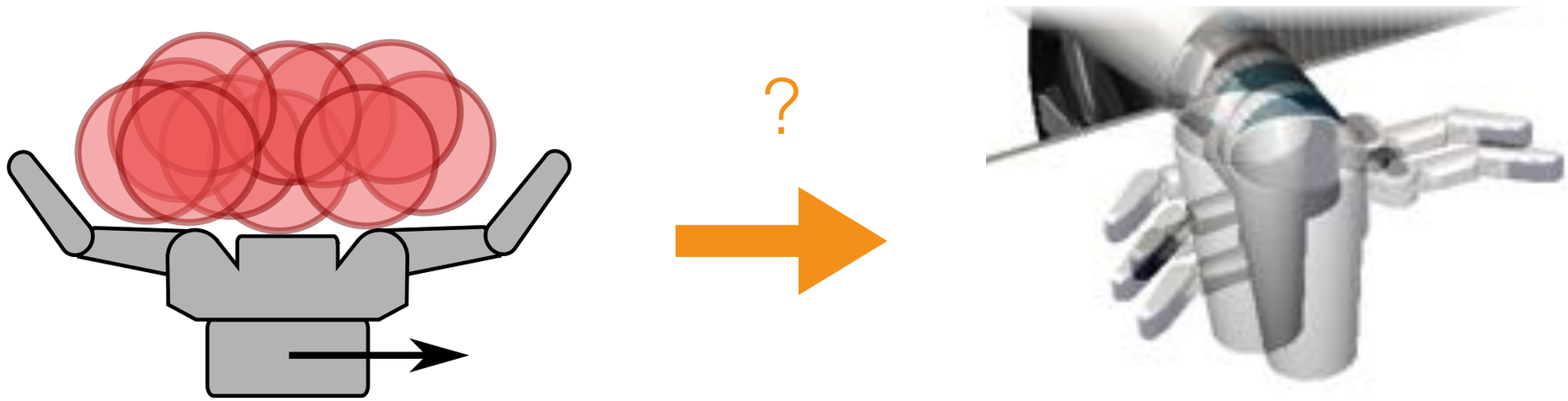
Policy performs better on HERB

M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” RSS, 2013.
M.C. Koval, N.S. Pollard, and S.S. Srinivasa. “Pre- and post-contact policy decomposition for planar contact manipulation under uncertainty.” IJRR, 2016.

Belief 2, Trial 1

SARSOP

(4x)

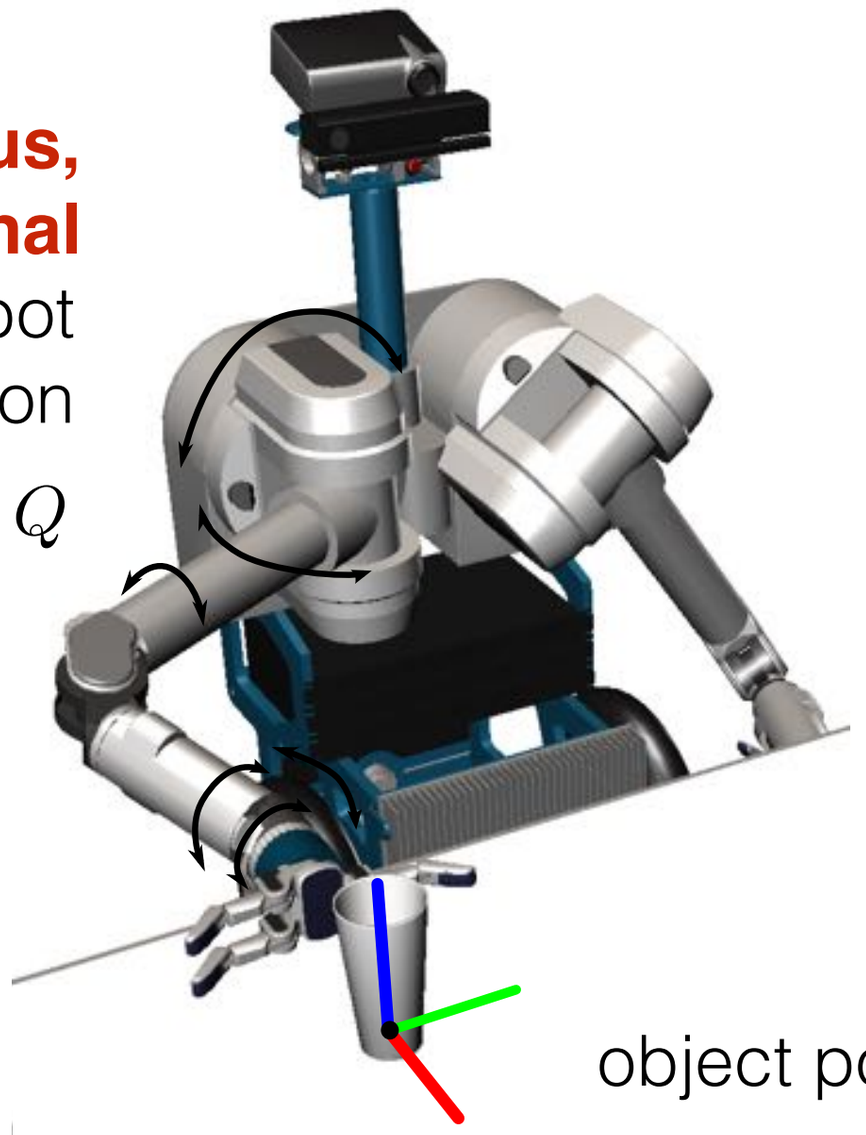


How can we cope with kinematic constraints?

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

continuous, high-dimensional robot configuration

$q \in Q$



object pose

$x \in SE(3)$

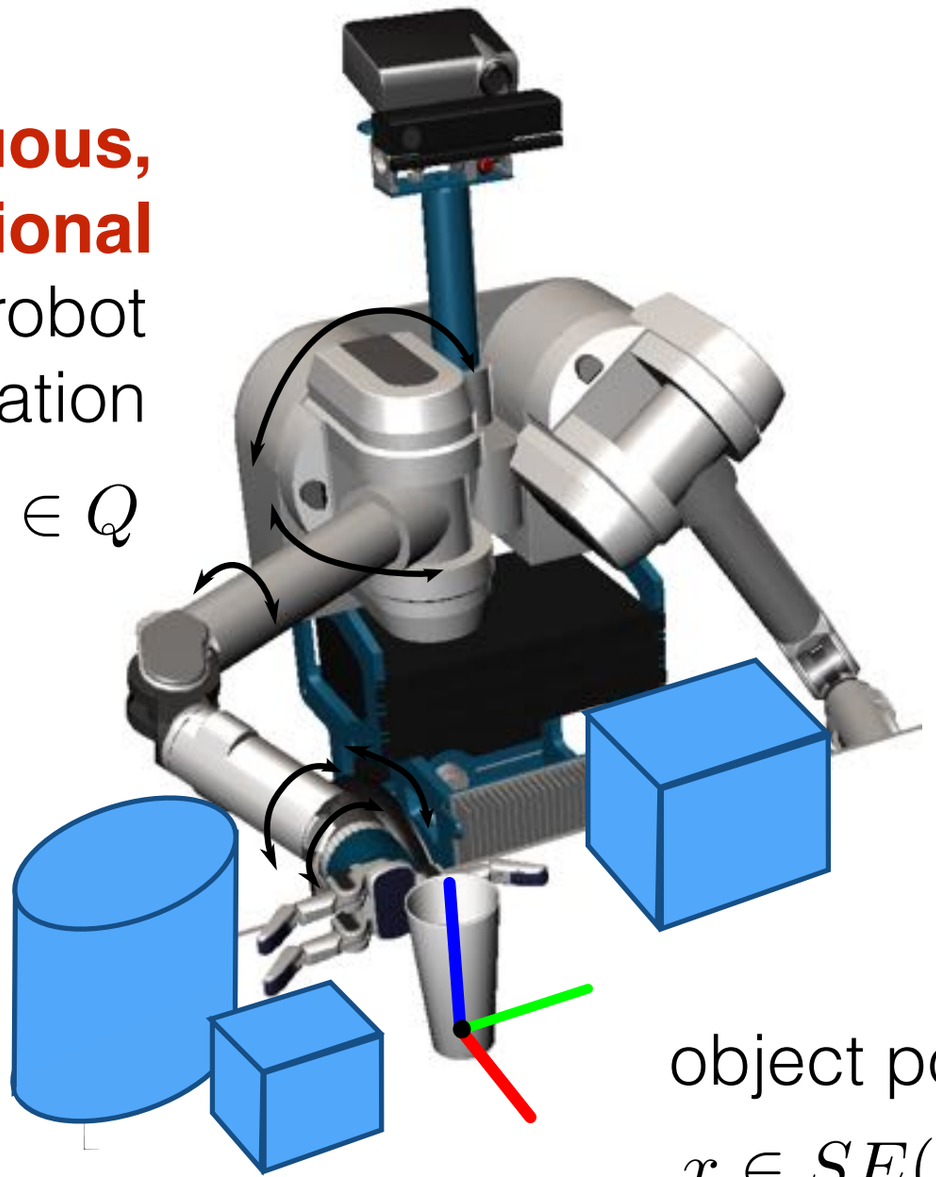
Plan in the robot-object joint configuration space

$$S = Q \times X$$

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

continuous, high-dimensional robot configuration

$q \in Q$



different obstacles

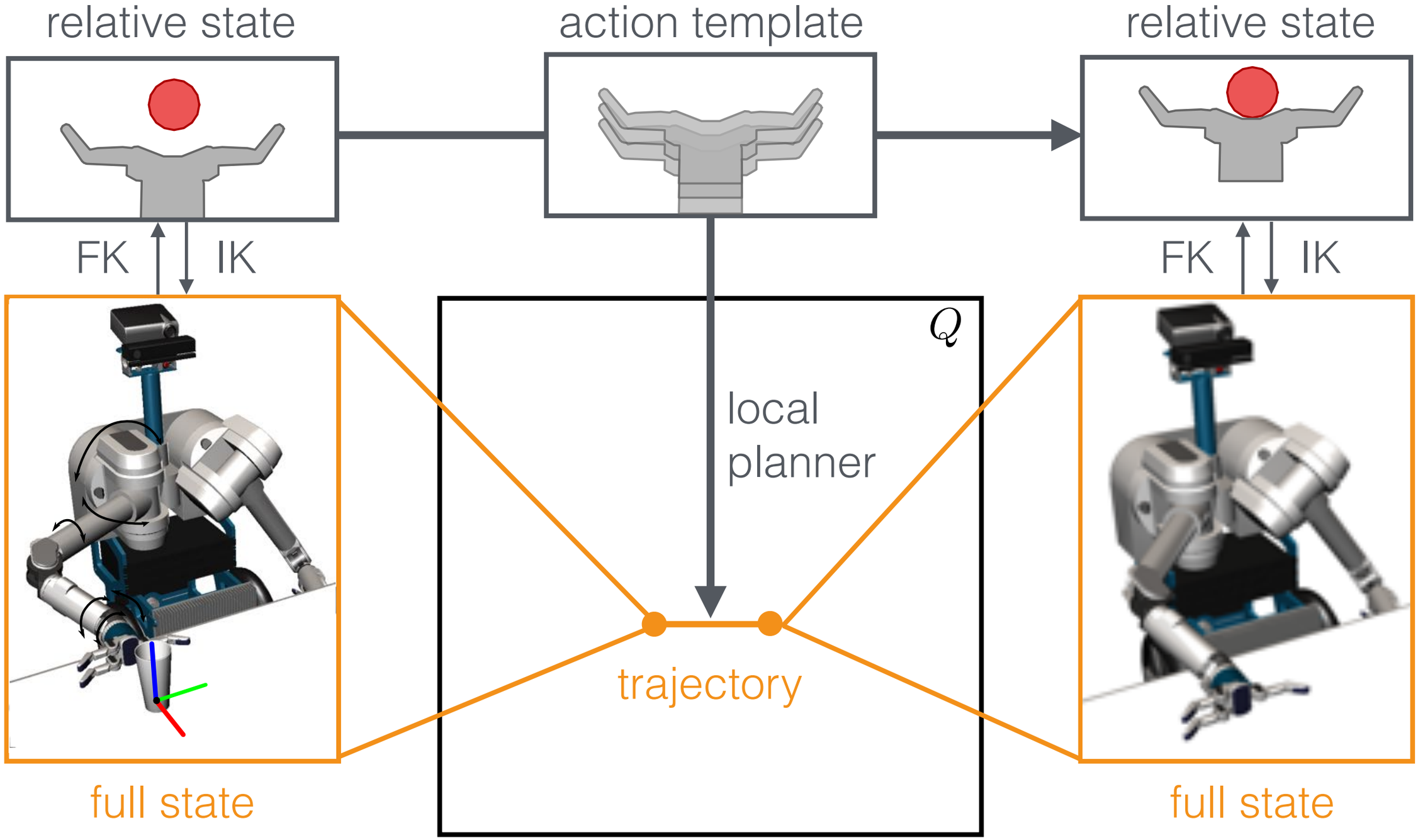
object pose

$x \in SE(3)$

Plan in the robot-object joint configuration space

$$S = Q \times X$$

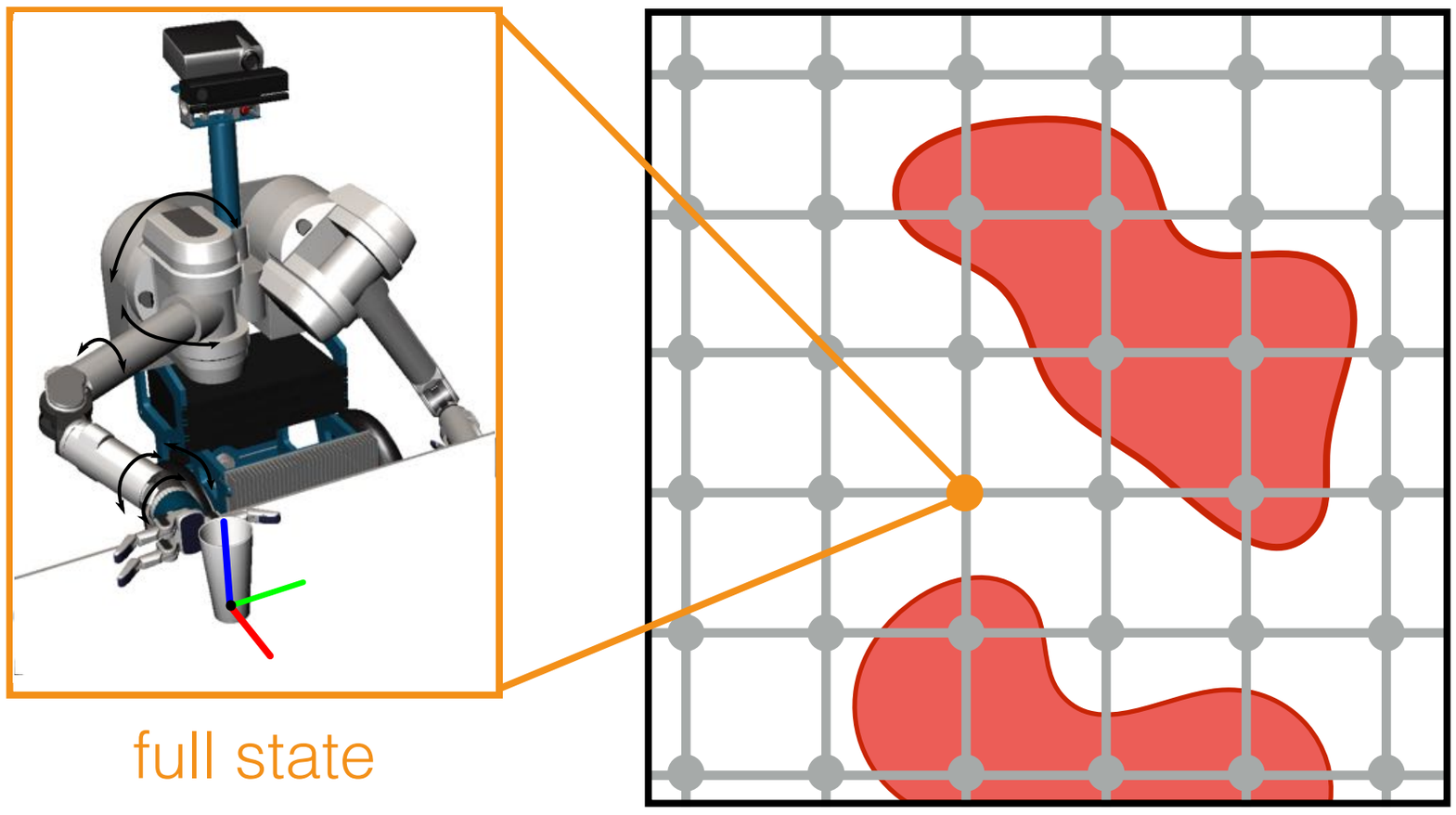
M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.



Plan using a finite set of action templates

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

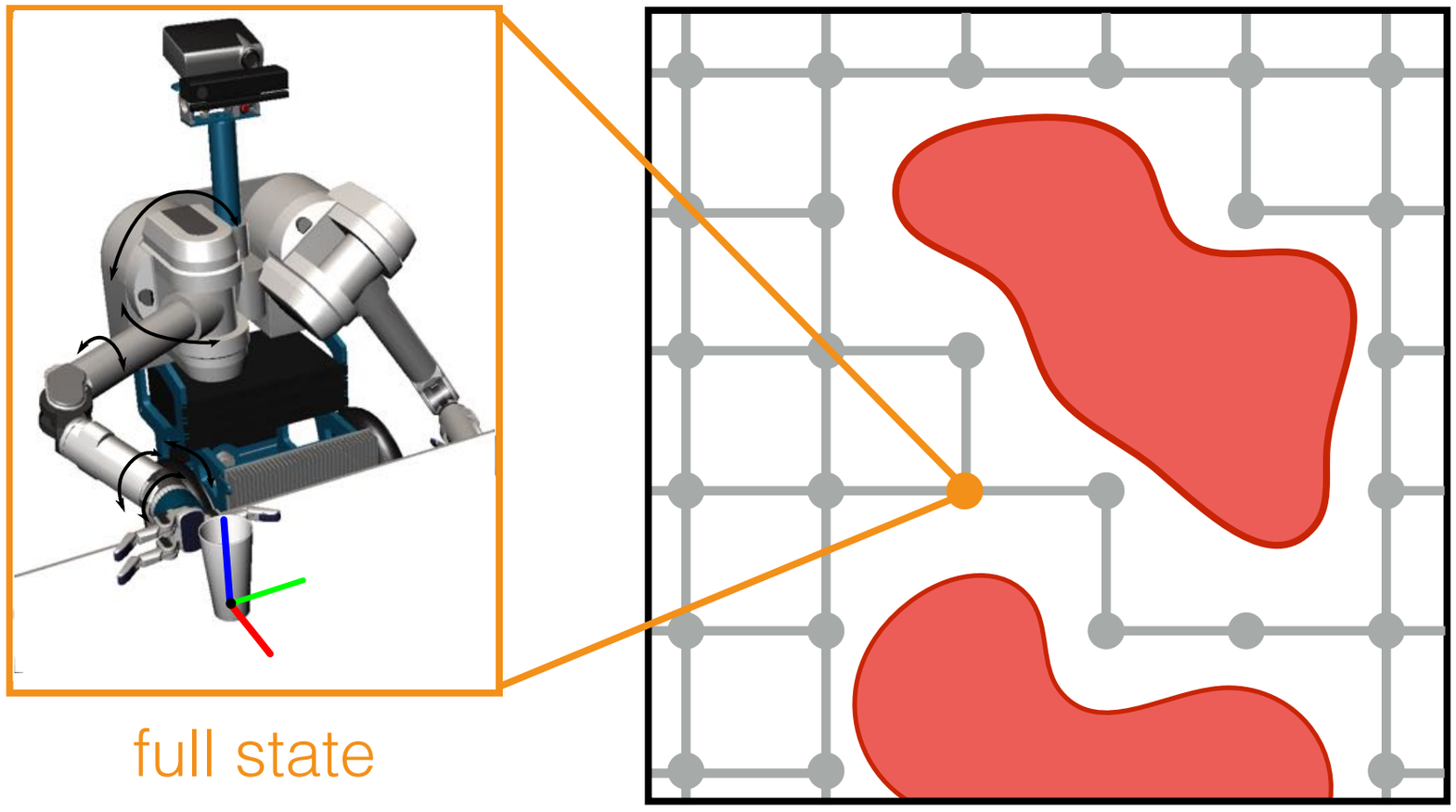
$$R(s,a) = \begin{cases} 0 & : s \in G \\ -\Delta t & : \text{otherwise} \end{cases}$$



Action templates form a lattice in C-space

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

$$R(s,a) = \begin{cases} 0 & : s \in G \text{ and } \text{IsFeasible}(s,a) \\ -\Delta t & : \text{otherwise} \end{cases}$$



Obstacles may invalidate action templates

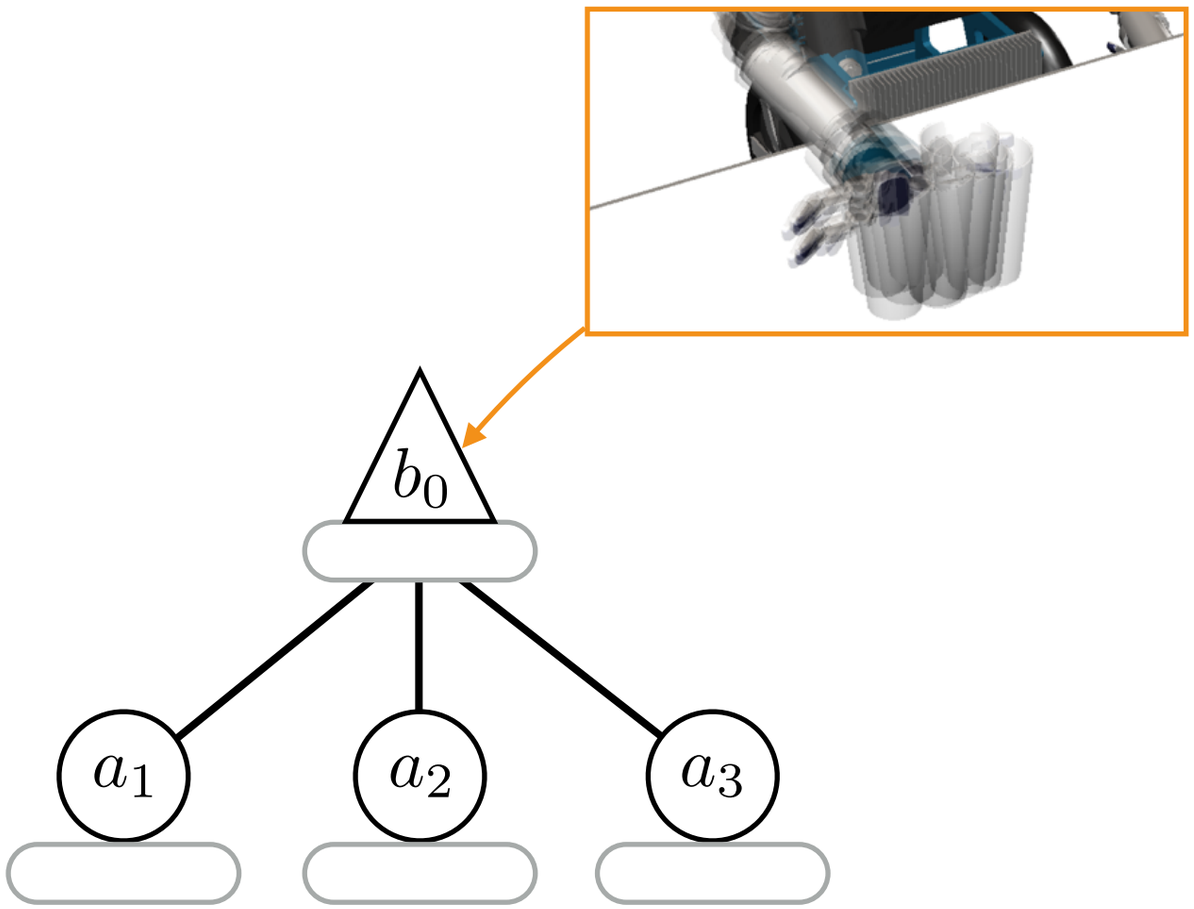
M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

feasible

infeasible

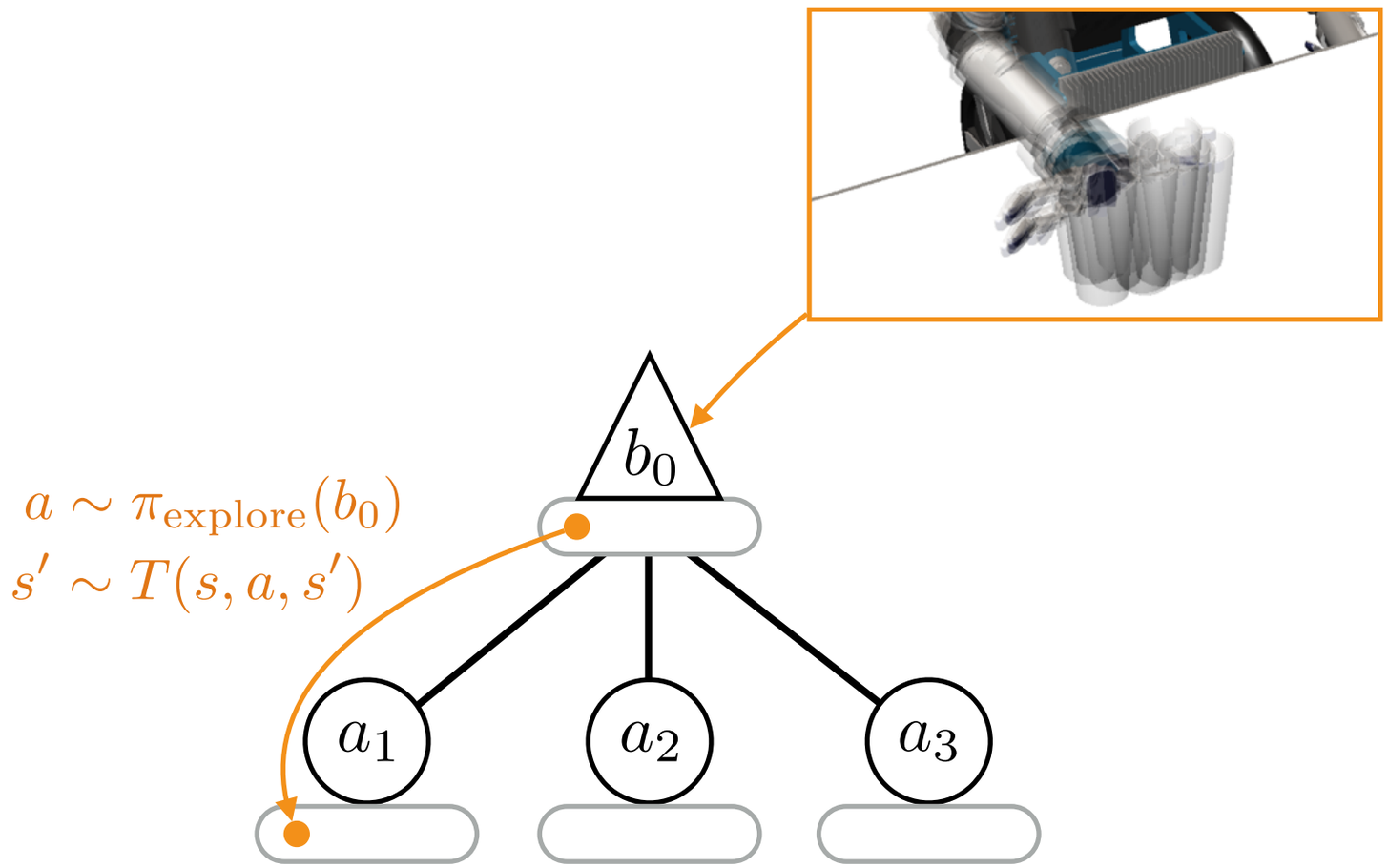
unreachable

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.



Plan using DESPOT, an online POMDP solver

D. Silver and J. Veness. "Monte-Carlo planning in large POMDPs." NIPS, 2010.
A. Somani, N. Yi, D. Hsu, and W.S. Lee. "DESPOT: Online POMDP planning with regularization." NIPS, 2013.



Plan using DESPOT, an online POMDP solver

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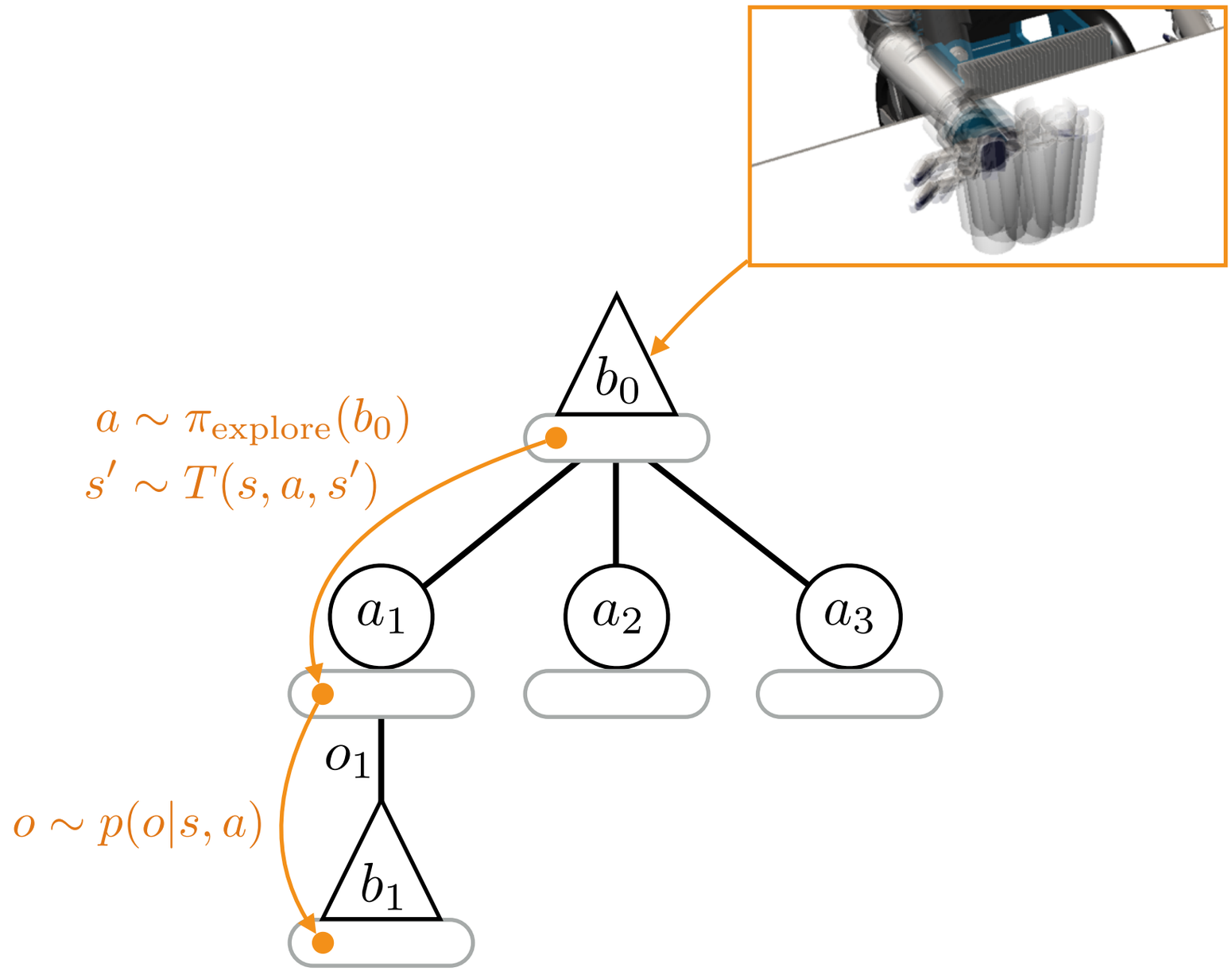

Plan using DESPOT, an online POMDP solver

D. Silver and J. Veness. "Monte-Carlo planning in large POMDPs." NIPS, 2010.
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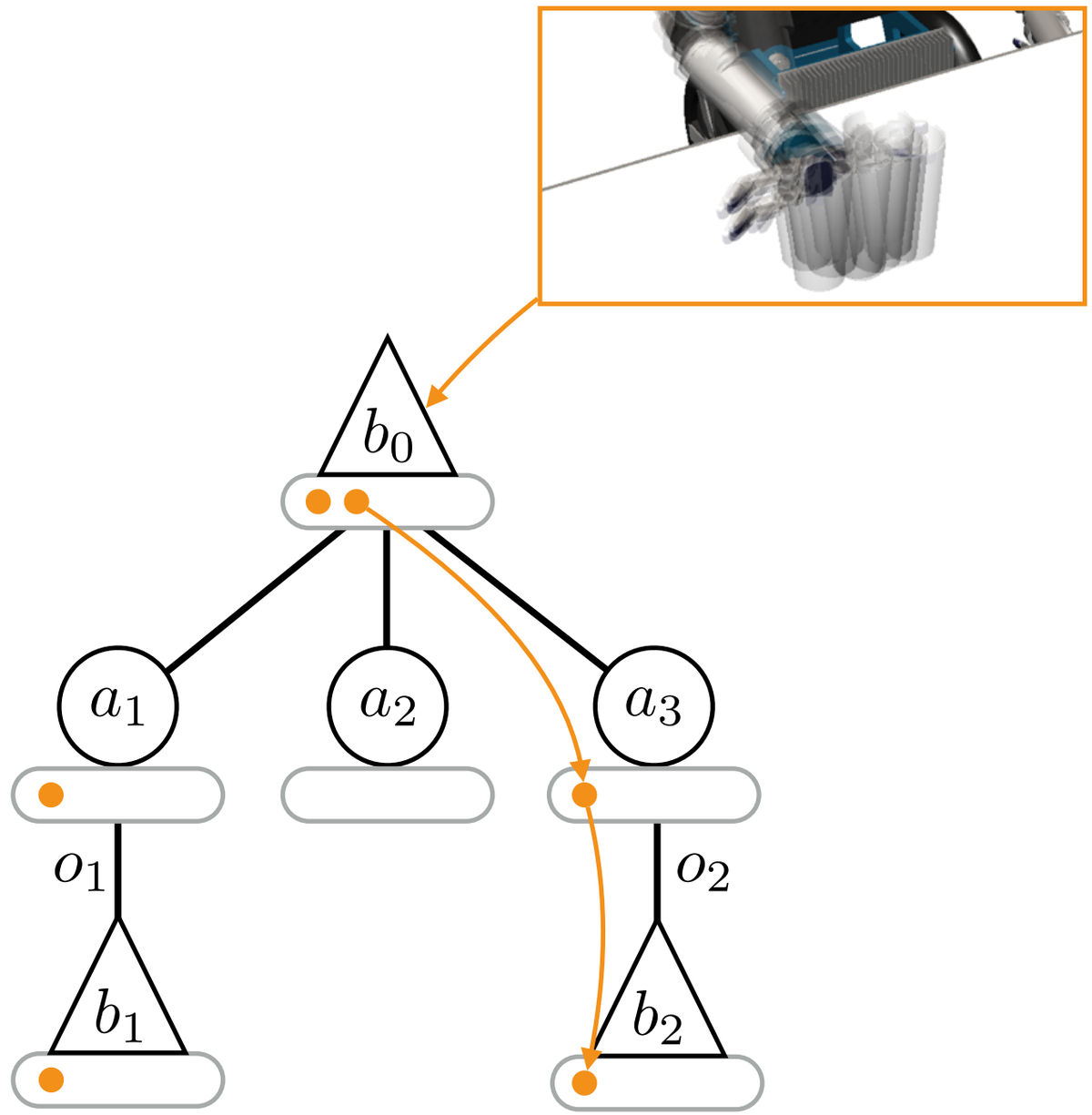
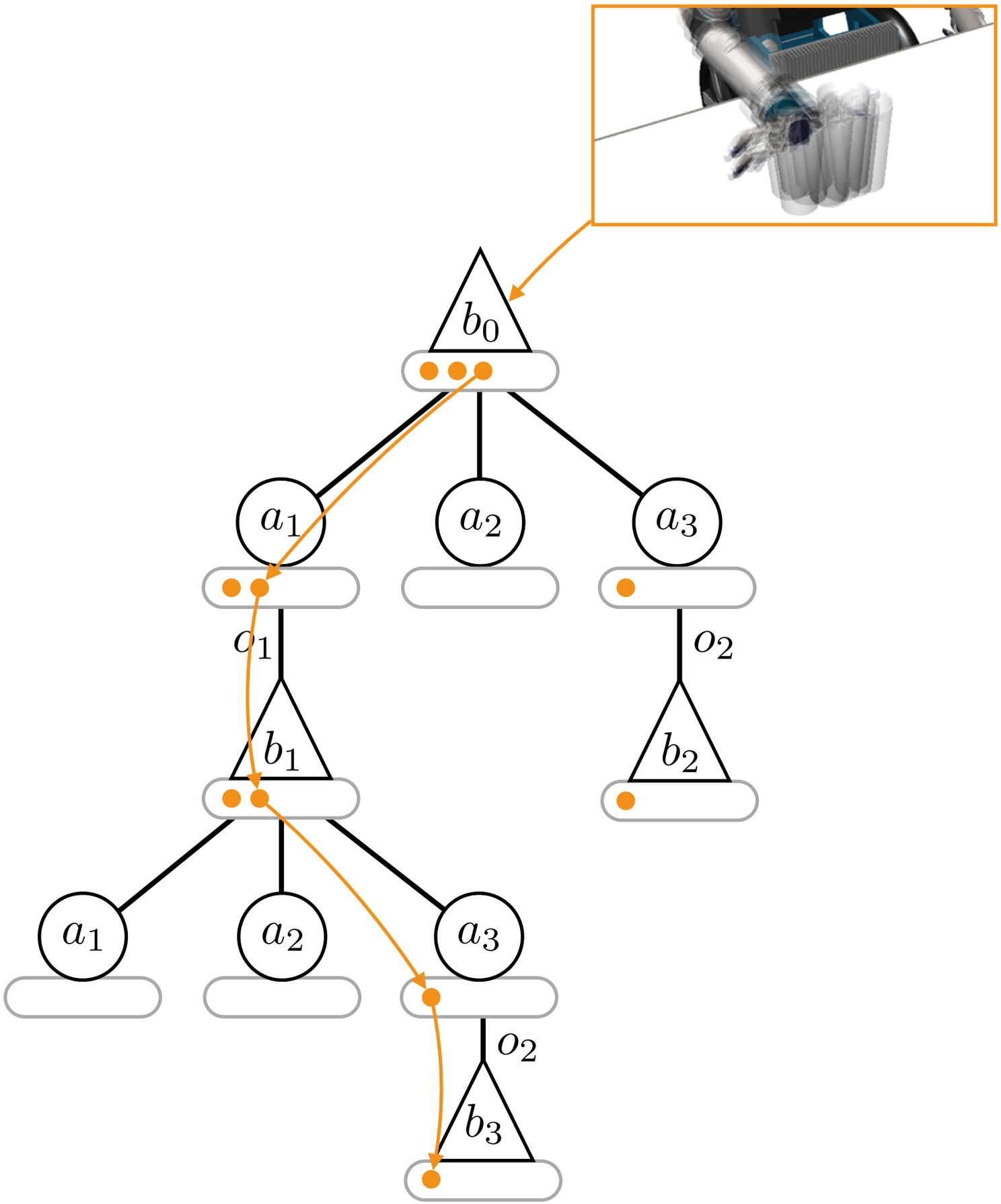
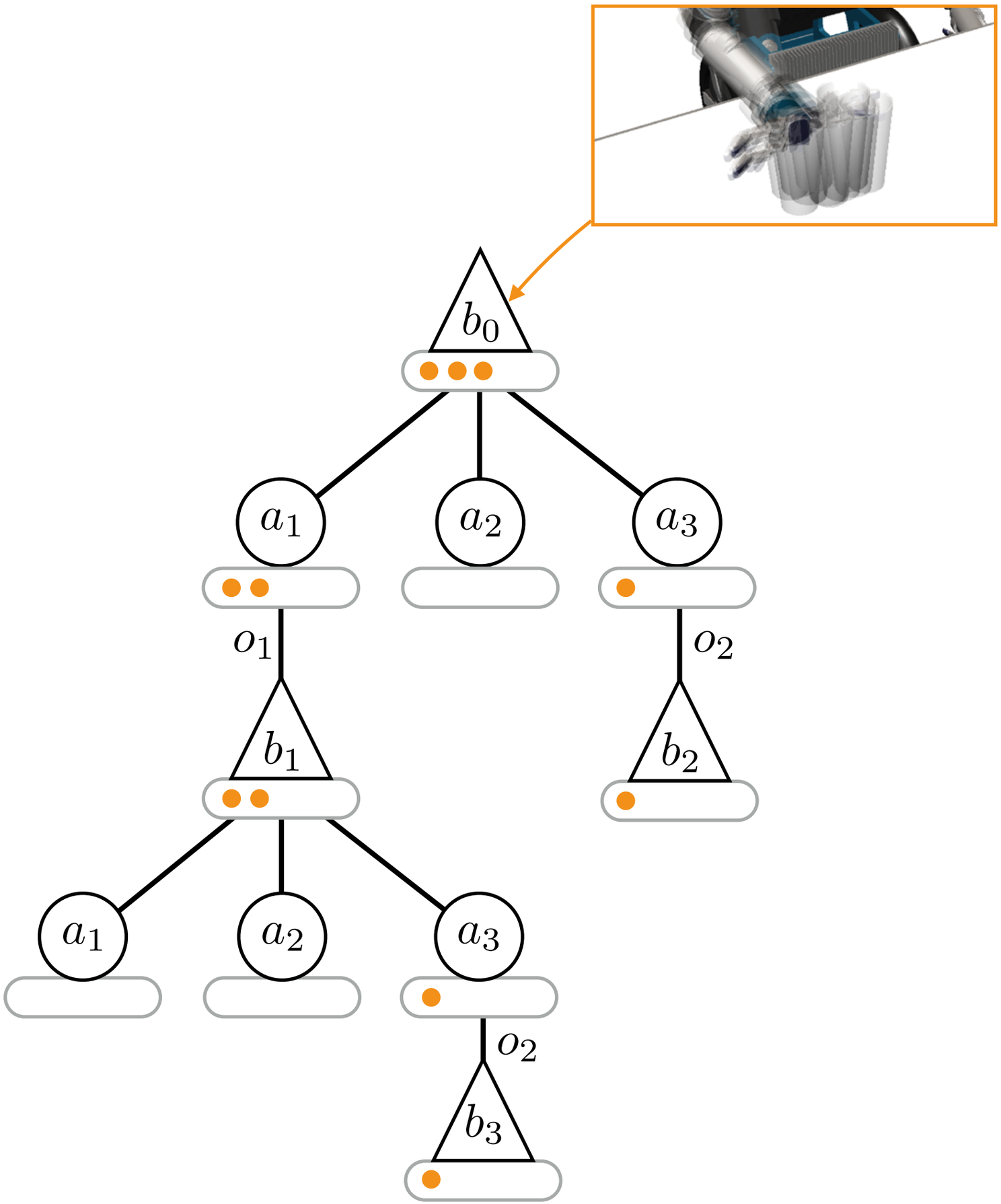


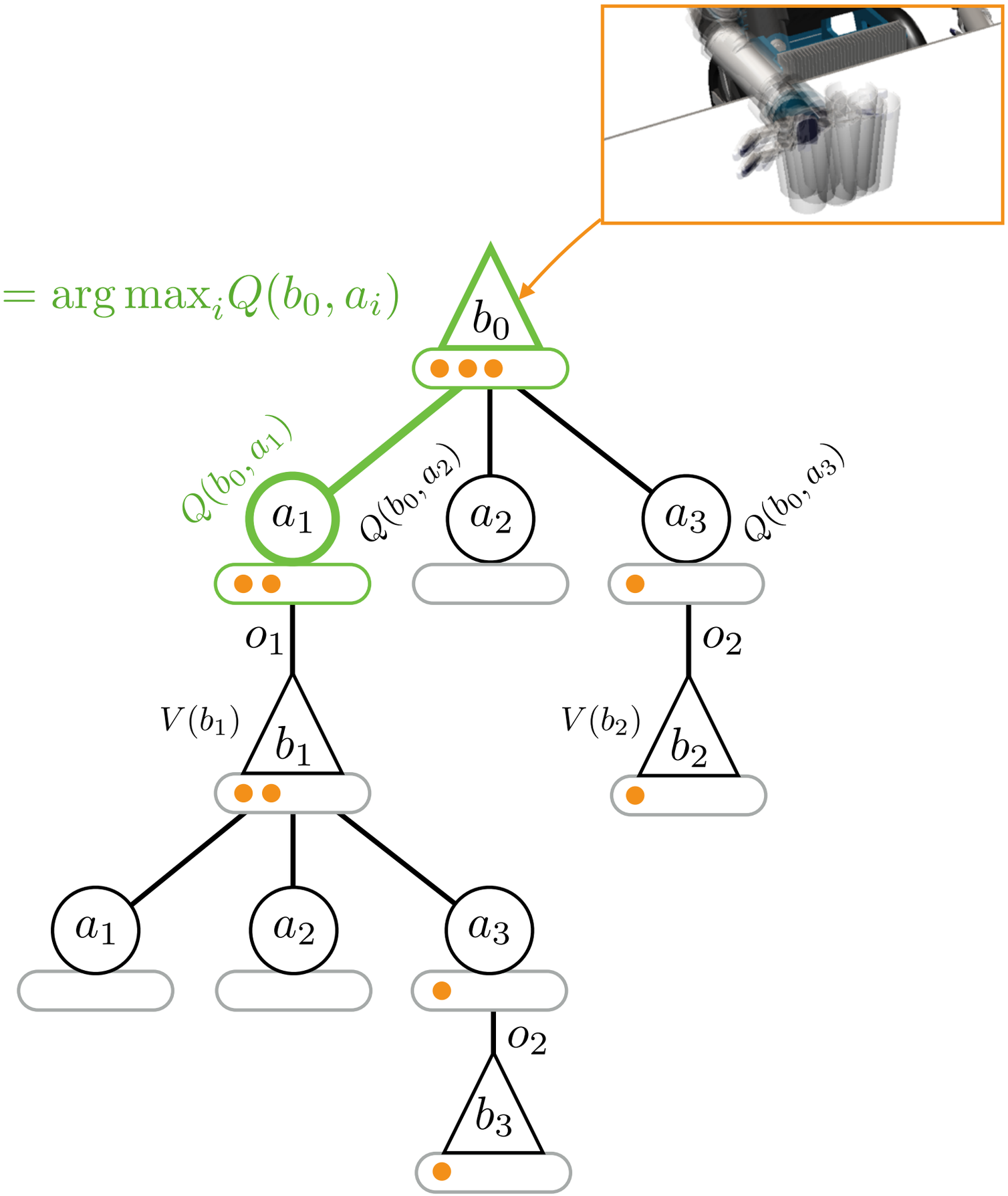
Plan using DESPOT, an online POMDP solver

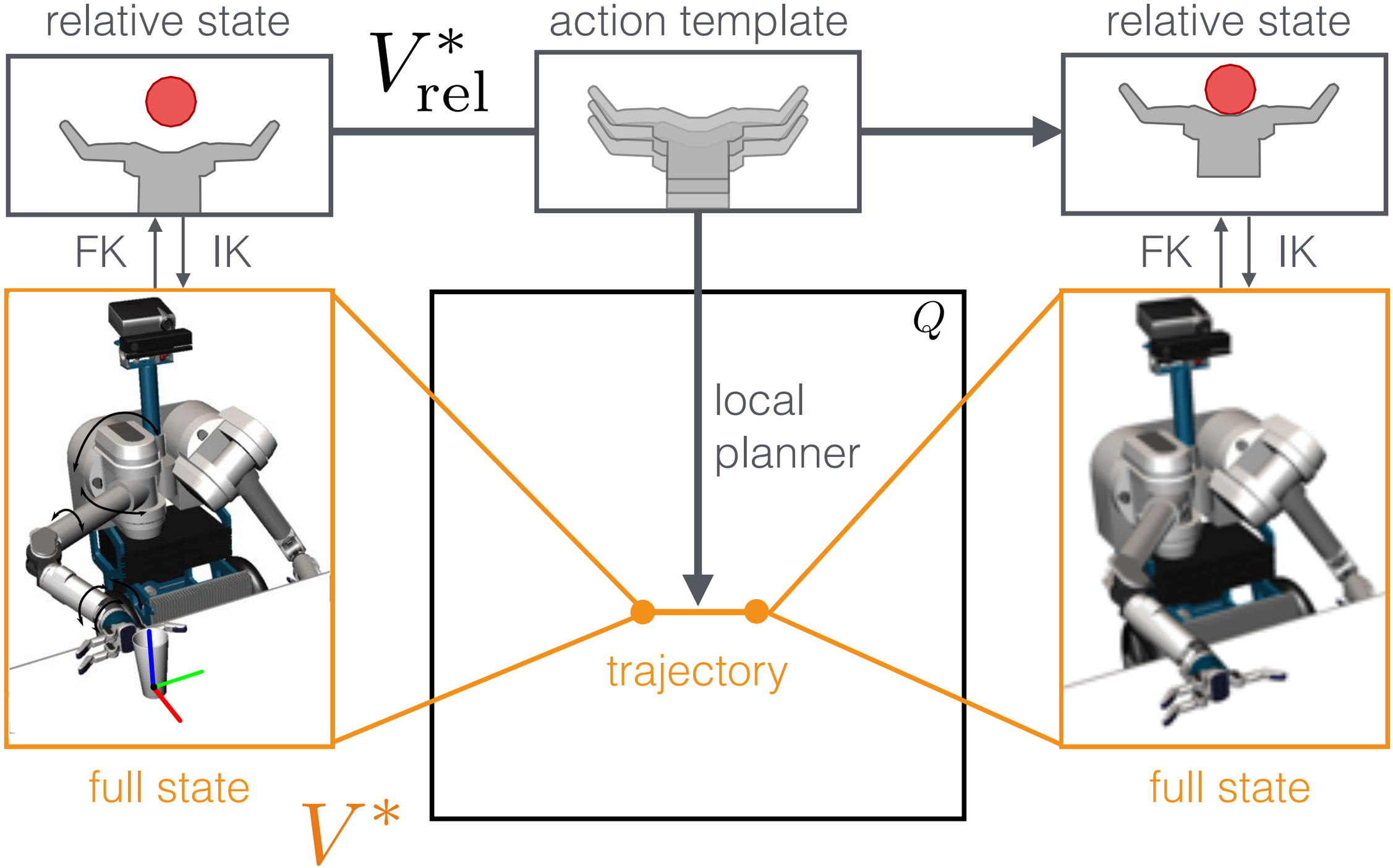
D. Silver and J. Veness. "Monte-Carlo planning in large POMDPs." NIPS, 2010.
A. Somani, N. Yi, D. Hsu, and W.S. Lee. "DESPOT: Online POMDP planning with regularization." NIPS, 2013.


b_0
a_1
a_2
a_3
o_1
o_2
b_1
b_2
a_1
a_2
a_3
o_2
b_3


b_0
a_1
a_2
a_3
o_1
o_2
b_1
b_2
a_1
a_2
a_3
o_2
b_3

$a^* = \arg\max_i Q(b_0, a_i)$





Plan using a finite set of action templates

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

Ignoring obstacles relaxes the problem.

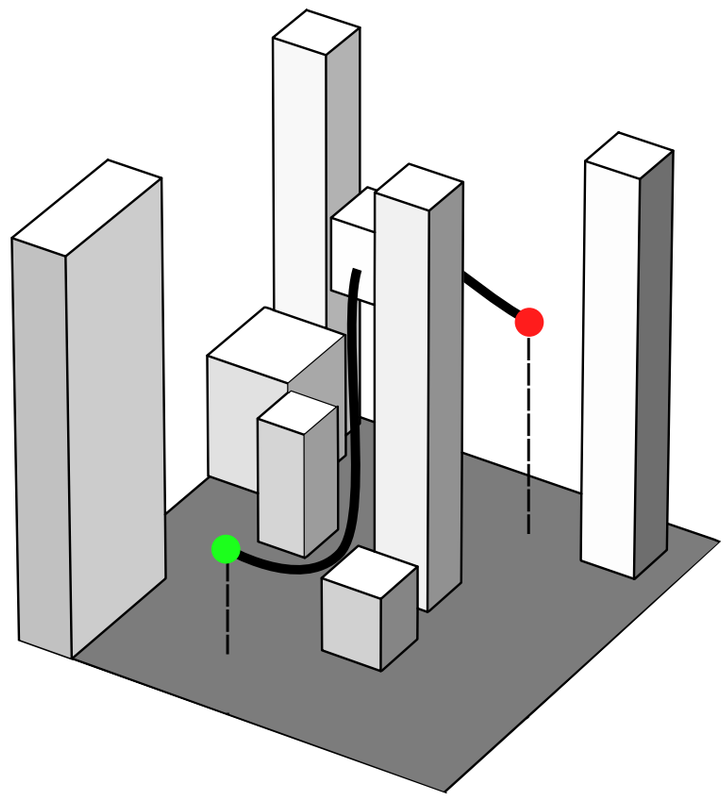
$$V^*_{\text{rel}} \geq V^*$$

hand-relative space
ignores obstacles

full state space
considers obstacles

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

full state space



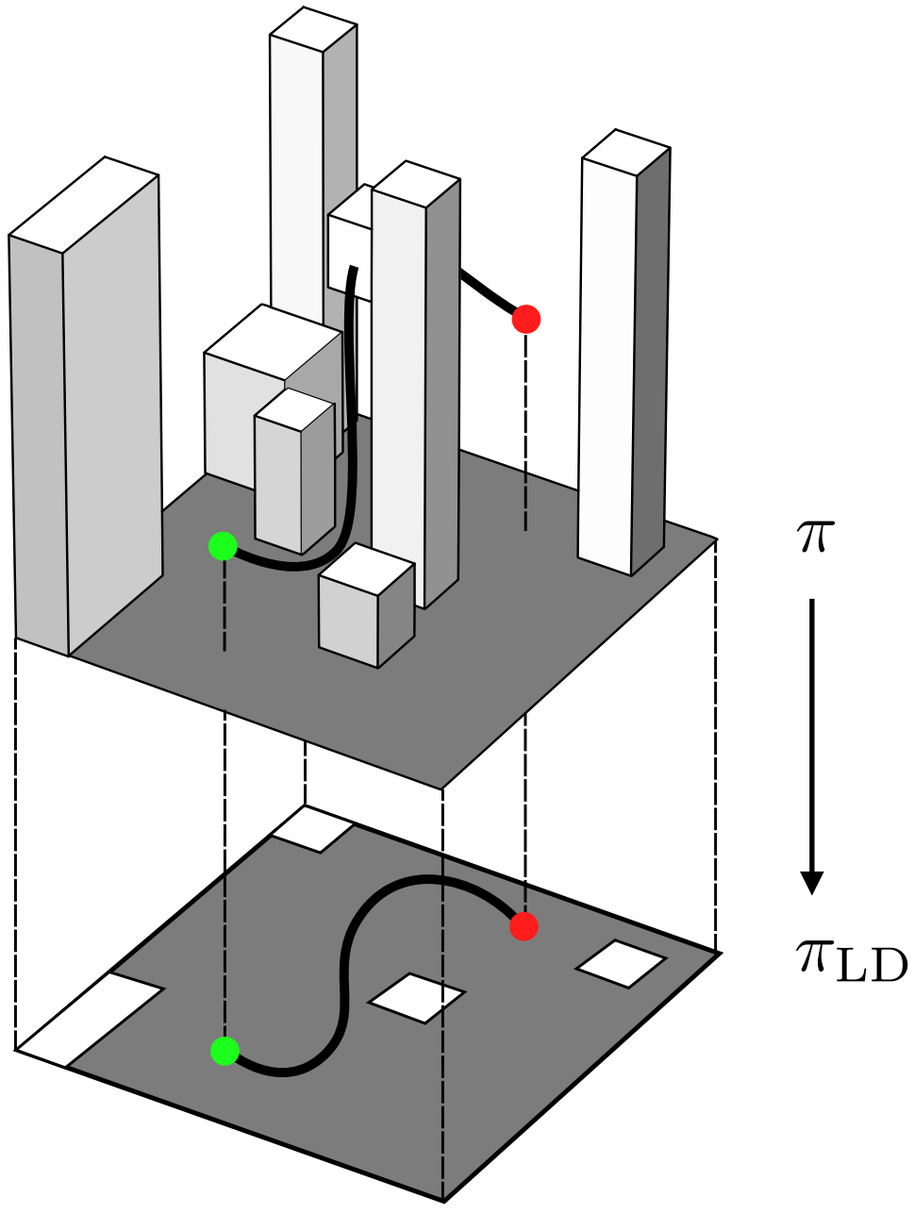
π

Project into a lower-dimensional space

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

full state space

hand-relative space

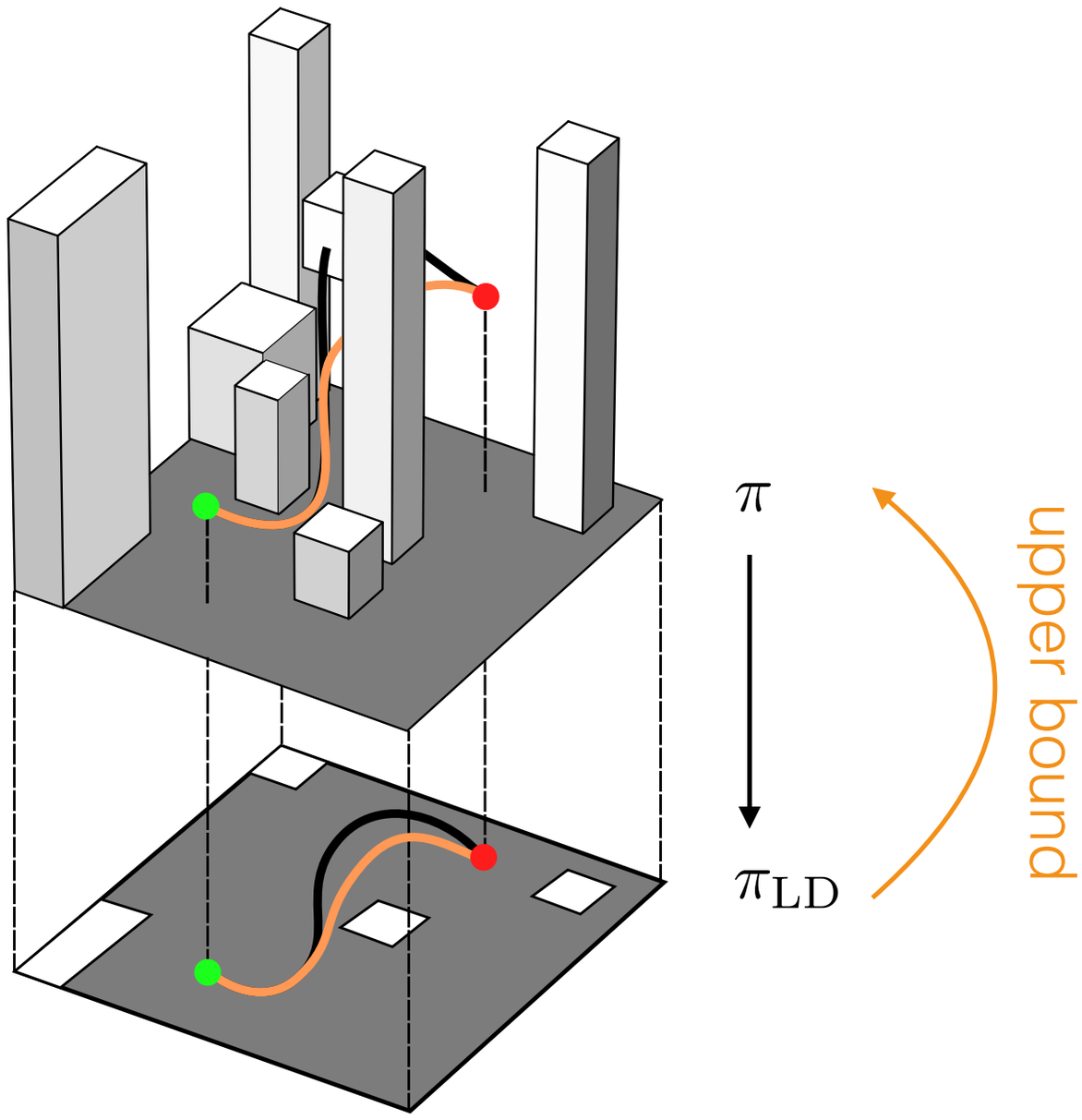


Project into a lower-dimensional space

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

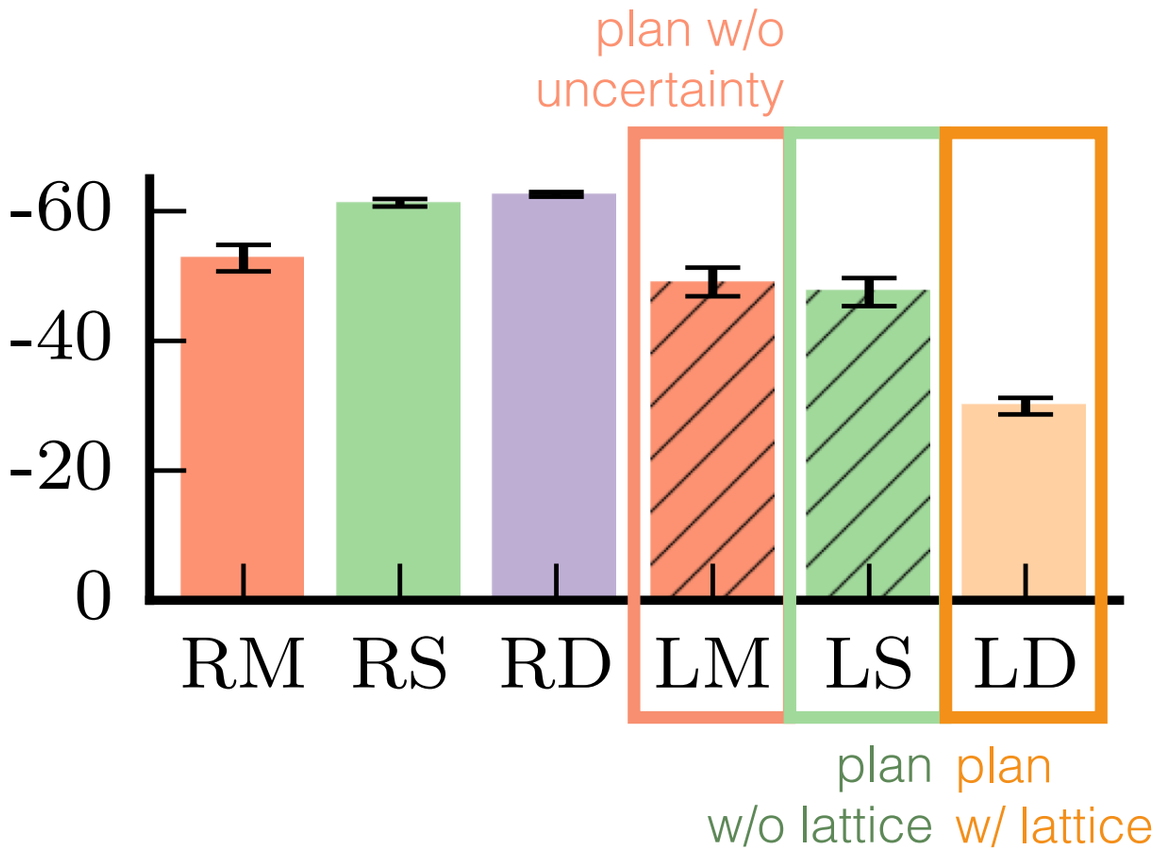
full state space

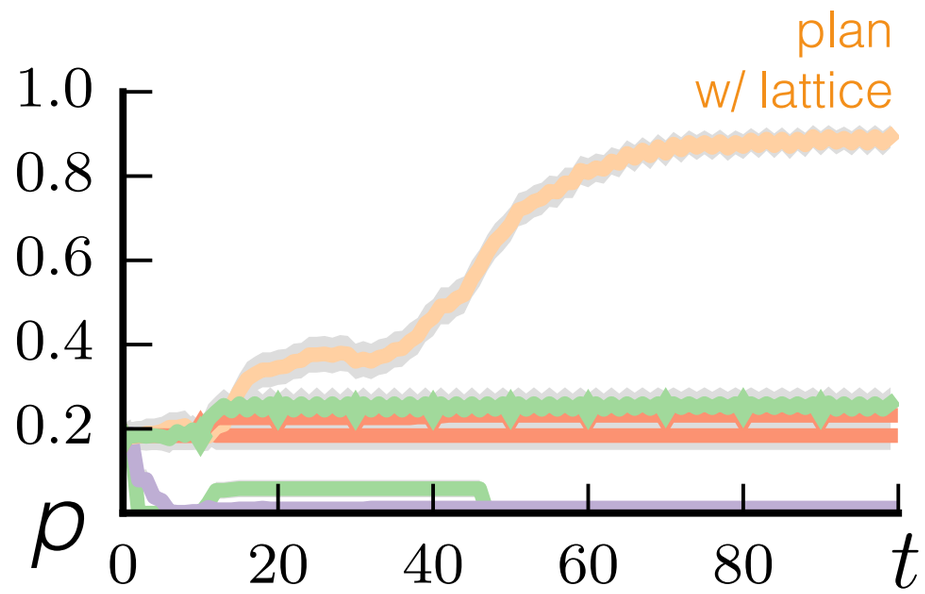
hand-relative space



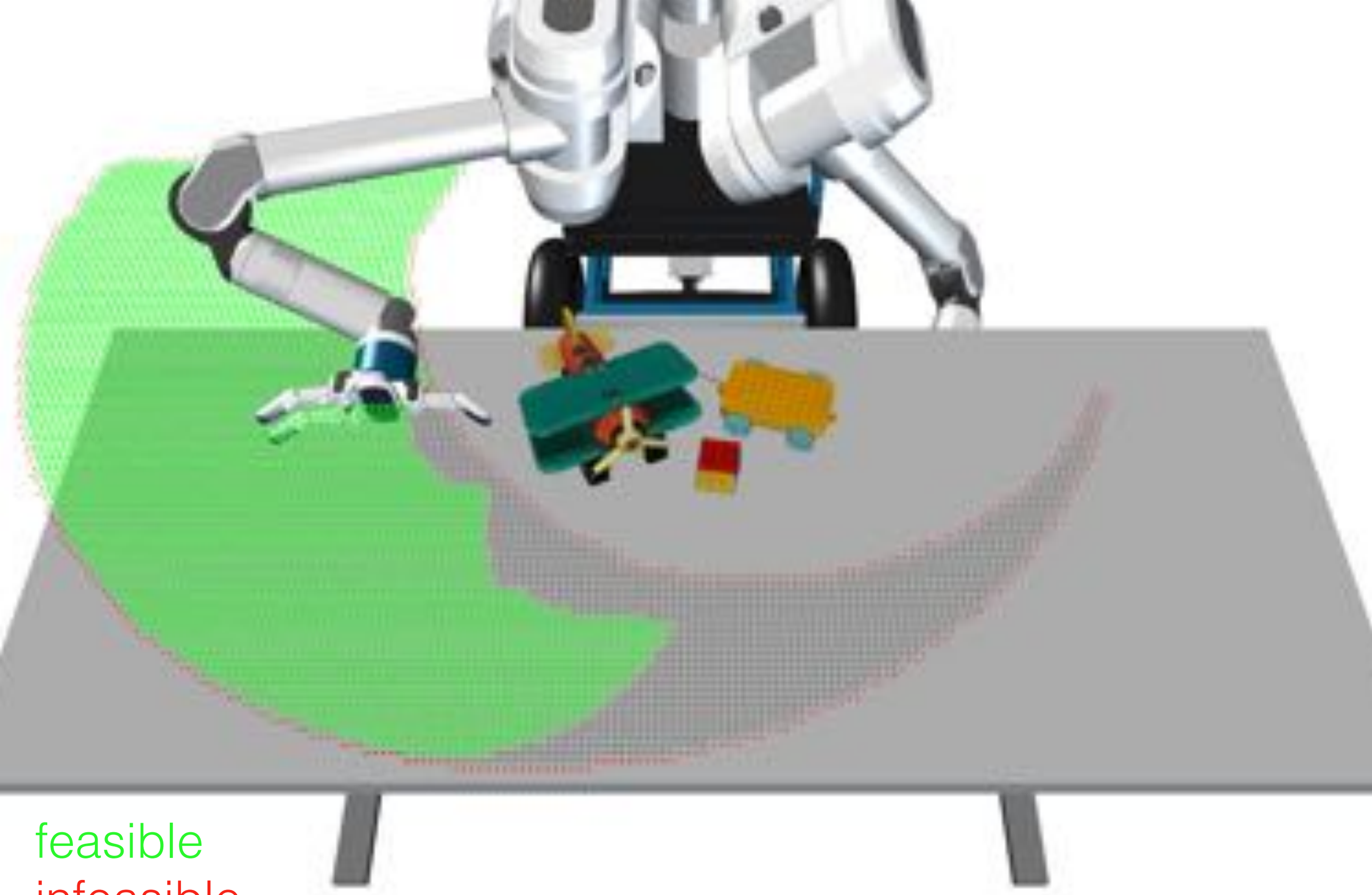
Use this bound to guide DESPOT in an online search

A. Somani, N. Ye, D. Hsu, W.S. Lee. "DESPOT: Online POMDP Planning with Regularization," NIPS, 2013.
M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.





M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.



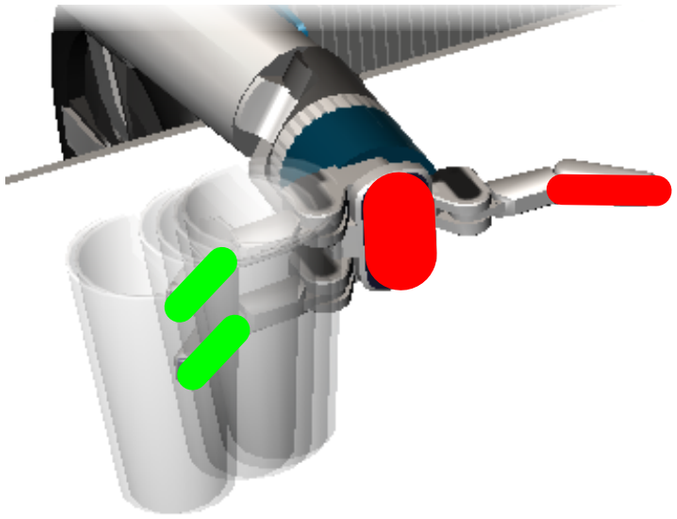
feasible
infeasible
unreachable

M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

feasible
infeasible
unevaluated

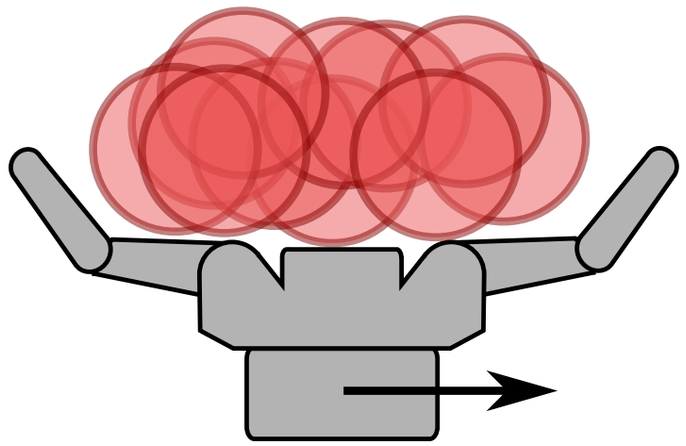
M.C. Koval, D. Hsu, N.S. Pollard, and S.S. Srinivasa. “Configuration lattices for planar contact manipulation under uncertainty.” CoRR, 2016.

state estimation



belief state

action selection

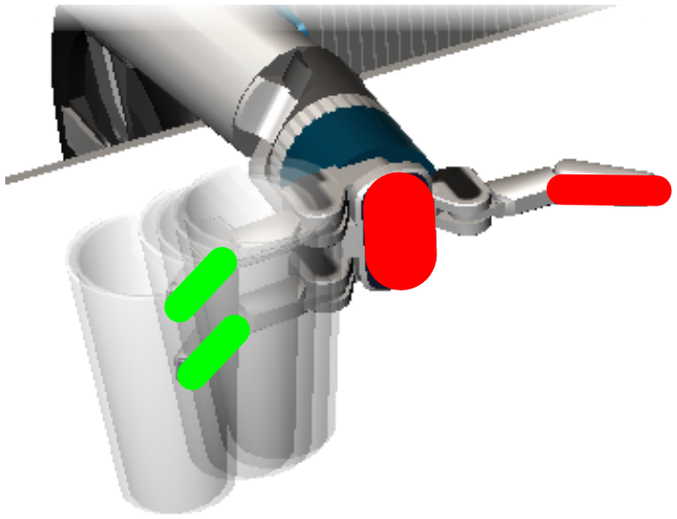


observation

action

environment

state estimation



belief state

action selection

observation

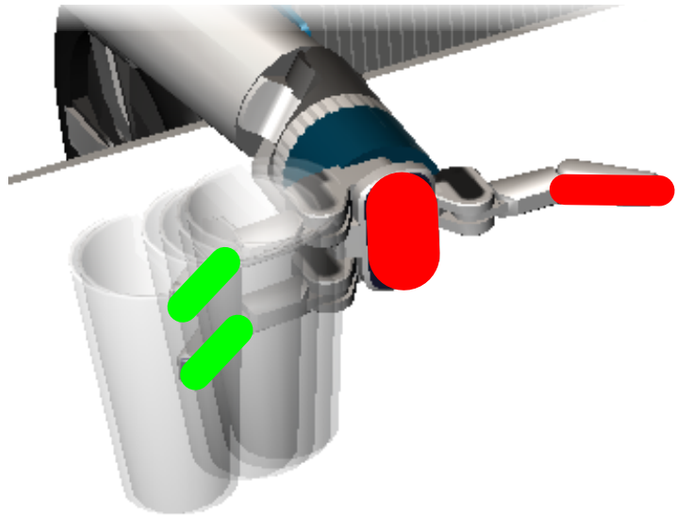
action

environment

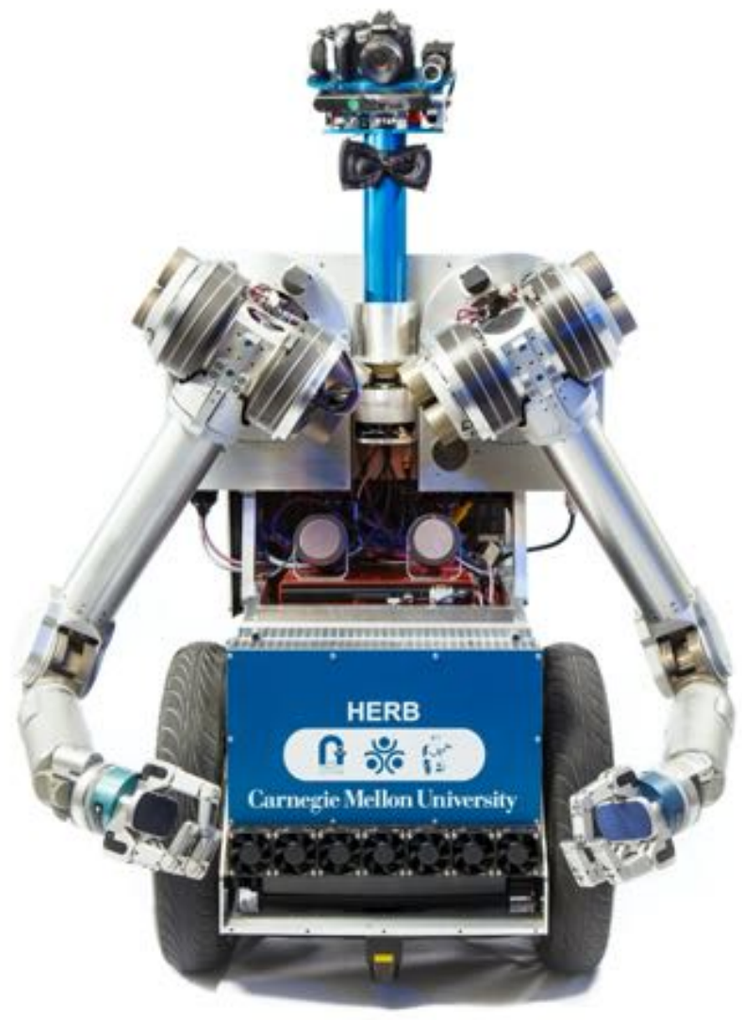
state estimation

belief state

action selection

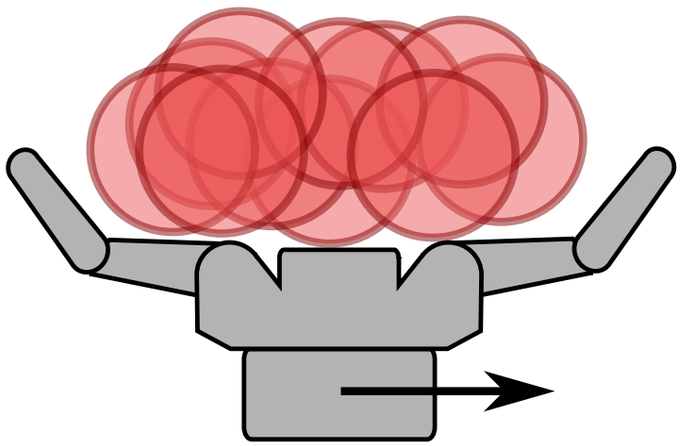


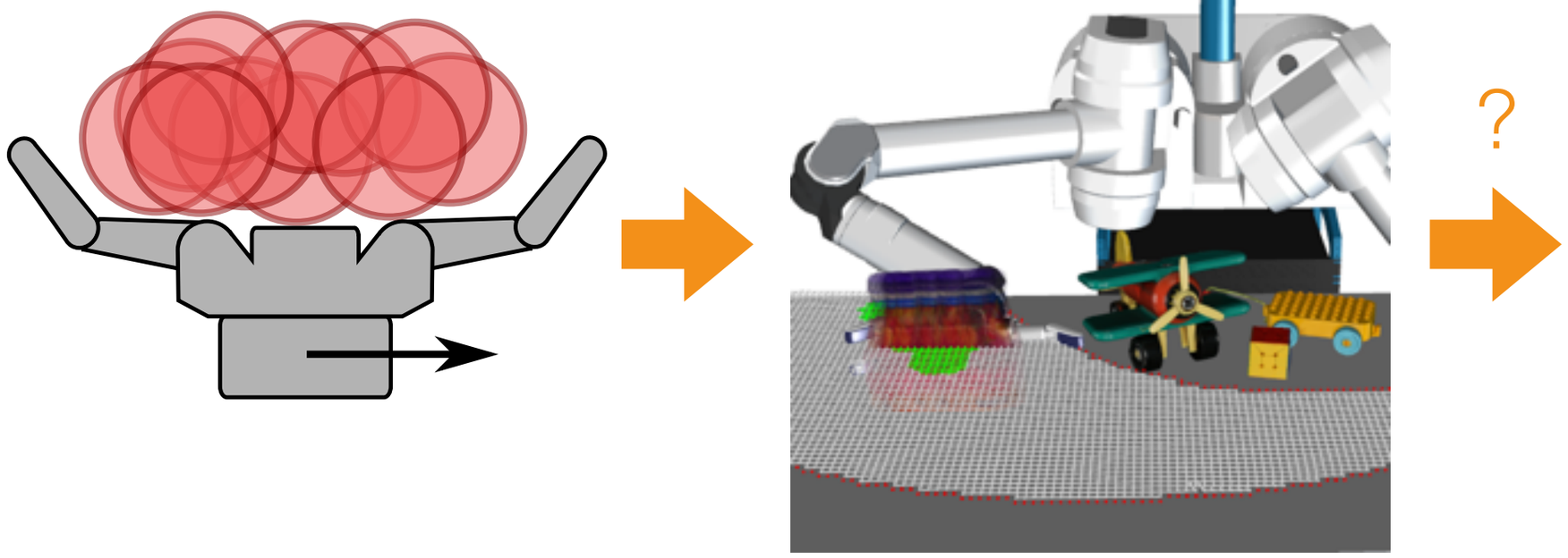
observation



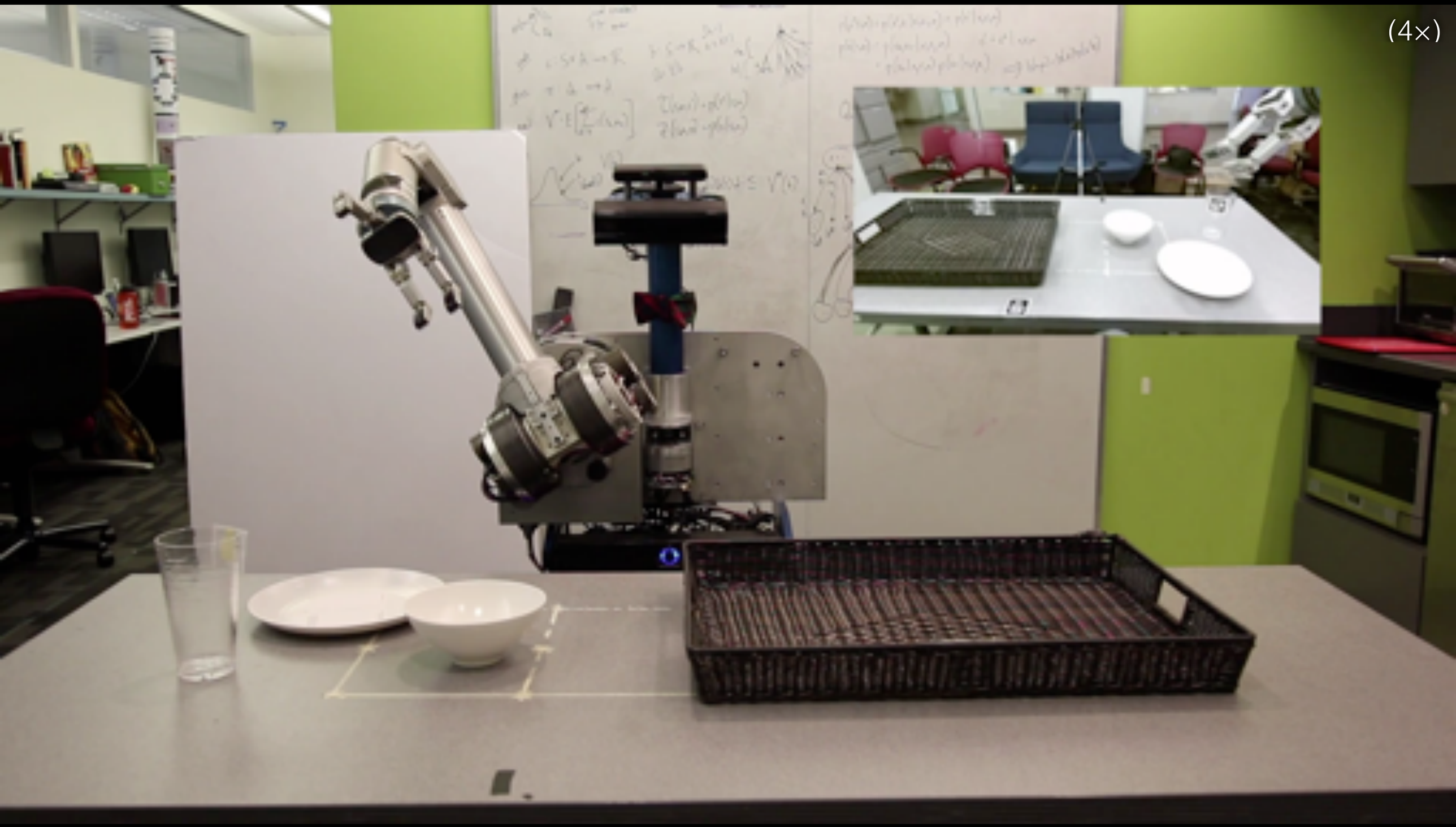
action

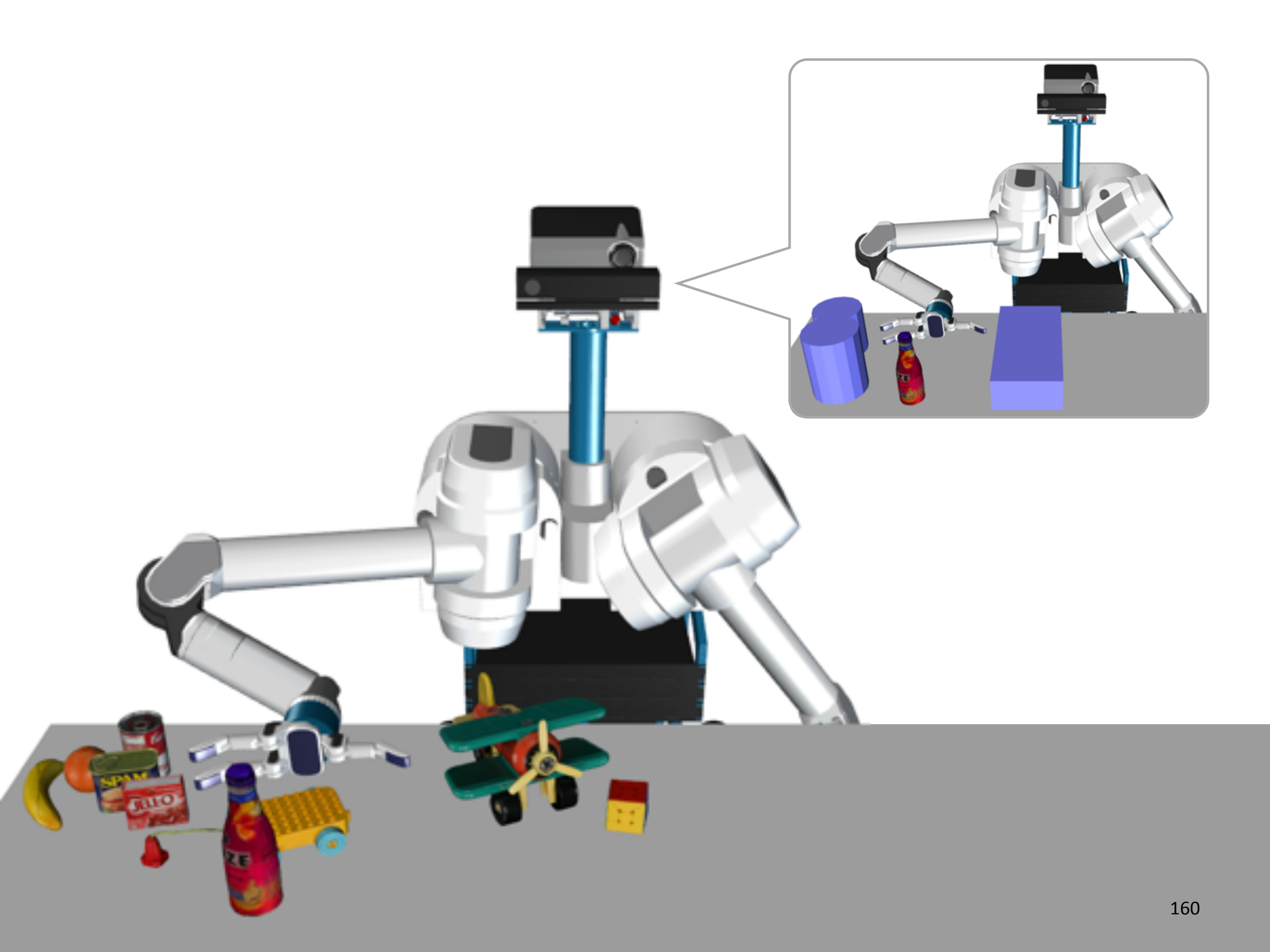
environment

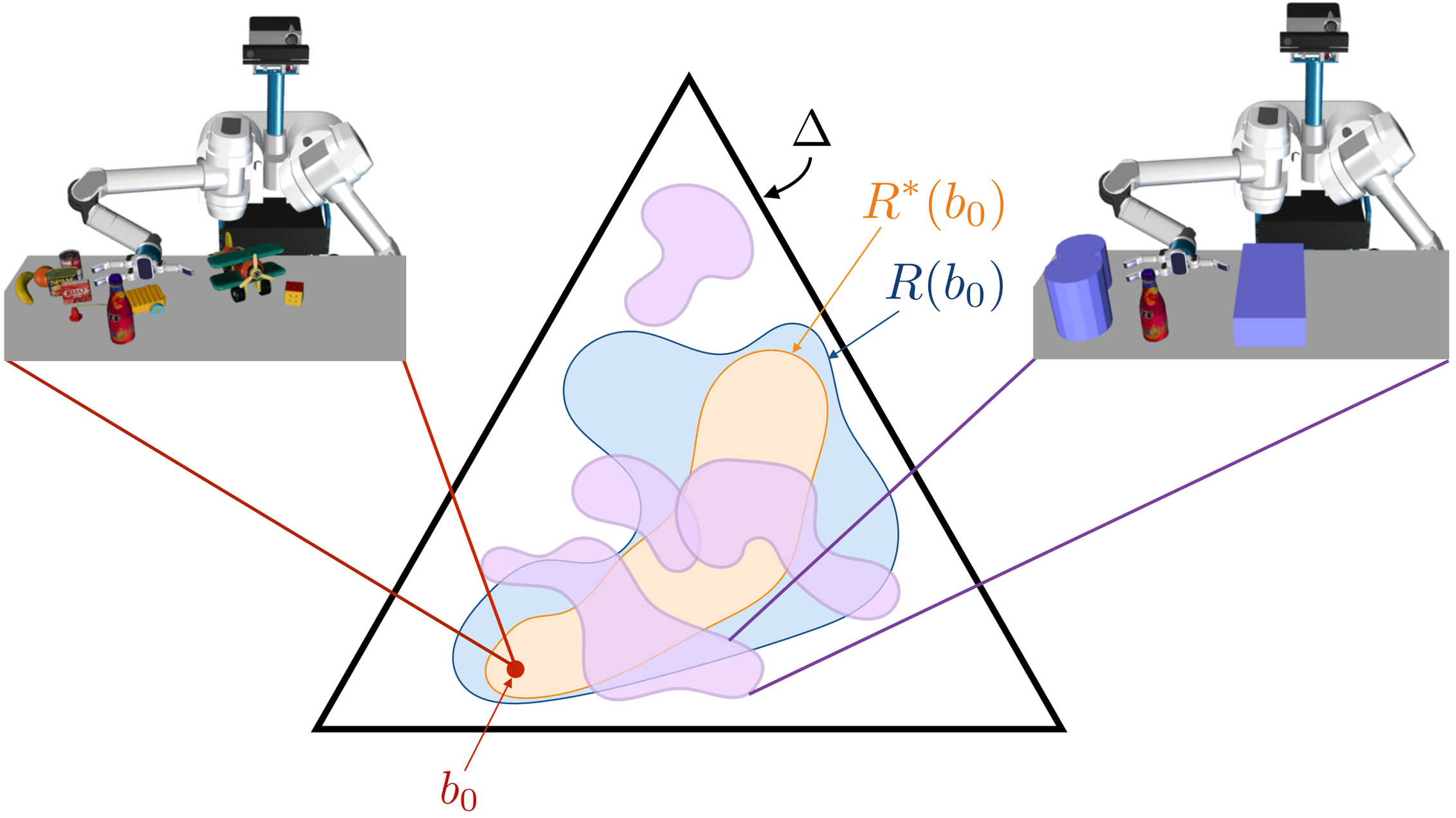


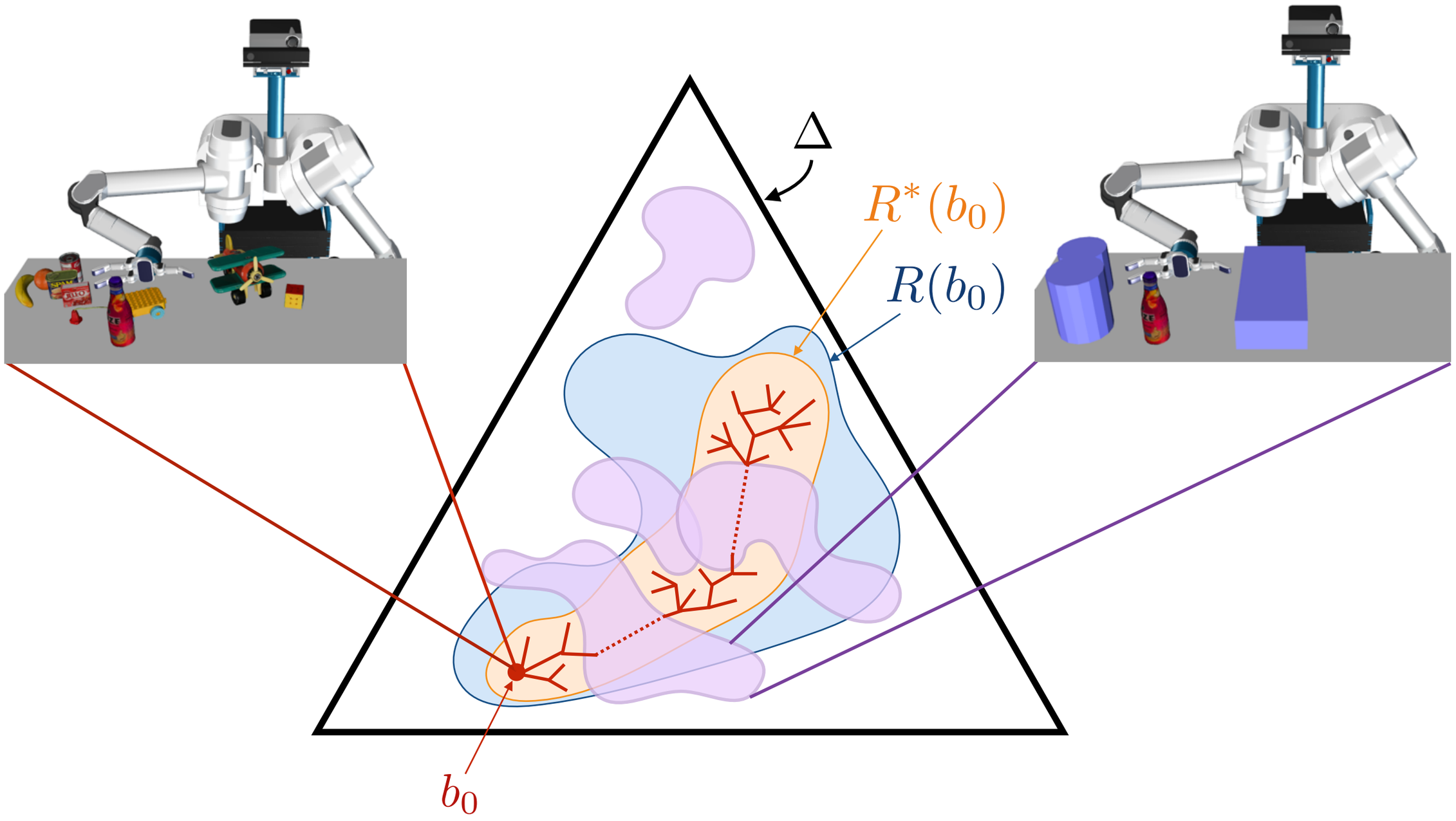


(4×)

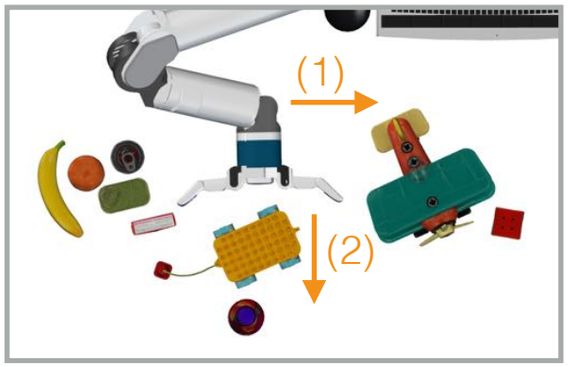




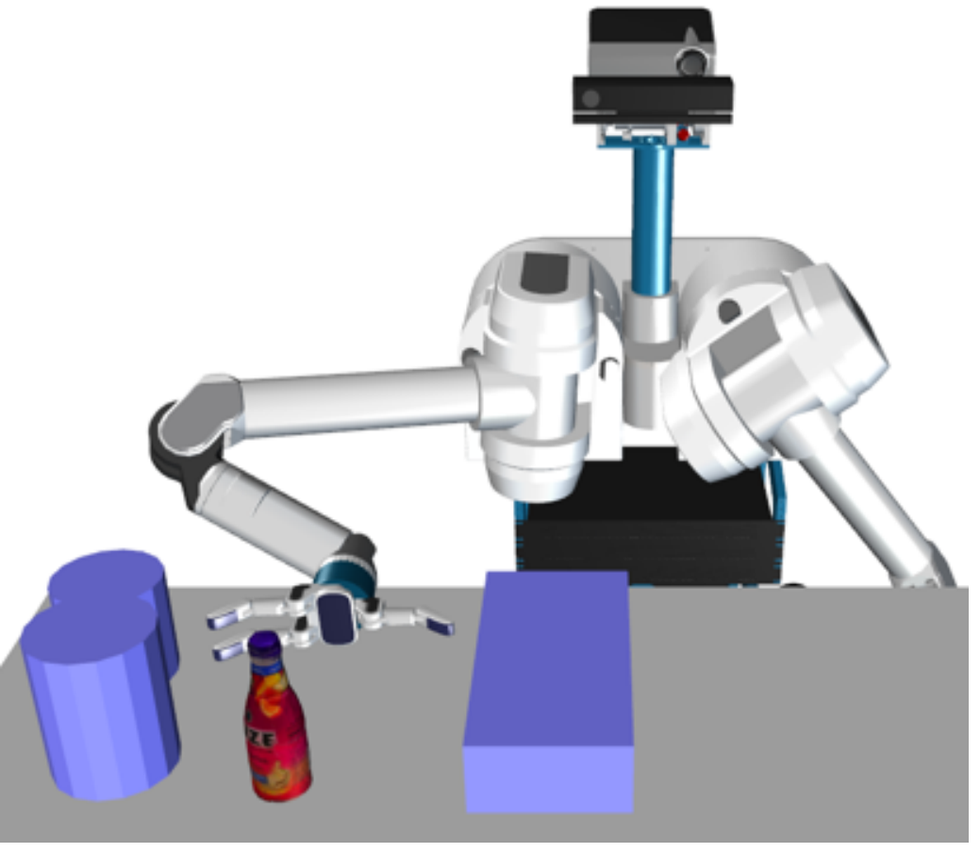

Δ
$R^*(b_0)$
$R(b_0)$
b_0


Δ
$R^*(b_0)$
$R(b_0)$
b_0

lower bound

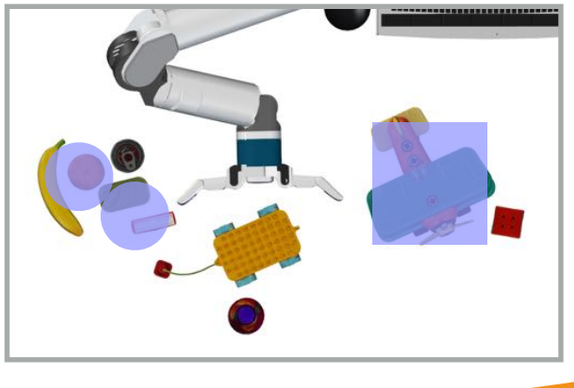


default policy

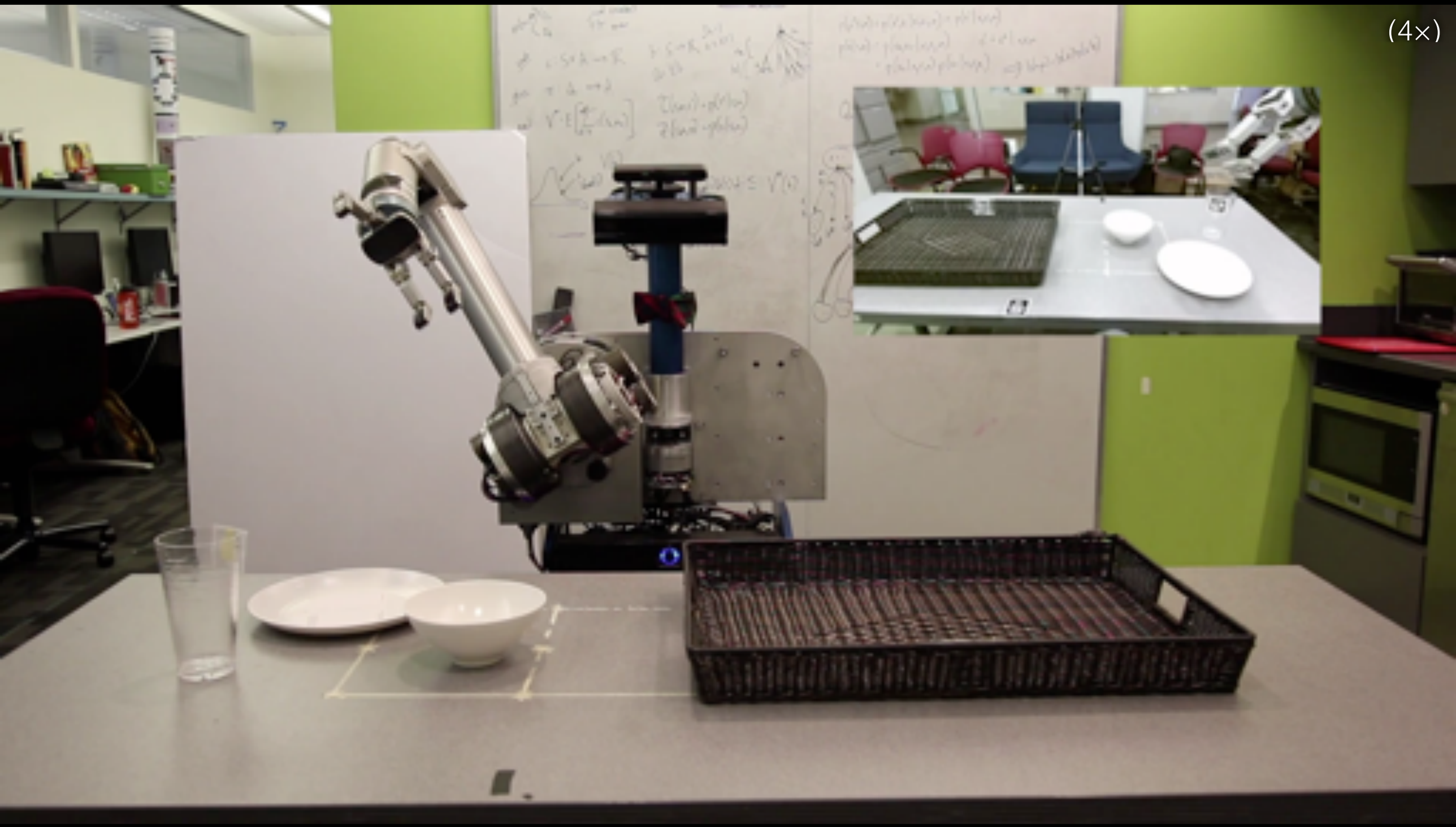


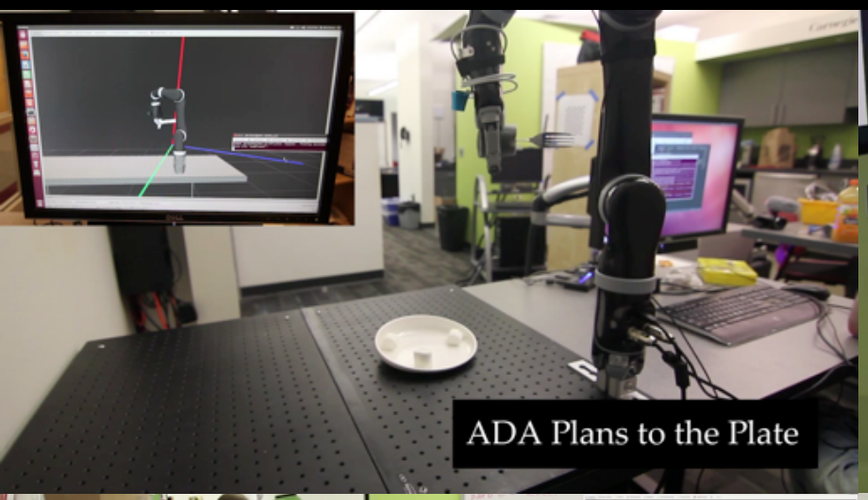
episodic interaction

relaxation

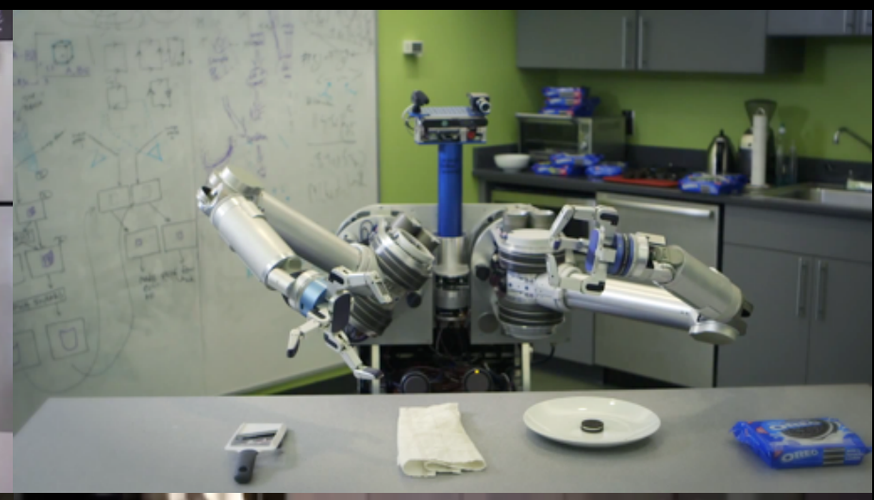


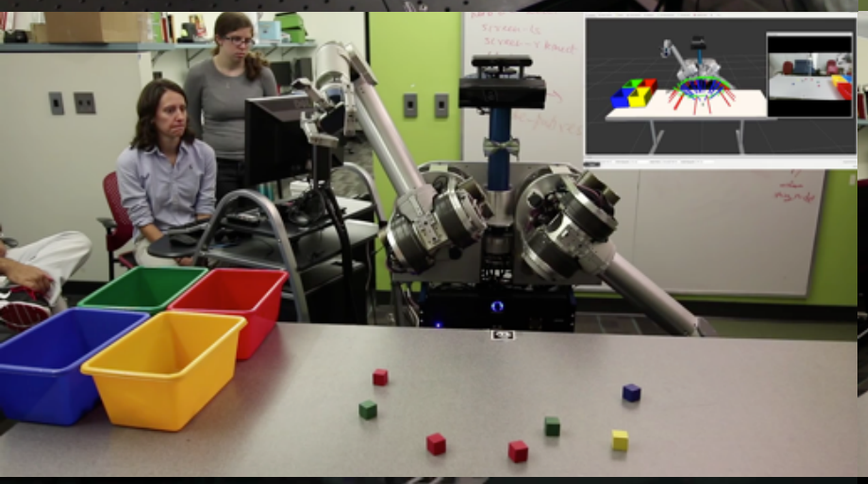
upper bound

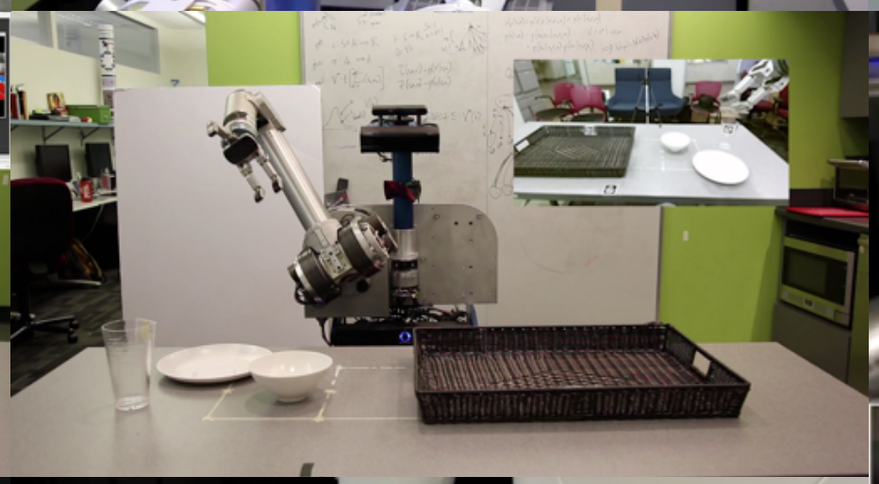

(4×)

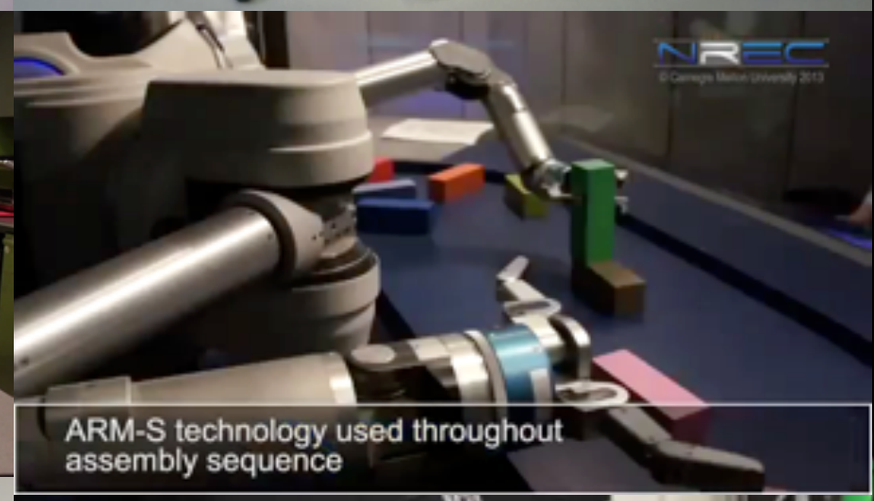

ADA Plans to the Plate

(4×)
Grasp book using force feedback

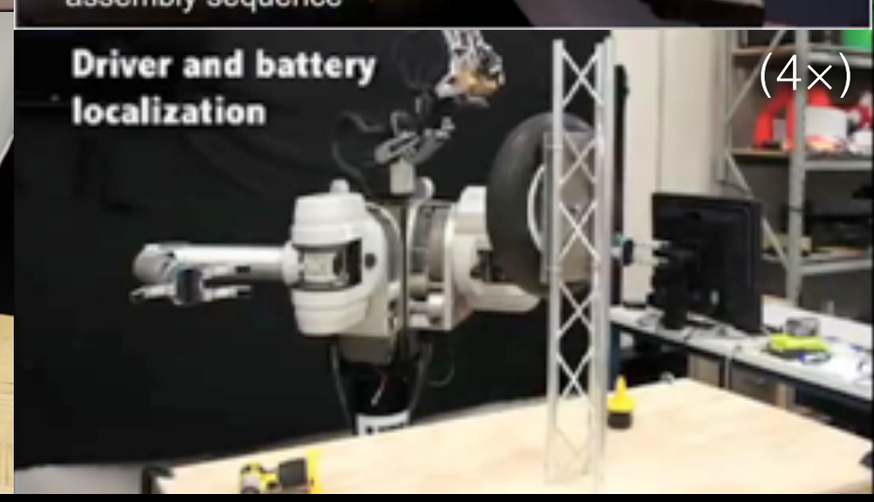







NREC
ARM-S technology used throughout assembly sequence

DARPA Autonomous Robotic Manipulation
NREC Team
PI: Drew Bagnell, Martial Hebert, Nancy Pollard
Team: Moslem Kazemi


Driver and battery localization
(4×)

A Bayesian Framework for Robust Manipulation via Contact Sensing

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This work was supported by a NASA Space Technology Research Fellowship (award NNX13AL62H), the National Science Foundation (awards IIS-1218182 and IIS-1409003), the DARPA Autonomous Manipulation Program, the Office of Naval Research (award N000141210613), and the Toyota Motor Corporation.