Leveraging Proprioceptive Feedback For Mobile Manipulation

Sisir Karumanchi
sisir.b.karumanchi@jpl.nasa.gov

Robotics Technologist
Manipulation & Sampling Group,
MOBILITY AND ROBOTIC SYSTEMS (Section 347)

Jet Propulsion Laboratory
California Institute of Technology

Background

JPL

2014- Current
Robotics Technologist
Manipulation and Sampling Group,
Supervisor: Dr. Paul G. Backes

MIT

2011-2014
Postdoc @ Robotic Mobility Group, MIT
Collaborating Researcher @ CSAIL, MIT
Advisors: Dr. Karl Iagnemma
Prof. Seth Teller
Prof. Russ Tedrake

University of Sydney

2010
PhD @ Australian Centre for Field Robotics,
The University of Sydney, Australia.
Advisors: Dr. Steve Scheding
Dr. Tim Bailey
Prof. Hugh Durrant-Whyte

JPL's Mobile Manipulation Lab

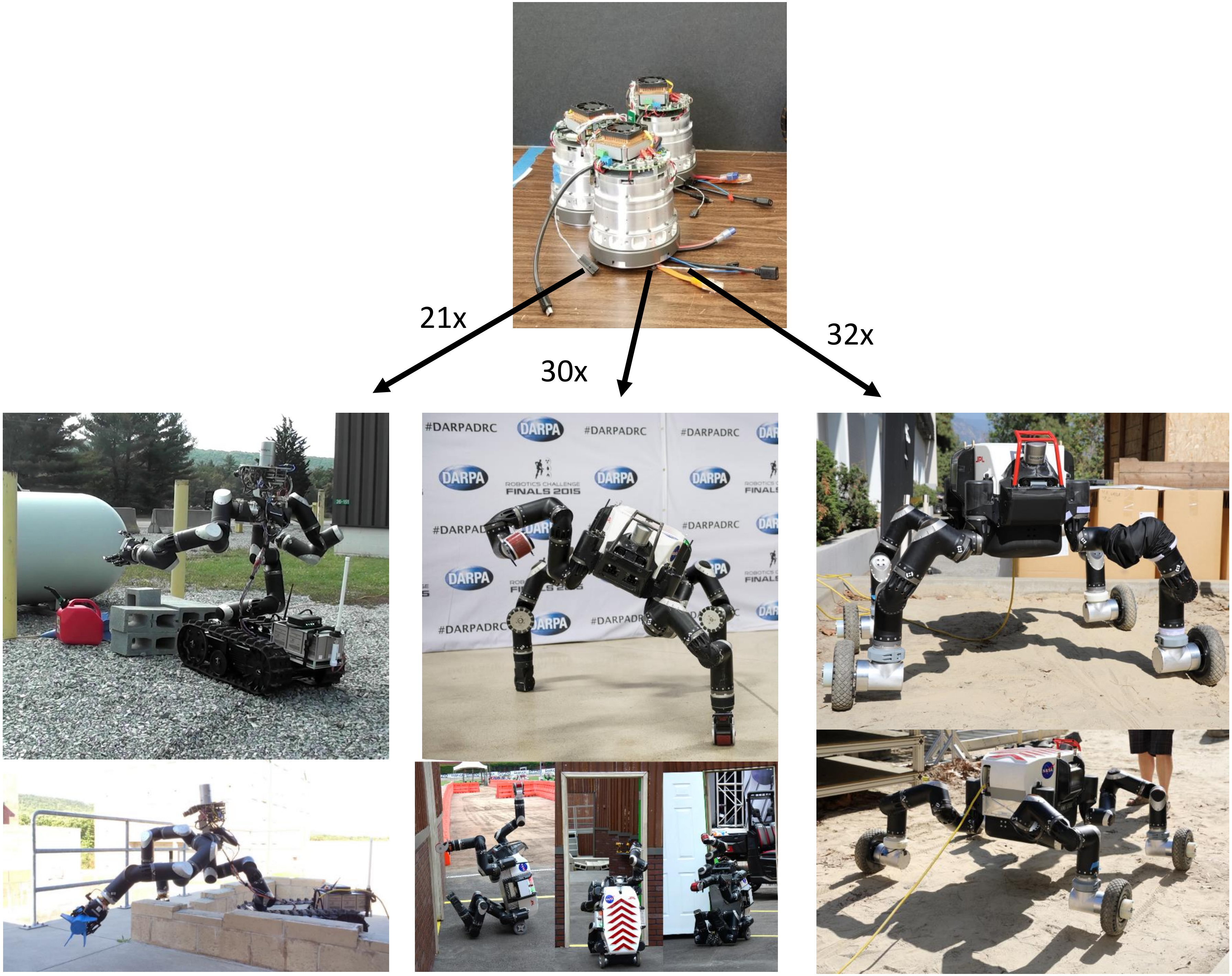
Acknowledgements

- Dr. Paul G. Backes, Group Supervisor, **Manipulation & Sampling Group**
- Brett Kennedy, Group Supervisor, **Robotic Vehicles and Manipulators Group**
- Prof. Joel Burdick, **Caltech**
- Chuck Bergh, Group Leader, **Robotic Hardware Systems Group**
- Kyle Edelberg, Robotics Software Engineer, **Manipulation & Sampling Group**
- Jay Jasper, Mechanical Engineer, **Robotic Climbers and Grippers Group**
- Ara Kourchians, Electronics, **Robotic Actuation and Sensing Group**
- Matt Burkhardt, PhD Student, **Caltech**
- Dr. Will Reid, Postdoc, **Robotic Mobility Group**
- Dr. Peyman Tavallali, Deep Learning Technologies Group, **Mission Control Section**

Two Types of Modular Actuators

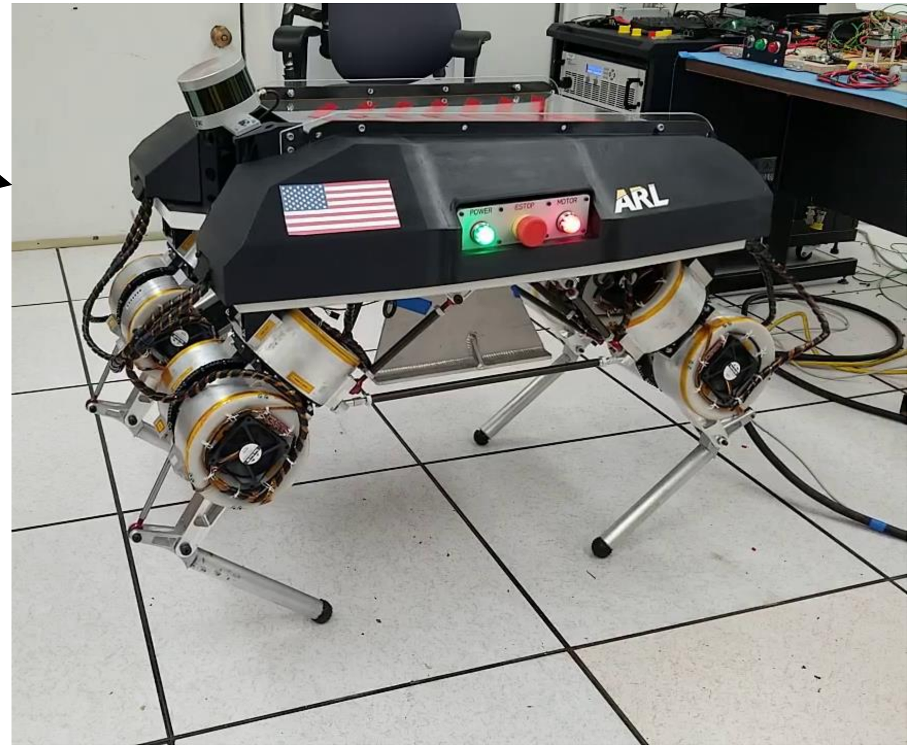
- Heavily geared (160:1)
- Onboard brakes

- Large diameter low-gear ratio
- high torque density and
- high back-drivability



21x
30x
32x
#DARPADRC
DARPA
ROBOTICS CHALLENGE
FINALS 2015
JPL

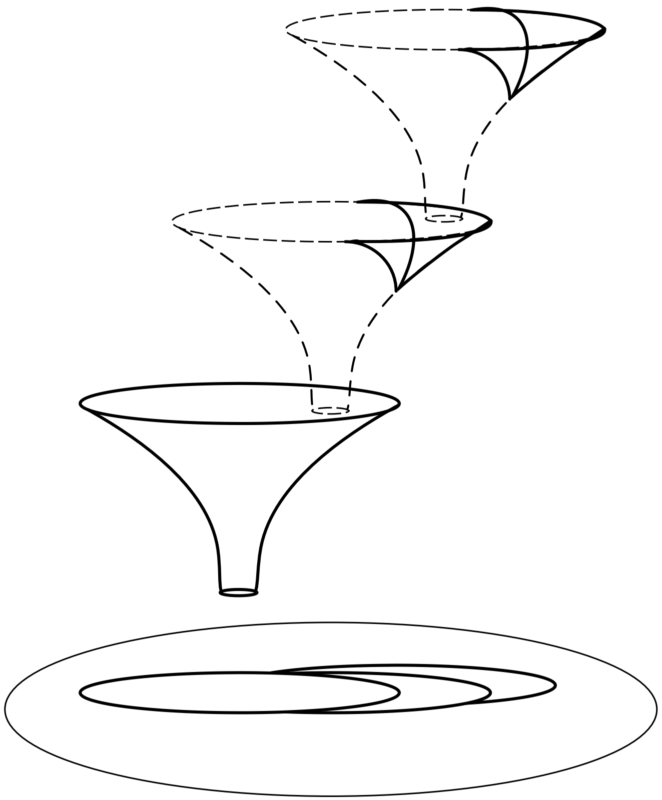
12x



Bag of Behaviors + Sequential Composition

Approach to Autonomy

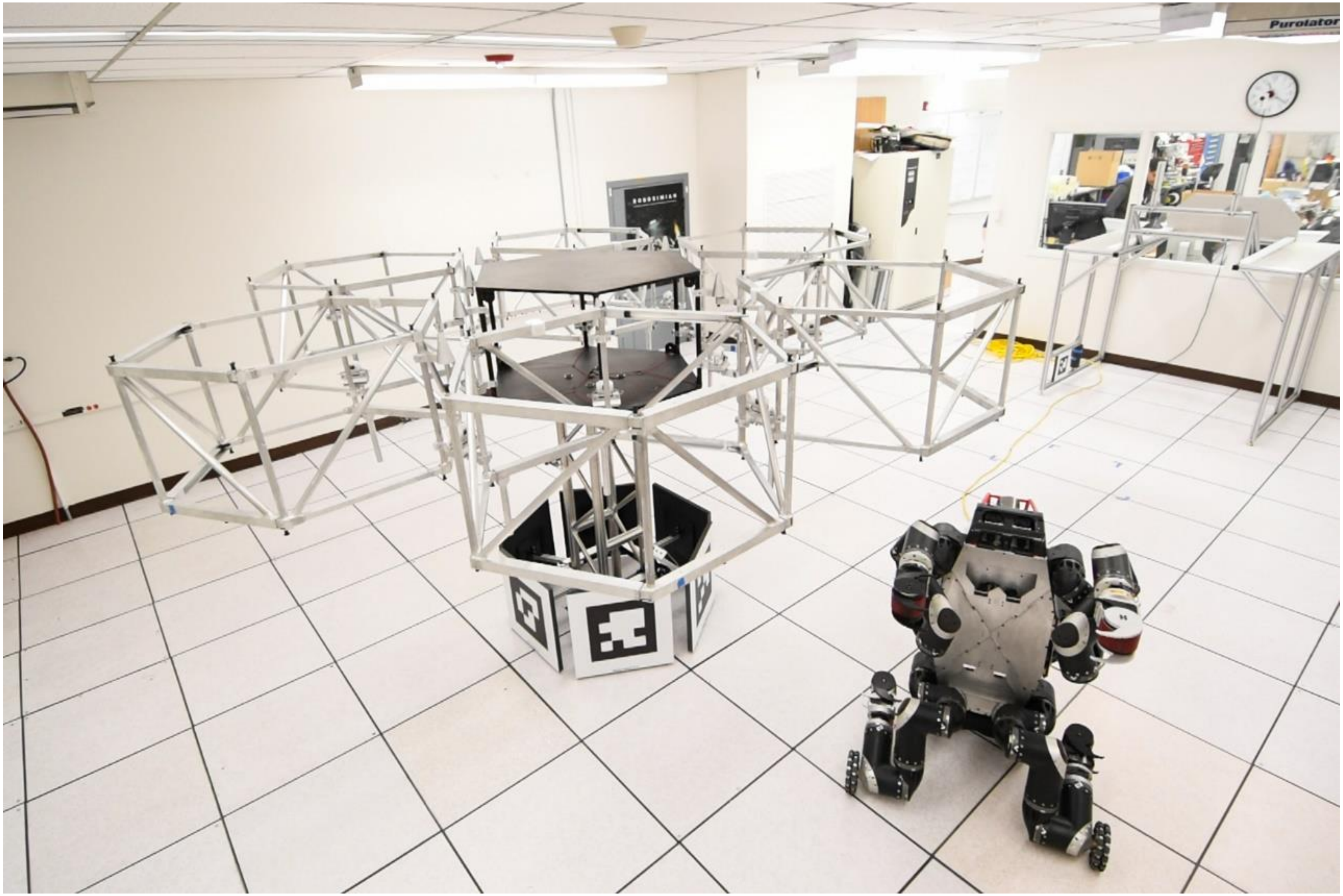
Sequential Composition



Goal point of each controller lies within the domain of attraction induced by the next lower controller.

Burridge, Robert R., Alfred A. Rizzi, and Daniel E. Koditschek. "Sequential composition of dynamically dexterous robot behaviors." *The International Journal of Robotics Research* 18.6 (1999): 534-555.

Autonomous Telescope Assembly



Autonomous Telescope Assembly

Jet Propulsion Laboratory
California Institute of Technology

In-Space Telescope Assembly Robotics Risk Reduction

In-Lab Demo 3: Three Consecutive Runs: Jan 17, 2017

Dr. Rudranarayan Mukherjee (PI), Dr. Sisir Karumanchi, Kyle Edelberg, Russell Smith, Blair Emanuel, Jason Carlton, Jeremy Nash, Dr. Junggon Kim, John Koehler, Charles Bergh, Brett Kennedy, Dr. Paul Backes

Jet Propulsion Laboratory, California Institute of Technology
Pasadena California 91109 USA

Program Manager: Dr. Lindsay Millard
DARPA Tactical Technology Office

URS268863

S. Karumanchi, et al., *"Payload Centric Autonomy for In-Space Robotic Assembly of Modular Space Structures"*, Journal of Field Robotics (JFR). 2018;1–17.

```
# Do truss 0
seq_run ISTAR_get_truss0.seq
seq_run ISTAR_insert_truss0.seq
seq_run ISTAR_tag0_return.seq

# Do truss 2
seq_run ISTAR_get_truss2.seq
seq_run ISTAR_tag2_setup_simple.seq
seq_run ISTAR_insert_truss2.seq
seq_run ISTAR_tag2_return.seq

# Do truss 3
seq_run ISTAR_get_truss3.seq
seq_run ISTAR_tag3_setup_simple.seq
seq_run ISTAR_insert_truss3.seq
seq_run ISTAR_tag3_return.seq

# Do truss 4
seq_run ISTAR_get_truss4.seq
seq_run ISTAR_tag4_setup_simple.seq
seq_run ISTAR_insert_truss4.seq
seq_run ISTAR_tag4_return.seq

# Do truss 5
seq_run ISTAR_get_truss5.seq
seq_run ISTAR_tag5_setup_simple.seq
seq_run ISTAR_insert_truss5.seq
seq_run ISTAR_tag5_return.seq

# Do truss 6
seq_run ISTAR_get_truss6.seq
seq_run ISTAR_tag6_setup_simple.seq
seq_run ISTAR_insert_truss6.seq
seq_run ISTAR_tag6_return.seq
```

The full end-to-end sequence is broken down into subtasks that are autonomously executed separately. Each subtask is specified by a command sequence that is stored in a sequence file. A command sequence is hierarchical including subsequences or sequence commands.

Sub-Sequence 1:

Autonomous Sequence to Pick up a Truss From the Truss Dispenser

```
# go and get truss from dispenser area
seq_run go_and_get_truss.seq
```

~70 Lines

```
# --------------------

# go to pregrasp
mob_run_wb_primitive pregraspreset

# unsqueeze hands
manip_unsqueeze

#find the 0th tag
ocu_find_tag man_upper left 0 1 0 0.3065

# go to pregrab_prepremanip pose, odo carrot
ocu_goto_navgoal truss 0 4 shortest 0

#find the 0th tag
ocu_find_tag man_upper left 0 1 0 0.3065

# go to pregrab_premanip pose, odo carrot
ocu_goto_navgoal truss 0 3 shortest 0

# back up so haz_right can see the tag
ctrl_drive_linear -0.5 0.1 0

#find tag5 (small) in haz right
ocu_find_tag haz_right right 0 1 5 0.162

# go to pregrab-manip pose, odo carrot
ocu_goto_navgoal tag 5 0 shortest 0
```

...

```
# ---------------------
# --- grab truss --- ---
# ---------------------

#cage fingers
seq_run dual_cage.seq

# reset posture
mob_run_wb_primitive pregraspreset

#find tag5 in haz right
ocu_find_tag haz_right right 0 1 5 0.162

# move each limb to premanip
ocu_goto_eegoal tag 5 2 0 limb1
ocu_goto_eegoal tag 5 1 0 limb4

# move each limb to manip
ocu_goto_eegoal tag 5 12 0 limb1
ocu_goto_eegoal tag 5 11 0 limb4

# squeeze
manip_squeeze 100

#close fingers
seq_run dual_close.seq
```

...

```
# --------------------
# --- pop and drive ---
# --------------------

# dual cart to pop pose
ocu_goto_eegoal tag 5 6 1 limb1

ctrl_drive_linear -0.01 0.1 0

# drive out
ctrl_drive_linear 1.5 0.1 0
```

Sequence files are made up of parameterized commands.

What we did not do

- No accurate calibration (precise not accurate)
- No external meterology
- No continuous fiducial tracking
- No long term memory

What we did do

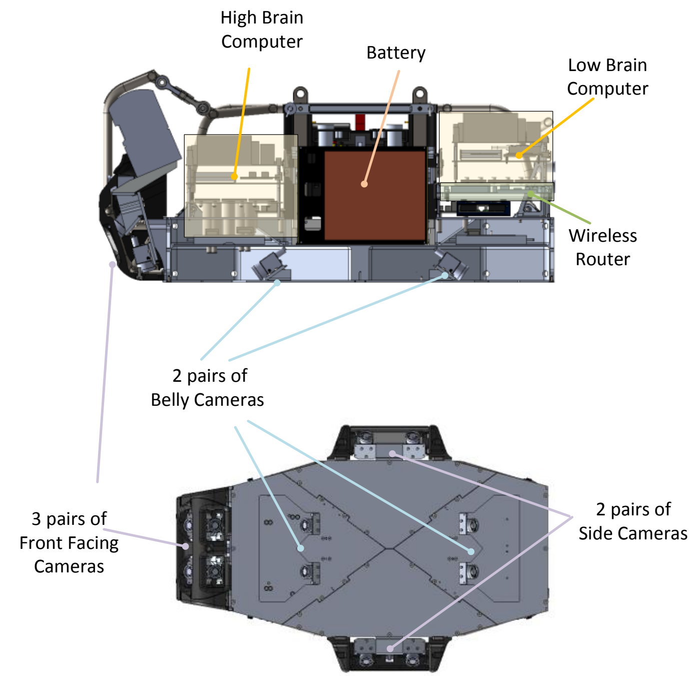
Gated Recognition

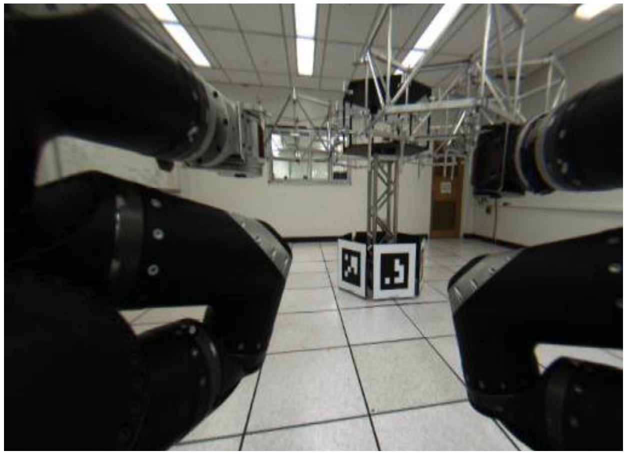
- Selected camera’s based on distance and angle
    - to prevent outliers

Funneling via construction

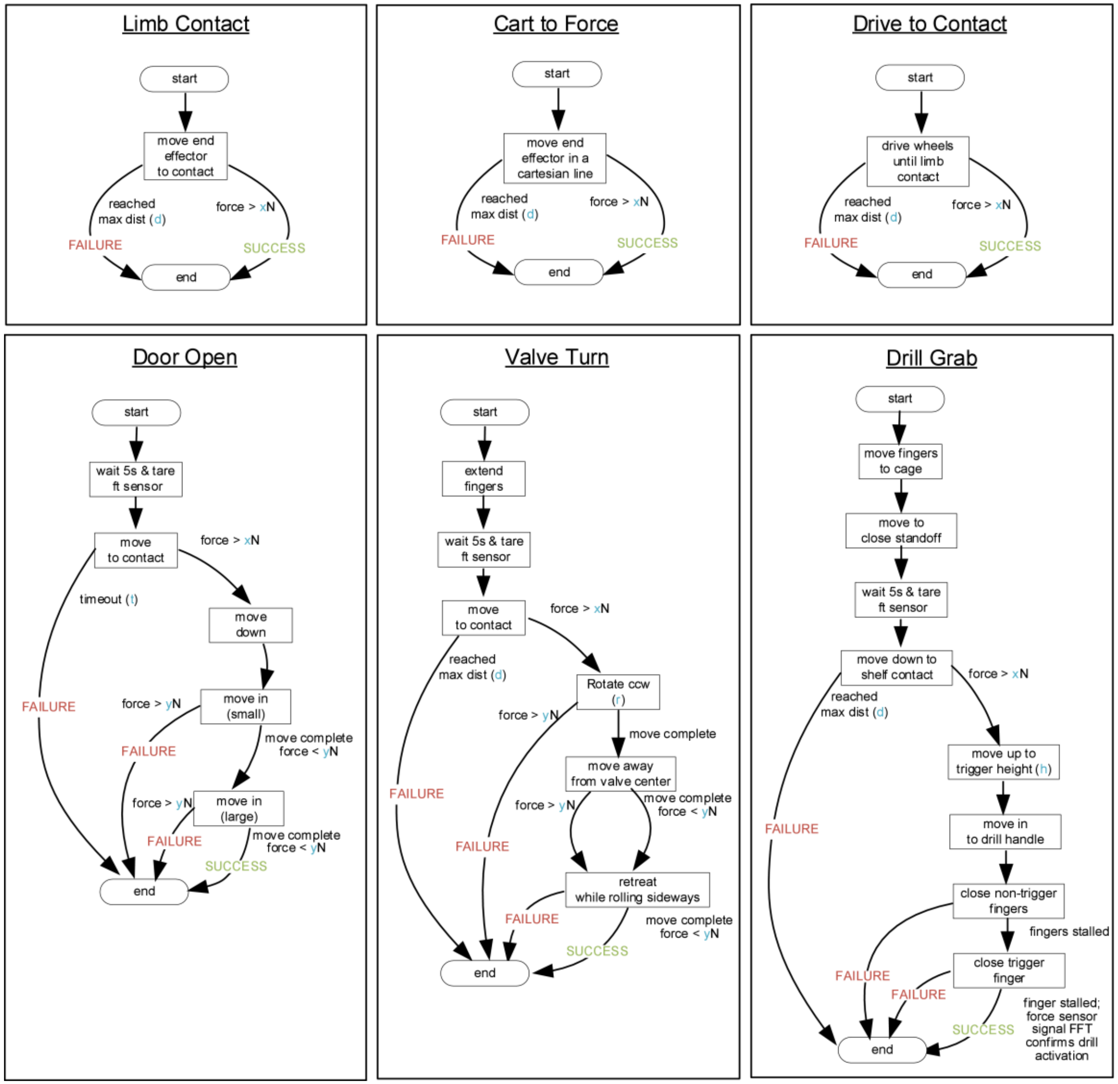
- big corrections at the beginning
- small corrections at the end

    chose behaviors that enabled the above
    by construction





Behaviors at the DRC



Proprioceptive feedback

"ego-centric sense of position & movement w.r.t the environment…"

"… of robot's body or a manipuland"

Proprioceptive Feedback

1. Why care?

2. How we used it in recent past?

3. Ongoing/Future work

Towards future NASA missions?

Proprioceptive Feedback & Mobile Manipulation

- Mobile Manipulation
  - Go somewhere and do something
- Do more with less sensing, task specification and *a priori* information.
- Using feedback to adjust a rough inaccurate task specification
  - Specfically setpoints in SE(3))

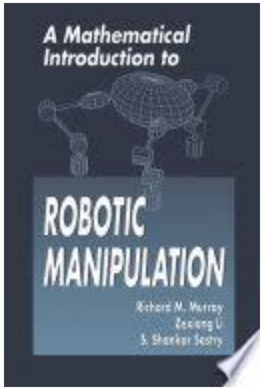
Ego-centric Feedback (SE(3))

$$T^{W}_{R/EE}(t + dt) = T^{W}_{R/EE}(t)e^{\hat{\xi}^{R}dt}$$

Vs.

$$T^{W}_{R/EE}(t + dt) = e^{\hat{\xi}^{W}dt}T^{W}_{R/EE}(t)$$

Using Notation from



Murray, R. M., Li, Z., & Sastry, S. S. A Mathematical Introduction to Robotic Manipulation.

Why Proprioceptive Feedback?

- Ego-centric
  - can offset requirements on localization performance
  - can offset sensitivity to worst case performance of recognition tasks
- Effective if correlated with task performance & control inputs
  - Can monitor task and do something about it
  - E.g. current feedback + high friction actuators is ineffective
    - good signal with control inputs
    - poor signal with task performance

Proprioceptive Feedback

1. Why care?

2. How we used it in recent past?

3. Ongoing/Future work

Towards future NASA missions?

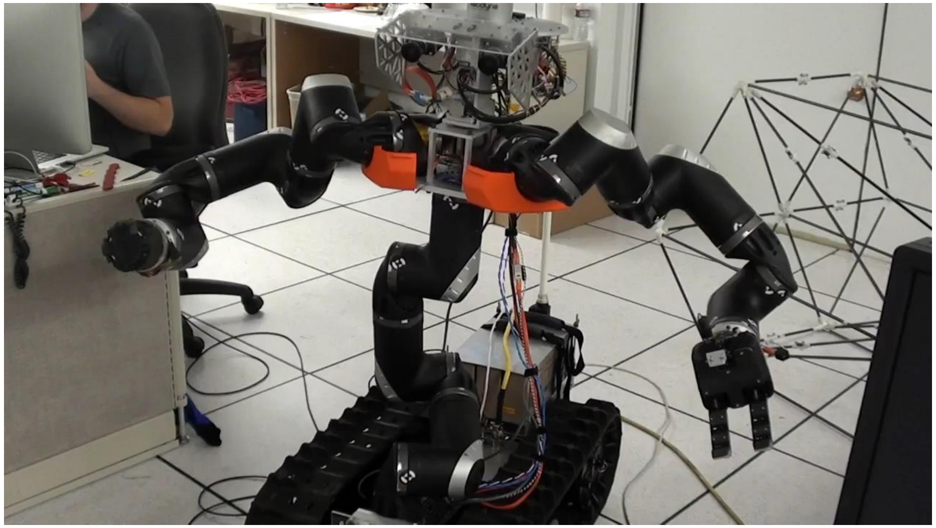
Force feedback behaviors

Using force measurements as a direction fix

(measurements on the tangent space of SE(3))

Virtual Compliance

Single Arm



2014

Dual Arm

2015

Posture control

For Locomotion

Whole-Body Posture & Admittance Control for Locomotion

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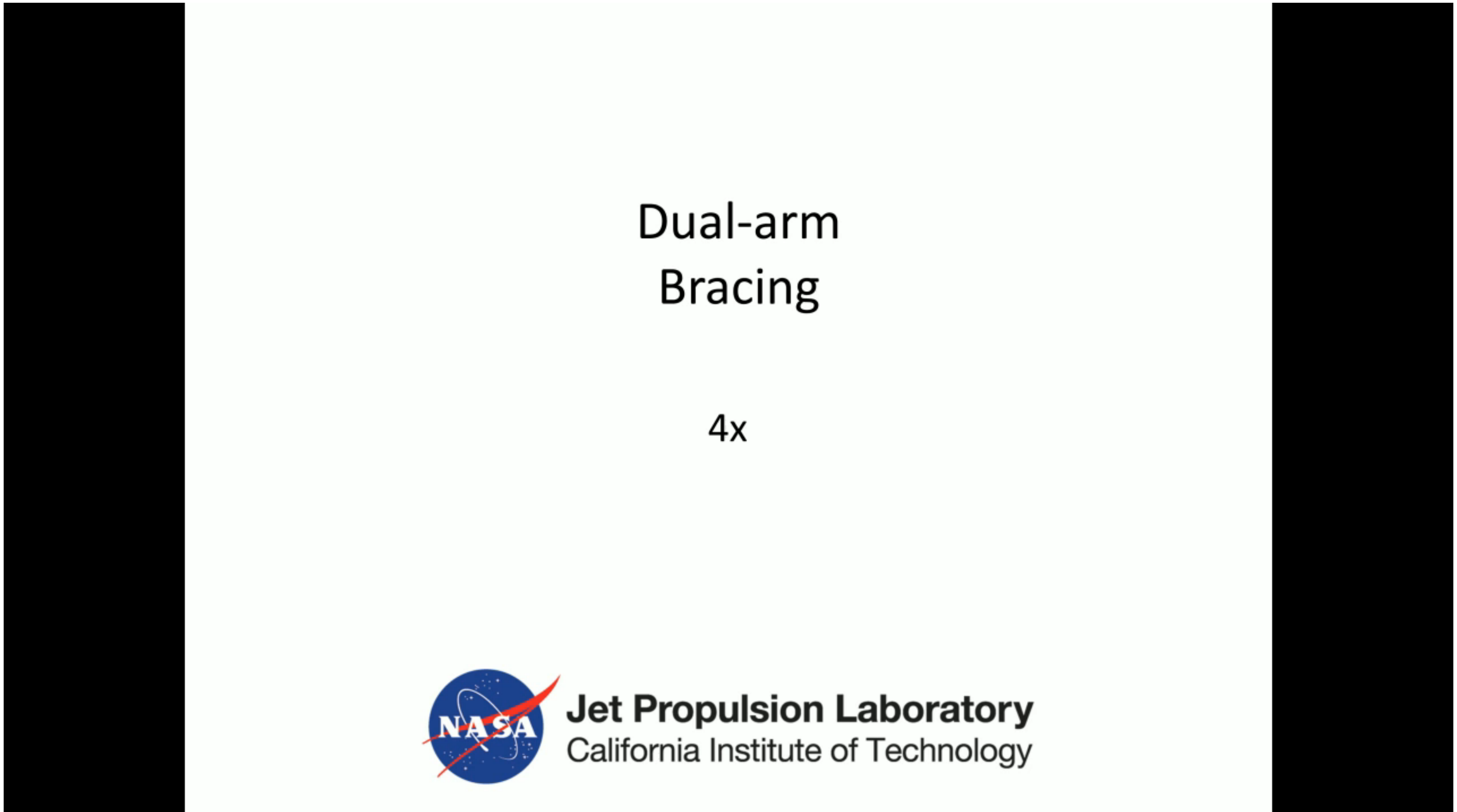
Bracing

EE wrench -> torso twist

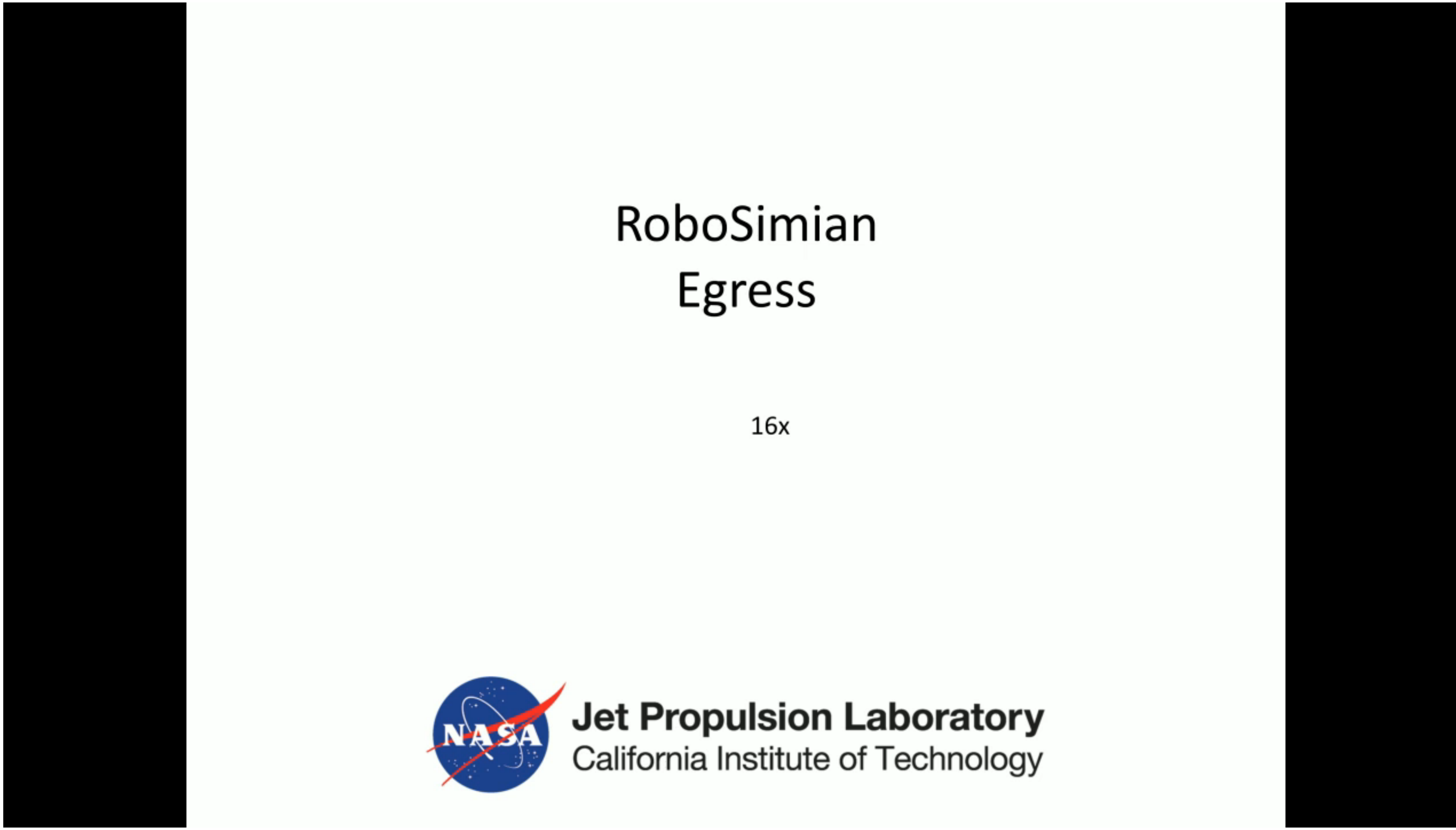


2014

- Easy to get into brace posture, hard to get out of it (actuator torque overload).
- When to unbrace?
    - Using braced EE force measurement to drive torso movement

DRC Egress

Mobile Manipulation as a Grasping Problem



- 3D Locomotion – Open loop trajectory following + Leg odometry
- Interspersed with force feedback behaviors to relieve internal force buildup
- Force closure problem

Dual Arm Squeeze

Heavy Payload
Shifting Contents

~40 lbs

Dual-arm Squeeze Behavior
Autonomy vs. Semi-autonomy

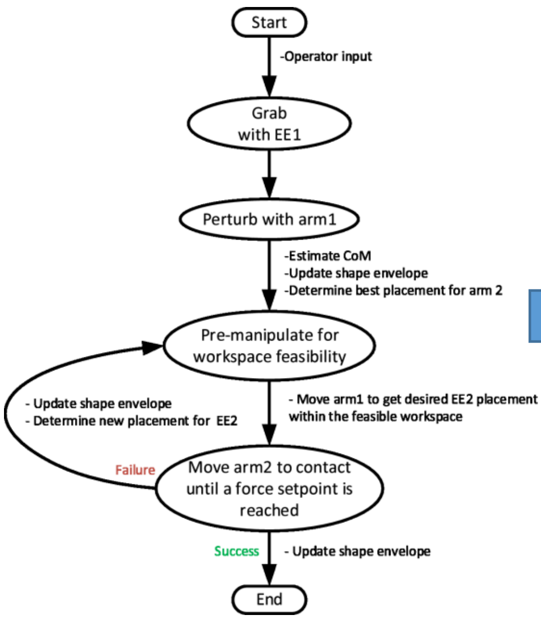
8x

Jet Propulsion Laboratory
California Institute of Technology

Probe and Adapt

Screw theory meets probability theory

One Behavior + N Objects
Random First Grasps

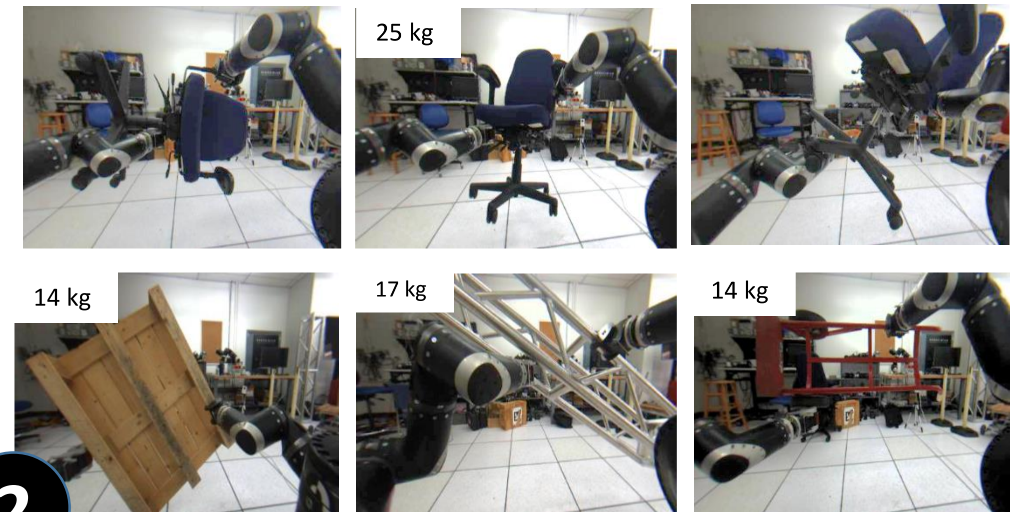


(a) Grasp 1 - Chair
(b) Grasp 2 - Chair
(c) Grasp 3 - Chair
(d) Grasp 4 - Chair
(e) Grasp 1 - Hand-truck
(f) Grasp 2 - Hand-truck
(g) Grasp 3 - Hand-truck
(h) Grasp 4 - Hand-truck
(i) Grasp 1 - Pallet
(j) Grasp 2 - Pallet
(k) Grasp 3 - Pallet
(l) Grasp 4 - Pallet
(m) Grasp 1 - Stanchion
(n) Grasp 2 - Stanchion
(o) Grasp 3 - Stanchion
(p) Grasp 4 - Stanchion
(q) Grasp 1 - Truss
(r) Grasp 2 - Truss

Unknown Bulky Objects

1

Estimating CoM and Shape of an unknown object via physical interaction

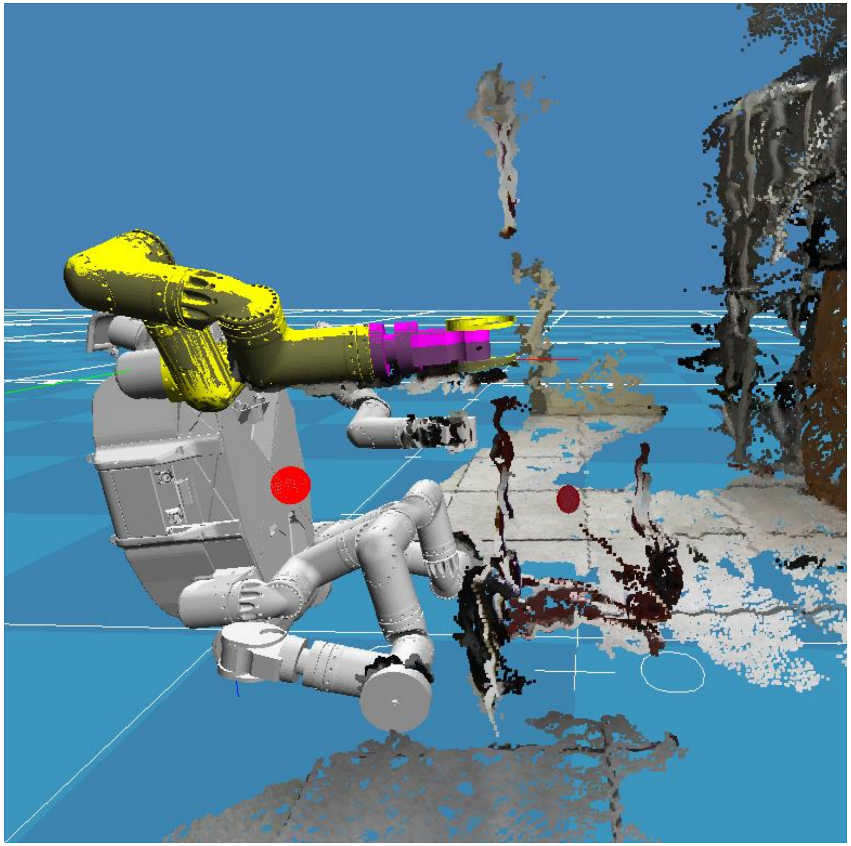


2

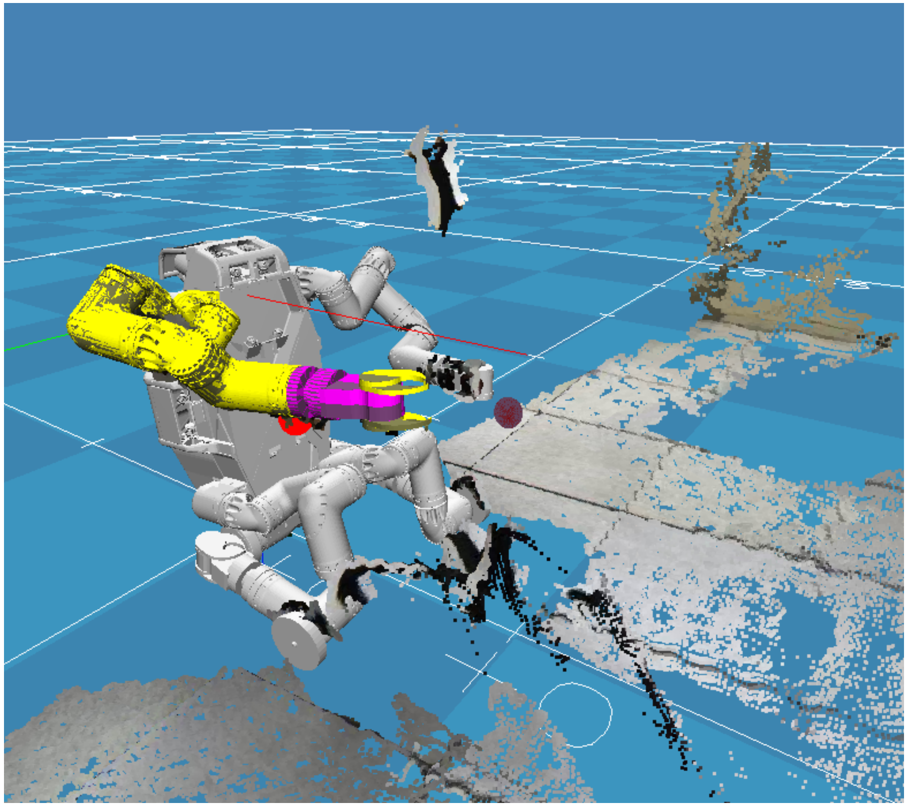
Automatic selection of second end effector based on iterative inference of CoM and Shape via force torque measurements only.

- Dual arm manipulation of unknown bulky objects
- Unknown inertial properties (weight and mass distribution).
- Severe self-occlusions in sensing field-of-view at close proximity.
- Using force torque measurements alone.
- Stable under disturbances from clutter
- Fast convergence with few trials.
- A Probe & Adapt Strategy.

Noisy Exteroception



Noisy Exteroception



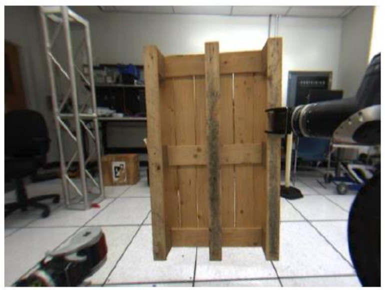
URS272240

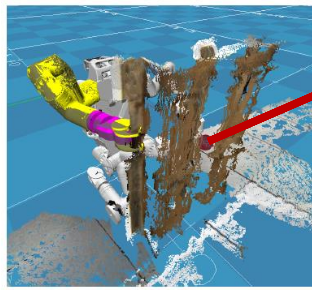
https://youtu.be/hQ_3PeVhk5E

M. Burkhardt, **S. Karumanchi**, K. Edelberg, J. Burdick, and P. Backes, ***"Proprioceptive Inference for Dual-Arm Grasping of Bulky Objects Using RoboSimian"***, IEEE International Conference on Robotics and Automation (ICRA), 2018

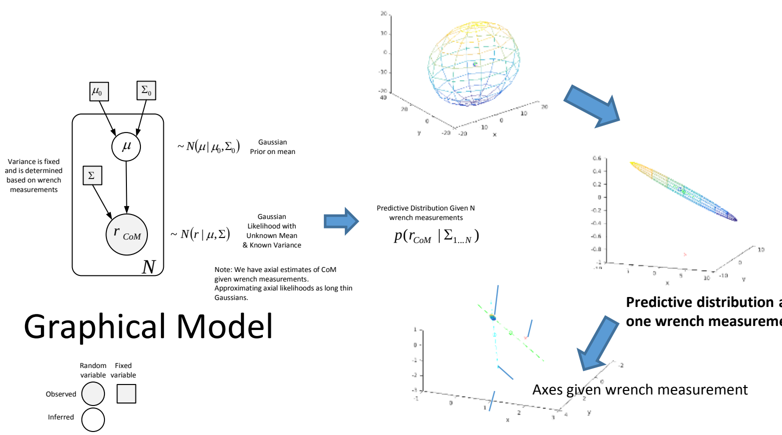
Inference Approach

CoM inference in a Bayesian Inference Framework





CoM
Estimate



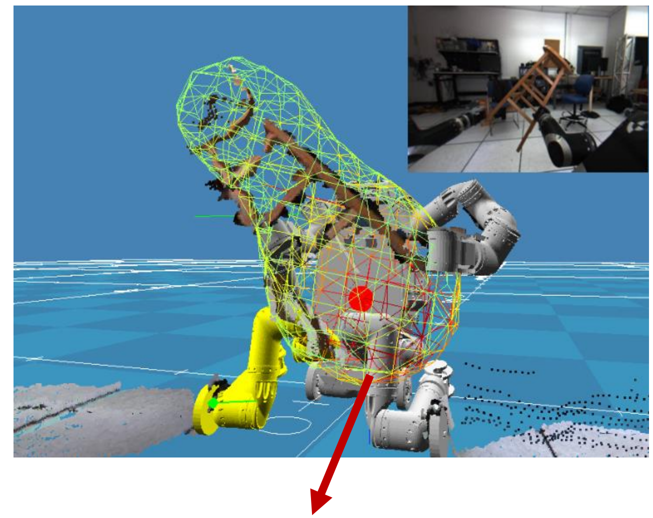
Graphical Model

Predictive distribution after one wrench measurements

Axes given wrench measurement

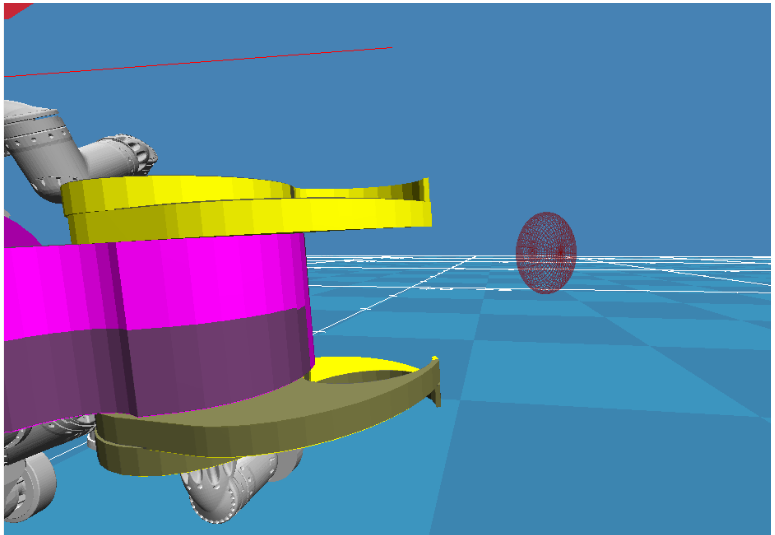
Predictive distribution after two wrench measurements

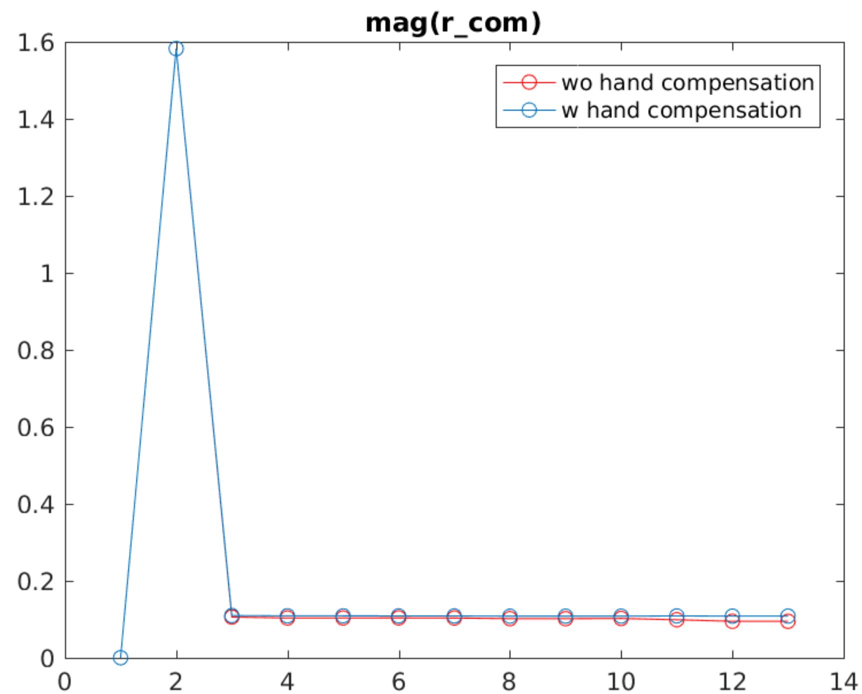
Shape inference in a Bayesian Inference Framework



Shape Estimate as an
Implicit Surface
(Mean shown as a Mesh;
Color implies Variance)

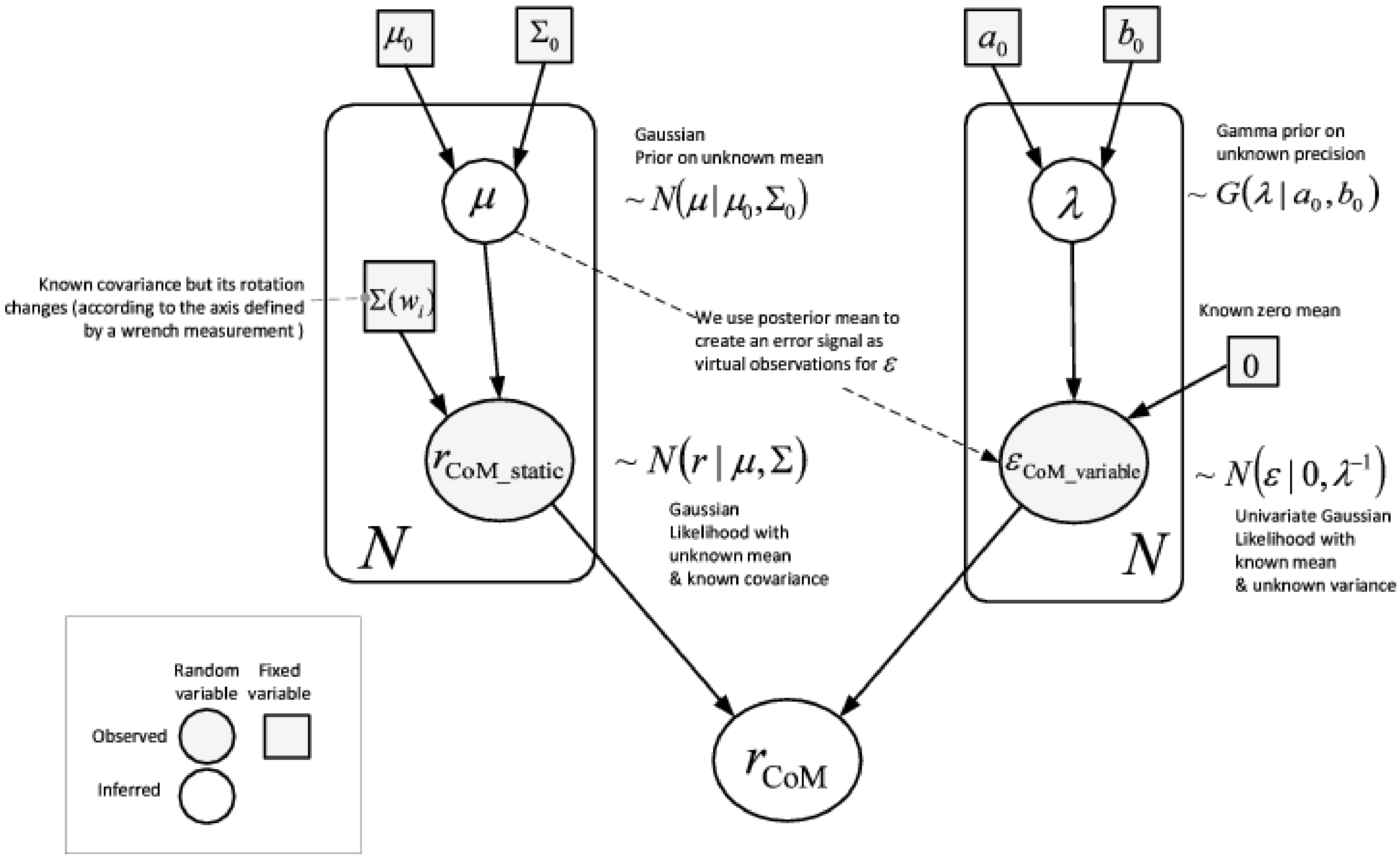
CoM Estimation

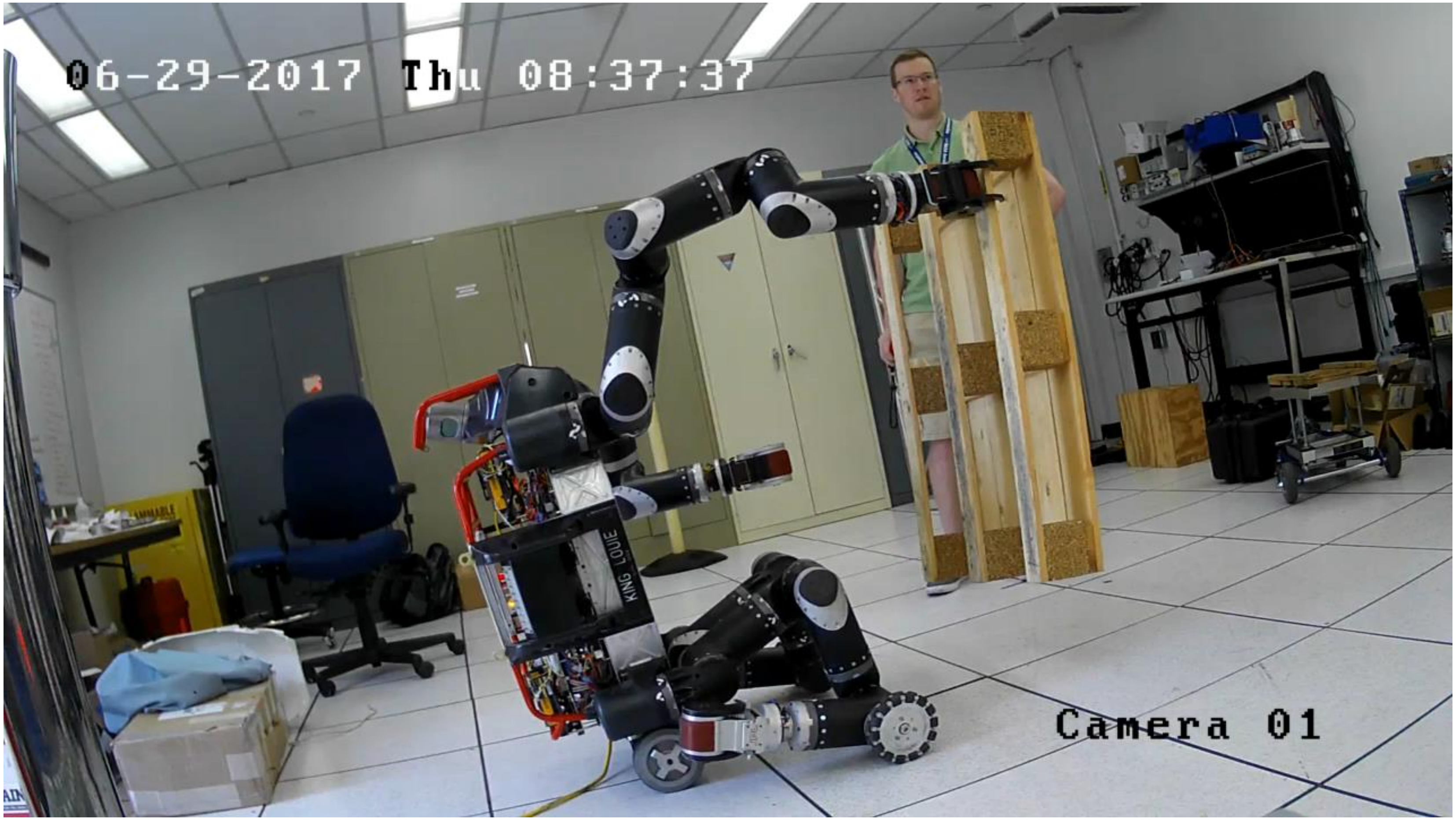




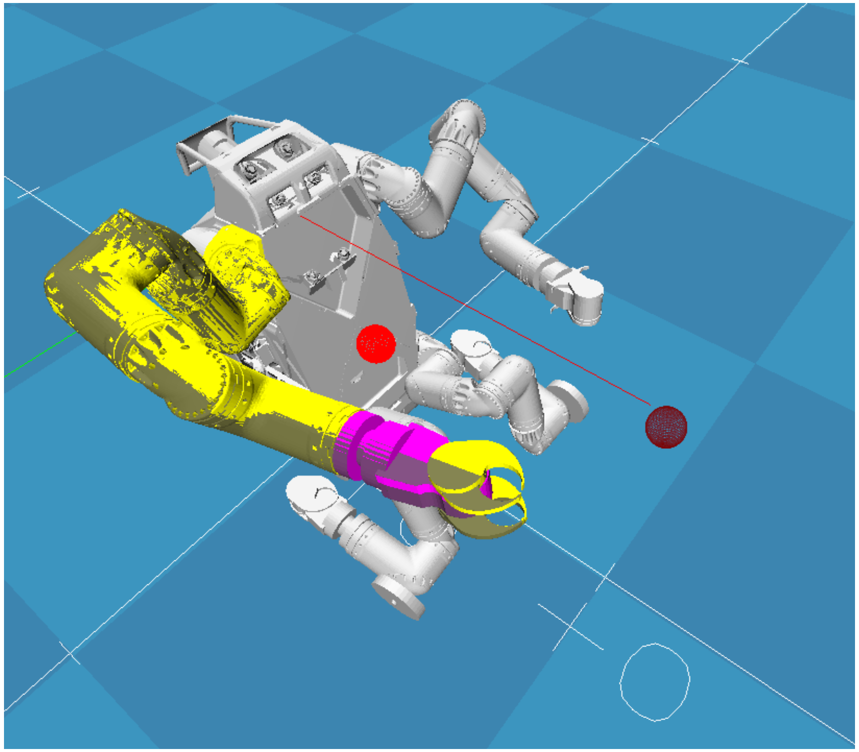
Fast Convergence

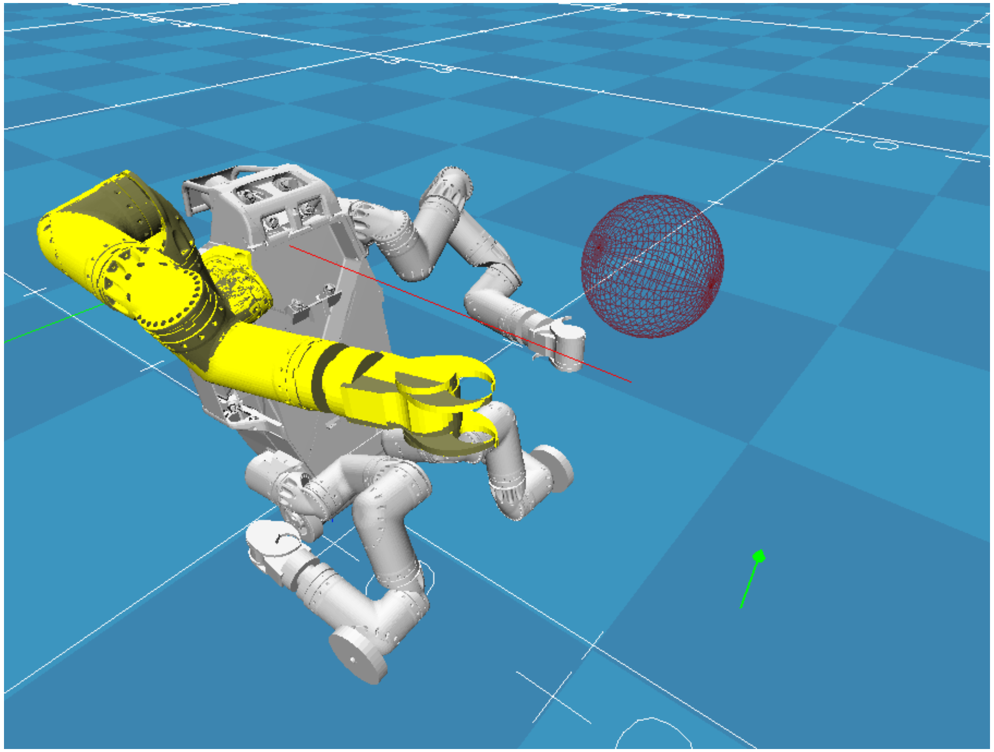
Enhanced CoM Estimation




06-29-2017 Thu 08:37:37
KING LOUIE
Camera 01

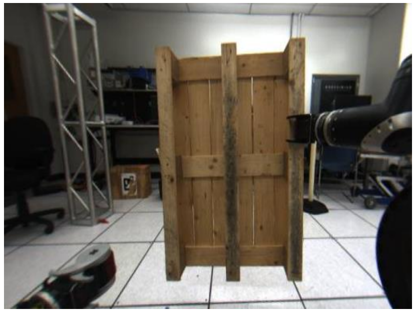
Under Disturbance

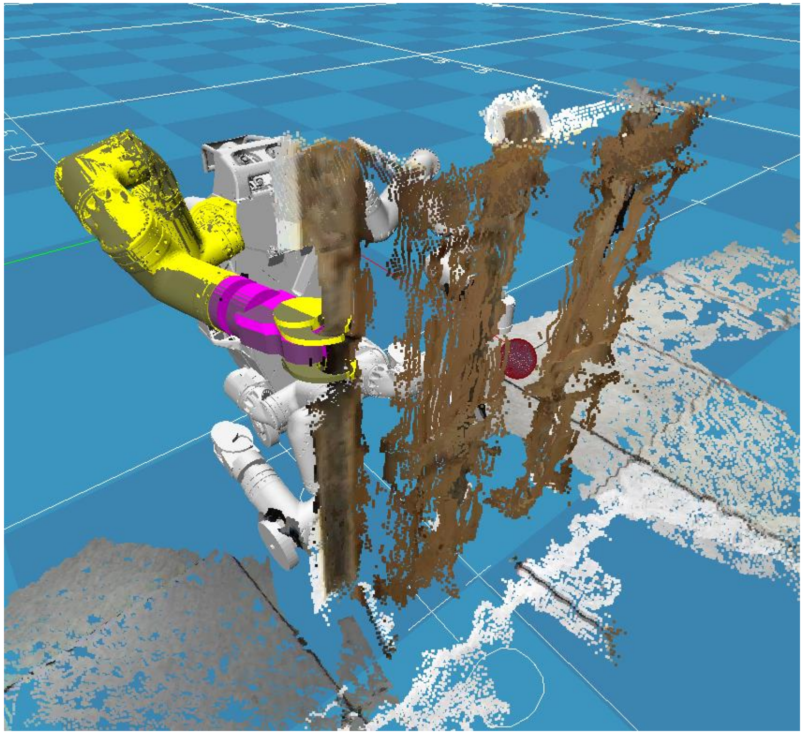


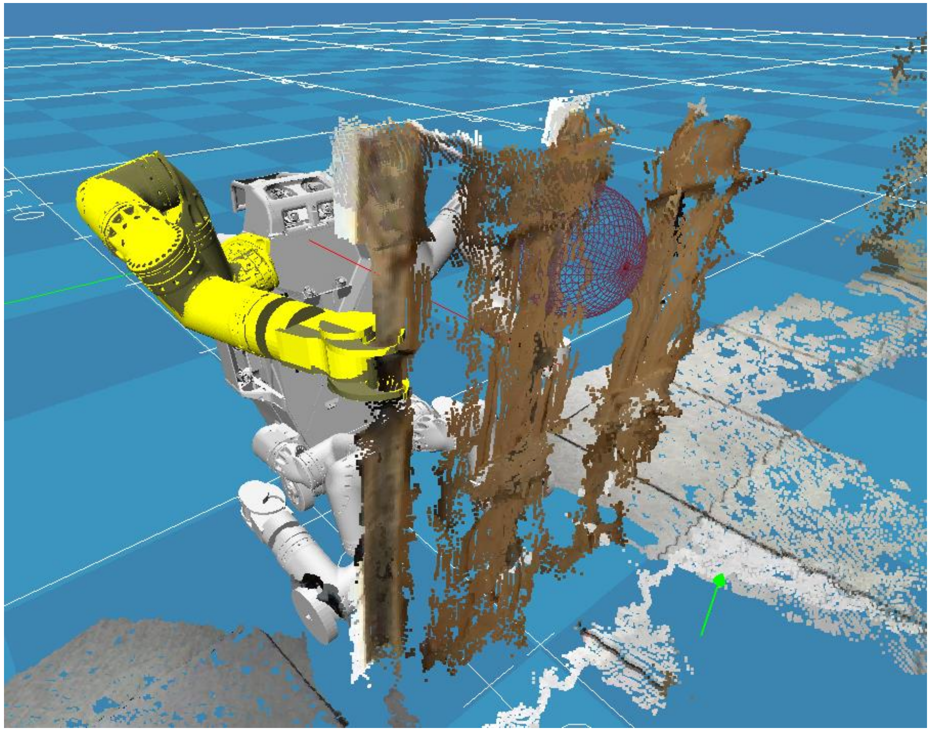


With Kicking

Under Disturbance







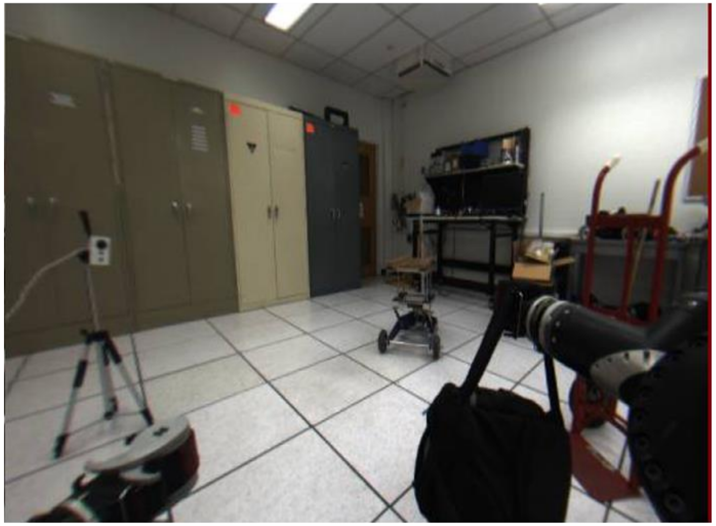
Deformable Objects

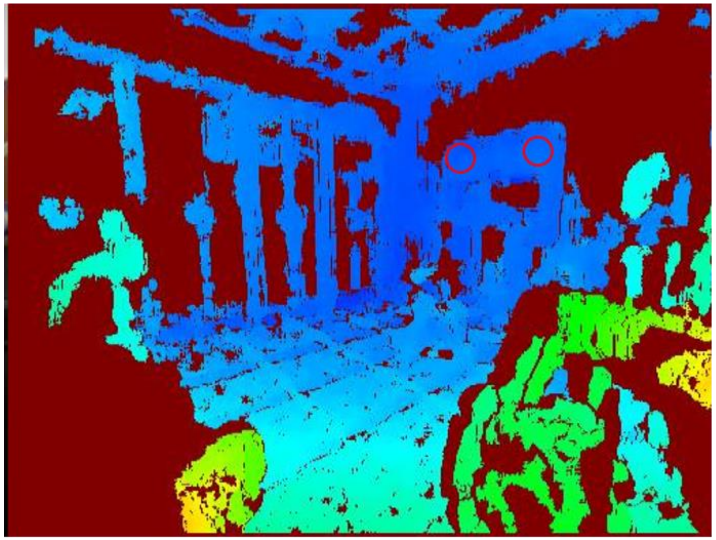
25 lbs

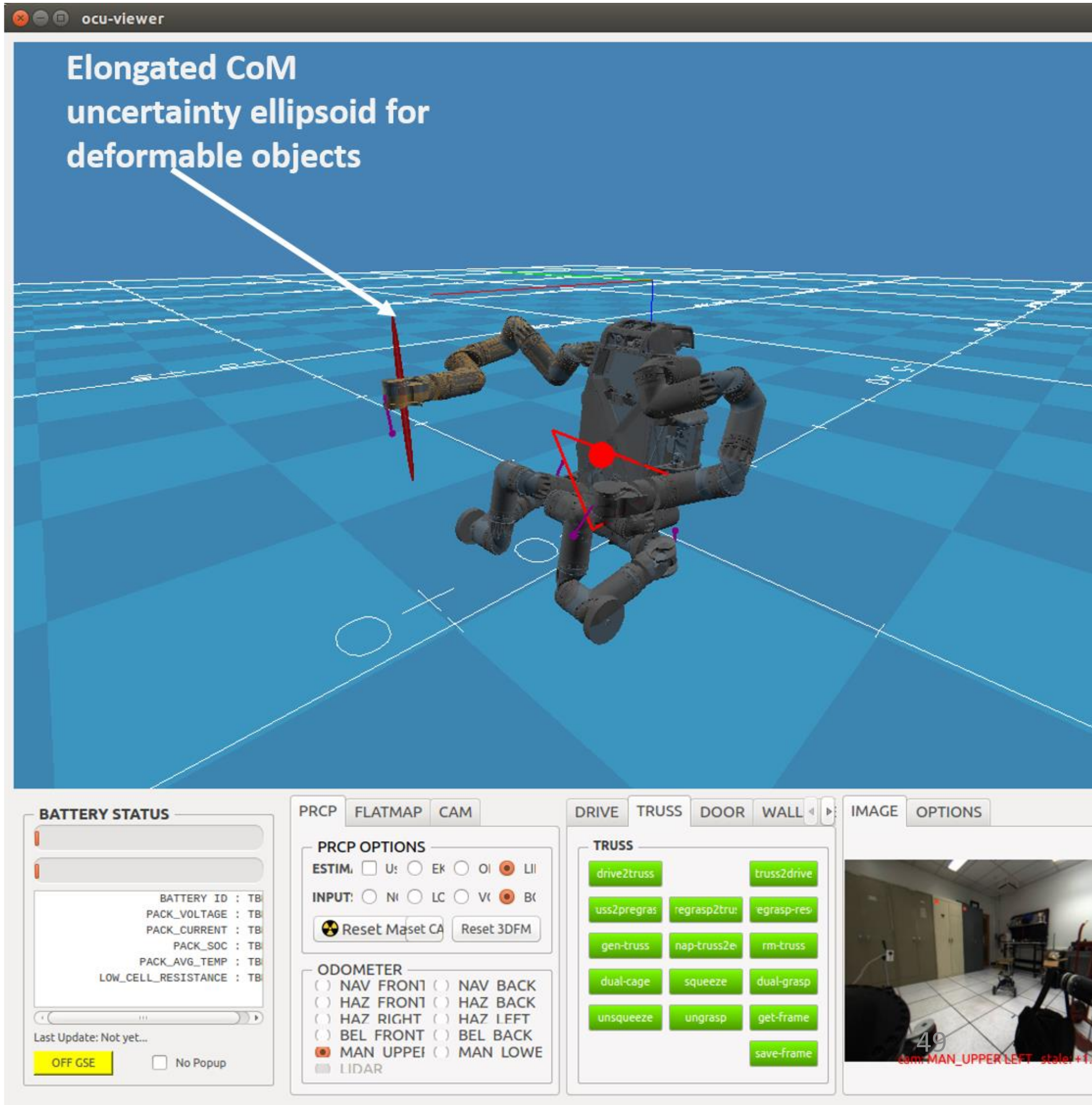
10 lbs

DEFORMABLE OBJECTS

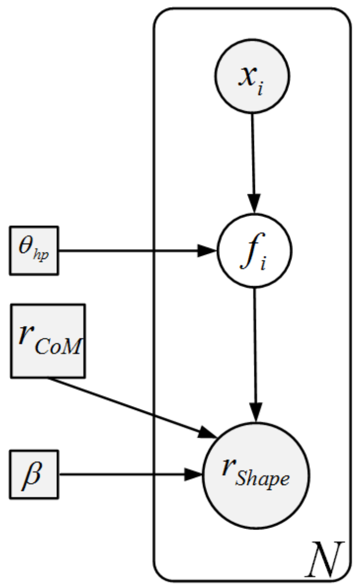
Deformable Objects







Shape inference in a Bayesian Inference Framework
(we expect wrench measurements to be noisy)

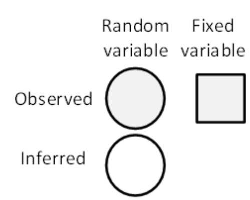


$x - \{\theta, \phi\} -$ Spherical Coordinates Of touch locations relative to CoM

$\sim N(0, K(.,.))$ Gaussian Process Prior for Non-linear Bayesian Regression

$\sim N(f_i, \beta^{-1} I)$ Gaussian Likelihood with Unknown Mean & Known Variance

Graphical Model



$$r_{shape} = r_{CoM} + f(\theta, \phi) + noise$$

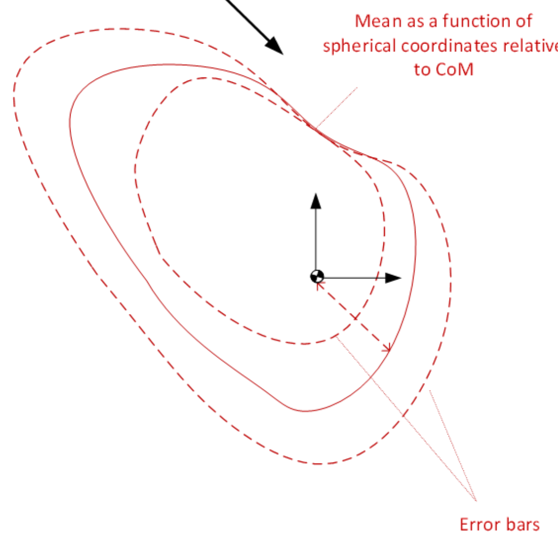
$noise \sim N(0, \beta^{-1} I)$

$f \sim N(0, K(.,.))$

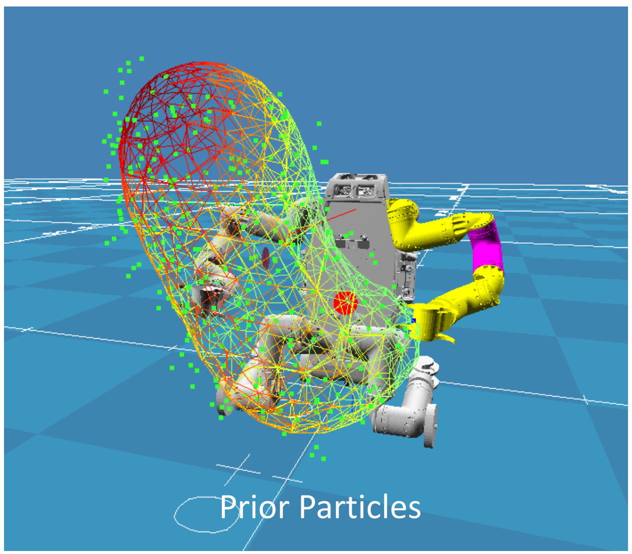
$K - Covariance\ Kernel$

Predictive Distribution

$$p(r_{shape} \mid r_{CoM}, \theta, \phi)$$

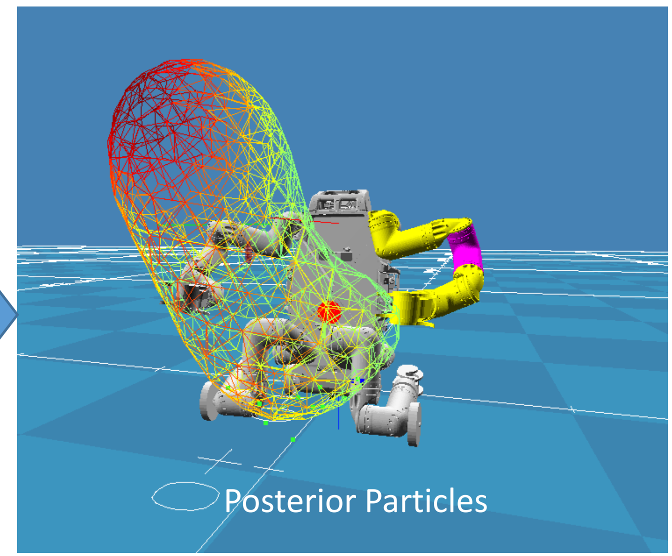


Automatically selecting goals for the second end effector



Particle Filter

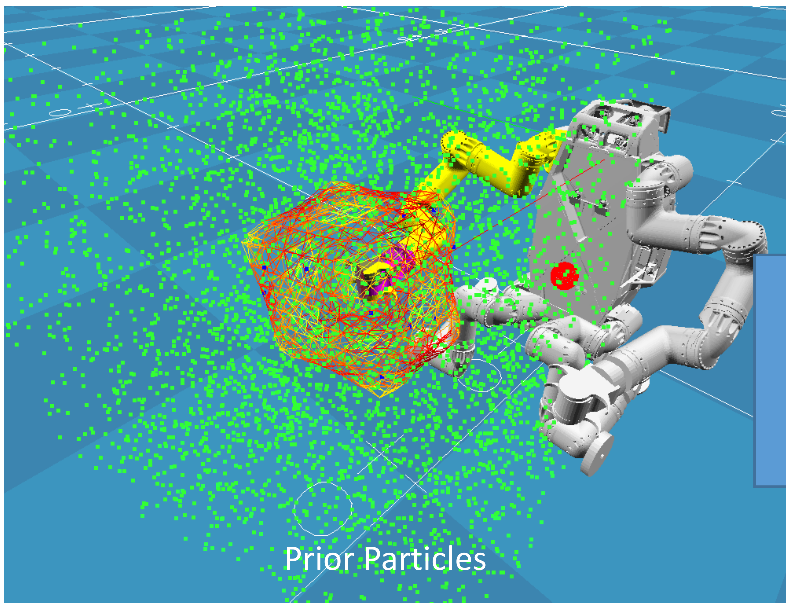
Bayesian Update on Candidate EE goals



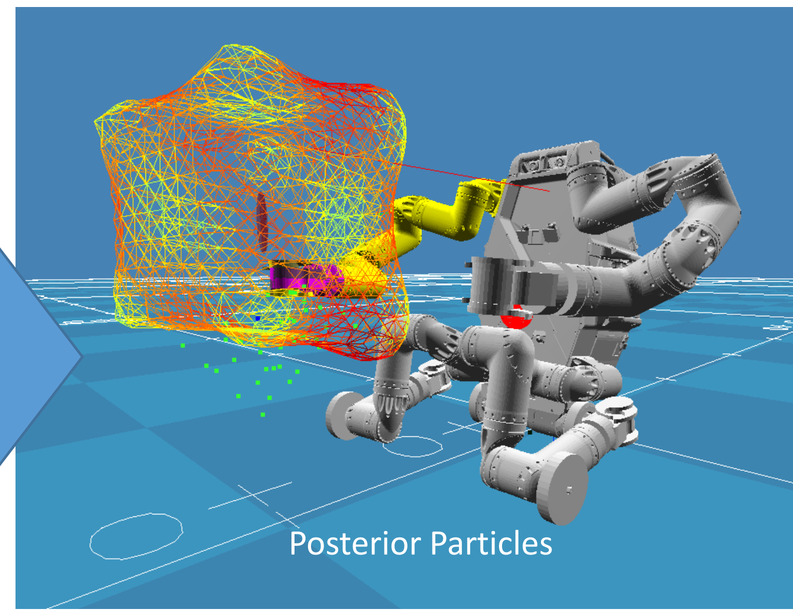
Next-best touch paradigm

Automatically selecting goals for the second end effector

Particle Filter Update (Low variance resampling)



Bayesian Update on Candidate EE goals



Next-best touch paradigm

Proprioceptive Feedback

1. Why care?

2. How we used it in recent past?

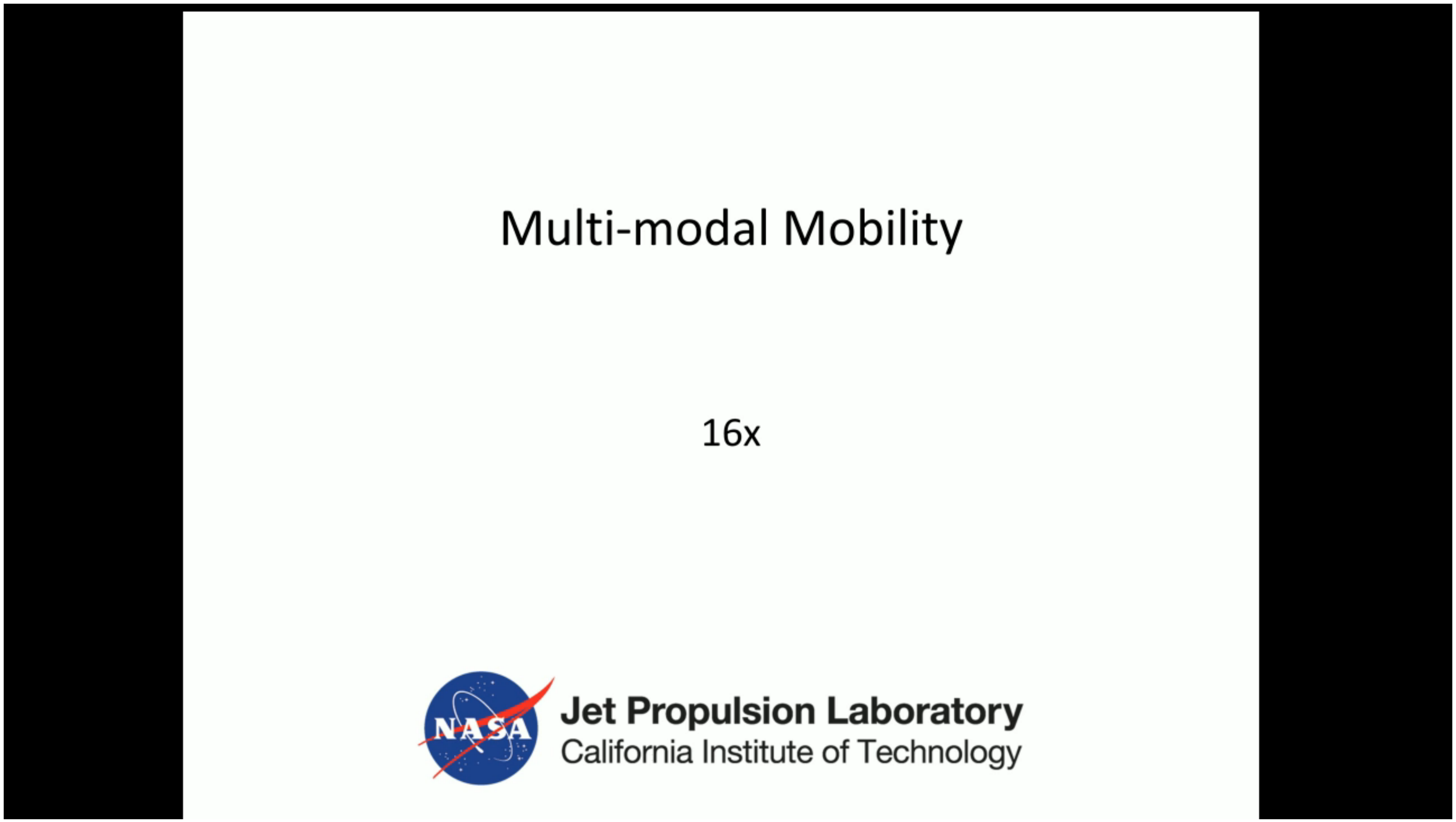
3. Ongoing/Future work

Towards future NASA missions?

Onboard Reasoning

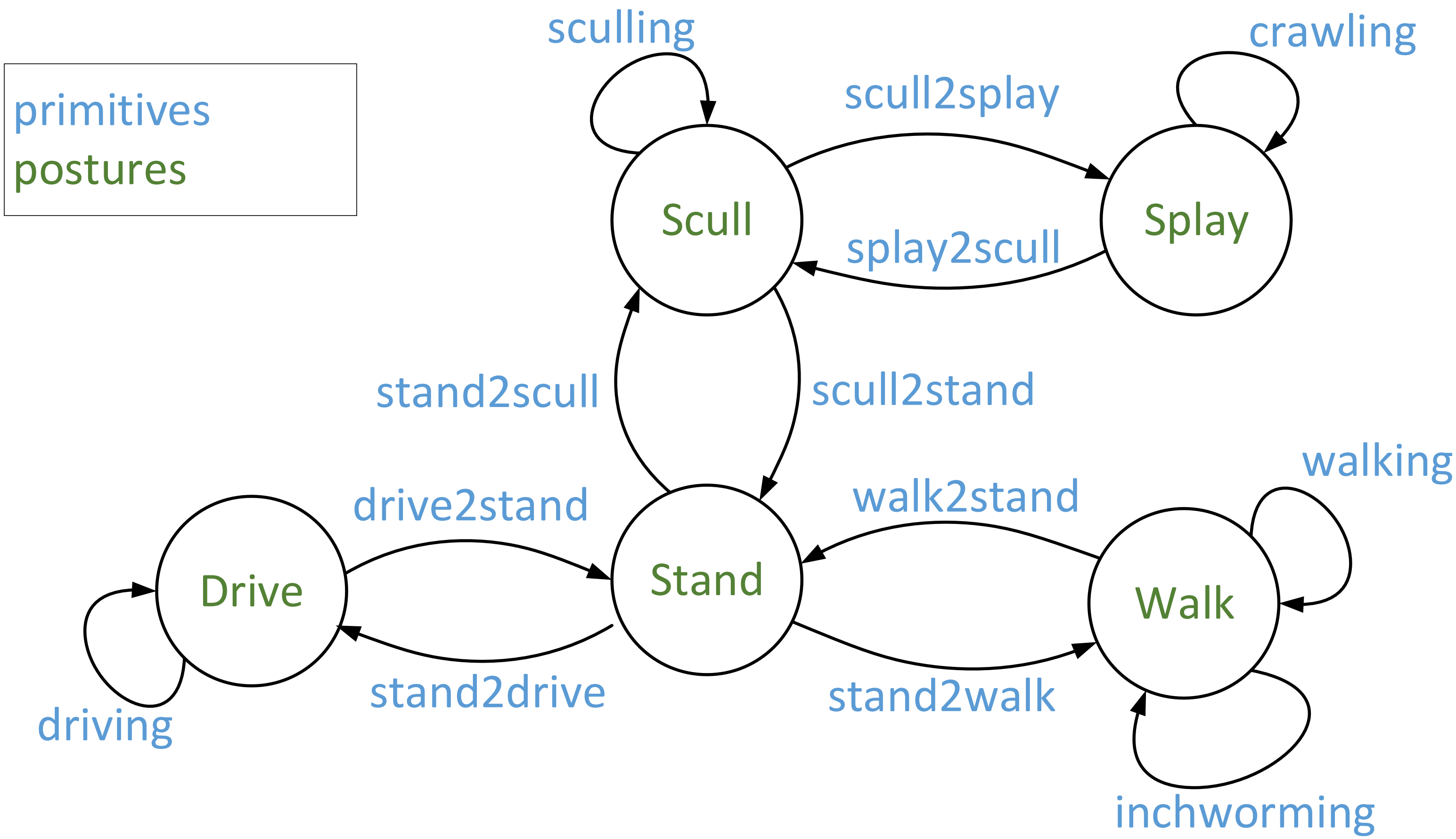
Redundant behaviors & Autoselection

Multi-modal mobility

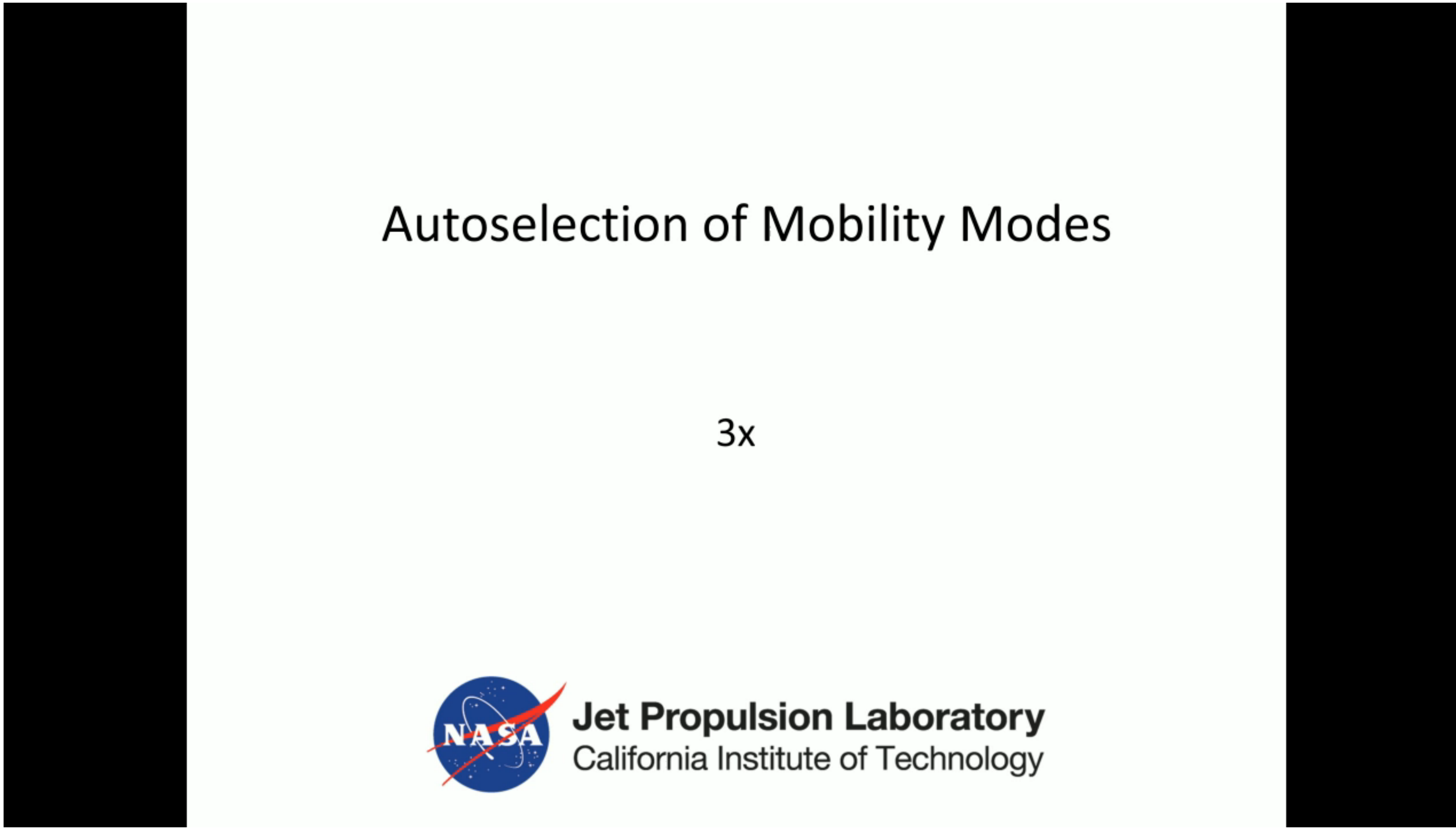


Feasibility Graph

Restricted space for multi-modal mobility



Offline Testing



3x

Multi-Armed Bandit Problem

- Reinforcement Learning (RL) Approach
  - N discrete actions Unobservable State
- Bounded operation on **Feasibility Graph**
  - Feasibility verified offline via extensive on-earth experimentation
- Mobility mode selection via **online performance monitoring**

Reward Signal for Reinforcement Learning
Units: Meters/Joule
translational progress per unit energy consumption

- Fundamental **exploration vs. exploitation** tradeoff.
  - Use a differential reward signal (expected vs. observed).
    - observed $=$ expected $\rightarrow$ exploit
    - observed $\neq$ expected $\rightarrow$ explore

Future NASA Missions

- Missions with Longer & Longer Comms Delays
- On-board autonomy
- Autonomy is a umbrella term
  - Auto Sequencing
  - Fault handling
  - Mission Planning
  - Determining Science value
  - Negotiating unknown harsh environments

Summary

- Simple behaviors generalize better.

- First Order:
  - Using feedback + optimization to adjust task set-points.
  - Does not need perfect localization and prior maps.

- Second Order:
  - Use probing and inference to select task set-points iteratively.

- Third Order:
  - Reason over redundant behaviors via RL on a behavior graph .