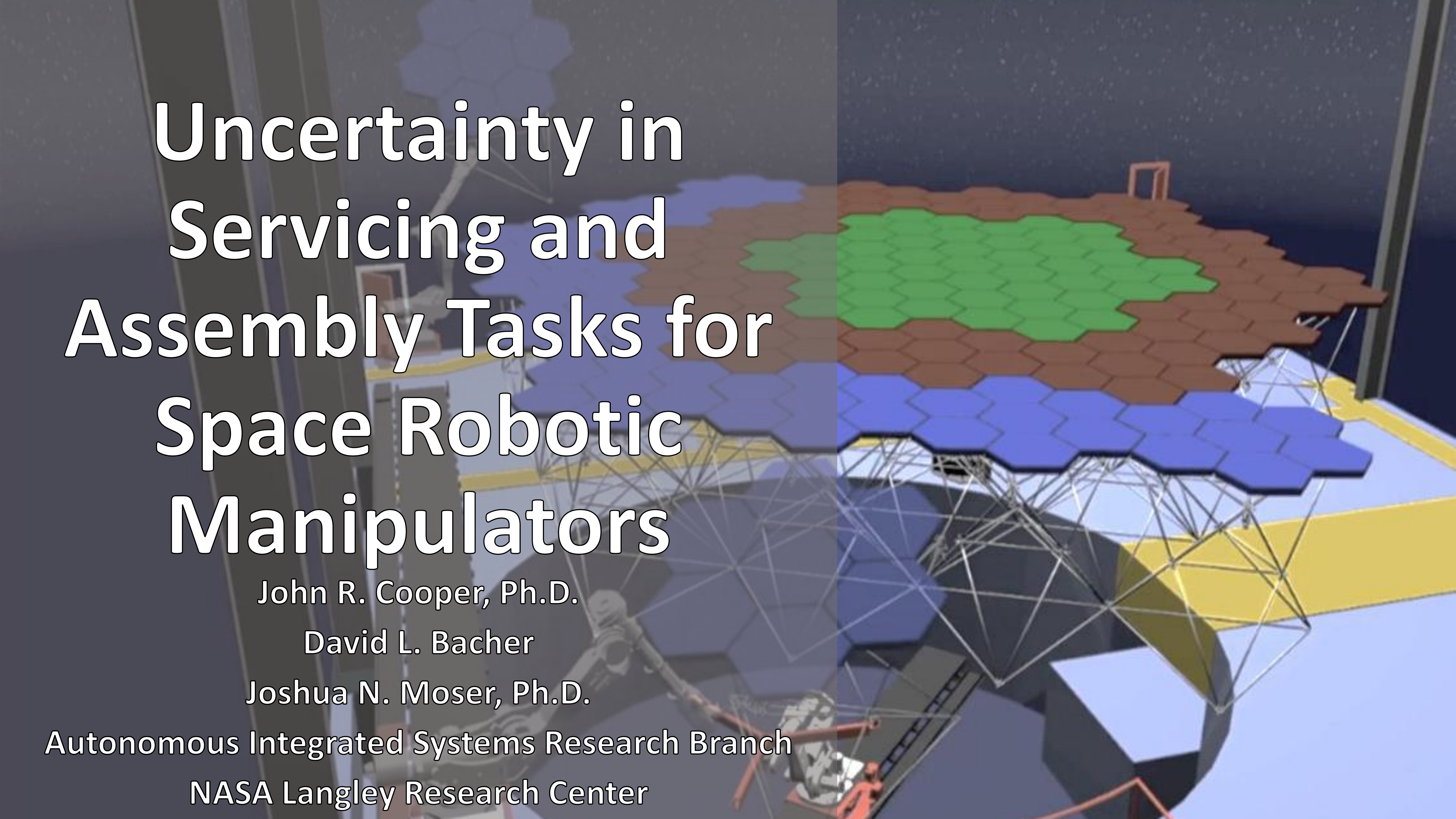

Uncertainty in Servicing and Assembly Tasks for Space Robotic Manipulators

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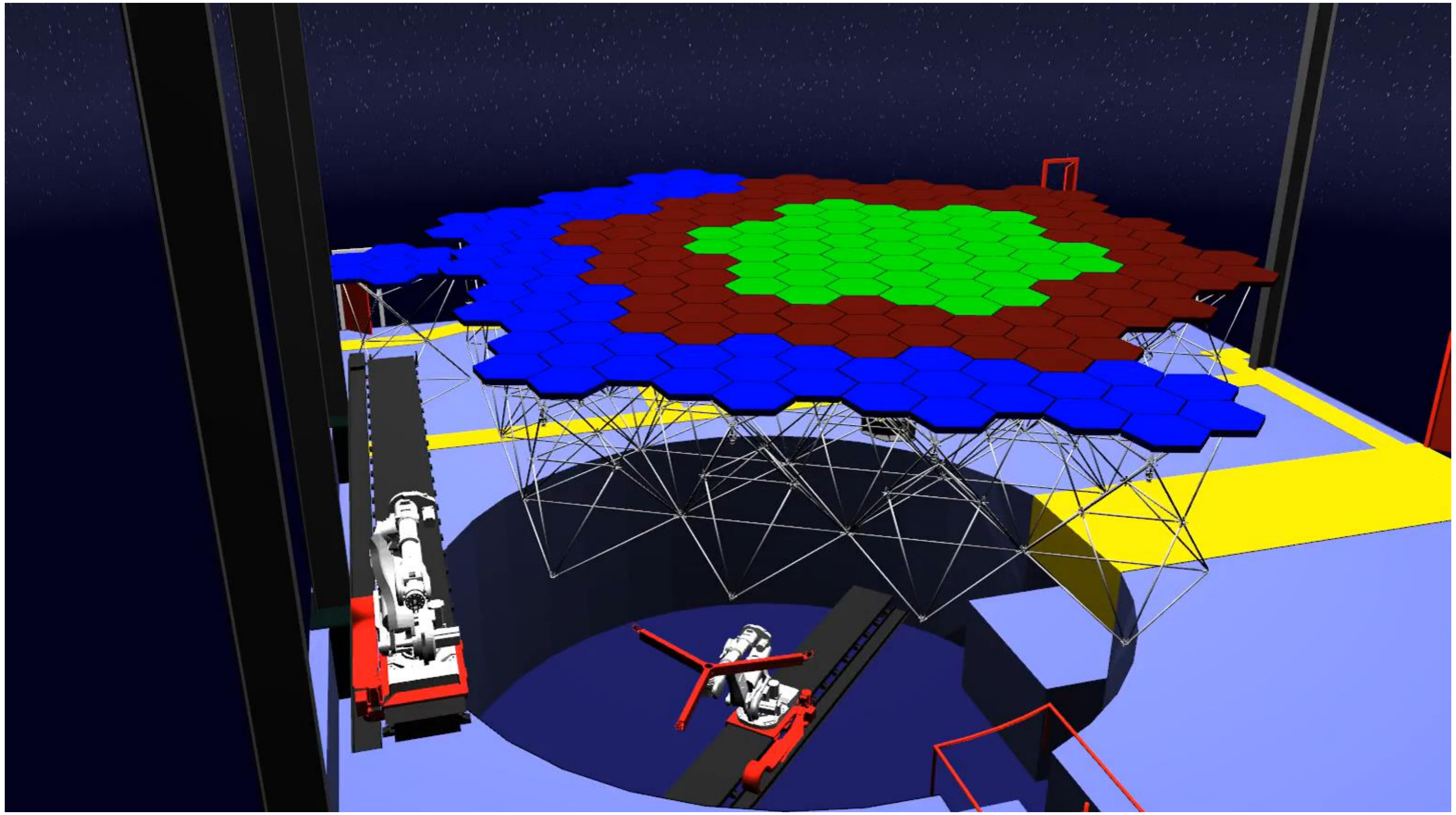
In-Space Assembled Telescope Ground Demo

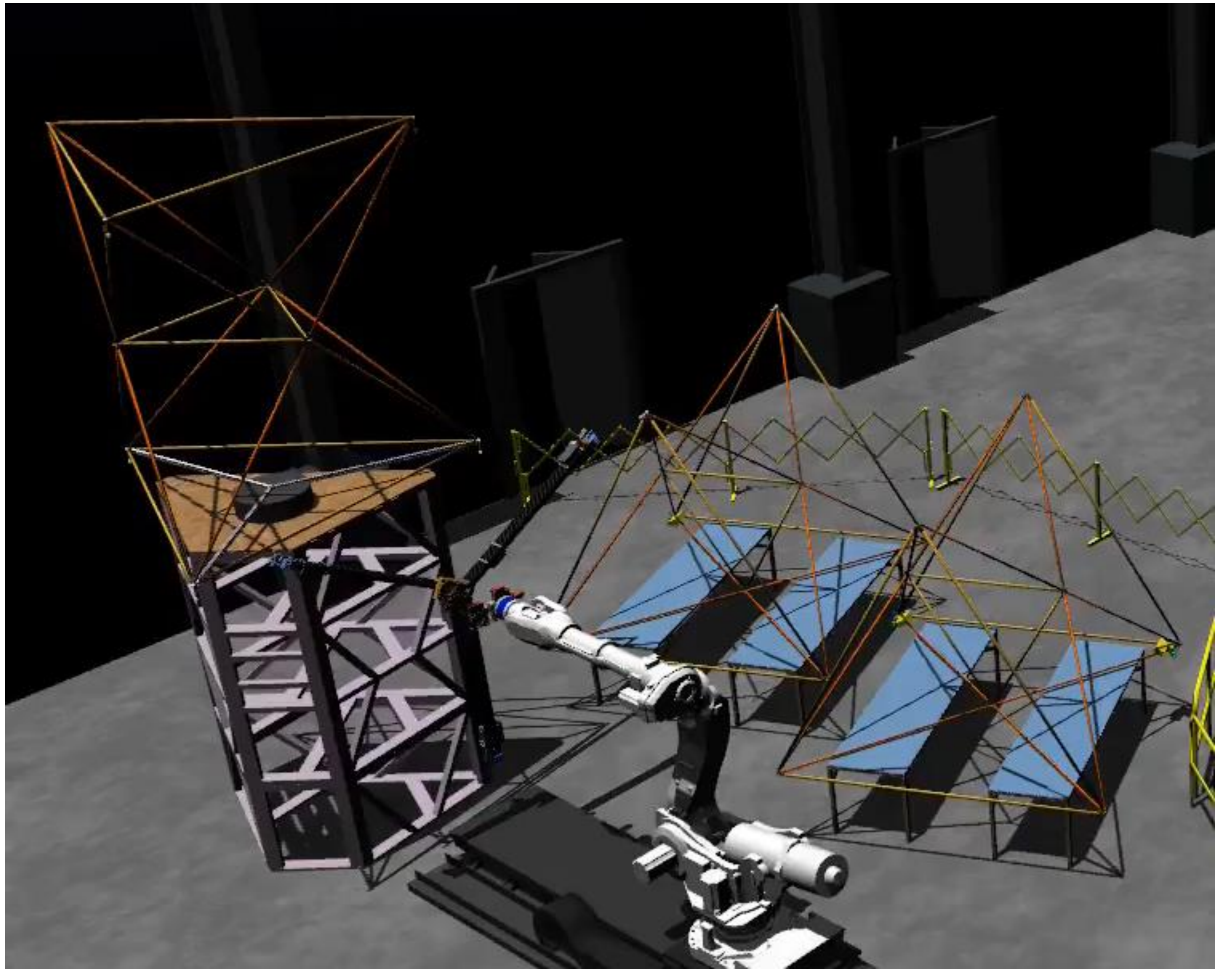
Langley Research Center

- Design reference mission based on in-Space Assembled Telescope study
- 20 m diameter mirror backbone structure
- Full scale assembly ground demonstration



Phase 1a Demonstration

- Three-truss assembly
  - Custom-designed Grapple Tool grabs Tri-Truss modules
  - Motion planned and executed
  - Grapple tool joins Tri-Truss nodes
- Robot must move between multiple poses to pick up payloads (tools, trusses, etc.)
- Three relevant capture envelopes:
  1. Pick up grapple tool
  2. Pick up tri-truss
  3. Place tri-truss
- Trajectories must be collision-free
- Trajectories must be generated for the present workspace
  - Uncertain
  - Dynamic



Trajectory Generator Block Diagram

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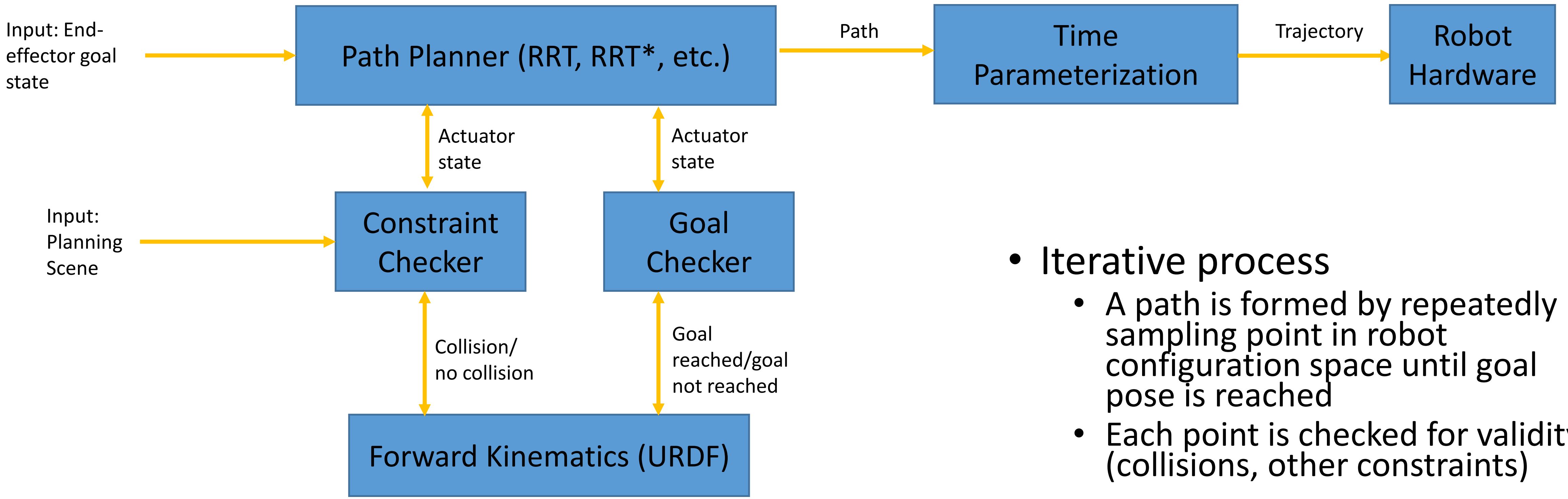

- Iterative process
  - A path is formed by repeatedly sampling point in robot configuration space until goal pose is reached
  - Each point is checked for validity (collisions, other constraints)
- Time is specified along the path according to max velocity and acceleration constraints
  - Create a trajectory from path

Planning Scene

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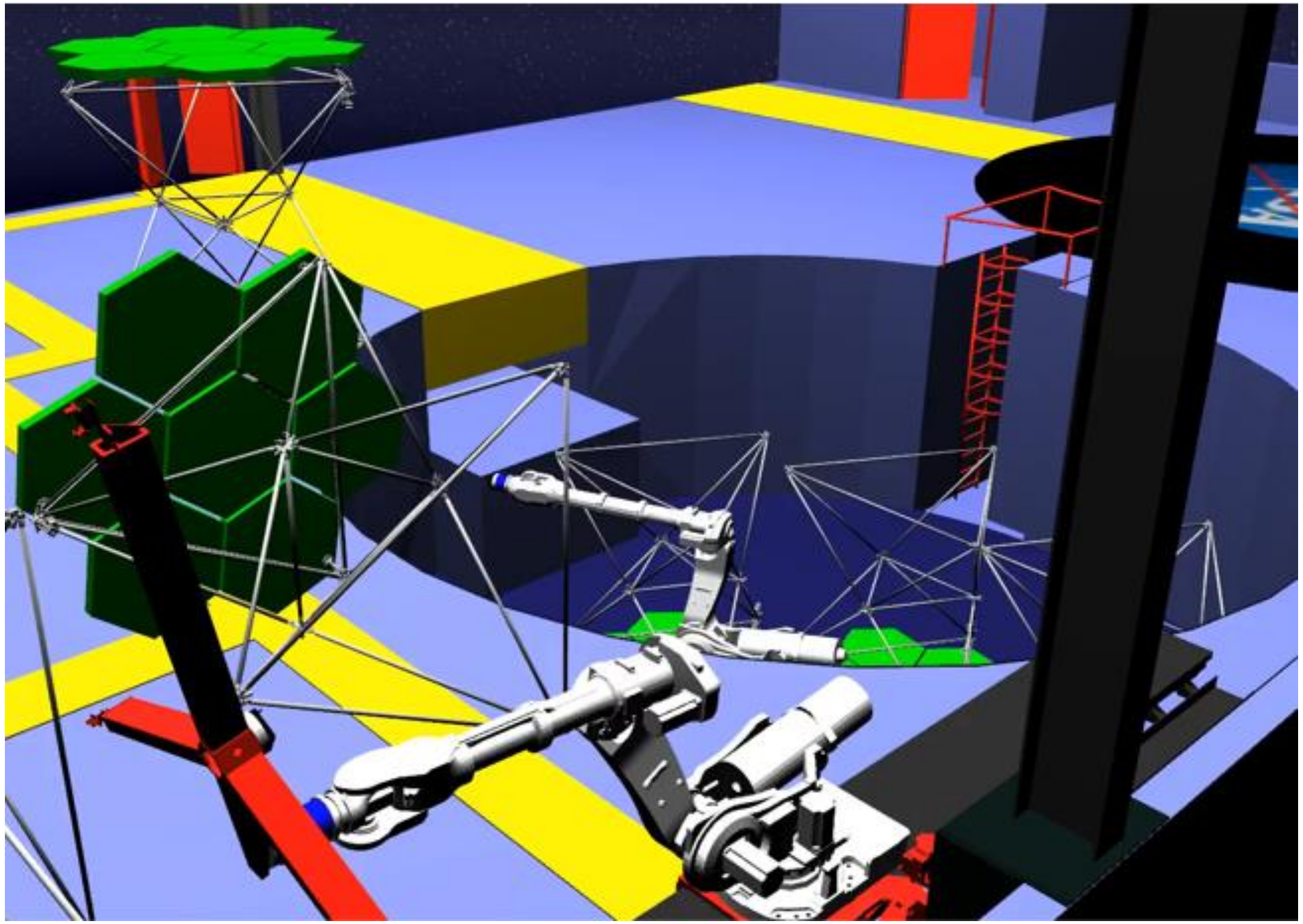
- Planning scene represents all objects in the robot's worksite
- A-priori known objects are represented as meshes
- Dynamic and/or uncertain objects detected from external sensors can be added to scene via occupancy map representation



Manipulator Kinematics

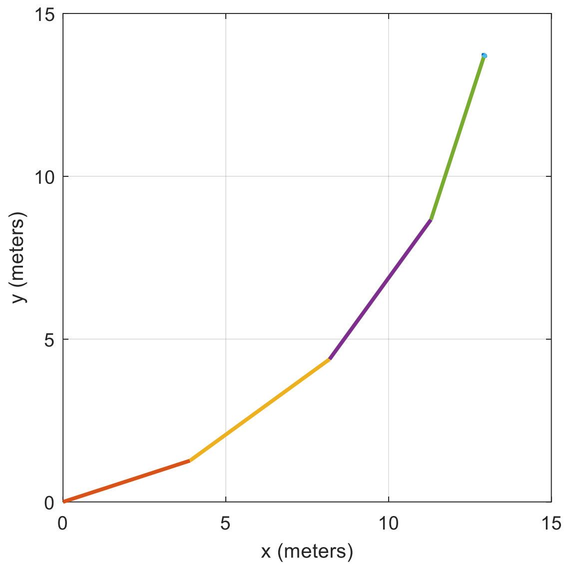
- End-effector variables a function of joint variables
- $x = f(q)$
- Differentiating shows us how end-effector variables change with joint variables
- $\delta x = \frac{df(q)}{dq}\delta q, \frac{df(q)}{dq} = J(q)$: manipulator Jacobian
- Our knowledge of x comes from sensor measurements of q, which may be noisy
- End-effector covariance related to joint covariance through Jacobian
- $C_x = J(q) C_q J^\top(q)$

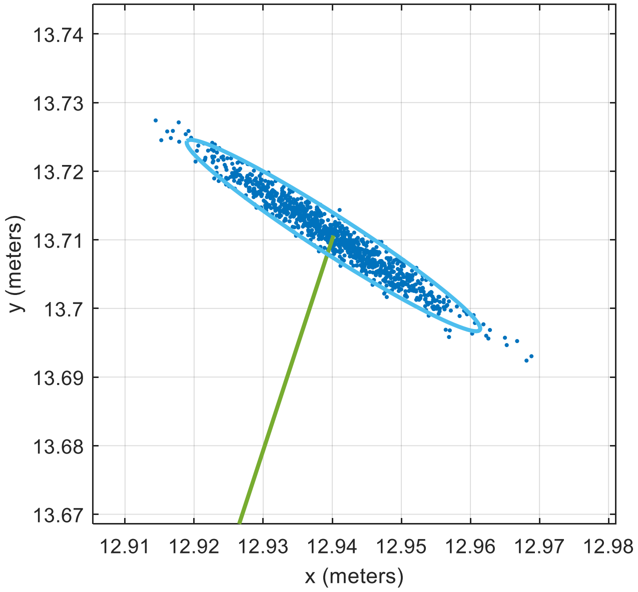
Manipulator Kinematics – Denavit Hartenberg Parameters

- End-effector variables as a function of 4 parameters per joint
- $x = f(d, \theta, r, \alpha)$
- $[Z_i] = \begin{bmatrix} \cos\theta_i & -\sin\theta_i & 0 & 0 \\ \sin\theta_i & \cos\theta_i & 0 & 0 \\ 0 & 0 & 1 & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}, [X_i] = \begin{bmatrix} 1 & 0 & 0 & r_{i,i+1} \\ 0 & \cos\alpha_{i,i+1} & -\sin\alpha_{i,i+1} & 0 \\ 0 & \sin\alpha_{i,i+1} & \cos\alpha_{i,i+1} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$
- $[T] = [Z_1][X_1][Z_2][X_2] \ldots [Z_{n-1}][X_{n-1}][Z_n][X_n]$
- Differentiating shows how end-effector variables change with joint variables
- $\delta x = \frac{df}{d\theta}\delta\theta, \frac{df}{d\theta} = J(\theta)$: manipulator Jacobian
- Our knowledge of x comes from measurements of d, θ, r, α, which may be noisy or contain other uncertainties
- End-effector covariance related to joint covariance through Jacobian
- $C_x = J(q) C_q J^\top(q)$

Uncertainty Ellipsoid

- Eigenvalues of covariance matrix correspond to the spread of data in direction of the corresponding eigenvector
- 2D example: $\frac{x_\lambda^2}{\lambda_{\max}} + \frac{y_\lambda^2}{\lambda_{\min}} = k^2$
- $k = \sqrt{-2\ln(1 - Pr)}$, where Pr is confidence threshold
- Setting $Pr = 0.99$ yields an ellipsoid that encloses 99% of the data
- **We want to ensure the capture envelopes relevant to our con-ops enclosed an ellipsoid with appropriate confidence threshold**





Kinematic Model Calibration

- Uncertainty in DH parameters can be mitigated through calibration

1. Take external measurements of real robot end-effector pose (Vicon, laser tracker, etc.)
2. Compare measurements to model output
3. Run optimization routine to find best fit DH parameters

$$\text{minimize } E(d,\theta,r,\alpha) = \left(x_{meas} - f(d,\theta,r,\alpha)\right)^2$$

- May need separate calibrations for different regions of the workspace due to gravitational sag
- Can use multiple calibration results to define uncertainty in DH parameters

Uncertainty Mitigation in Path Planning

- Path planning algorithm is sample-based
- Each sample checked for collisions and whether it satisfies goal state conditions
- If covariance ellipsoid is not enclosed within capture envelope, the sampled state is not a feasible goal state
- Note it's possible for the end-effector to be in the correct pose with too large uncertainty ellipsoid
- Including this extra goal check increases likelihood of mission success
- Alternatively, include metric for uncertainty in numerical inverse kinematics optimizer to find best goal state up front

<u>Path Planning Algorithm</u>

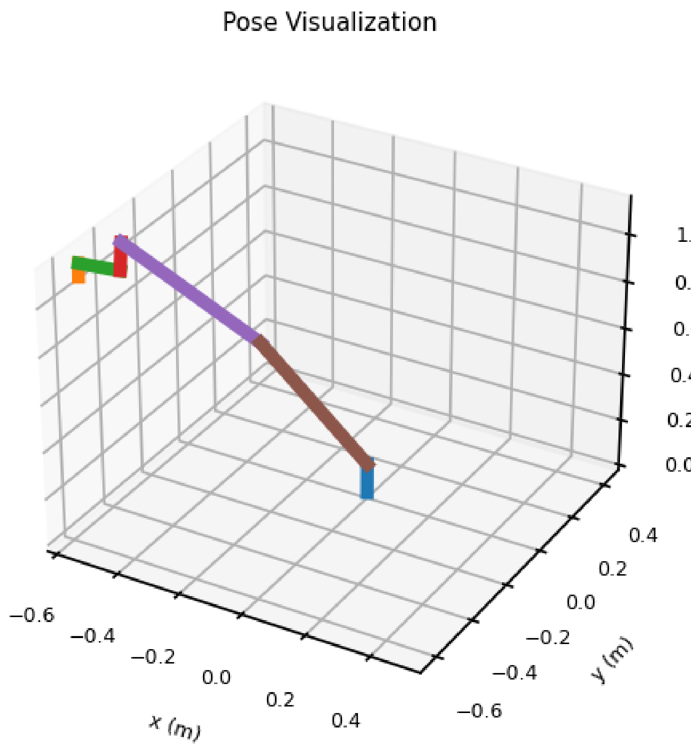
```
for n iterations:
    sample a joint space
    if sample is feasible:
        add sample to tree
        if sample is a goal state:
            goal <- sample
        rewire tree for optimization
```

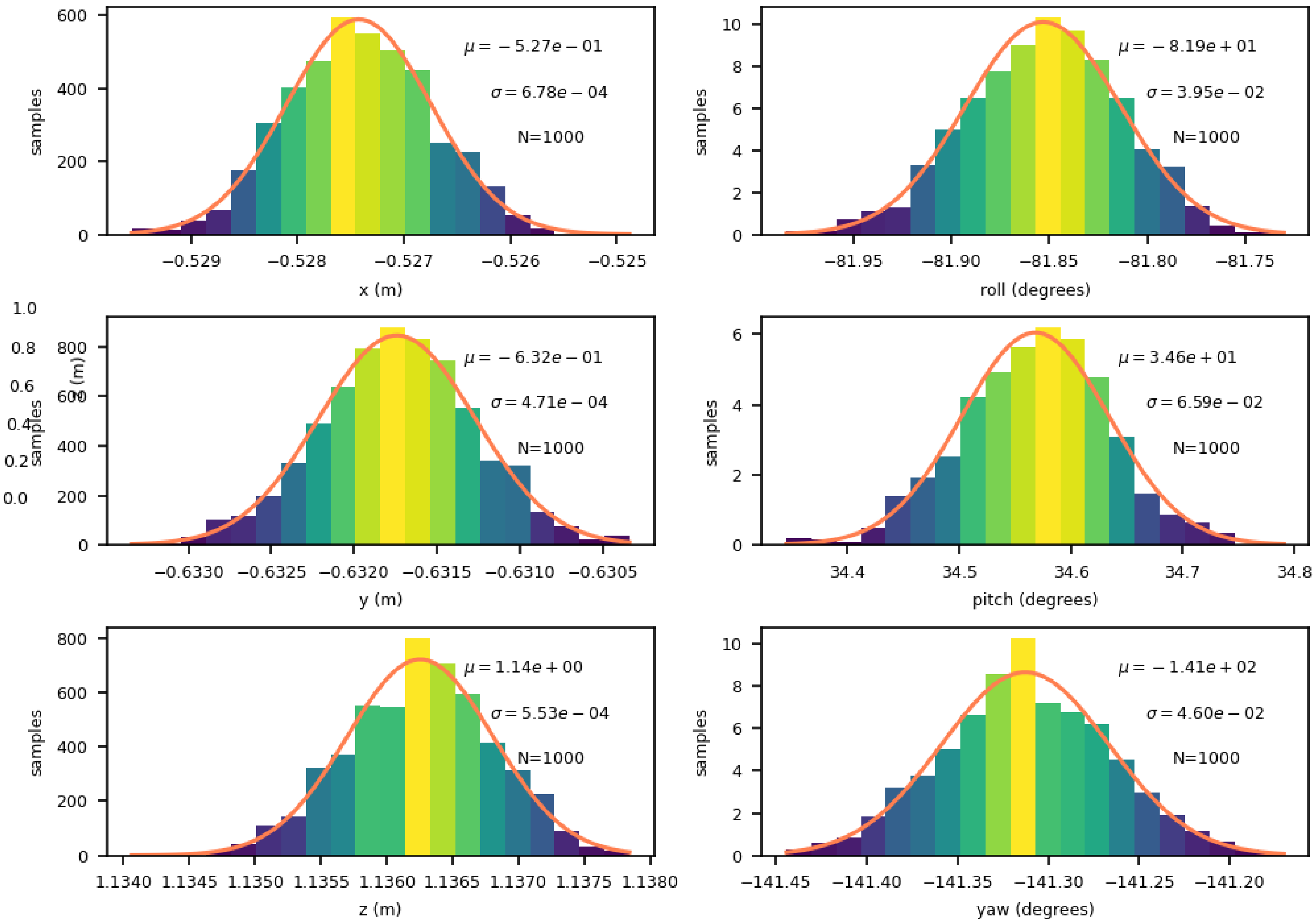
Monte Carlo Analysis

- Example: UR10 manipulator
  - AksIM encoder accuracy +/- 0.1 degrees
    - Interpret as 99% confidence interval (3 x std. dev.)
- Monte Carlo sampling of joint angles within kinematic model
- Plot histogram of results and fit normal distribution
- Perform for several nominal poses

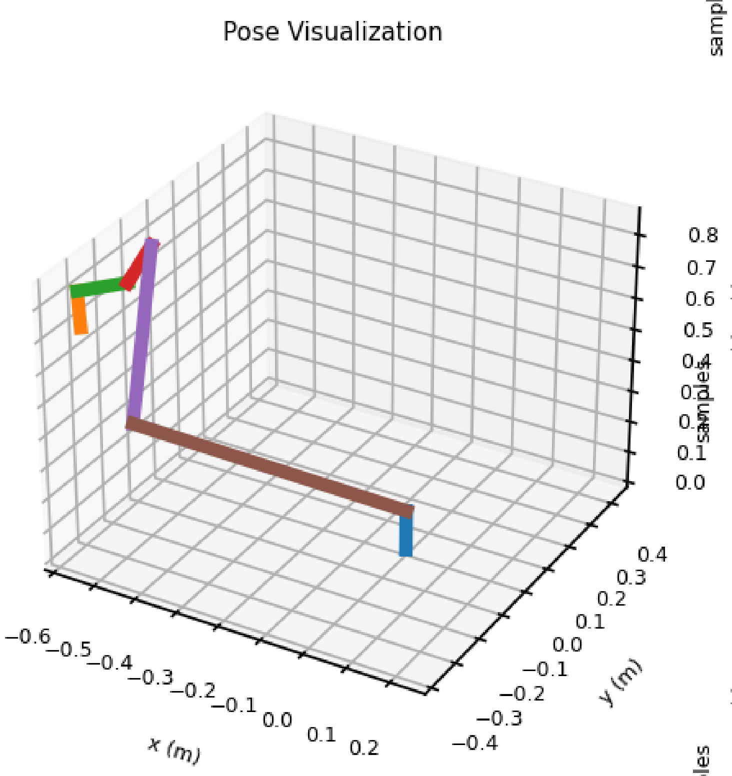
UR10				
Kinematics	theta [rad]	r [m]	d [m]	alpha [rad]
Joint 1	0	0	0.1273	$\pi/2$
Joint 2	0	-0.612	0	0
Joint 3	0	-0.5723	0	0
Joint 4	0	0	0.16394	$\pi/2$
Joint 5	0	0	0.1157	$-\pi/2$
Joint 6	0	0	0.0922	0

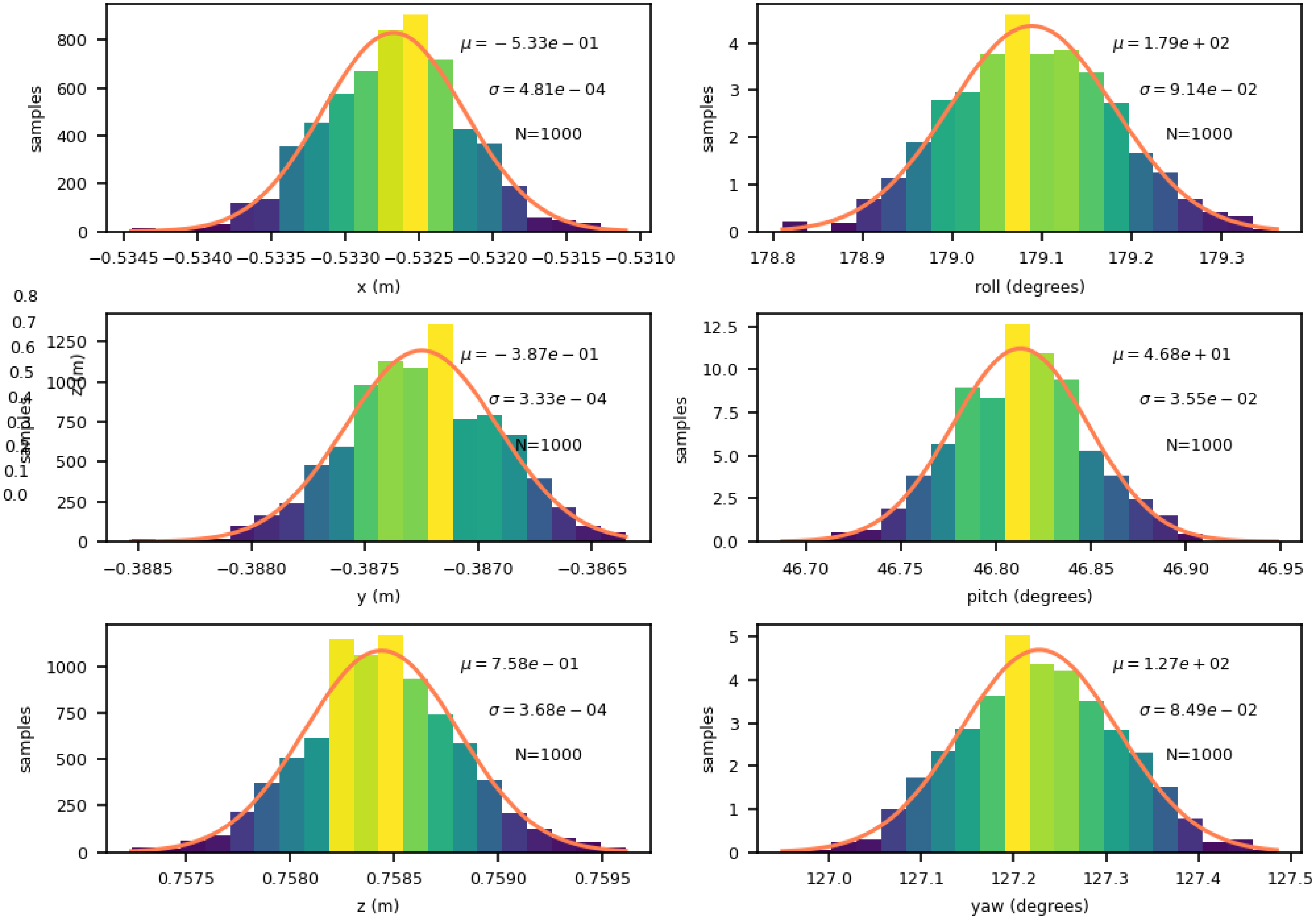
Pose 1


Pose Visualization
x (m)
y (m)
z (m)
−0.6
−0.4
−0.2
0.0
0.2
0.4
0.0
0.2
0.4
0.6
0.8
1.0

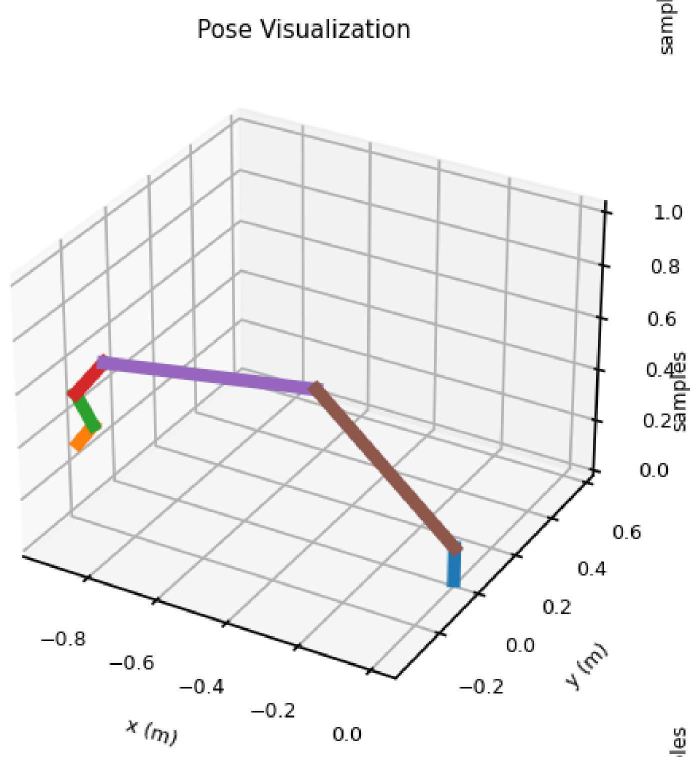

samples
x (m)
$\mu = -5.27e-01$
$\sigma = 6.78e-04$
N=1000
roll (degrees)
$\mu = -8.19e+01$
$\sigma = 3.95e-02$
N=1000
y (m)
$\mu = -6.32e-01$
$\sigma = 4.71e-04$
N=1000
pitch (degrees)
$\mu = 3.46e+01$
$\sigma = 6.59e-02$
N=1000
z (m)
$\mu = 1.14e+00$
$\sigma = 5.53e-04$
N=1000
yaw (degrees)
$\mu = -1.41e+02$
$\sigma = 4.60e-02$
N=1000

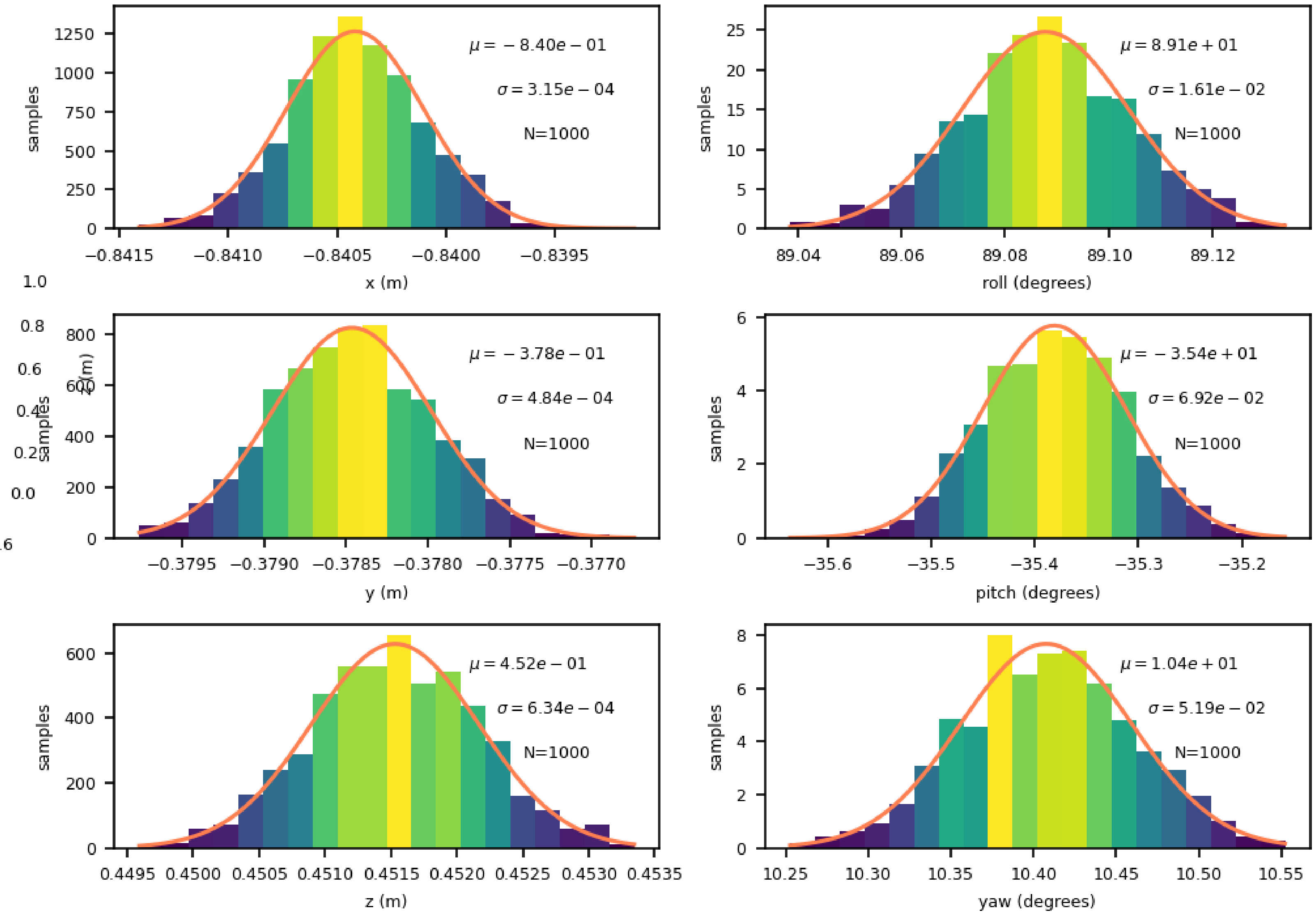
Pose 2


Pose Visualization
x (m)
y (m)
z (m)
−0.6
−0.5
−0.4
−0.3
−0.2
−0.1
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8


samples
x (m)
$\mu = -5.33e-01$
$\sigma = 4.81e-04$
N=1000
roll (degrees)
$\mu = 1.79e+02$
$\sigma = 9.14e-02$
N=1000
y (m)
$\mu = -3.87e-01$
$\sigma = 3.33e-04$
N=1000
pitch (degrees)
$\mu = 4.68e+01$
$\sigma = 3.55e-02$
N=1000
z (m)
$\mu = 7.58e-01$
$\sigma = 3.68e-04$
N=1000
yaw (degrees)
$\mu = 1.27e+02$
$\sigma = 8.49e-02$
N=1000

Pose 3


Pose Visualization
x (m)
y (m)
z (m)
−0.8
−0.6
−0.4
−0.2
0.0
−0.2
0.0
0.2
0.4
0.6
0.0
0.2
0.4
0.6
0.8
1.0


samples
x (m)
$\mu = -8.40e-01$
$\sigma = 3.15e-04$
N=1000
roll (degrees)
$\mu = 8.91e+01$
$\sigma = 1.61e-02$
N=1000
y (m)
$\mu = -3.78e-01$
$\sigma = 4.84e-04$
N=1000
pitch (degrees)
$\mu = -3.54e+01$
$\sigma = 6.92e-02$
N=1000
z (m)
$\mu = 4.52e-01$
$\sigma = 6.34e-04$
N=1000
yaw (degrees)
$\mu = 1.04e+01$
$\sigma = 5.19e-02$
N=1000

Minimizing End Effector Pose Uncertainty

$\delta x = J(q)\delta q$

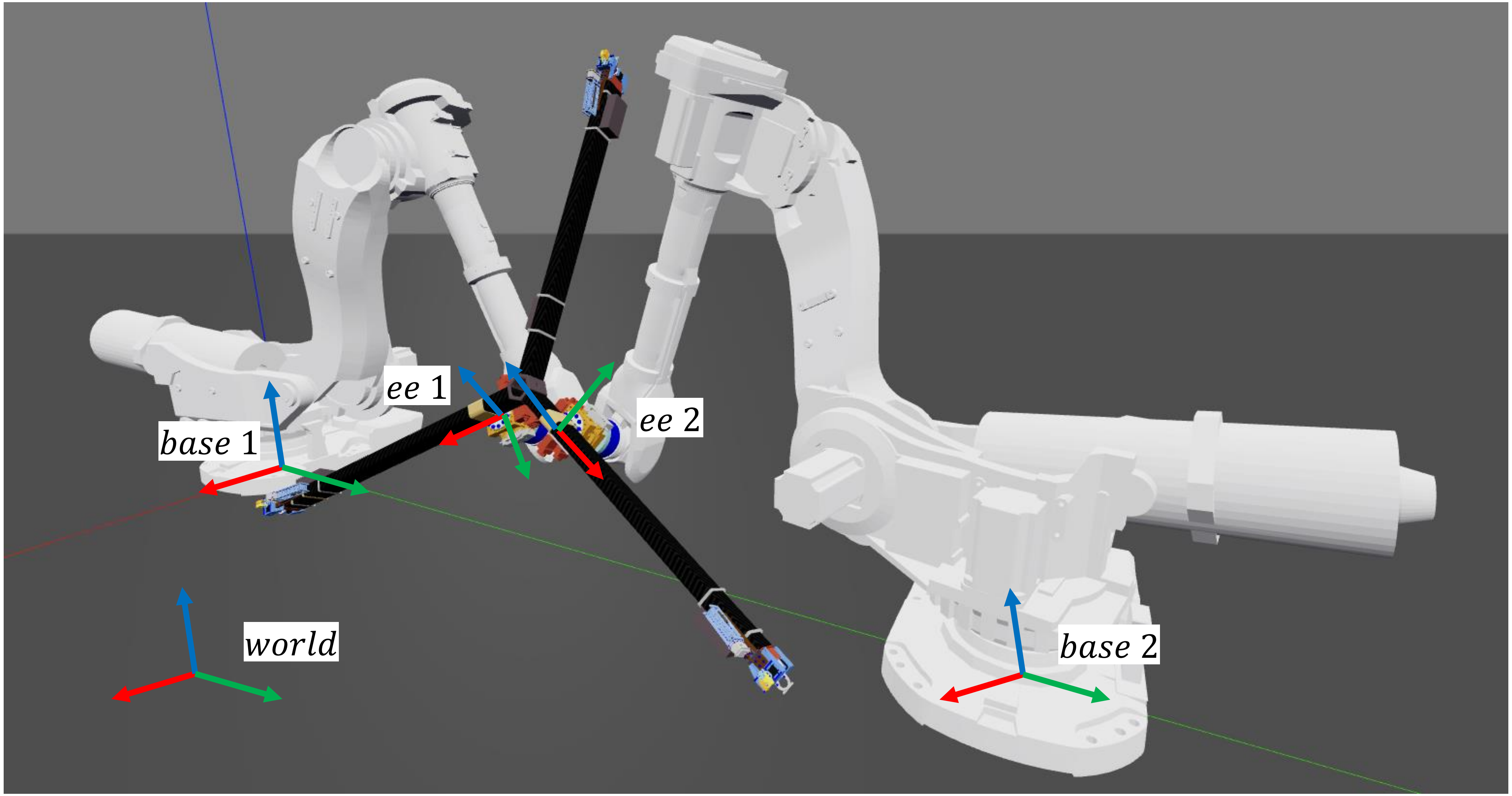
Then: $||\delta x|| \leq ||J(q)||_F ||\delta q||$

Where: $||J(q)||_F = \sqrt{Trace(J(q)^T J(q))}$: Frobenius Norm

Decreasing the Frobenius Norm decreases the bounds on uncertainty

$\boldsymbol{\delta x}$ is minimized by minimizing $||\boldsymbol{J(q)}||_{\boldsymbol{F}}$

Coordinate Frames



PASS PI: Bill.Doggett@nasa.gov
Autonomy Tech Lead:
john.r.cooper@nasa.gov

Handoff Pose Separation

At handoff, the end effectors have a known difference in pose, which can be expressed as a 4x4 SE(3) matrix:

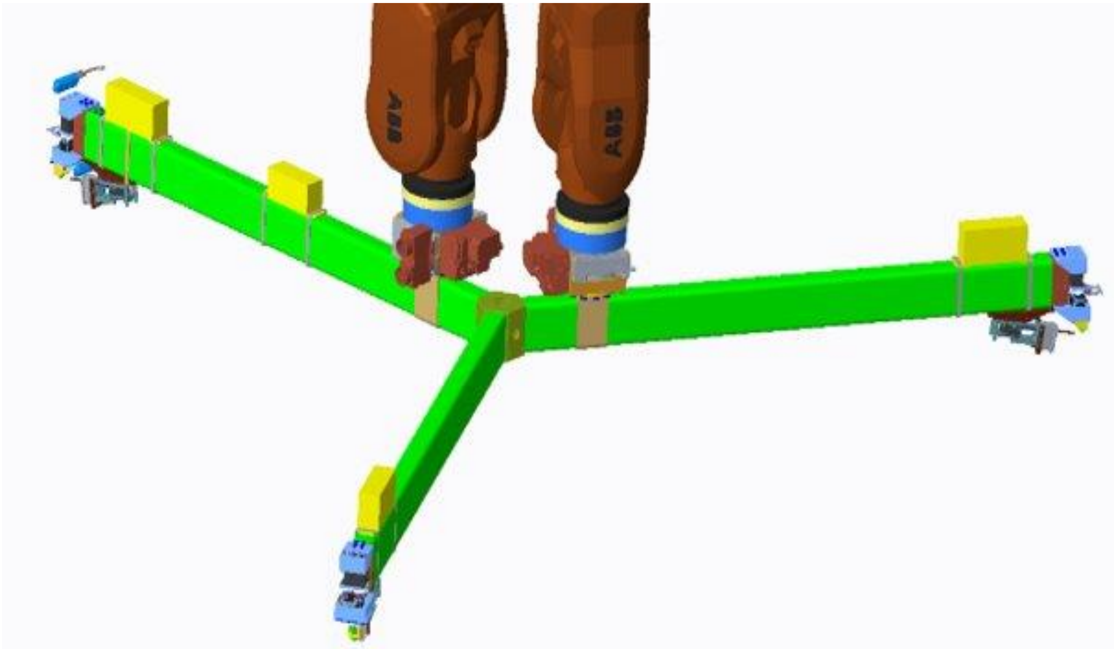
$$SE(3) = \begin{bmatrix} R_{11} & R_{12} & R_{13} & t_1 \\ R_{21} & R_{22} & R_{23} & t_2 \\ R_{31} & R_{32} & R_{33} & t_3 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where:

t: translation coordinates

R: elements of the rotation matrix

Let T^*_{e12} be a transformation matrix from the pose of ee1 to the pose of ee2 in the ee1 frame



The handoff transformation matrix is defined by the grapple tool design:

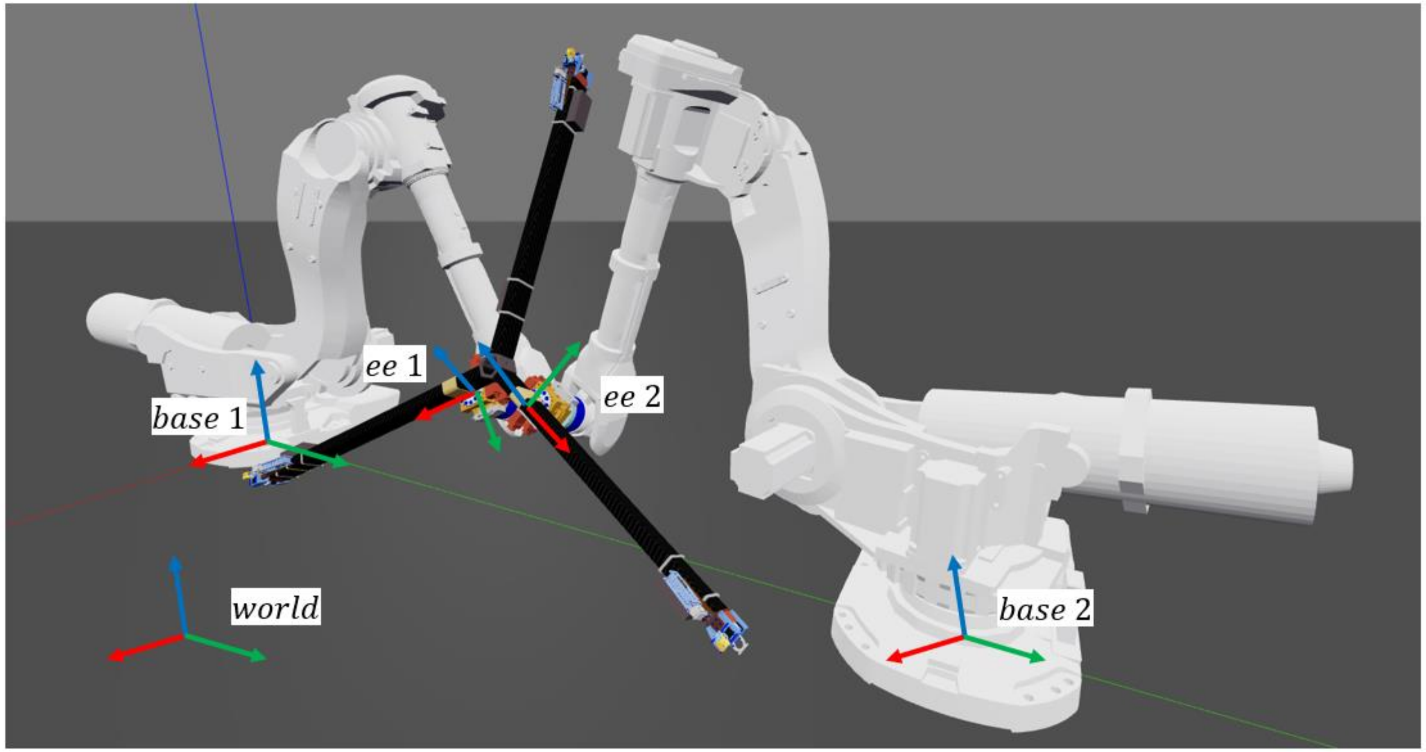
$$T^*_{e12} = \begin{bmatrix} -.5 & -.866 & 0 & -.375 \\ .866 & -.5 & 0 & .217 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Optimization Problem Formulation

$$T_{e1} = f_1(q_1): world \rightarrow ee\ 1$$

$$T_{e2} = f_2(q_2): world \rightarrow ee\ 2$$

$$T_{e12} = {T_{e1}}^{-1} T_{e2}: ee\ 1 \rightarrow ee\ 2$$



$$\min c(q_1, q_2) = \|J_1(q_1)\|_F + \|J_2(q_2)\|_F$$
$$s.t.\ {T_{e1}}^{-1} T_{e2} = T^*_{e12}$$
$$d_{min}(q_1, q_2) > 0$$

d_{min}: a function that returns the minimum distance between each robot and all other objects in the scene to prevent obstacles

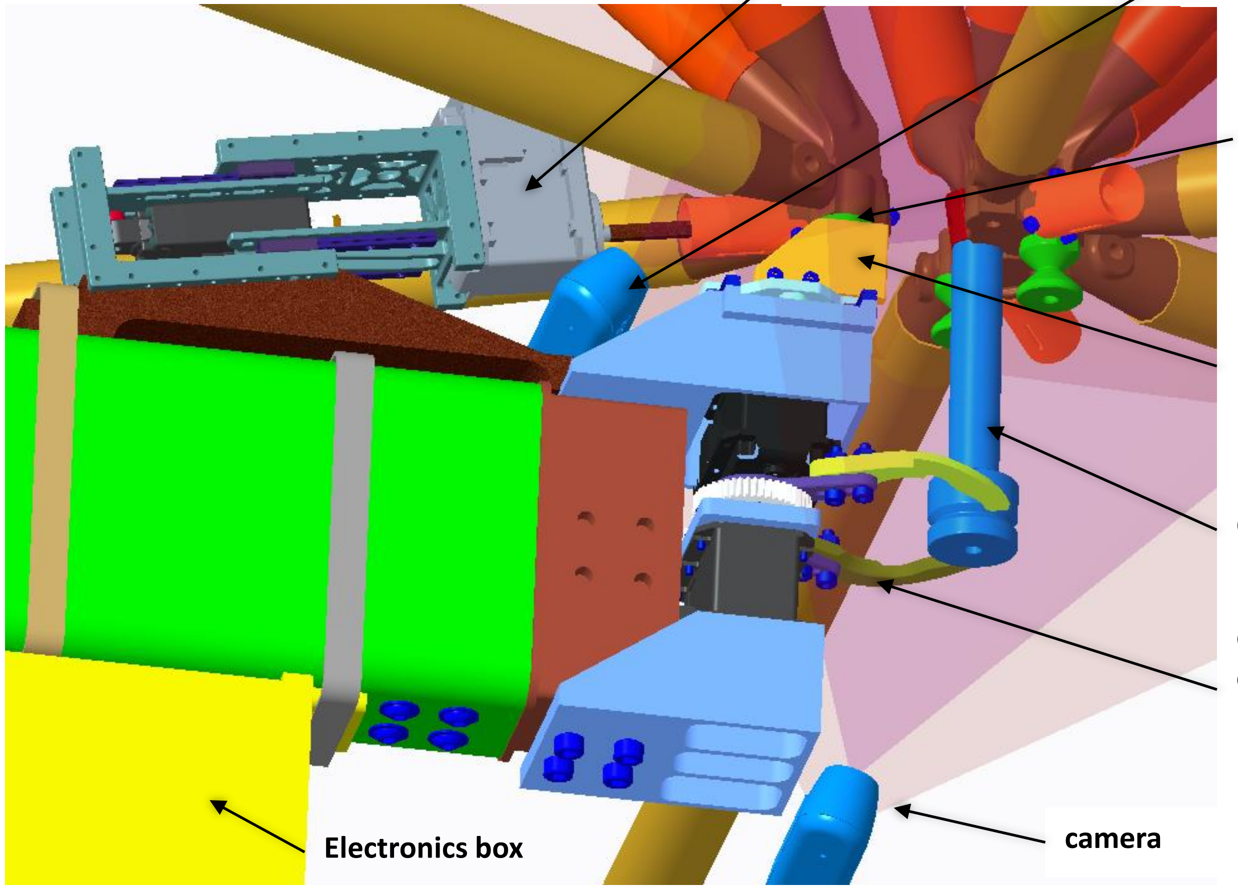
Object Pose Estimation Overview

- Algorithm that estimates pose of objects for robot to interact with from camera image and point cloud
  - Use convolutional neural network (CNN) to segment object image
  - Match object pixels to points
  - Use optimization to align CAD model with point cloud to get pose
- Used as a visual-servo sensor
- Need to understand uncertainty in these estimates and relate to capture envelopes
- Source of uncertainty:
  - Sensor noise
  - CNN performance
  - Cost function in optimization

These can each be tweaked if analysis shows uncertainty is too large

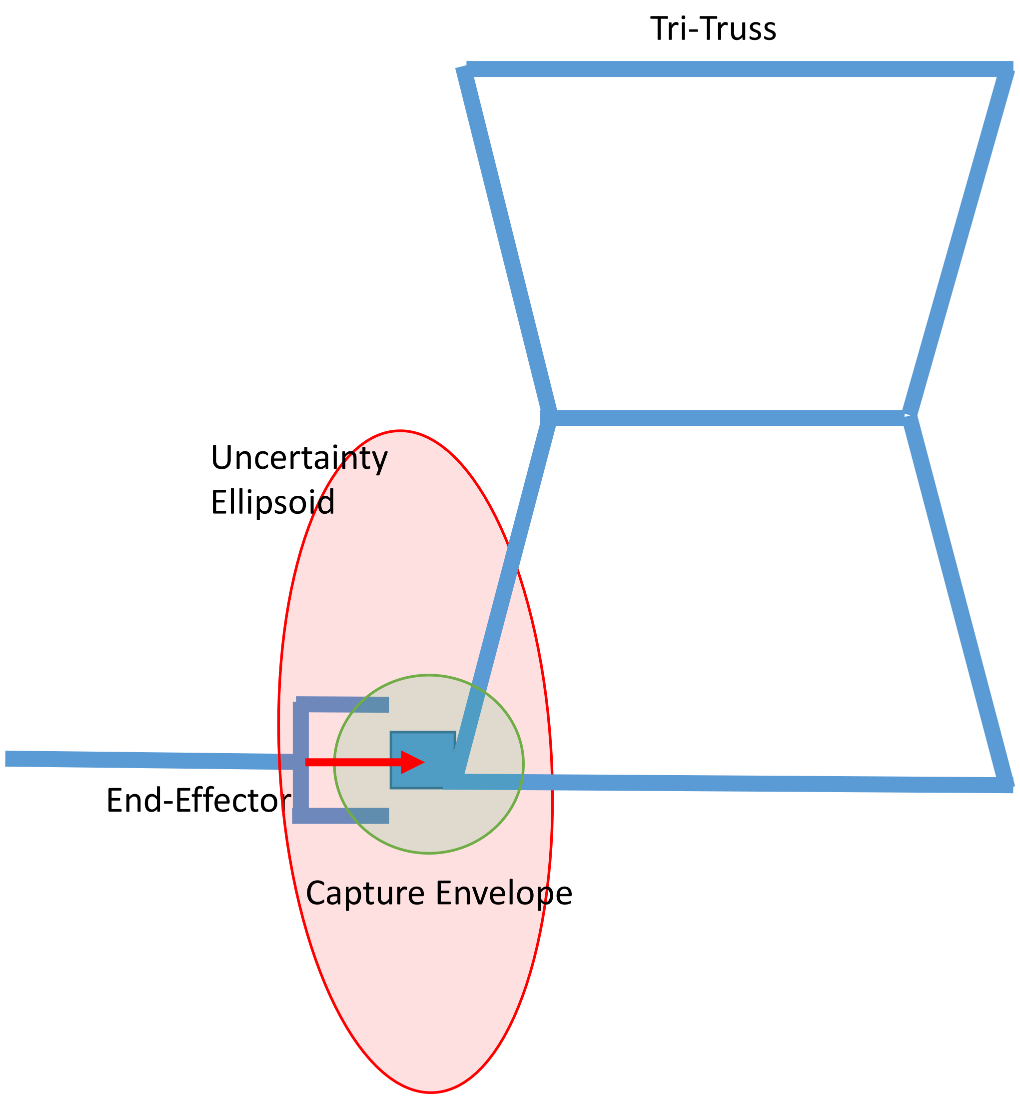
Capture Con-ops

- Grapple tool must be positioned such that capture fingers can grasp capture post and post fingers can grasp grapple post
- Each finger mechanism has a dedicated camera/LiDAR sensor package for pose estimation

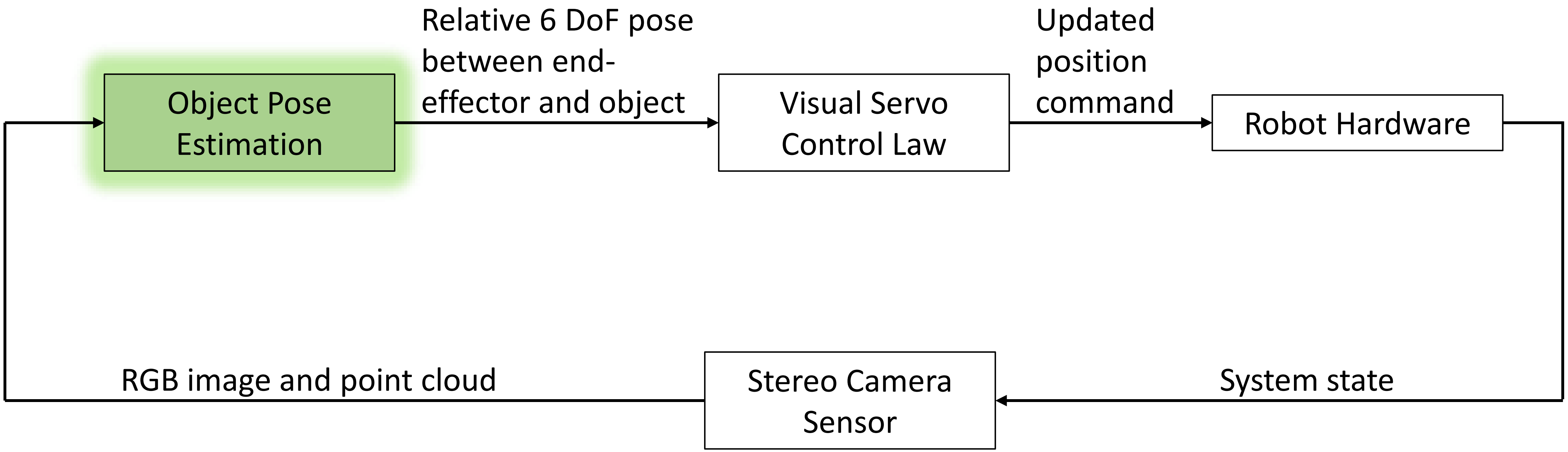


Grapple Con-Ops

1. Manipulator moves to "pre-pose" capture point
2. Object pose estimation algorithm provides relative pose between end-effector and capture target
3. Object pose estimation vector used to generate offset command for end-effector

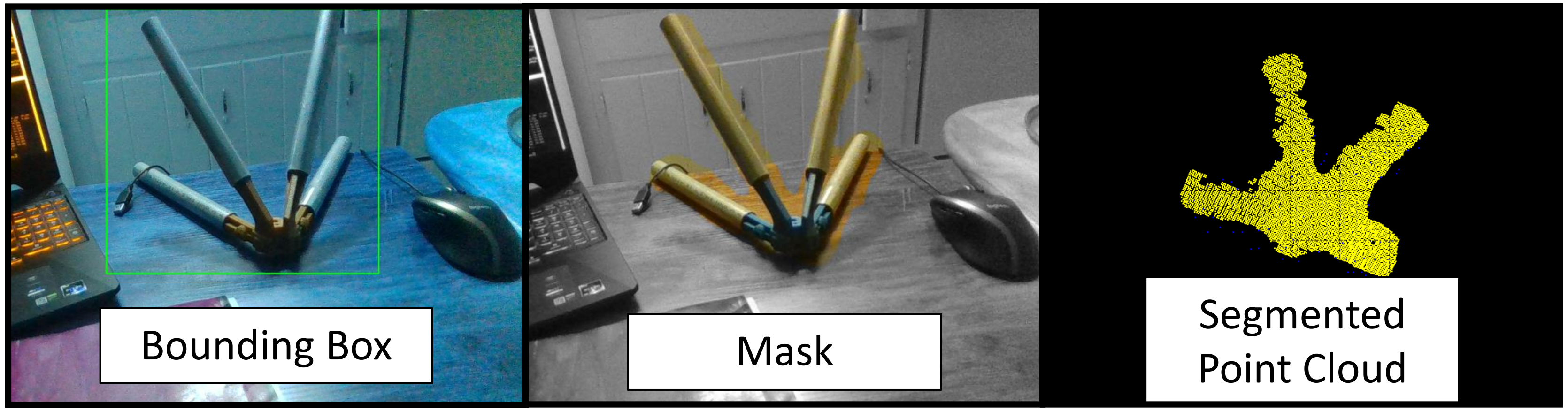


Visual Servo Control Loop

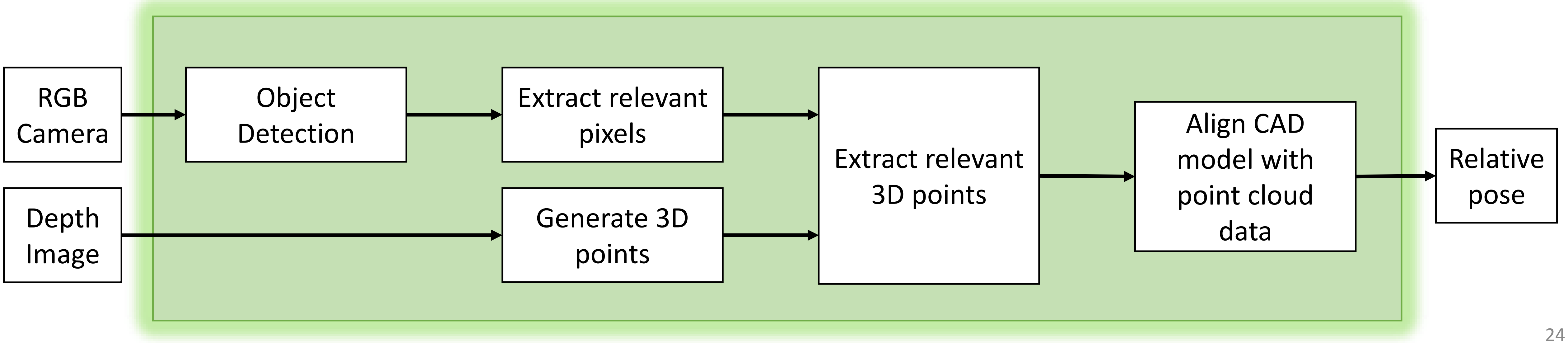


Pose Estimation Pipeline

Intel Realsense D405 depth camera

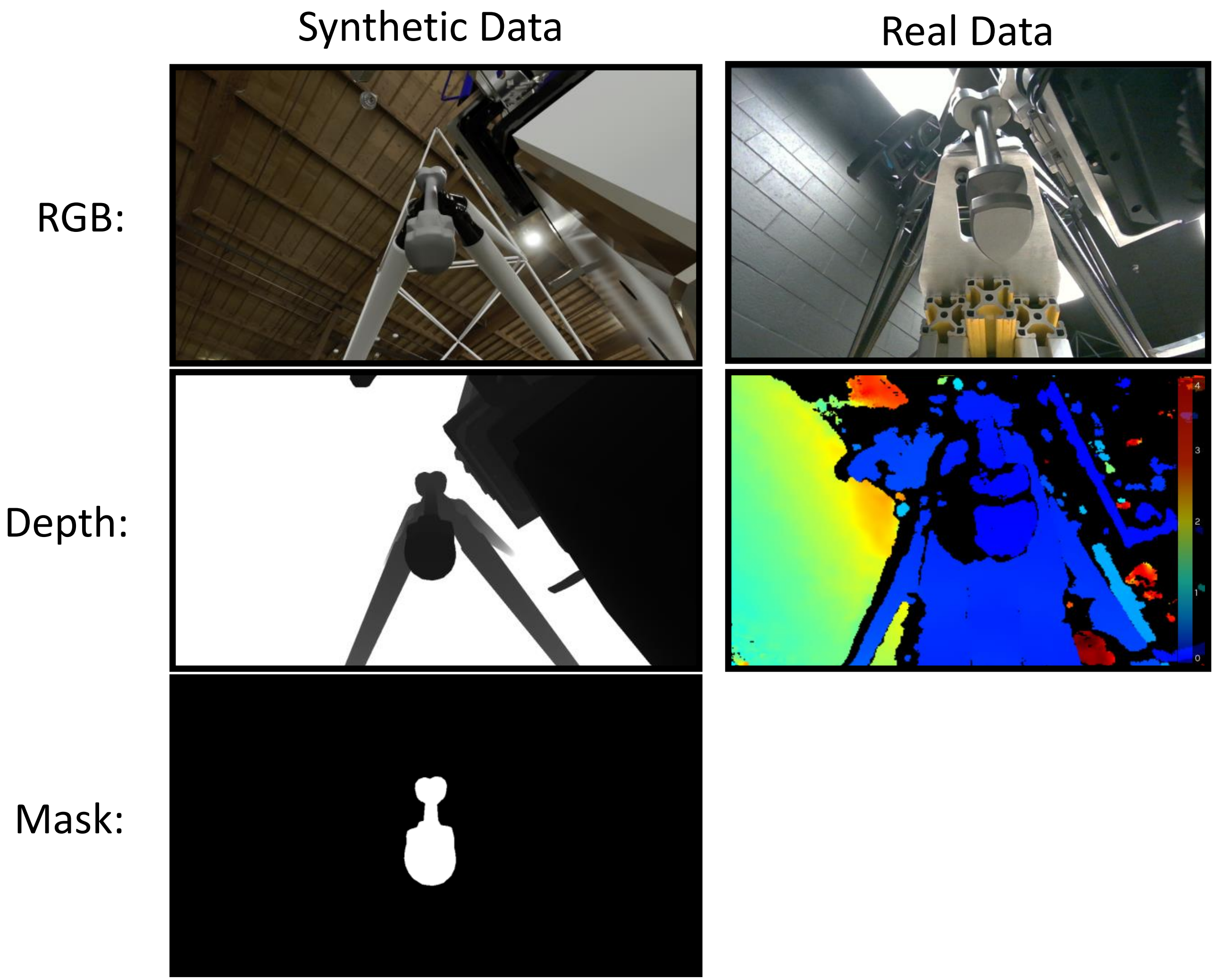


Pose Estimation Block Diagram



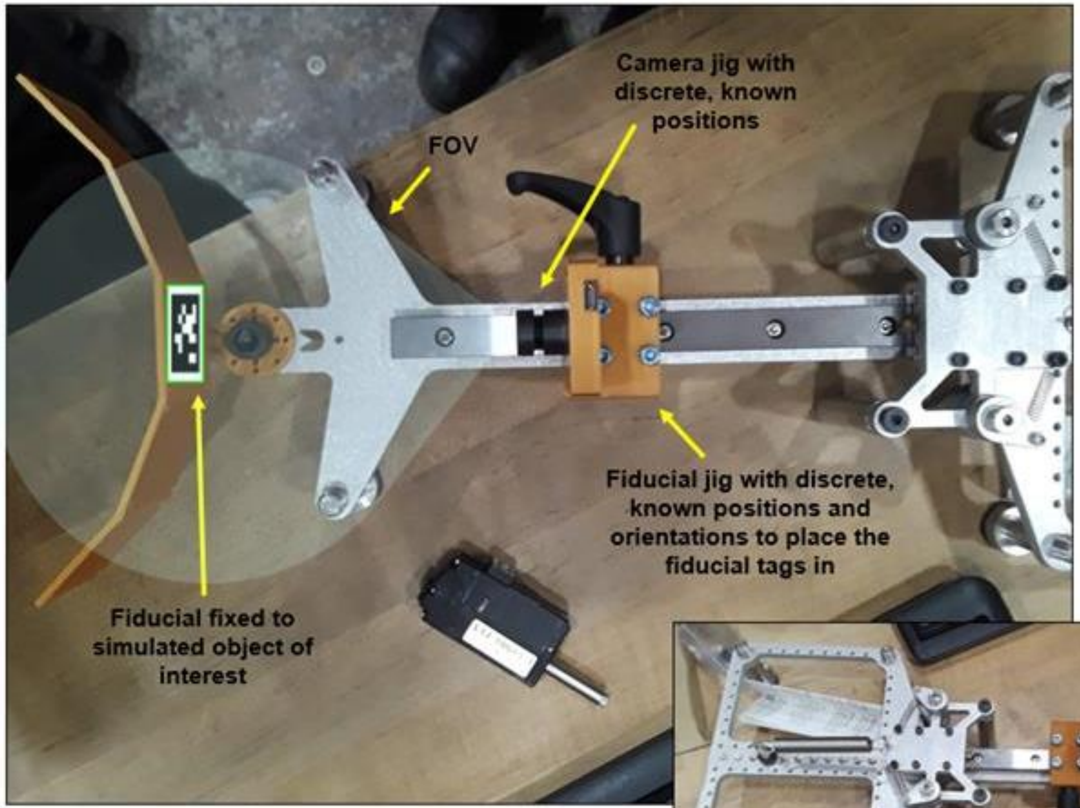
Testing Approach

- Generate a large dataset of synthetic images and point clouds with ground truth for relative pose
  - Import CAD models into rendering software
  - Generate point cloud from mesh
  - Control pose of object and camera
  - Add noise to image and point cloud
    - Real noise characteristics can be measured from physical sensor
- Independent variables to define different test cases:
  - Workspace region
  - Lighting conditions
  - Material properties
  - Target object
- Evaluate error between estimated pose and true pose



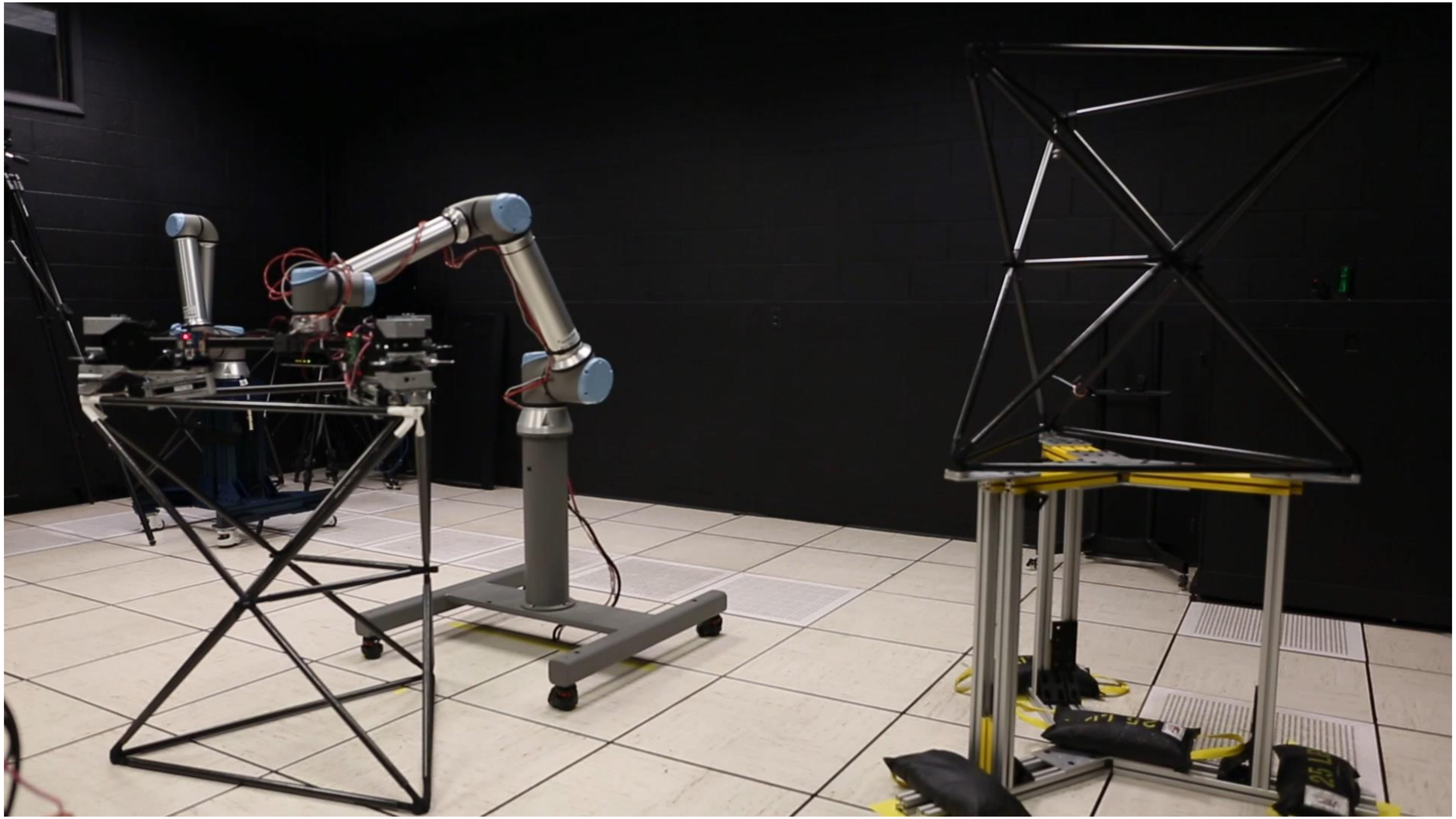
Verification of Synthetic Data

- Need to verify algorithm performs similarly on real data
- Build a test rig with discrete mounting points for both camera and test article
- Create a set of synthetic data that matches all test rig combinations
- Compare pose estimate on synthetic data and real data



Similar Test Rig

Truss Placement Hardware Test



Summary

- Many sources of uncertainty
  - Modeling
  - Sensor noise
  - Machine learning accuracy
- Mitigations
  - Use uncertainty quantification to design capture envelopes
  - Choose goal poses with minimum sensitivity