

# Real-Time Simulation for in-the-loop Grasping

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# Introduction

- Simulation can be a powerful tool
- Typically used *Off-Line* due to real-time constraints
- However, it can be a powerful *On-Line* tool as well
- Can be used in predictive, *Feed-Forward* way for grasping and manipulation tasks

# Timeline

## Past:

- Low Dimensional Posture Subspaces: Eigengrasps
- Online Grasping
- Data Driven Grasping

## Present:

- Blind Grasping using Tactile Feedback
- Improved Grasp Quality Measures

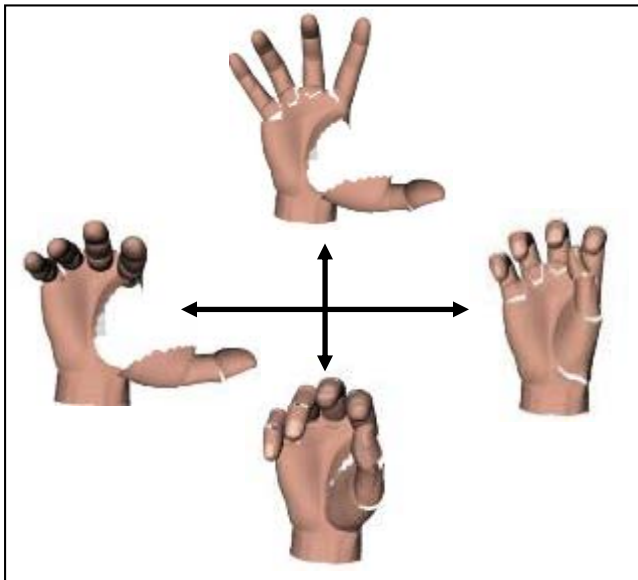
## Future:

- Brain Control Interfaces for Grasping

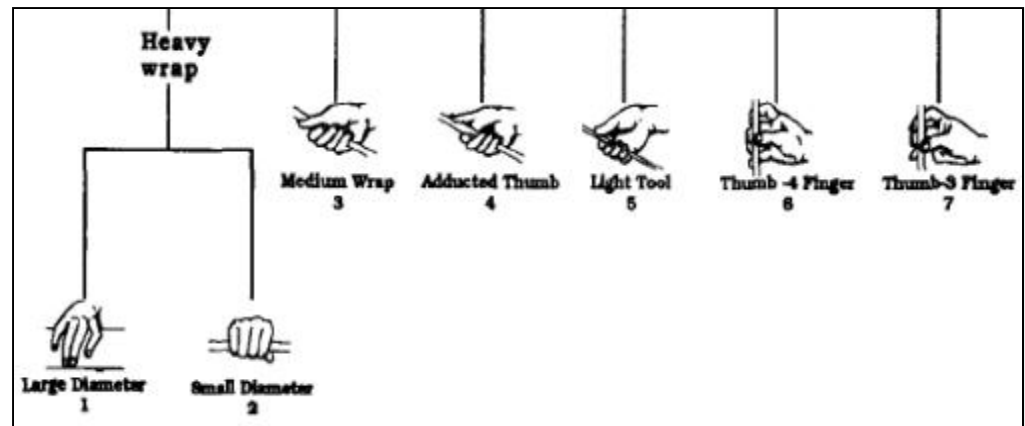
# Eigengrasps

- Can be seen as generalization of grasp taxonomy [Napier '56, Cutkosky '89, Iberall '97, etc.]

continuous subspace

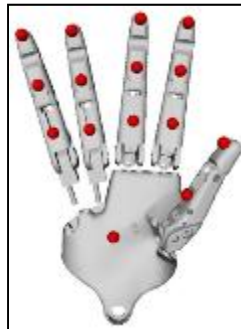
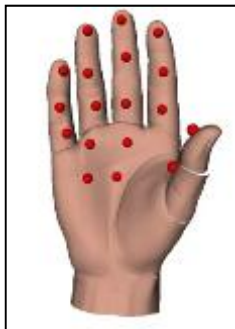
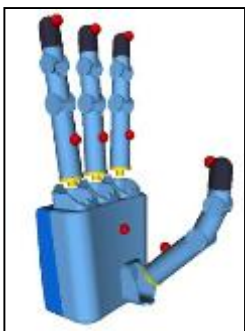


discrete points, Cutkosky '89



## Grasp planning using Eigengrasps\*

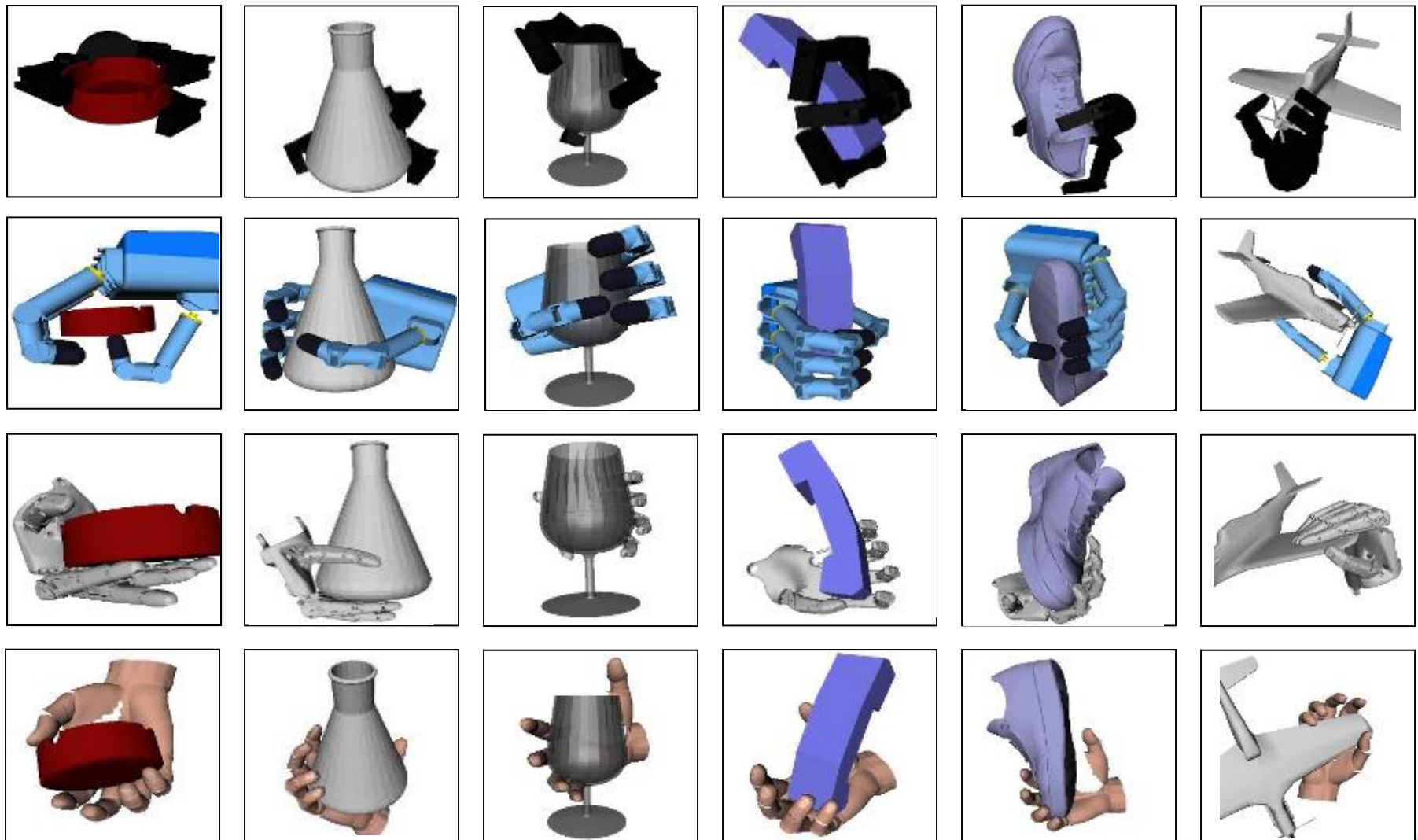
- Energy function formulation attempts to bring pre-specified contact locations on the palm in contact with the object



- Simulated annealing search is performed over 8 over 8 variables
  - 6 for wrist position / orientation
  - 2 eigengrasp amplitudes

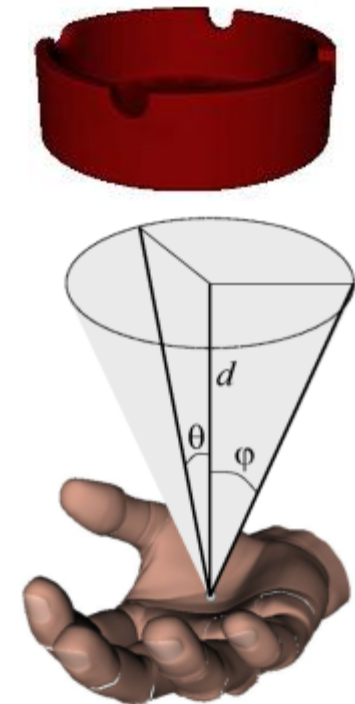
\*M. Ciocarlie and P. Allen, Hand Posture Subspaces for Dexterous Robotic Grasping, IJRR, 2009

# Grasp Planning Examples



# Interactive Grasp Planning

- Hand posture: **2 variables** (eigengrasp amplitudes)
- Hand position:
  - user not expected to fully specify final position
    - affects interaction, can not handle noise
  - **3 variables** to re-parameterize hand approach:
    - $d$ ,  $\theta$  and  $\varphi$  define a conical search space
- Total: **5 variables**
  - loops of 2000 Simulated Annealing iterations
  - continuously update base hand position
  - search does not get stuck if one loop fails
  - best pre-grasps tested for form-closure





# Robotic Grasping: A Data Driven Approach





# Is Grasping Indexable?

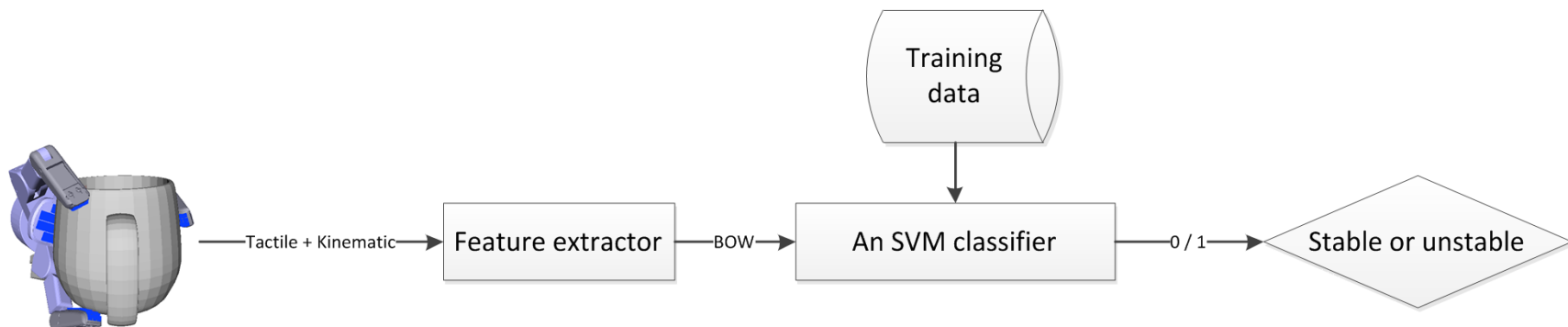
- Many previous attempts to taxonomize grasps
- Is there a finite set of grasps we can pre-compute?
- If so, can we build an **indexable database** of grasps?
- Given a **novel object** to grasp, can we find a **similar grasp**?
- Some Problems:
  - **Lots of objects** to grasp...
  - **Lots of DOF** in a hand (~20 + 6 in human hand)...
  - **Lots of robotic hands**...
- Intractable? But maybe not....

## Building the Columbia Grasp Database

- Simulated annealing in a **eigengrasp** space
- 8 dimensions: 6 pose + 2 eigenvectors
- 1,814 objects at 4 scales = 7,256 objects to grasp
- Grasps evaluated in *Graspt!* simulator for 4 hands
- 6 compute-months on multicore workstations
- Contains over 250,000 **form-closure** grasps
- Includes **pre-grasp** poses, contact points, and Ferrari-Canny **quality metrics**
- A **new tool** for the grasping community
- Available at [grasping.cs.columbia.edu](http://grasping.cs.columbia.edu)

# Learning Grasp Stability via Tactile Sensing\*

- **Problem:** Can we estimate the stability of a grasp given its tactile and kinematic sensor information?
  - a mapping  $f: \{Tactile, Kinematic\} \Rightarrow stability$
- A machine learning approach to learn from grasp samples
  - Need a large range of objects with different sizes and hand poses
  - **Simulate** different grasping situations



A simple procedure of grasp stability estimation

\*Hao Dang and Peter Allen, Learning Grasp Stability, ICRA 2012

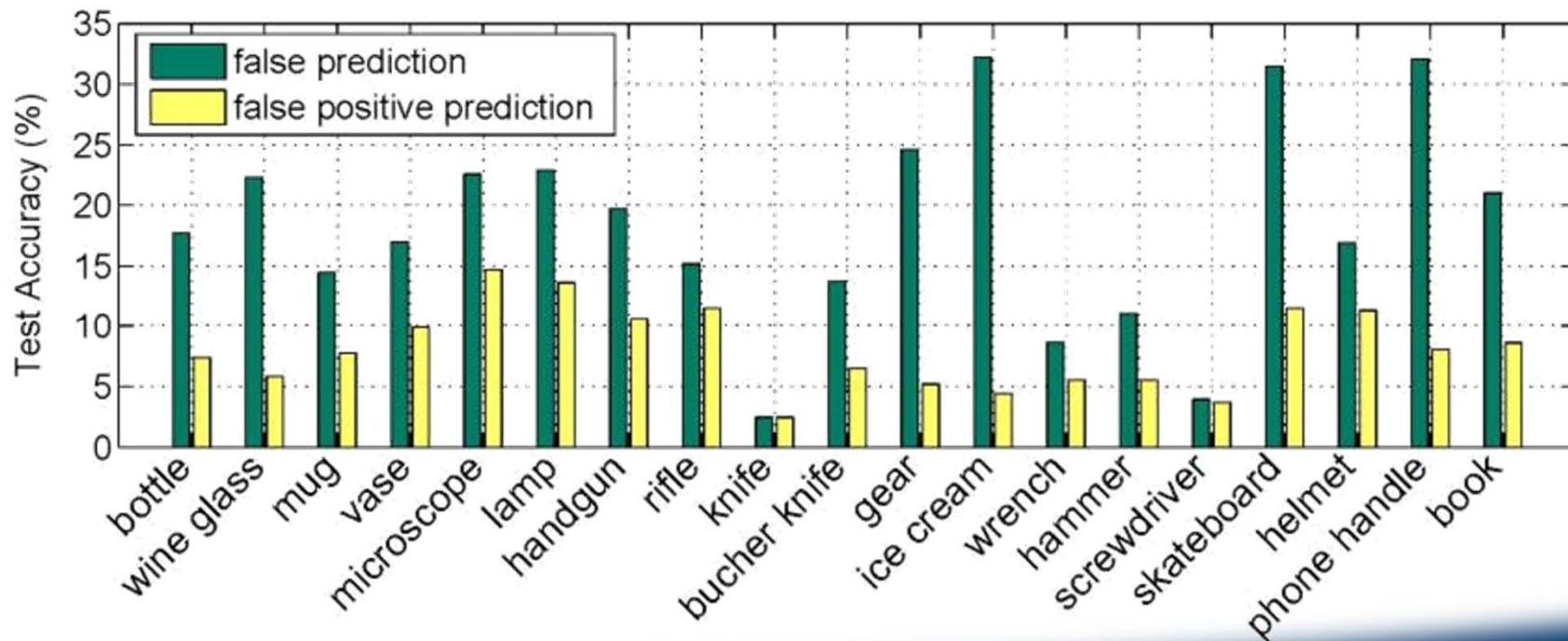
# Experiments

- Equipment
  - A Barrett hand with 96 tactile sensors (simulated and real)
- Grasp set contains 24,000 grasps, training : test = 2/3 : 1/3
- Building a contact dictionary
  - Extract contacts from all the grasp samples in a training set
  - Cluster the contacts using K-means algorithm
  - Cluster centers represent discretized geological centers of contacts



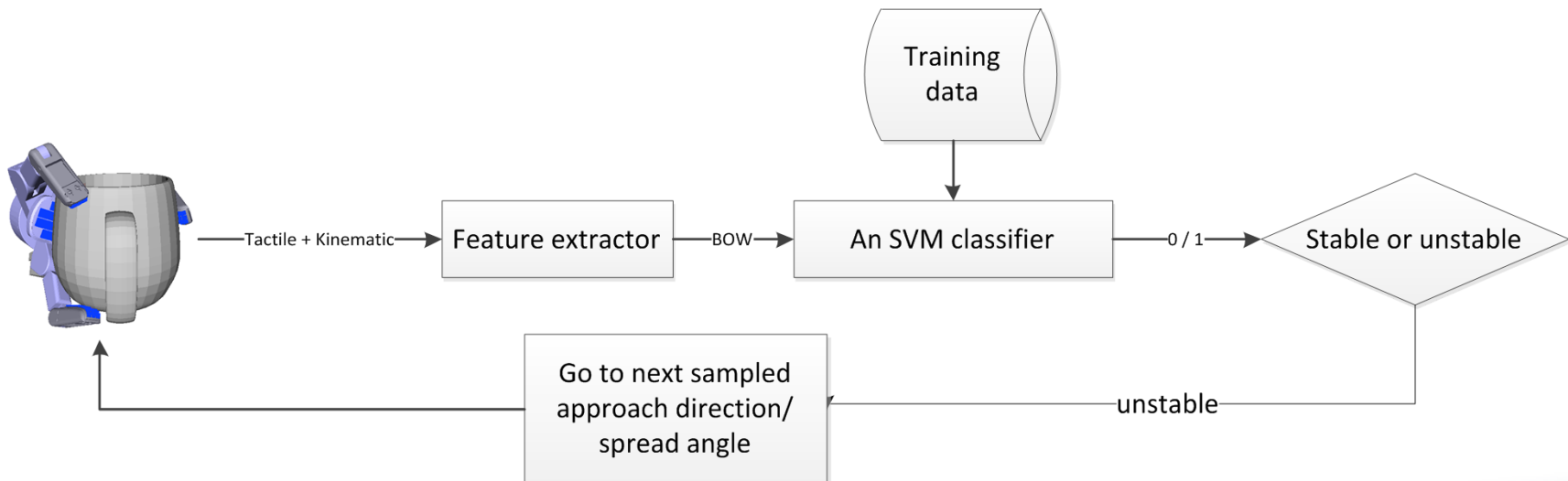
# Experiments

- Simulation experiment
  - An SVM is trained based on a training set of 2/3 grasps
  - Tested against the remaining 1/3 grasps



# Experiments

- Physical experiment
  - Using the same SVM trained in the simulation experiment
  - Uniformly sample approach direction and spread angle
  - Try out sample poses sequentially and lift object up if classified stable



A simple loop for physical experiment

# Experiments

- General grasping performance
  - Different objects
  - Different surface materials and weights



Three example grasps



# Experiments










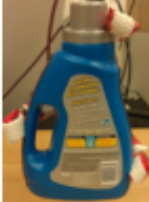


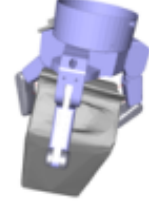







Object	Mass (kg)	# of exp	Success	Success rate
Mug	0.43 -0.93	30	28	93%
Paper wipe box	0.17	10	9	90%
Pencil cup	0.09	10	9	90%
Candle box	0.11	10	9	90%
Decorative Rock	0.28	10	6	60%
Canteen w/o cover	0.5 -0.75	20	15	75%
Canteen w/ cover	0.5 -0.75	20	17	85%
Total	0.09 -0.93	110	93	84.6%

## Discussion

- Stability can be learned using tactile and kinematic data
- Knowledge can be transferred from simulation to a physical world
- Reasonably good stable grasp detector in a stable grasp exploration process
- Limitations
  - Accuracy of sensor modeling
    - Contact distribution
  - Sensor coverage
    - A source of error

# Improved Grasp Quality Metric\*

- P(fc)
  - 35 successes
- Epsilon Quality
  - 16 successes
- 100% improvement

	Best Grasp ranked by $\epsilon_{gws}$			Best Grasp ranked by P(fc)		
	Simulated Grasp	Physical Grasp	Grasp Metrics	Simulated Grasp	Physical Grasp	Grasp Metrics
<b>Flashlight</b>			$\epsilon_{gws} = 0.18$ P(fc) = 75% Lift Test Success: 0/10			$\epsilon_{gws} = 0.15$ P(fc) = 99% Lift Test Success: 10/10
<b>Drill</b>			$\epsilon_{gws} = 0.13$ P(fc) = 62% Lift Test Success: 6/10			$\epsilon_{gws} = 0.12$ P(fc) = 95% Lift Test Success: 8/10
<b>Detergent Bottle</b>			$\epsilon_{gws} = 0.33$ P(fc) = 79% Lift Test Success: 2/10			$\epsilon_{gws} = 0.31$ P(fc) = 97% Lift Test Success: 5/10
<b>Drink Carton</b>			$\epsilon_{gws} = 0.38$ P(fc) = 86% Lift Test Success: 8/10			$\epsilon_{gws} = 0.37$ P(fc) = 100% Lift Test Success: 10/10
<b>False Rock</b>			$\epsilon_{gws} = 0.35$ P(fc) = 75% Lift Test Success: 0/3			$\epsilon_{gws} = 0.319$ P(fc) = 98% Lift Test Success: 2/3

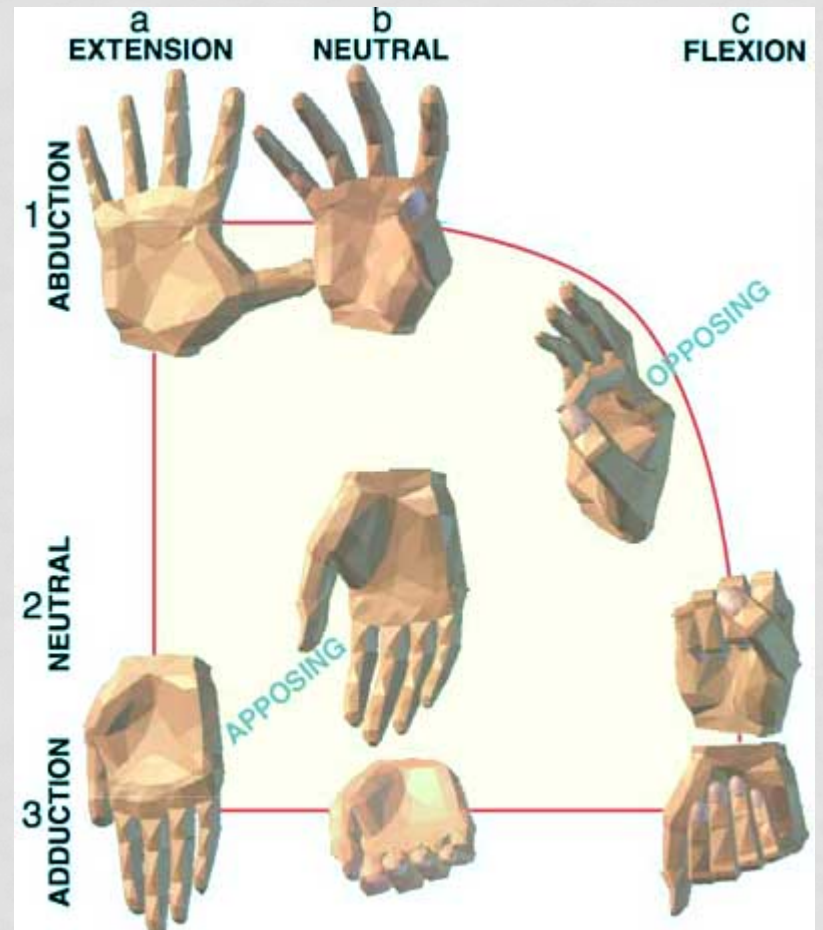
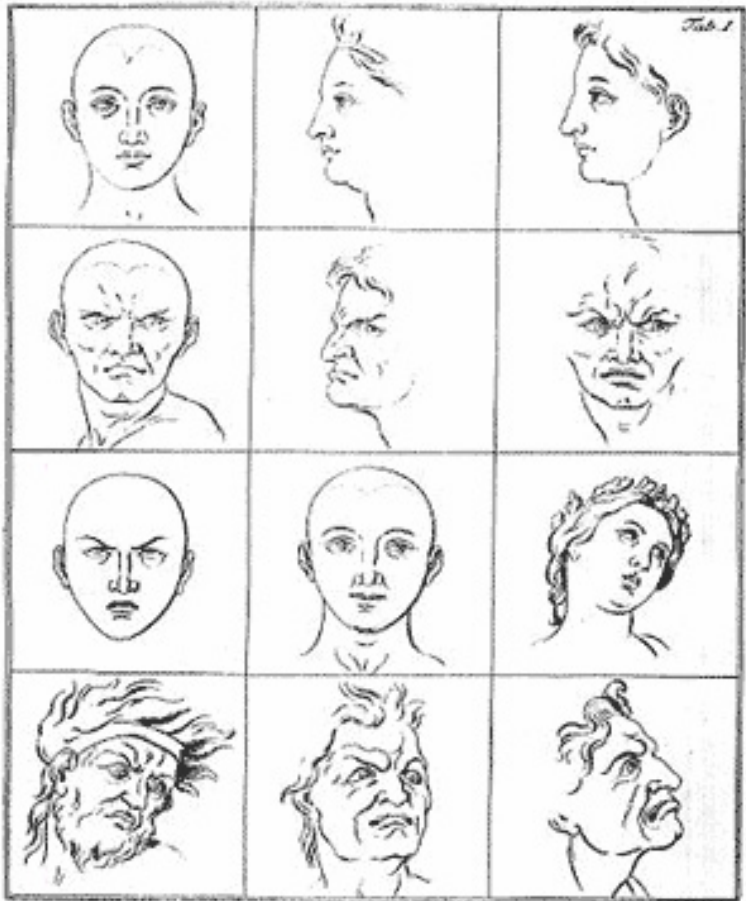
\*J. Weisz and P. Allen, Pose Error Robust Grasping from Contact Wrench Space Metrics, ICRA 2012

# HUMAN-ROBOT INTERFACES FOR ASSISTIVE GRASPING

- Need for assistive robotics
  - 400,000 spinal cord injuries, 50% below neck paralysis
  - 5 M stroke patients
  - Aging worldwide population
- Grasping for Transport is a critical issue in assistive robotics
  - 'tasks identified "high priority" by users with disabilities are picking up miscellaneous objects from floor or shelves as well as carrying objects' [1]

[1] "Neuromuscular diseases in the mda program," 2008,  
<http://www.mdaua.org/disease/40list.html>

# GRASPING WITH YOUR FACE

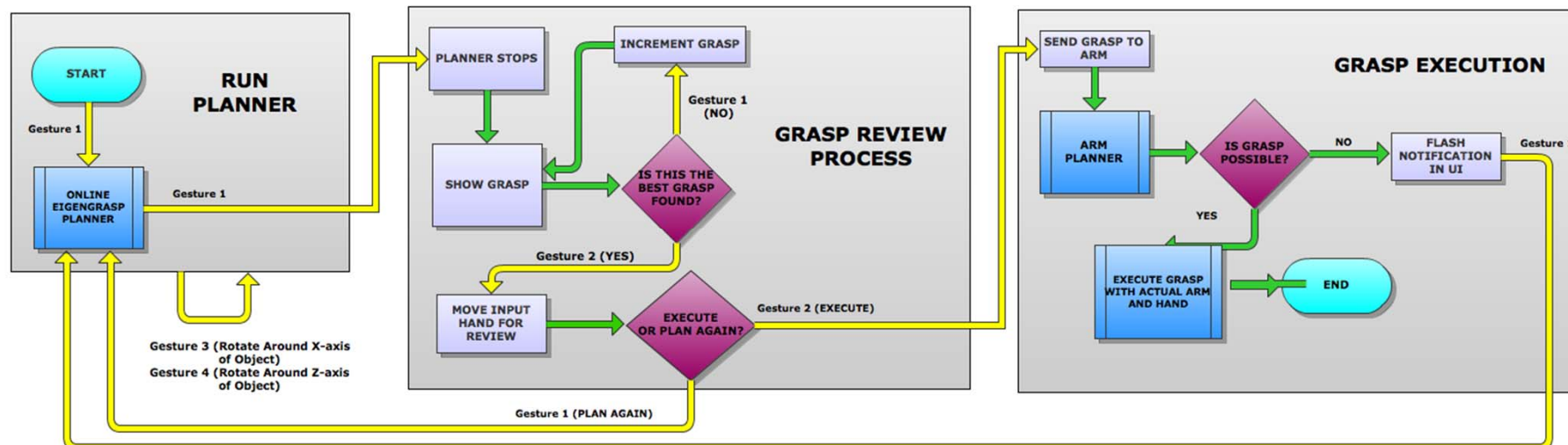
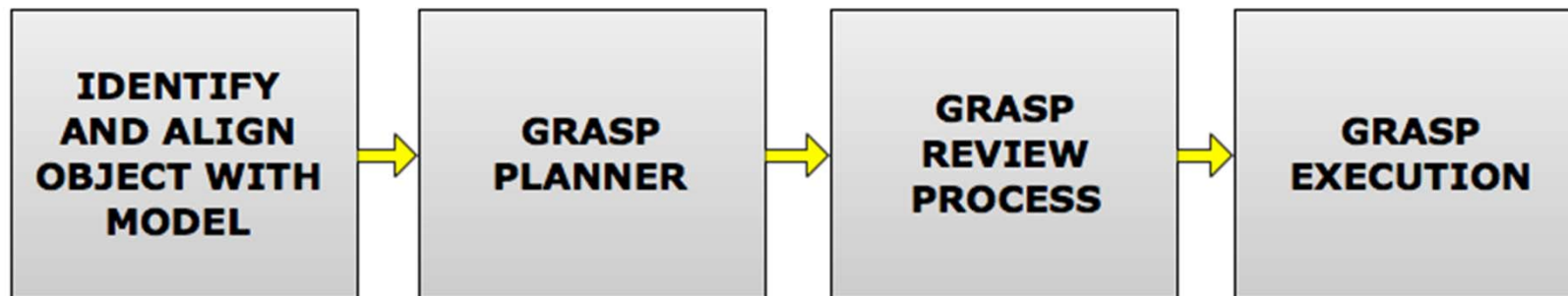




# ONLINE BCI SYSTEM FOR GRASPING

- Grasp target selection and localization via 3D vision
- Online Multi-DOF hand configuration planning
- **Grasping simulator-in-the-loop**
- Approach trajectory planning
  
- Input is low dimensional signal via an inexpensive, non-invasive BCI
  
- [4 simple facial gestures are sufficient!](#)
  
- System Components
  - Emotiv EPOC EEG Headset
  - Kinect Vision System
  - Graspl! and Eigengrasp Online Planner
  - Staubli Robotic Arm
  - Barrett Hand

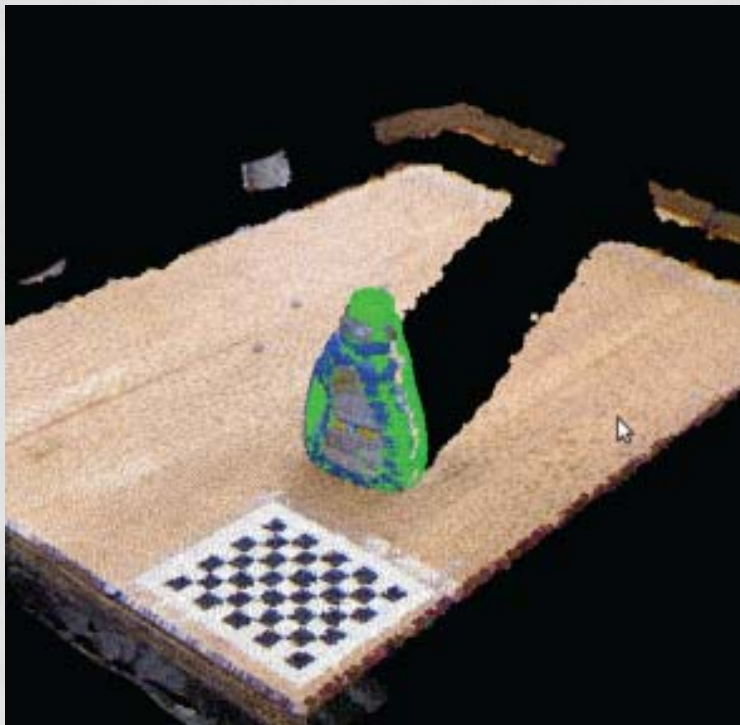
# OVERVIEW OF WORKFLOW





# 1. OBJECT IDENTIFICATION AND LOCALIZATION

- Depth image from Kinect range sensor
- Point cloud alone is not sufficient to predict grasp quality
- Identify objects using features generated from pairs of oriented points and a variant of RANSAC (Papazov 2011)

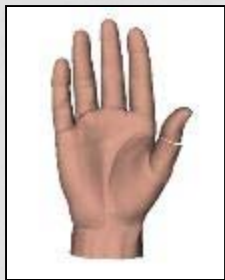


- RGB projection onto point cloud
- Blue is actual bottle (from RGB)
- Green is determined model

Registered model sent to Graspl! simulator

## 2. GRASP PLANNING

- A grasp can be considered a point in a high-dimensional hand configuration space



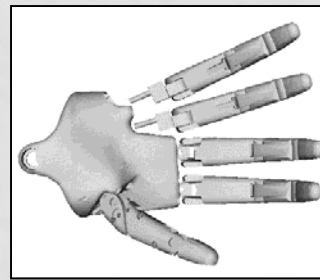
20 DOF



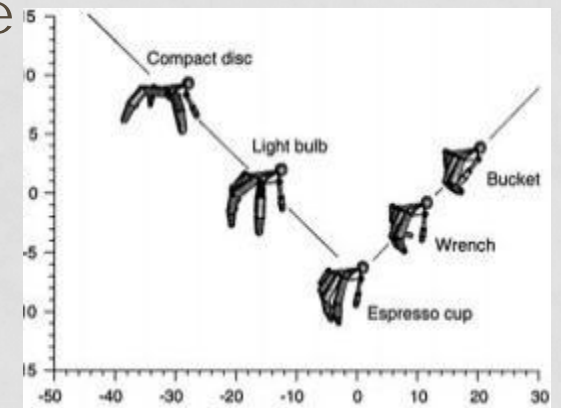
12 DOF



4 DOF



14 DOF



- Low-dimensional subspaces can approximate most of the variance needed for common grasping tasks (Santello et al.)
- PCA on large dataset of human joint angles during grasping
- 2 PC's contain approx. 85% of the variance!
- Continuous grasp subspace approximates common grasp posture

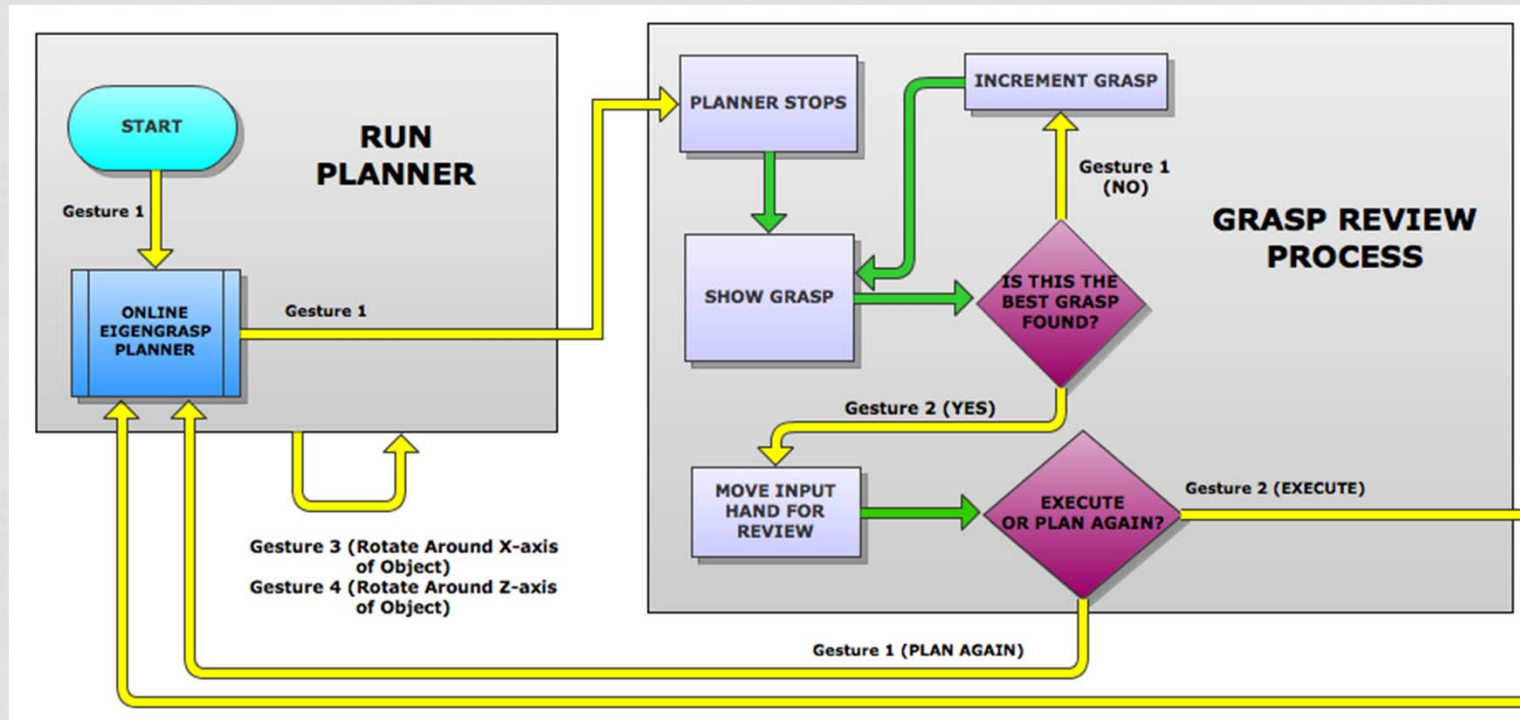
*e.g.*  $\mathbf{p} = a_1 \mathbf{e}_1 + a_2 \mathbf{e}_2$

## 2. GRASP PLANNING

- User is presented with a simulation world containing the hand, the object, and a surface
  - Gesture 1: a “click,” used to progress through stages
  - Gesture 2: confirm execution (want low false alarm rate)
  - Gesture 3: Rotate hand around x-axis, continuous
  - Gesture 4: Rotate hand around y-axis, continuous

<b>Gesture</b>	<b>Run Planner</b>	<b>Review Grasps</b>	<b>Execution</b>
1	start/stop planner	cycle through grasps	restart
2	n/a	select grasp	confirm grasp
3	rotate around x-axis	n/a	n/a
4	rotate around z-axis	n/a	n/a

## 2. GRASP PLANNING

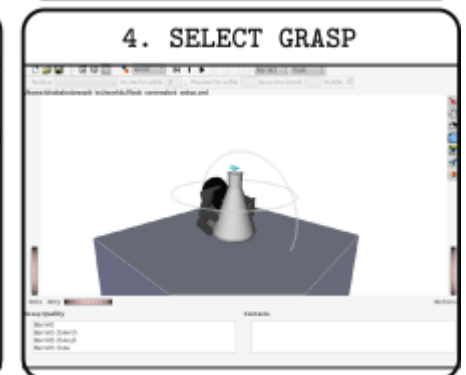
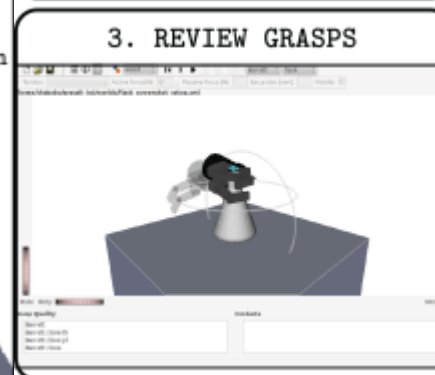
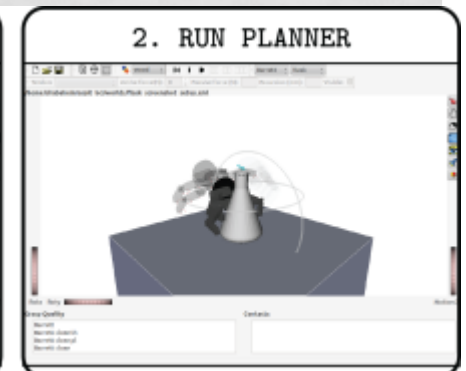
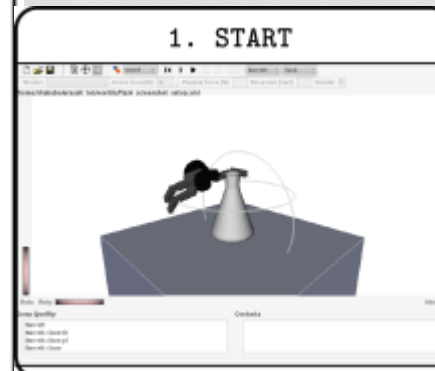
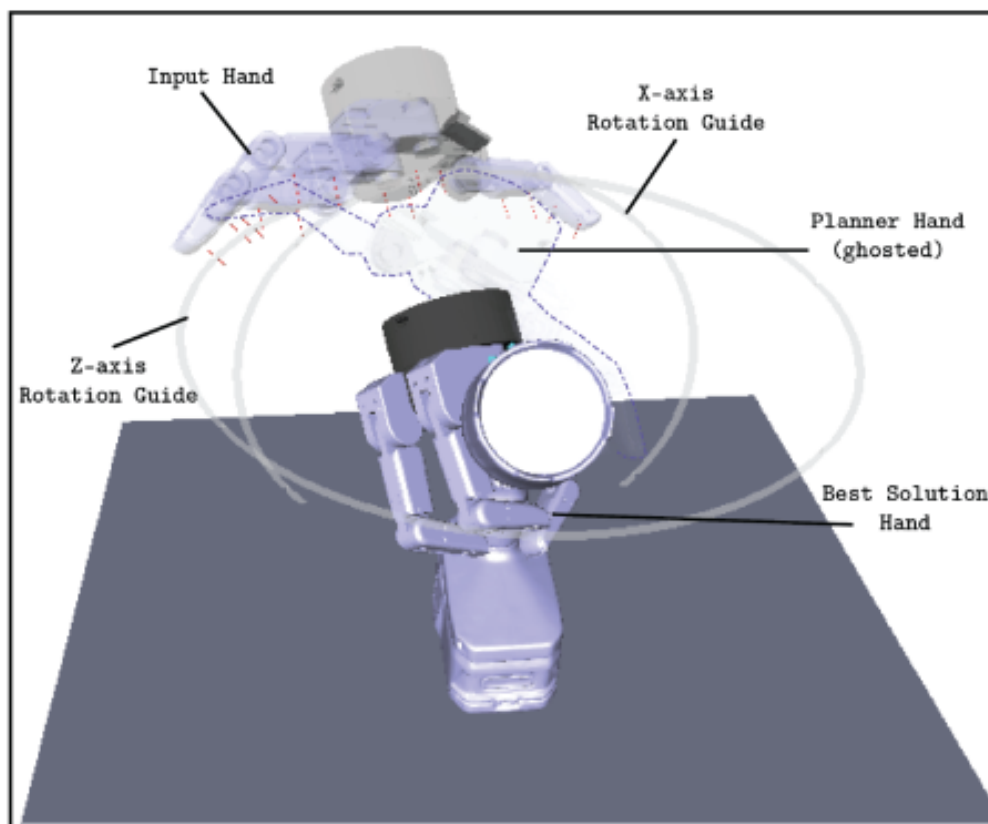


- User chooses approach direction which guides planner
- Planner populates list of suggested grasps
- User selects grasp to execute



## 2. GRASP PLANNING

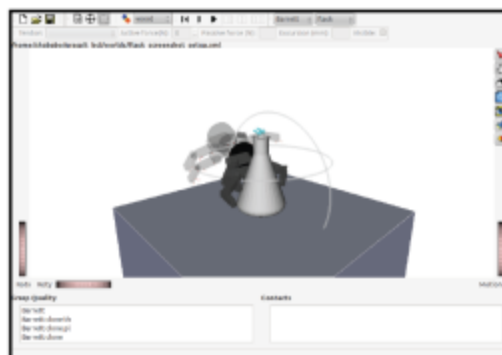
- Simulation UI during planning



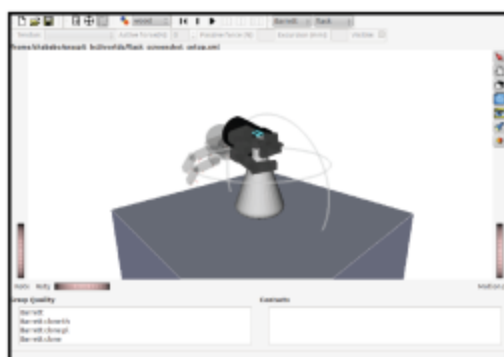
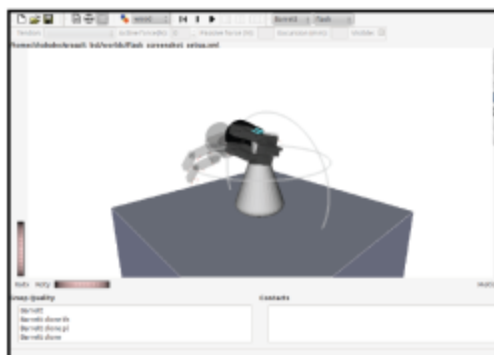
# 2. GRASP PLANNING

## GRASP PLANNER SOLUTION SET

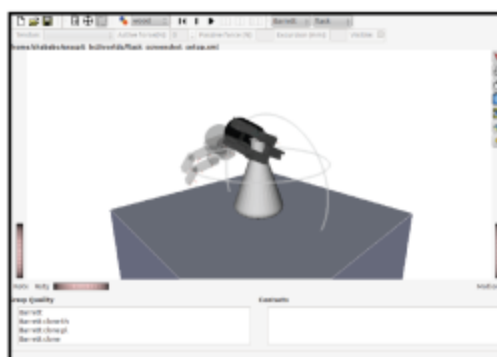
Rank: 1  
Energy: -1.370  
Iteration: 1195



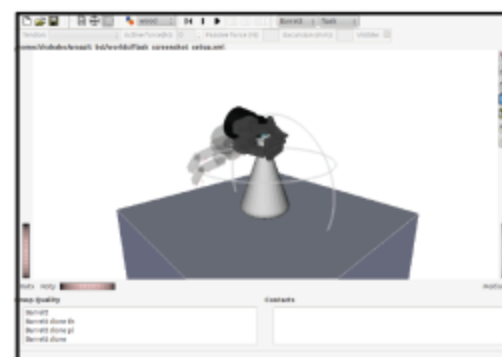
Rank: 2  
Energy: -1.832  
Iteration: 1831



Rank: 3  
Energy: -1.790, Iteration: 1824



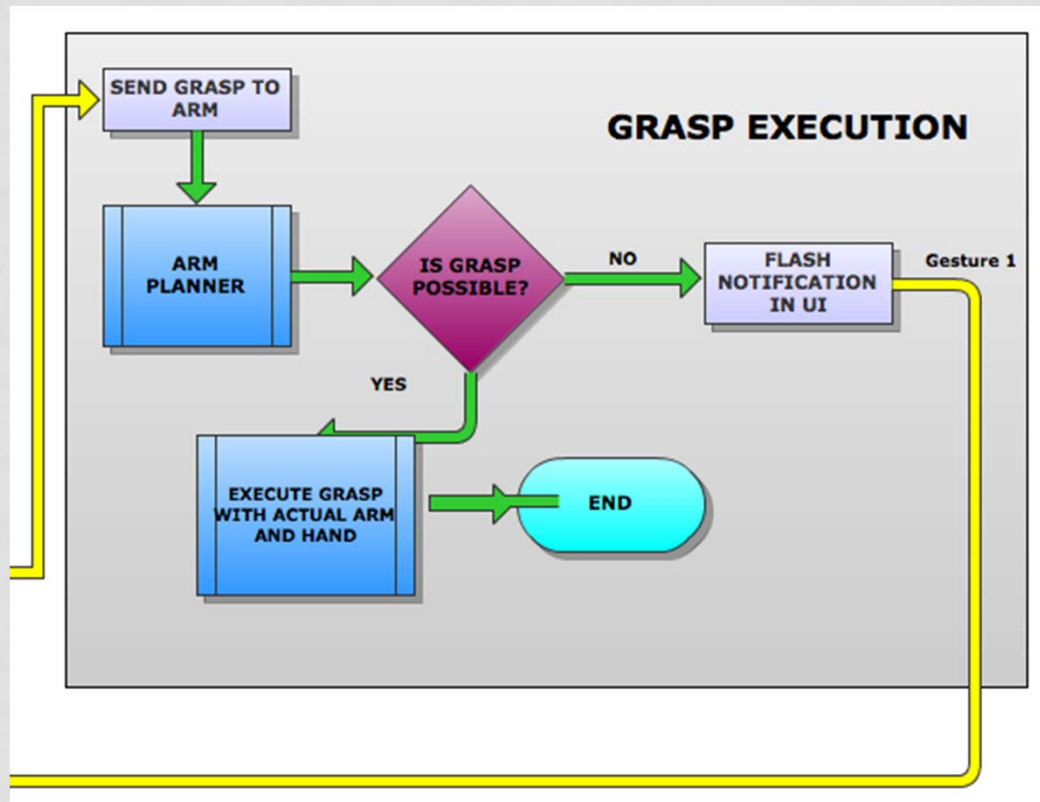
Rank: 4  
Energy: -1.335, Iteration: 956



Rank: 5  
Energy: -2.107, Iteration: 956

# 3. EXECUTION

- Arm planner determines if selected grasp is achievable
- If arm can't execute grasp, user is notified, can restart planner
- Previously selected grasp now influences planner



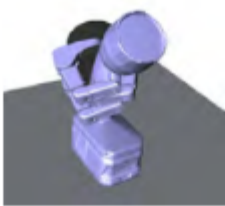

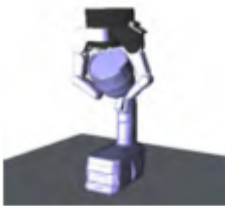

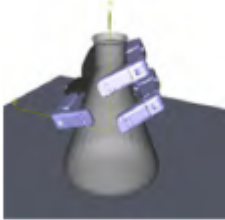


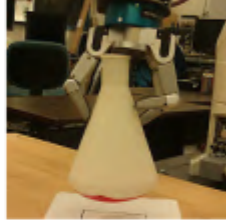




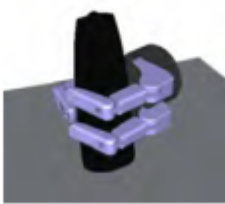

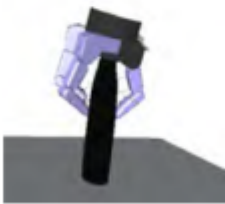

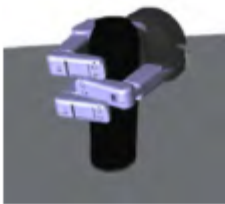





# RESULTS

5 Objects

2 grasps/object

100% success rate

Object	Results			
	Approach 1		Approach 2	
	Simulation Grasp	Physical Grasp	Simulation Grasp	Physical Grasp
Flashlight				
Flask				
Detergent Bottle				
Shampoo Bottle				
Shaving Cream				

# DISCUSSION

- End-to-End system for BCI grasping
- Uses simple, non-invasive BCI
- Human-in-the-Loop design is a powerful paradigm
- User control is best when at high level
- Still some open issues:
  - Learning component for BCI interface
  - EEG vs. EMG signals
  - UI design
  - Grasping amid clutter

# Recap

- Simulation is a powerful tool, **both online and offline**
- Data Driven approaches to grasping are quite promising, for known and novel objects
- New User Interfaces for grasping need to be developed for Human-in-the-Loop tasks
  - Assistive Robotics
  - Learning by Demonstration