Visual Perception of Inertial Affordances

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Affordances

- Visual indicators of object properties

Affordances

- Visual indicators of object properties

- Generalize to novel objects and tasks

Goals

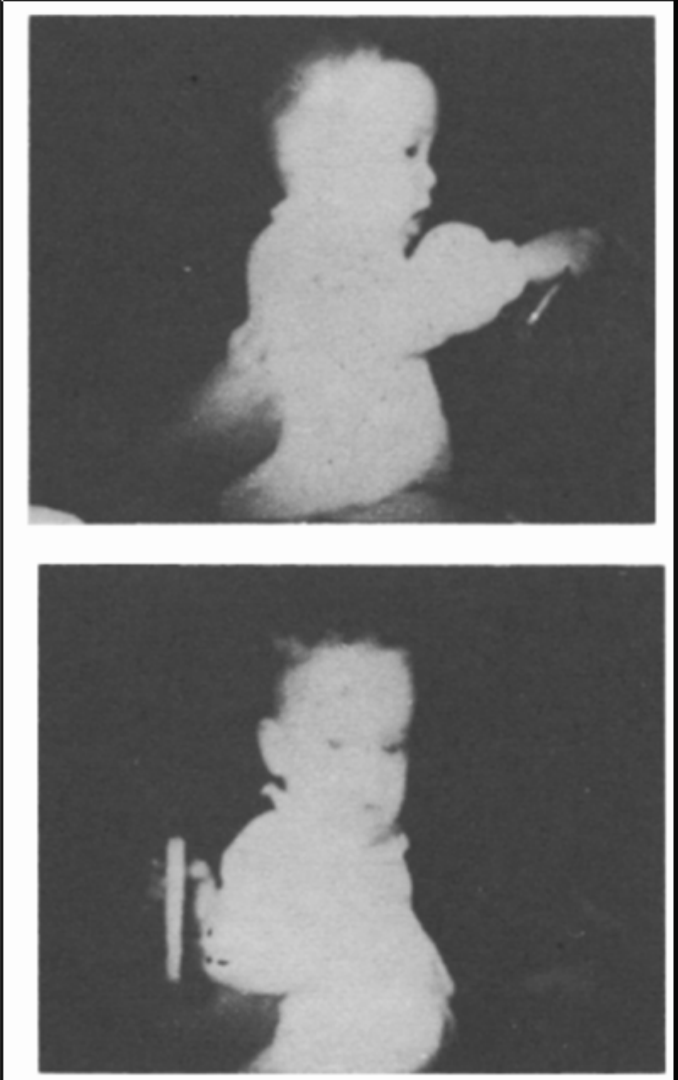
- Describe a computational framework that:
  - capture human ability to generalize quickly to novel objects and tasks
  - allows a robot to learn and use the relationship between objects’ visual features and their physical behavior

Goals

- Use the framework to:
    - Explain a human experiment
    - Suggest a new experiment, and predict it’s results

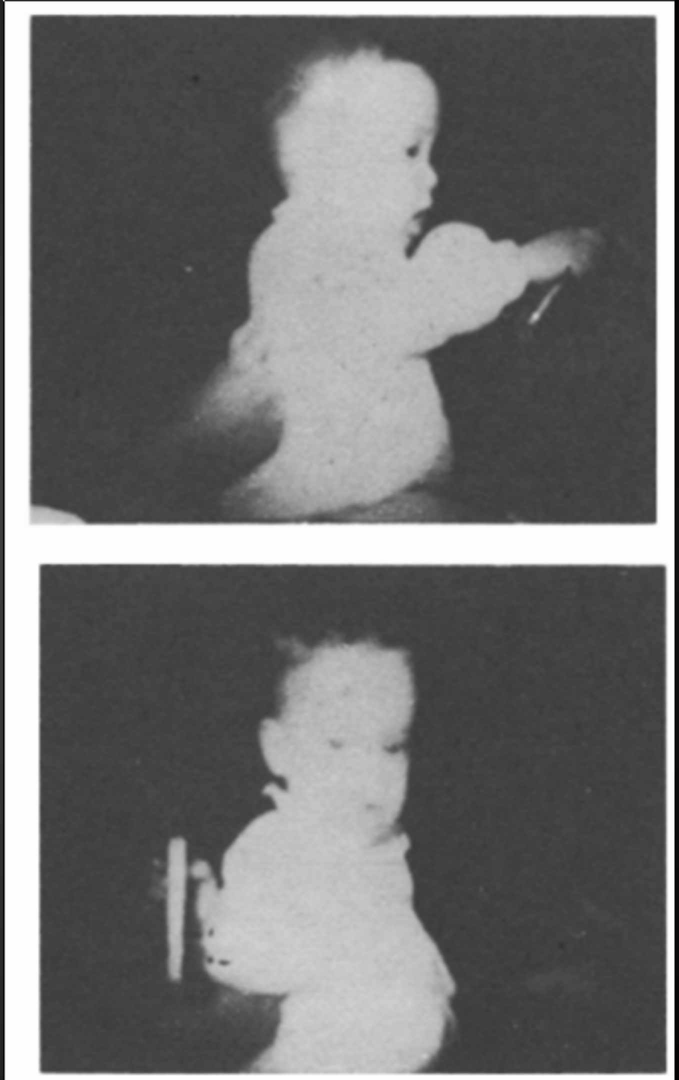
Evidence in Infants

- Mounoud and Bower, 1974 (MB) presented infants with a set of brass rods of increasing length



Evidence in Infants

1. Infants grasp each of a set of 4 rods during learning phase
2. Amount of vertical arm movement recorded 250ms after object released by experimenter
3. Movement amplitude decreases as more objects are presented
4. Amplitude increases again with a height-matched but hollow decoy rod



Evidence in Infants

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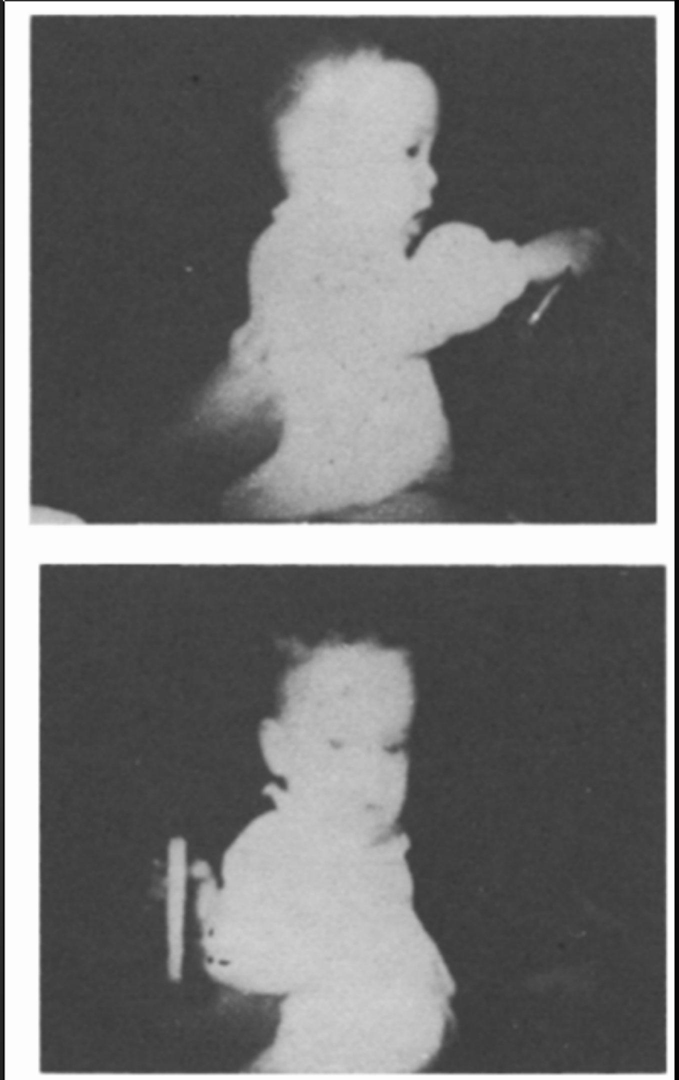


Mounoud and Bower Implications

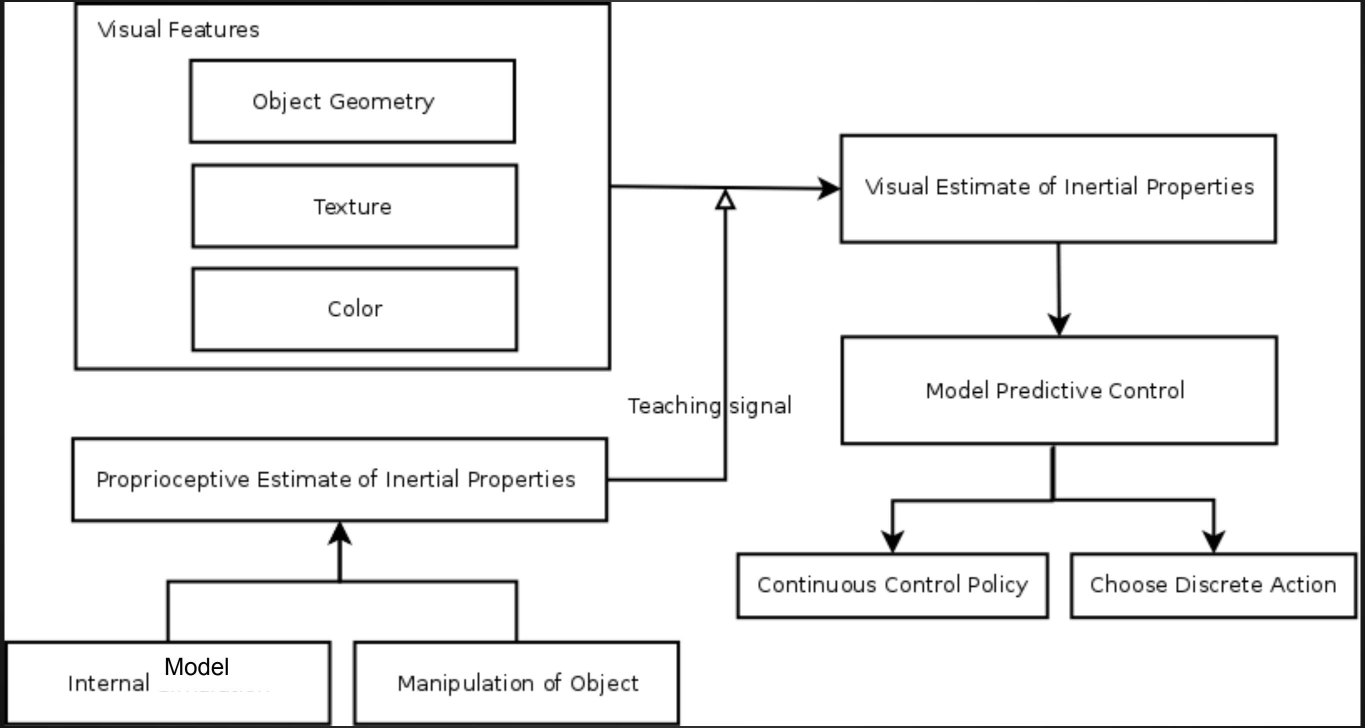
- Infants are using visual information about objects to estimate object properties
- Infants are using estimates to plan anticipatory forces for future grasps

Proposed Approach

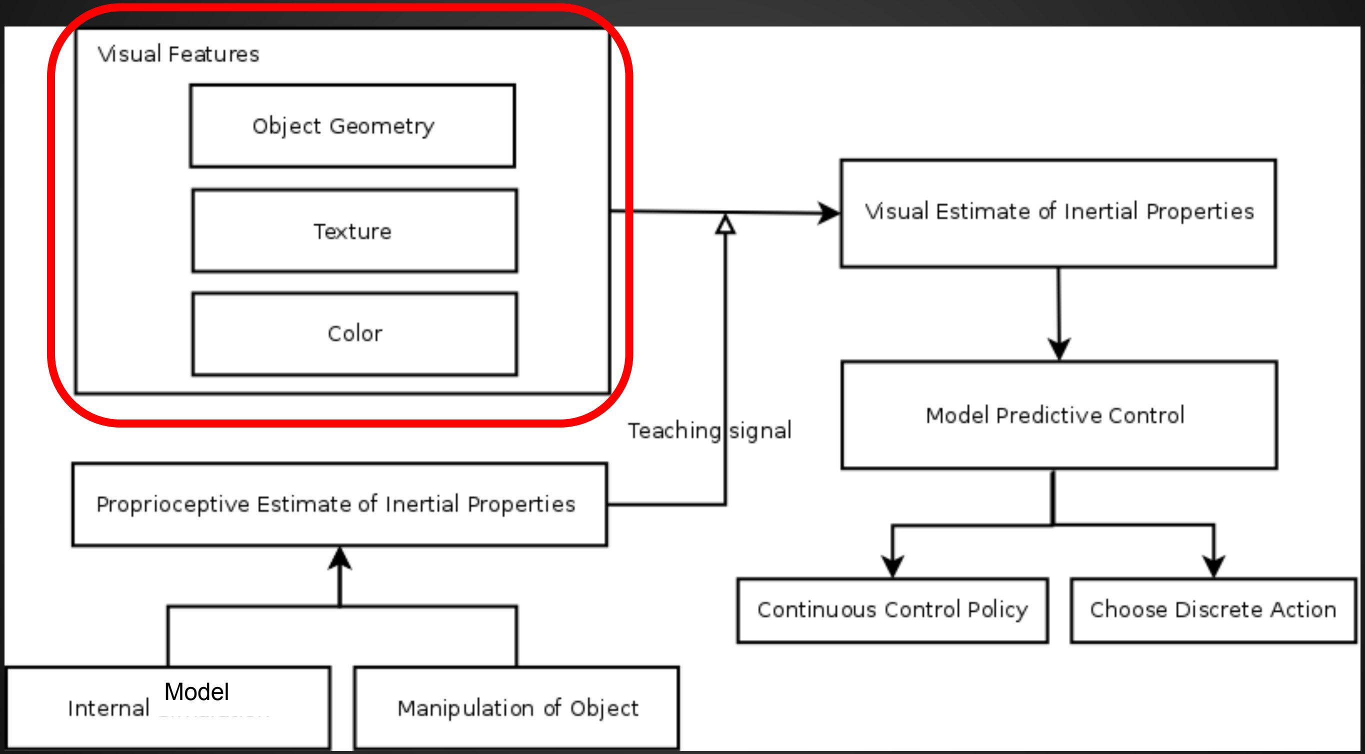
3 part system:

1. **Visual Features**
2. **Proprioceptive Experience**
3. **Model-Predictive Control**

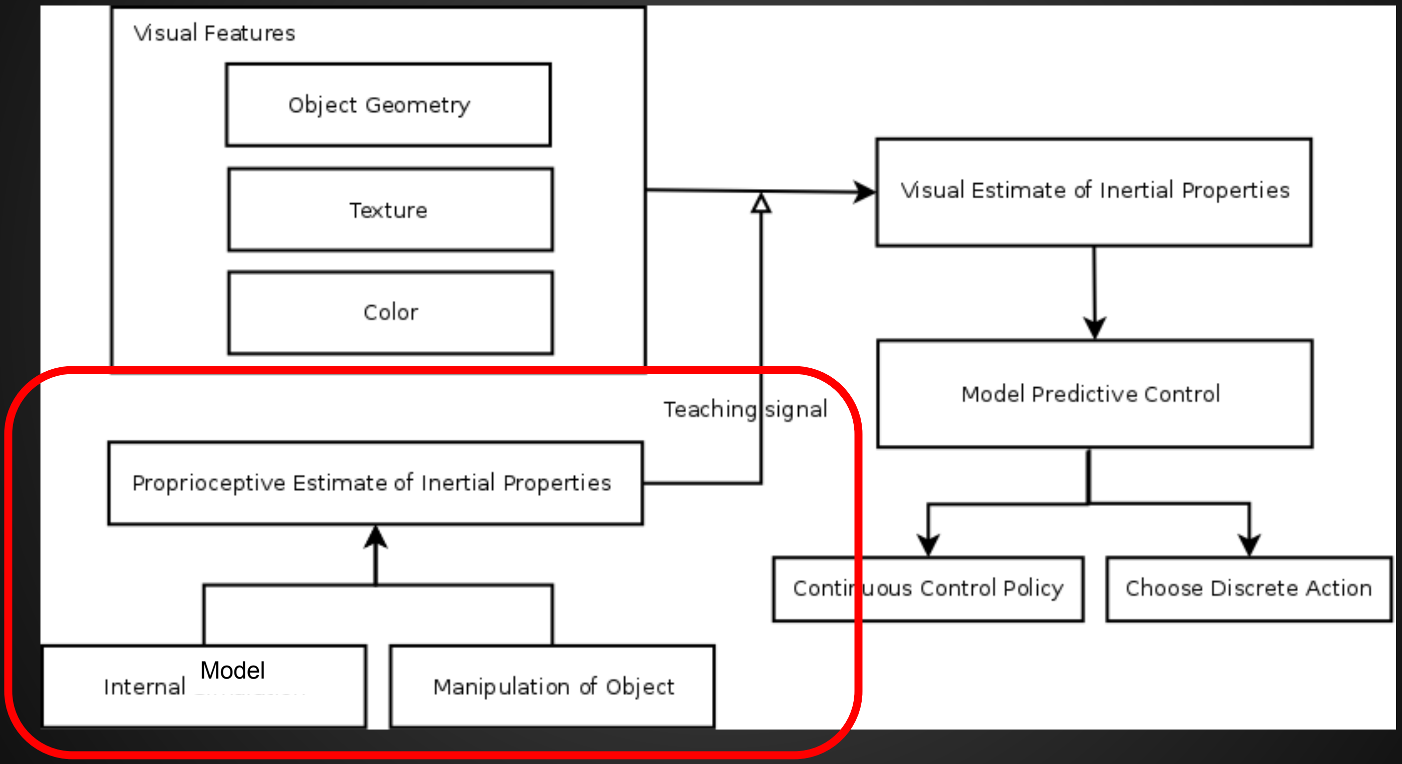
Proposed Approach



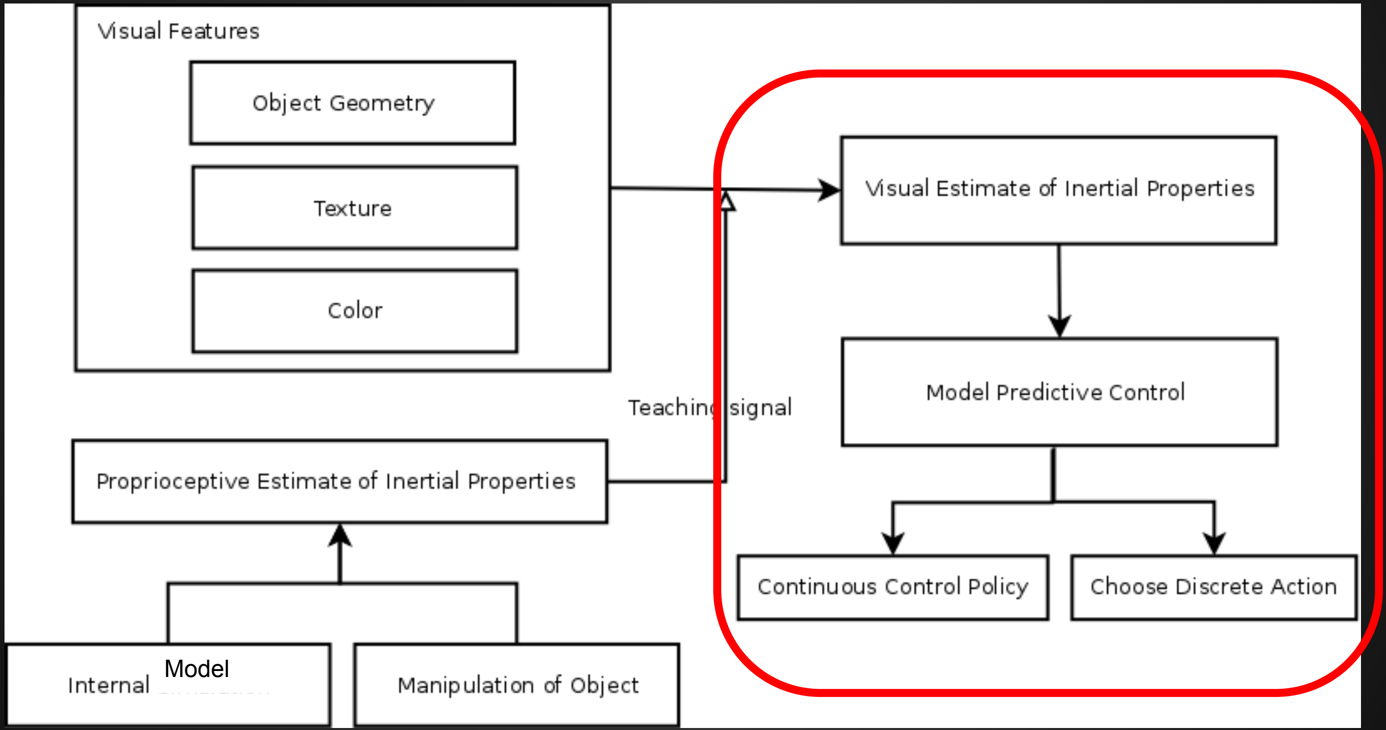
1. Visual Features



2. Proprioceptive experience



3. Model Predictive Control

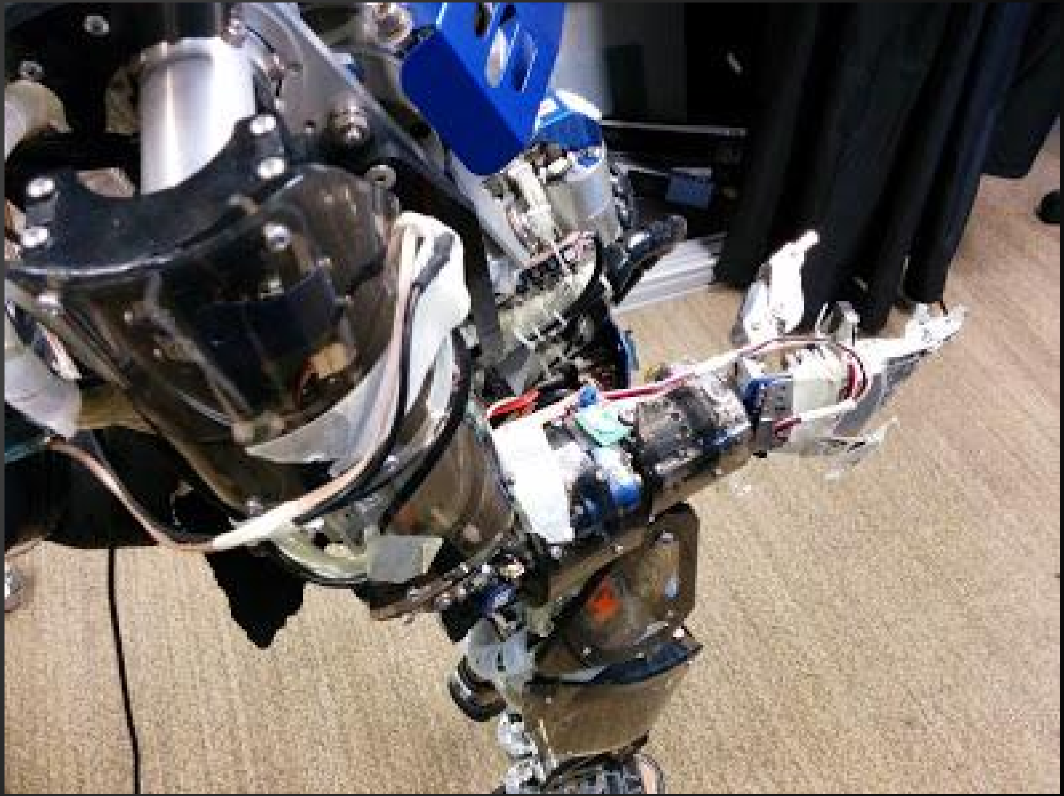


Experiments

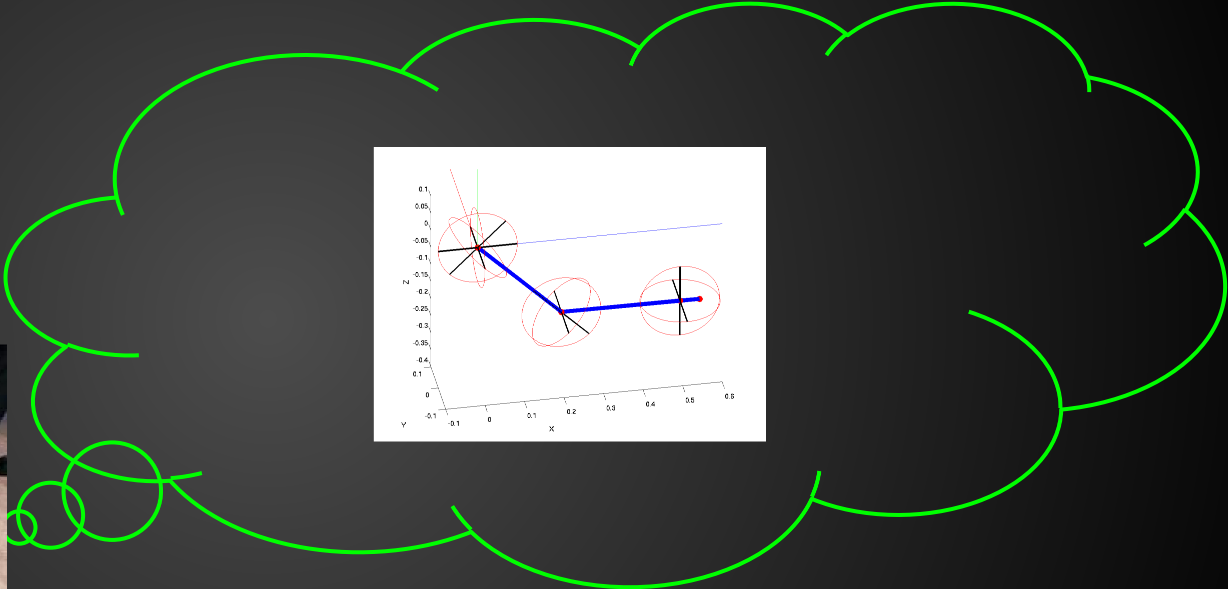
1. MB Experiment
2. Suggested new experiment
3. Generalization to novel object and novel task

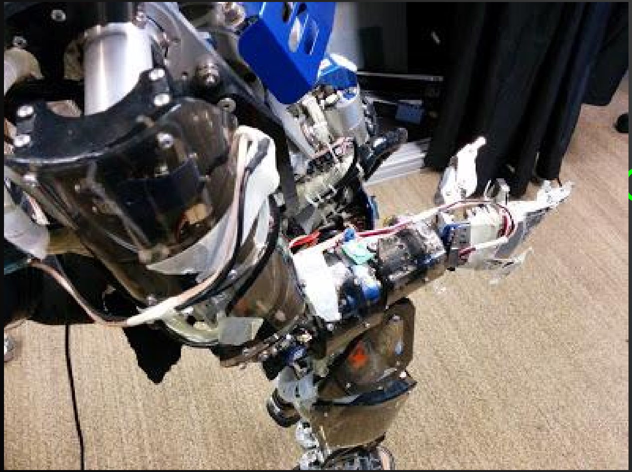
Robot Arm

- 7 degrees of freedom



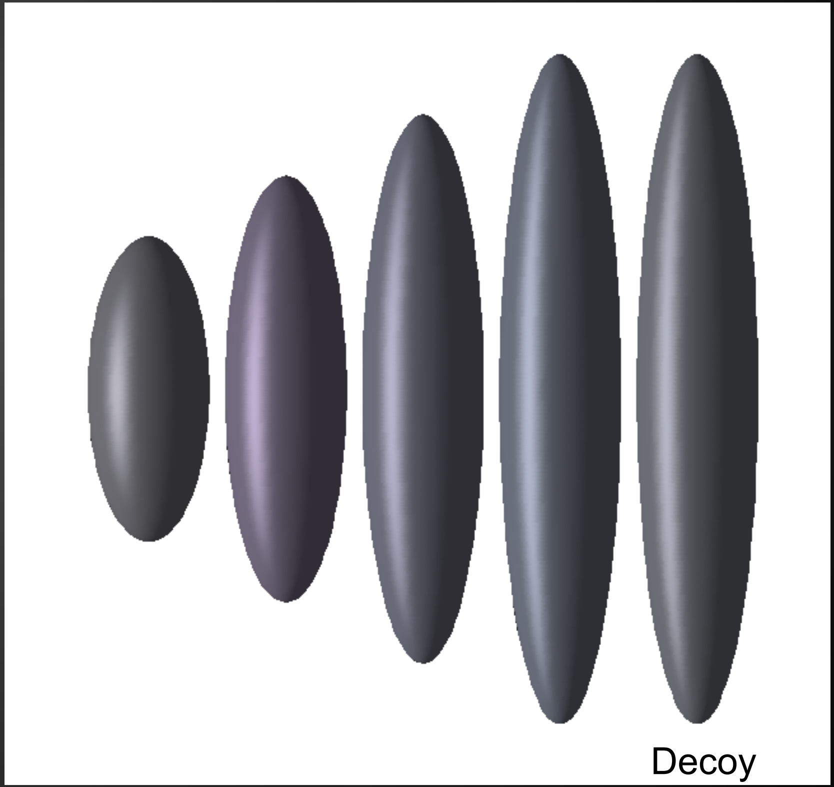
Internal Model for MPC





Experiment 1: Replicating Mounoud and Bower

- 4 rods given to robot
- MPC tries to hold arm level
- Measure vertical displacement when rod is given



Proposed Approach in Context

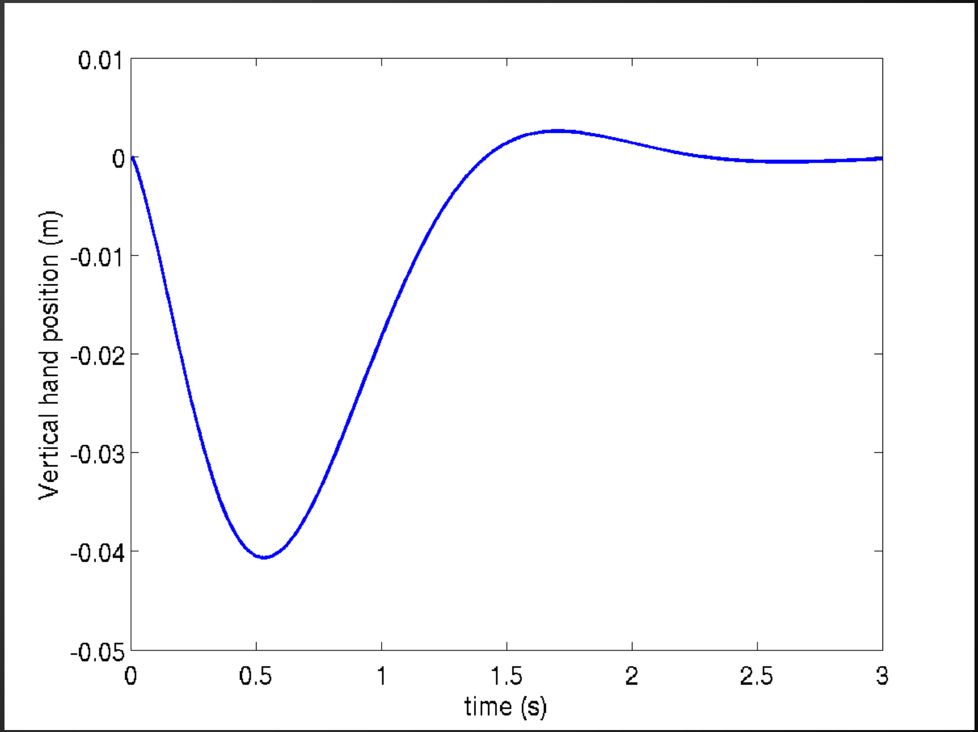
1. When shown an object, robot extracts visual features:
    a. 2d contours
    b. texture
    c. color

Proposed Approach in Context

2. Robot uses visual features to estimate object 3D geometry and density. These determine the estimate of the object's inertial properties.

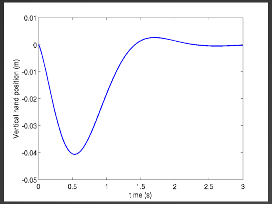
Proposed Approach in Context

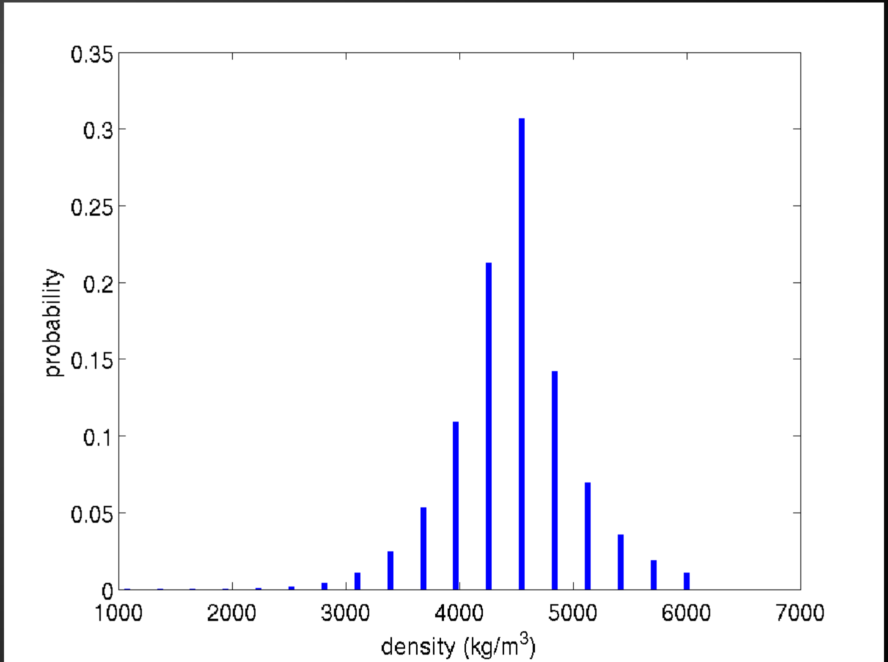
3. MPC tries to hold arm level when given the object, and records resulting torques and arm positions



Proposed Approach in Context

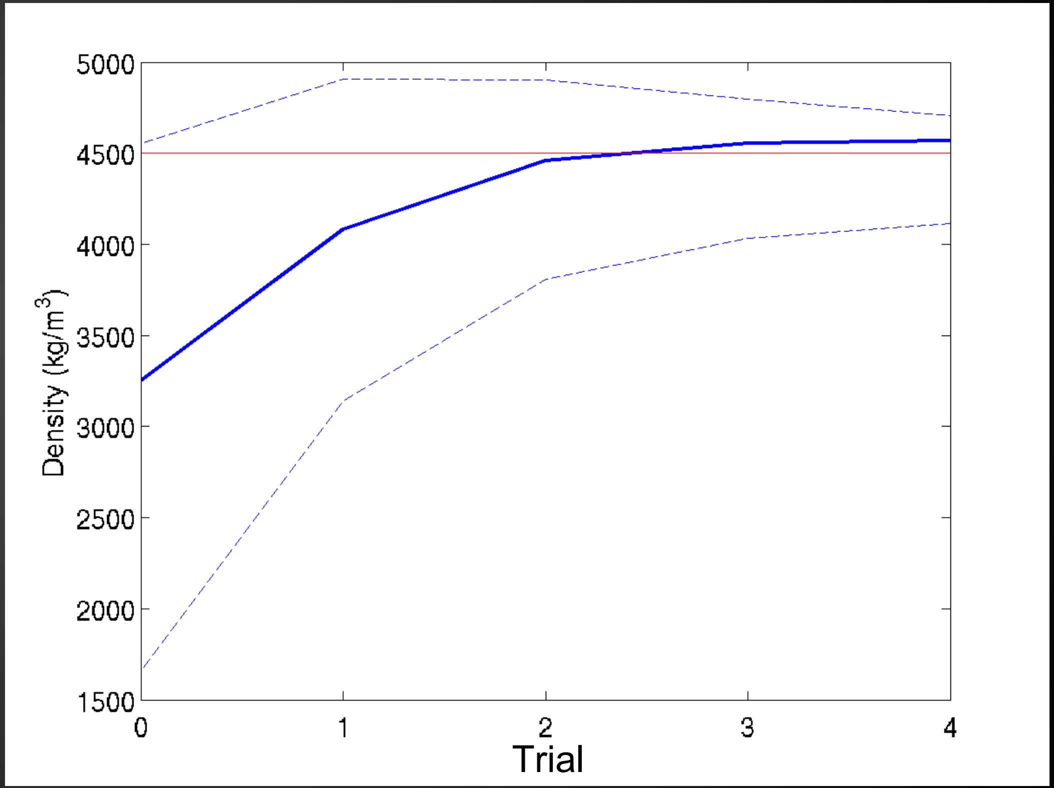
4. Proprioception teaches visual module about density, and therefore changes estimate of object’s inertial properties



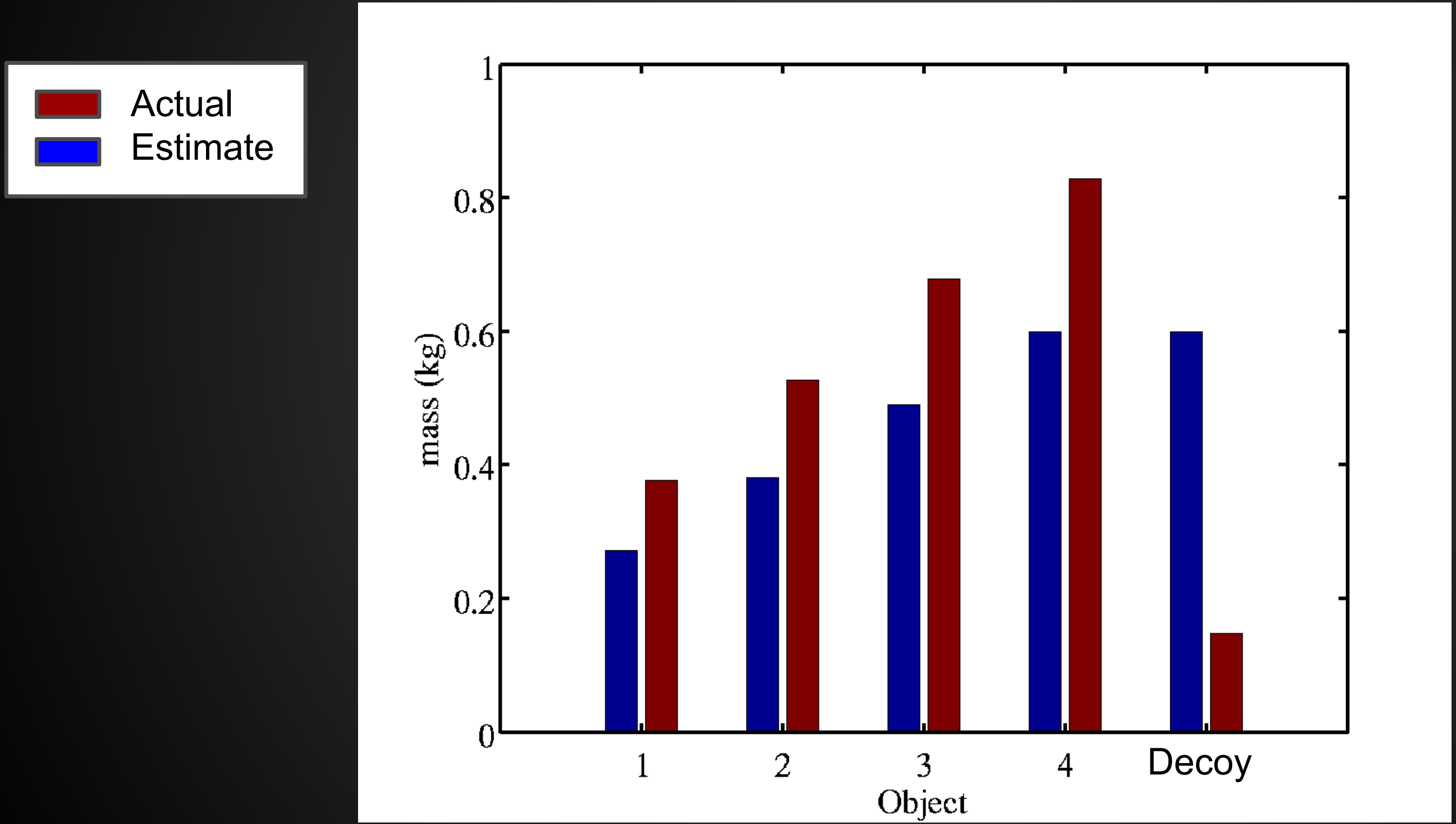


Results: Estimating Inertial Properties

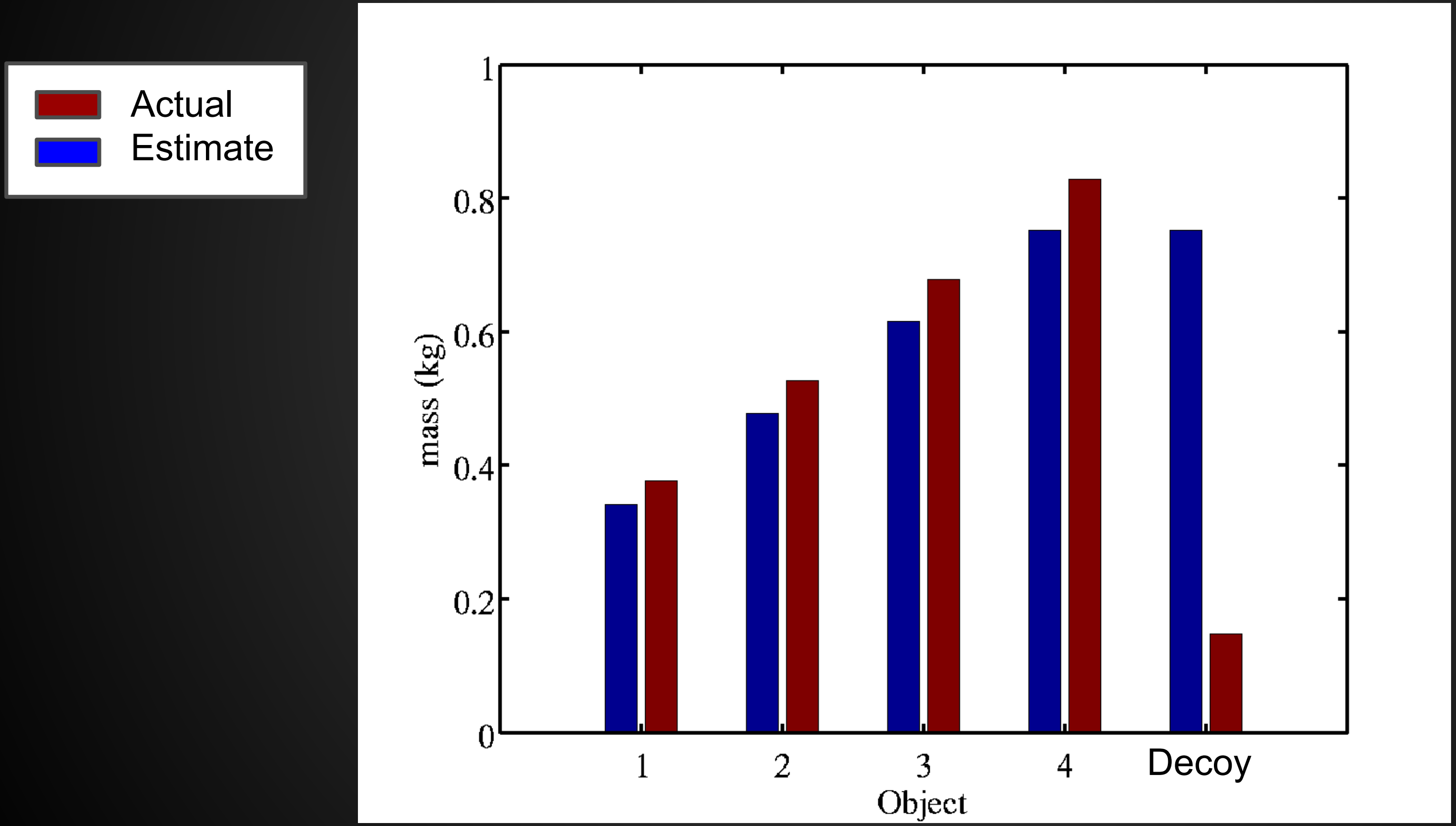
Material density estimate improves after experience, which improves estimate of object's inertial properties, which improves accuracy of MPC plans



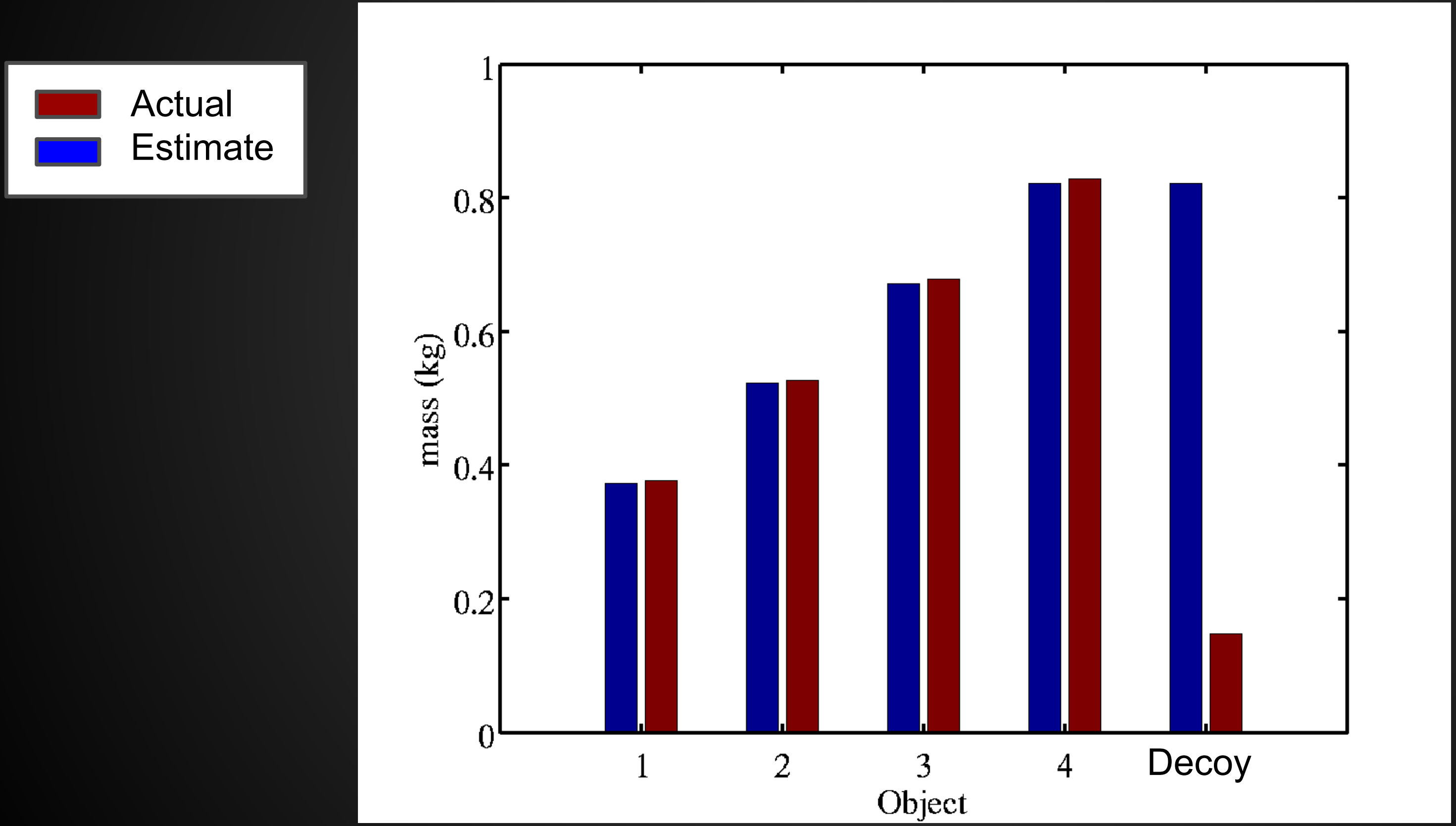
Object Mass Estimates - Trial 0



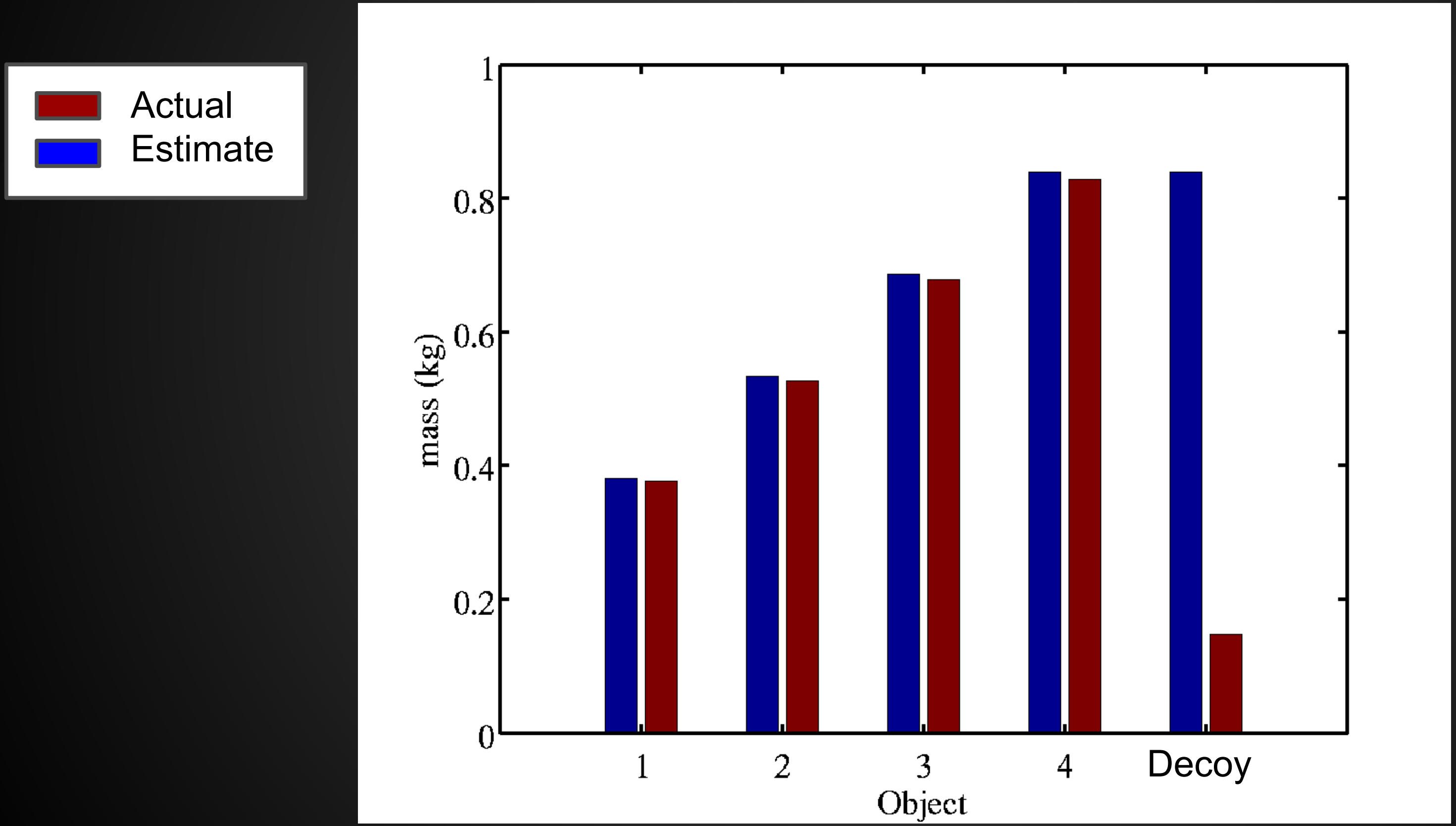
Object Mass Estimates - Trial 1



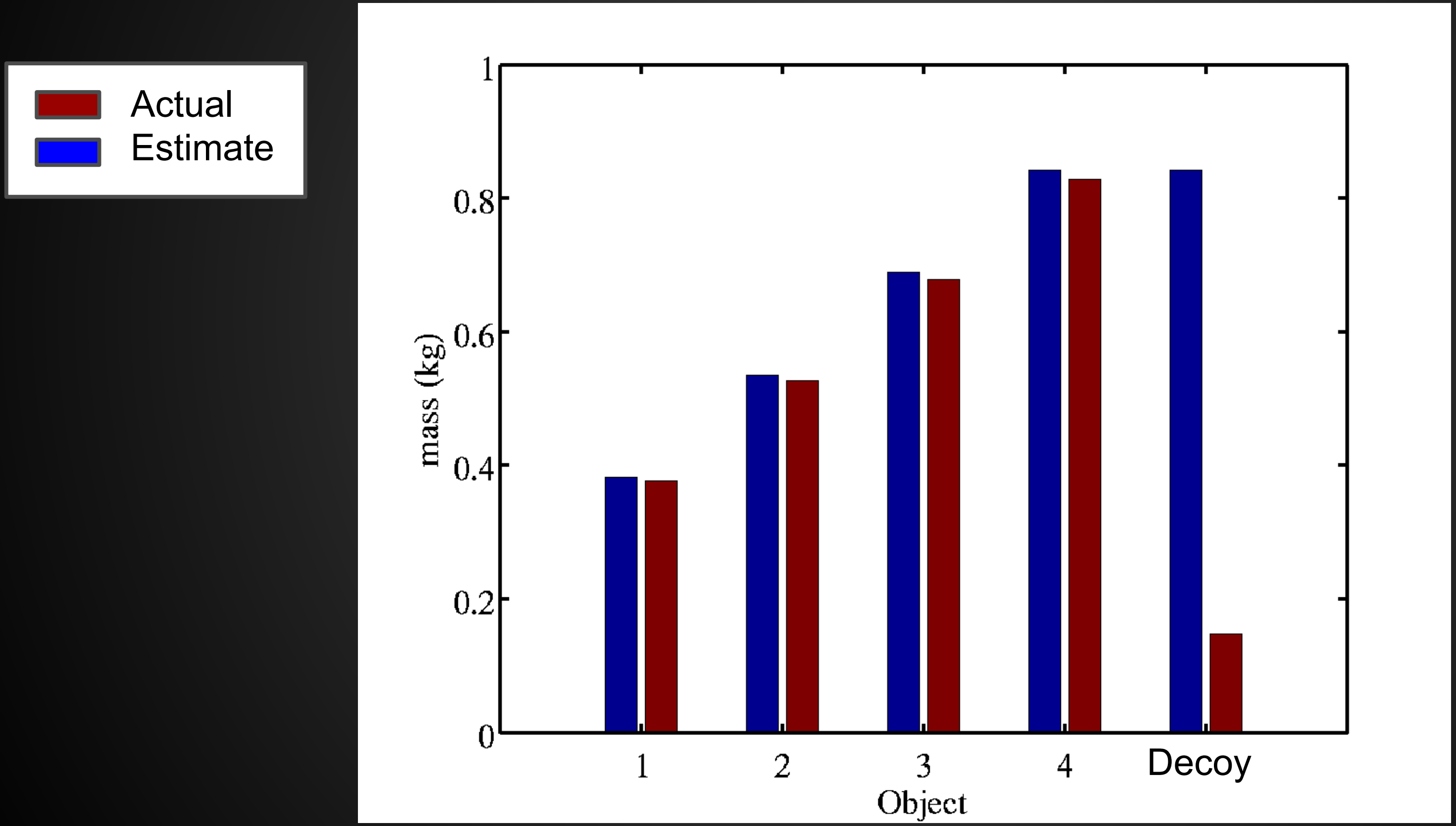
Object Mass Estimates - Trial 2



Object Mass Estimates - Trial 3

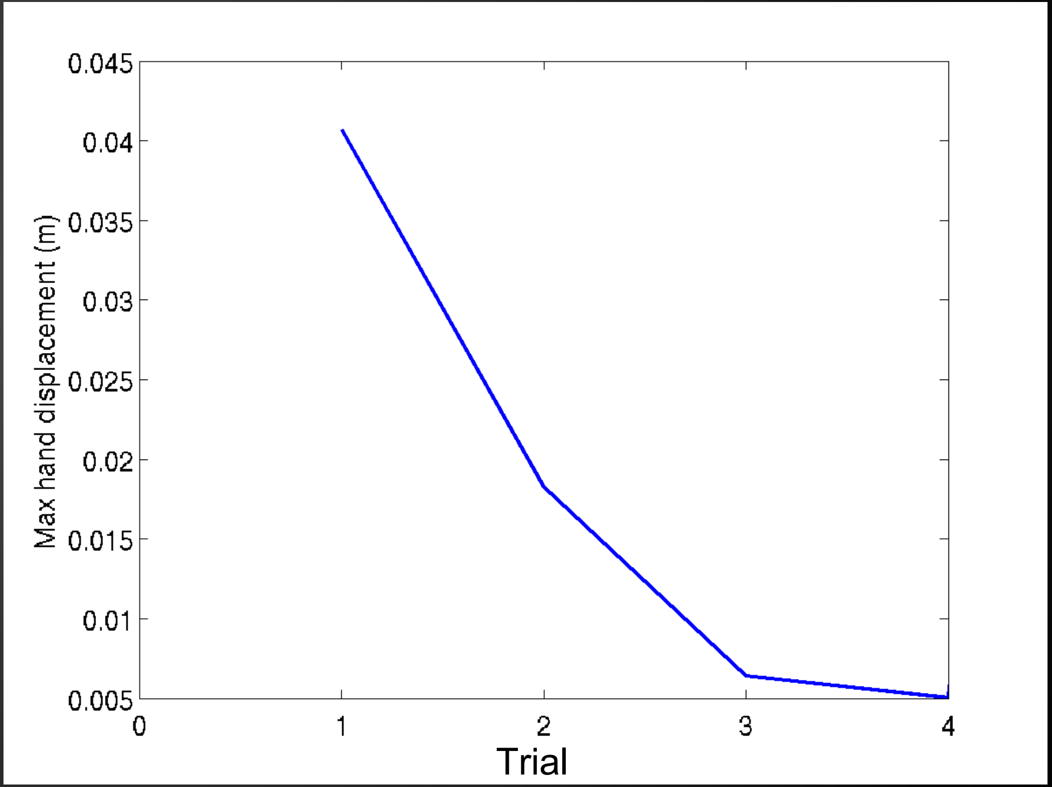


Object Mass Estimates - Trial 4



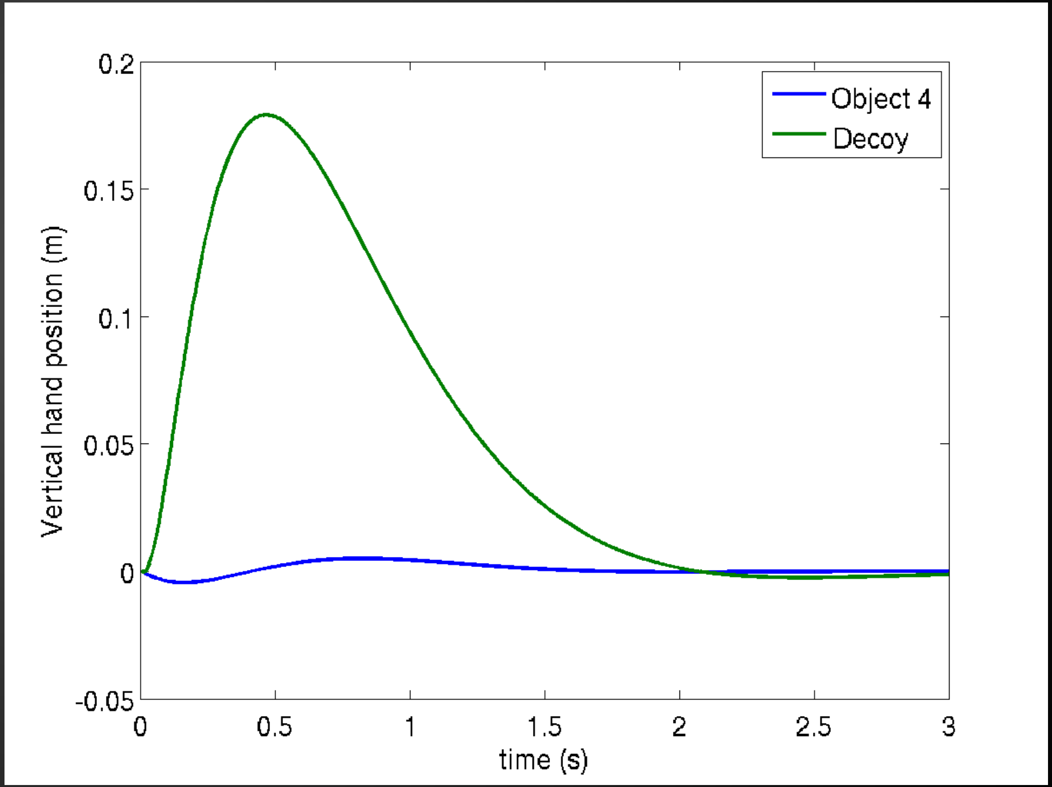
Results: Hand displacement

As in MB infants, hand displacement reduced in subsequent trials



Results: Response to Decoy

As with MB, arm lifts dramatically when presented with hollow decoy



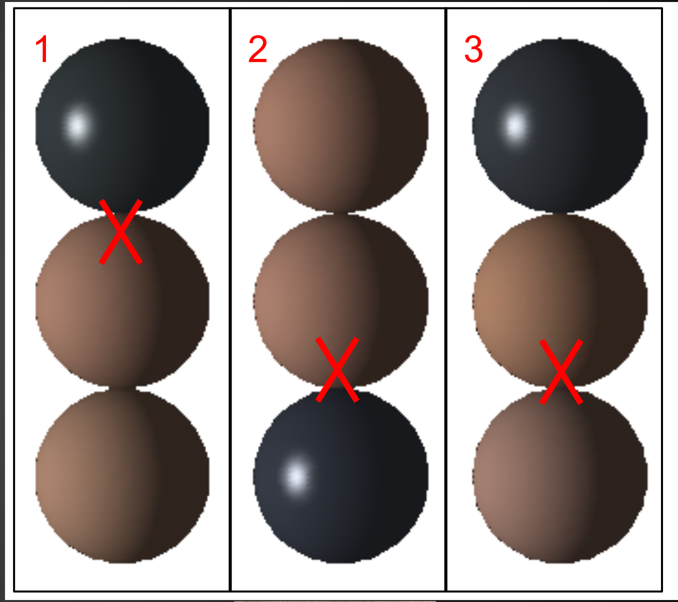
Experiment 2: MB Follow-up

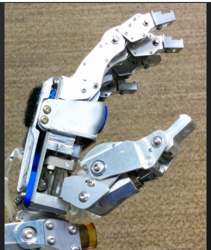
- Our proposed framework suggests a new experiment to run
- We can run this experiment with our framework to generate a prediction

- Decoy objects with same mass, but different centers of mass, will show similar effect

Experiment 2: MB Follow-up

- 3 compound objects with the **same mass** presented to robot
- Decoy object has appearance of the first but inertial properties of the second

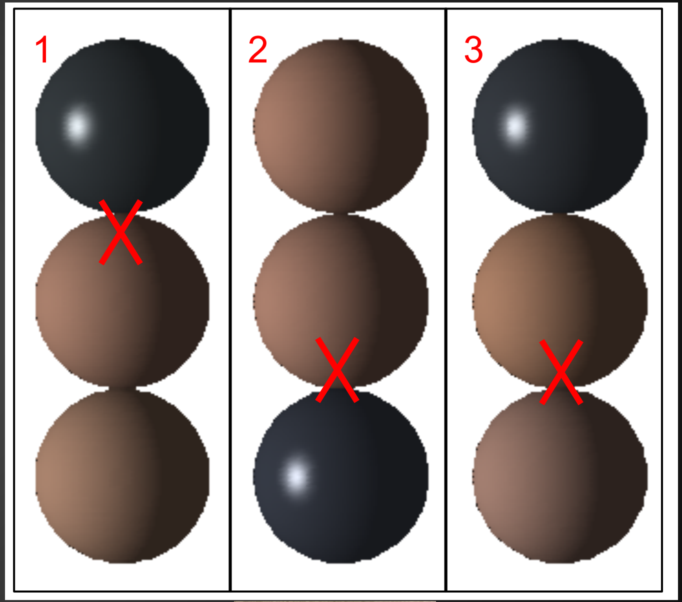


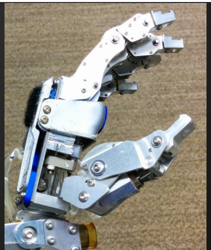


Decoy

Experiment 2: Procedure

- 5 trials: First 2 objects presented twice each. Decoy presented on trial 5.
- On each trial goal is to hold object level

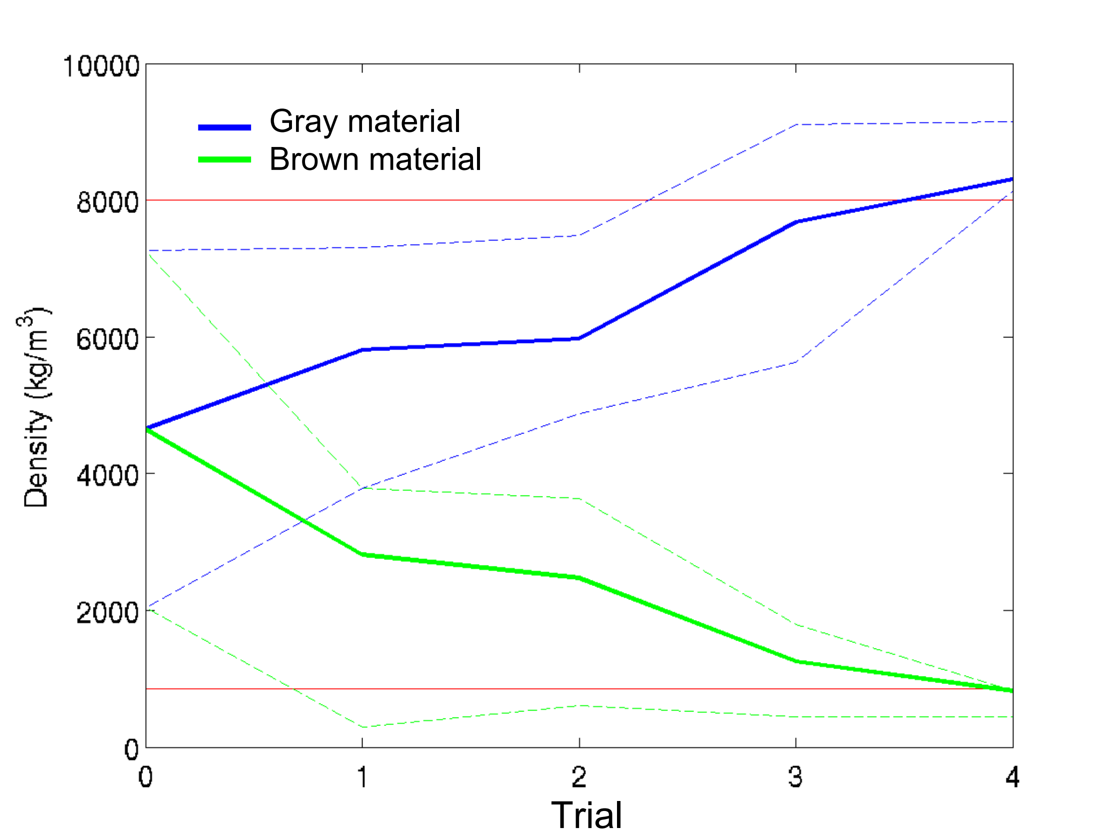




Decoy

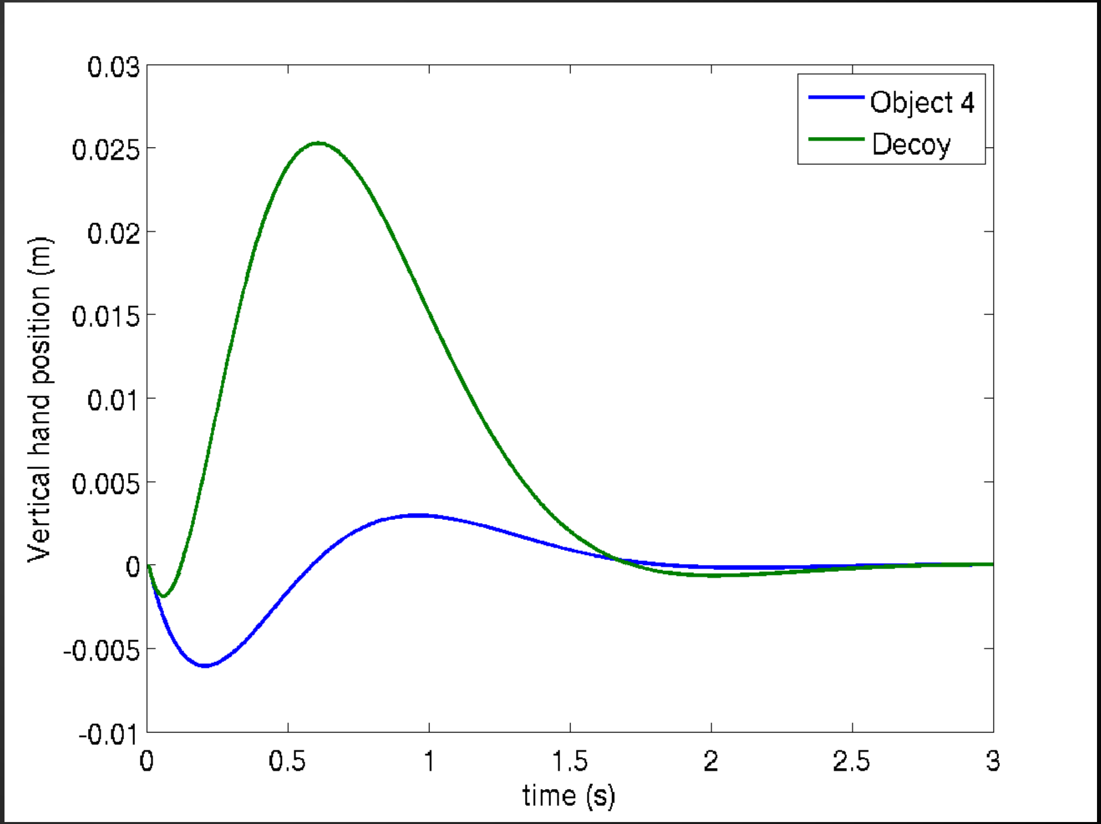
Density estimate

Each material's density estimate improves across trials, even though neither material presented in isolation



Response to Decoy

- Small decoy response error is observed despite mass being the same.



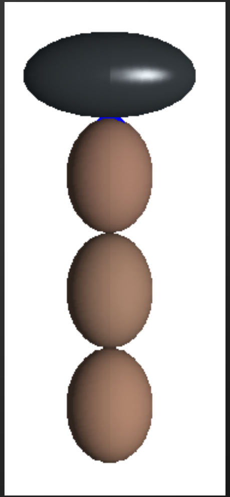
Novel Objects

Experiment 3: Novel Object

- Use MPC to estimate grasp that requires least energy to hit a target with a given force

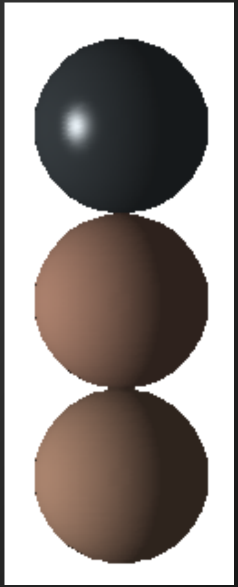
Task:
move tip of object through a set of 3D waypoints

Object:



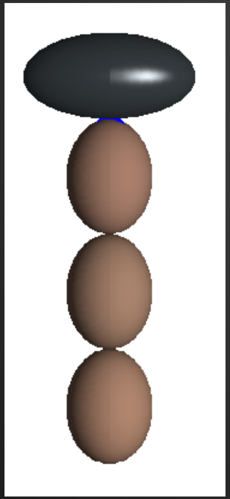
Experiment 3: Outline of a trial

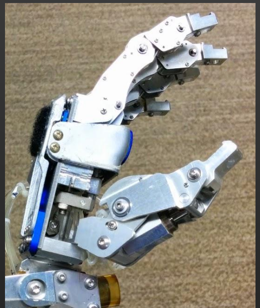
1. Robot is given a training object, uses MPC to hold it level

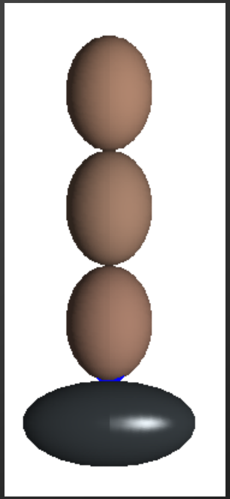


Experiment 3: Outline of a trial

2. Robot is presented with a novel object, and asked to grasp from top or bottom



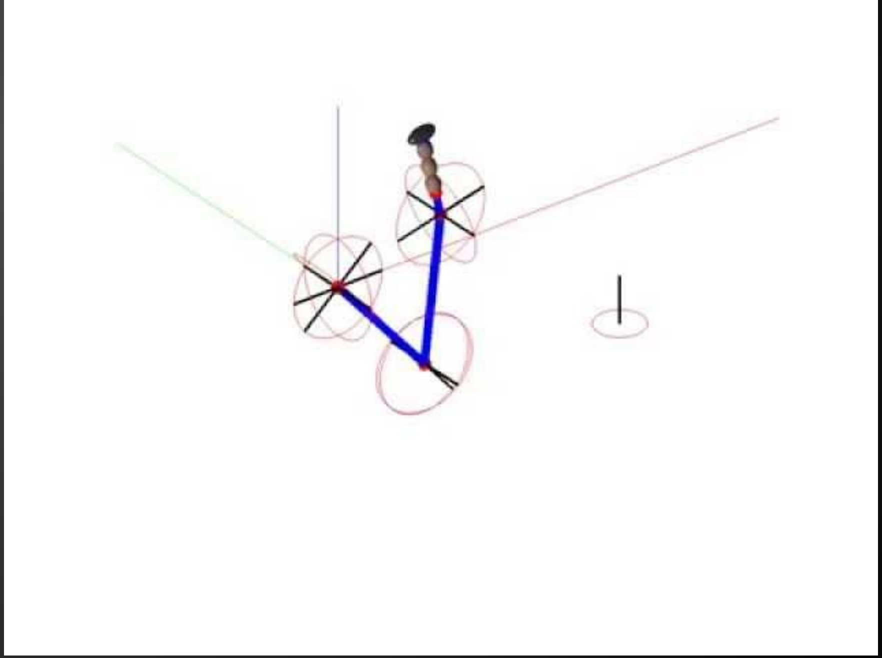




Experiment 3: Making a choice

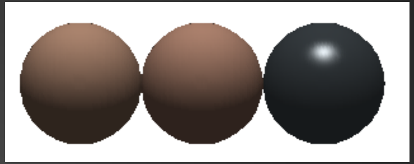
- Choose grasp that requires least energy to hit a target with high force.

The correct answer:



Experiment 3: Trial

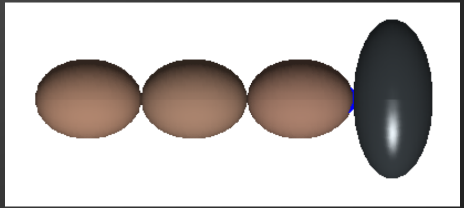
Training object:



Training Task:

Hold object at arms length

Test object:



Test Task:

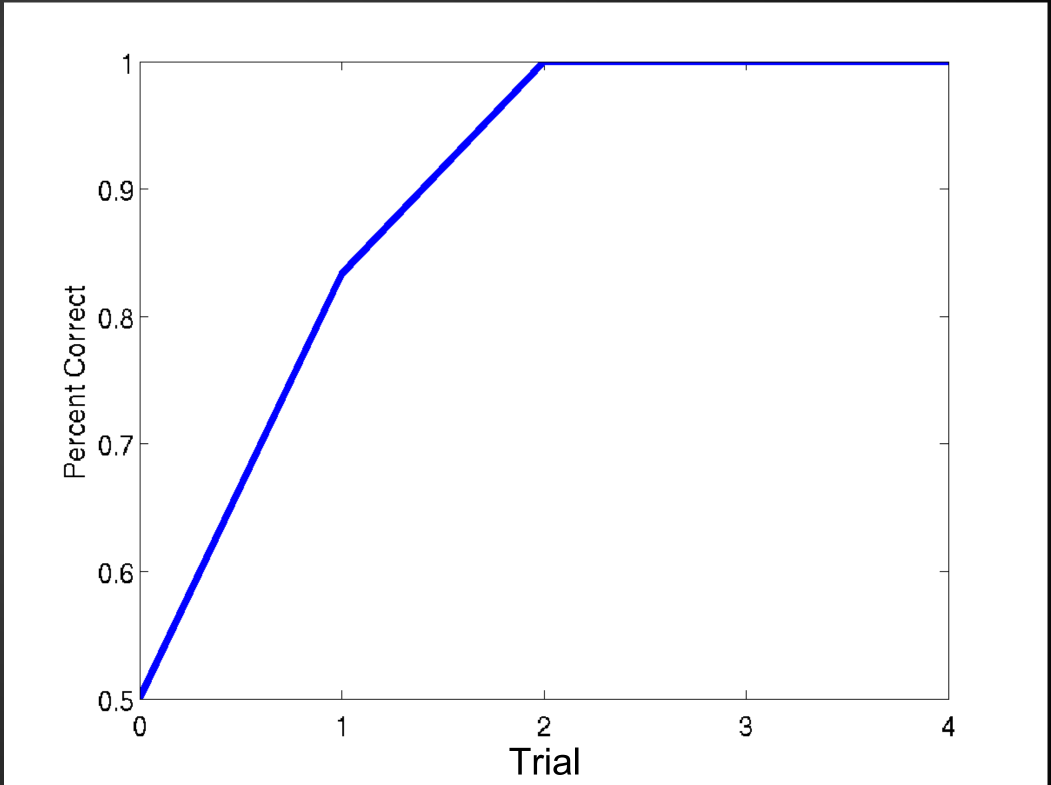
Choose grasp for hammering, never hold object

Experiment 3: Procedure

- Independent variable: Number of trials with training objects
- Dependent variable: Proportion of grasps correctly chosen
- Experiment repeated 15 times with different random seeds to give proportions

Experiment 4: Results

Accuracy increases with experience



Generalization across objects and tasks

- 3D geometry estimation is applicable across objects
- 3D geometry plus density provides inertial properties
- Inertial properties plus MPC provides plans for any object

Conclusions

- Framework learns to manipulate new objects for new tasks
- Framework explains an existing experiment, suggests a new experiment, and predicts results
- Can be implemented on a robot