Assistive Robotics

COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

THE NEED FOR ASSISTIVE ROBOTIC GRASPING

- Growing population with limited mobility
  - 400,000 spinal cord injury patients worldwide
  - 50% experience below neck paralysis
  - 5 Million stroke patients
  - Aging worldwide population
- Full time care is expensive and difficult
- **Improving autonomy increases quality of life**

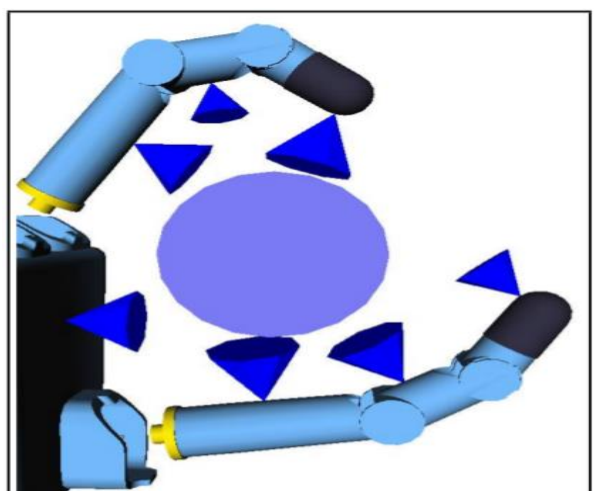
THE CENTRAL ROLE OF GRASPING

● Transport is reported as a critical issue for disabled people.

- Grasping is the first step in many tasks
- It is also the hardest part in many tasks
  - Explicitly involves contact with the environment.
  - Avoiding contacts is relatively easy. Purposeful contact requires precise control.

THE EIGENGRASP PLANNER

- Planning in a reduced dimensional subspace
- 20 DOF human hand space can be approximated with Principal Component Analysis (PCA)
- First 2 Eigenvectors of PCA cover 80% of normal grasps
- Uses simulated annealing to efficiently search 2-DOF space
- Given approach direction, stable grasps found
- User can control approach direction

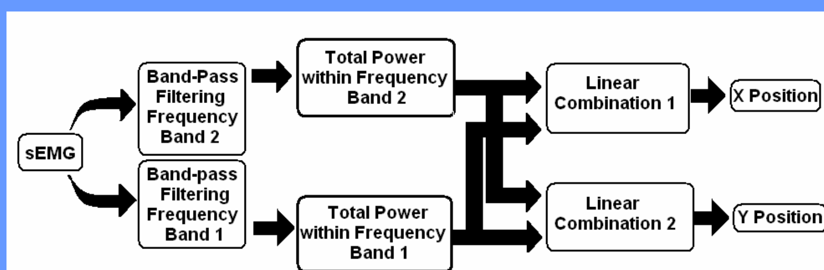


On-Line Interactive
Dexterous Grasping

Grasping and Assistive Robotics

- We can use the “smarts” in our grasp planner to assist in grasping tasks for disabled
- User can supply “minimal” info to grasp planner
- User can confirm/reject planner choices
- Can use low-bandwidth, simple-to-use interfaces

EMG Interfaces and Grasping Pipelines: Shared Control



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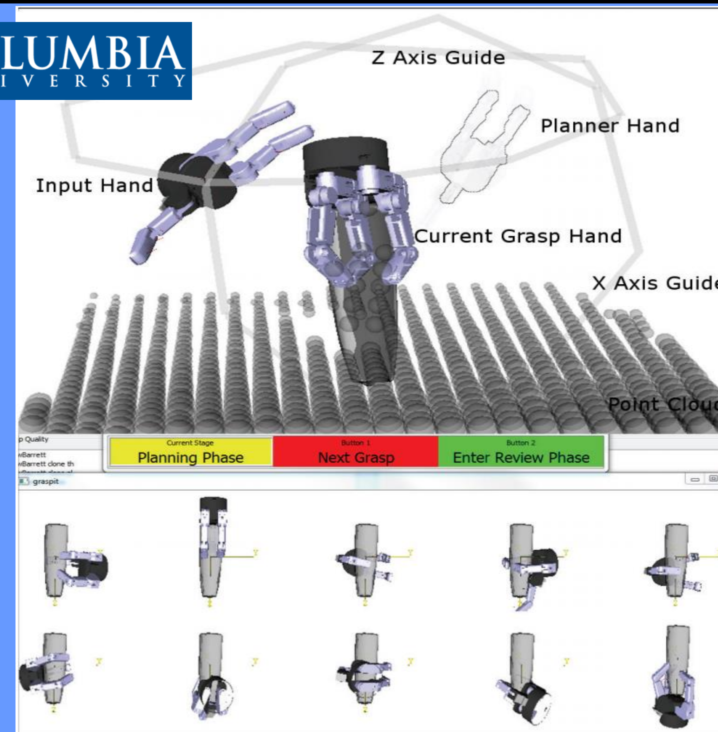
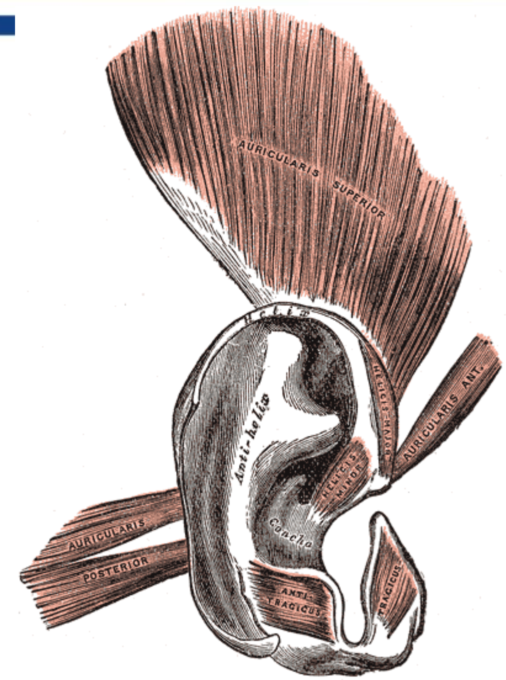


- Small, non-invasive EMG sensor
- Many possible locations on body
- Accurate and Repeatable Selection
- Dual-Frequency response
- Increases Information Transfer Rate

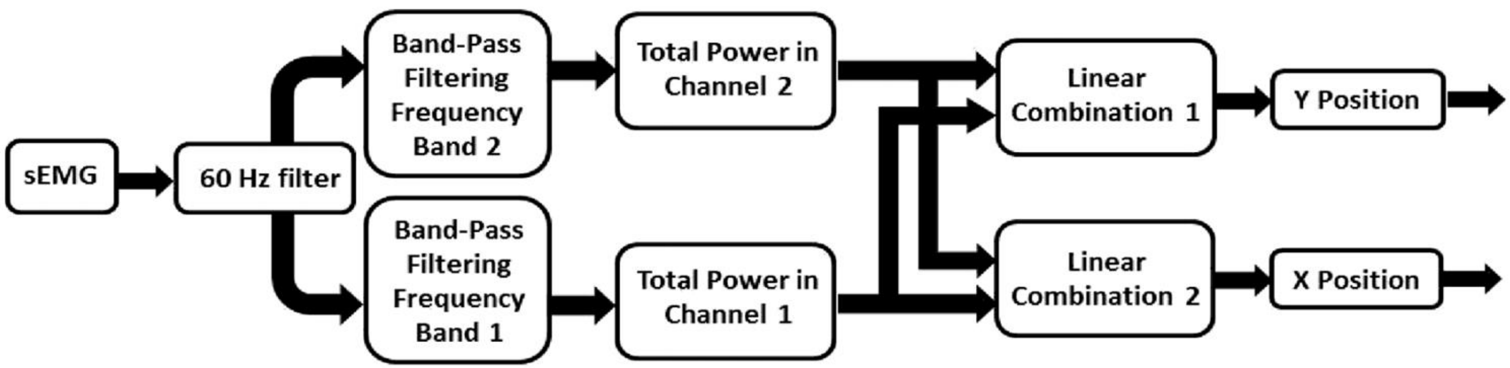
- UI simplifies grasp selection
- Robustness to uncertainty, object location, end effector pose
- Can grasp wide variety of objects
- Operates in cluttered environments

Surface EMG recording



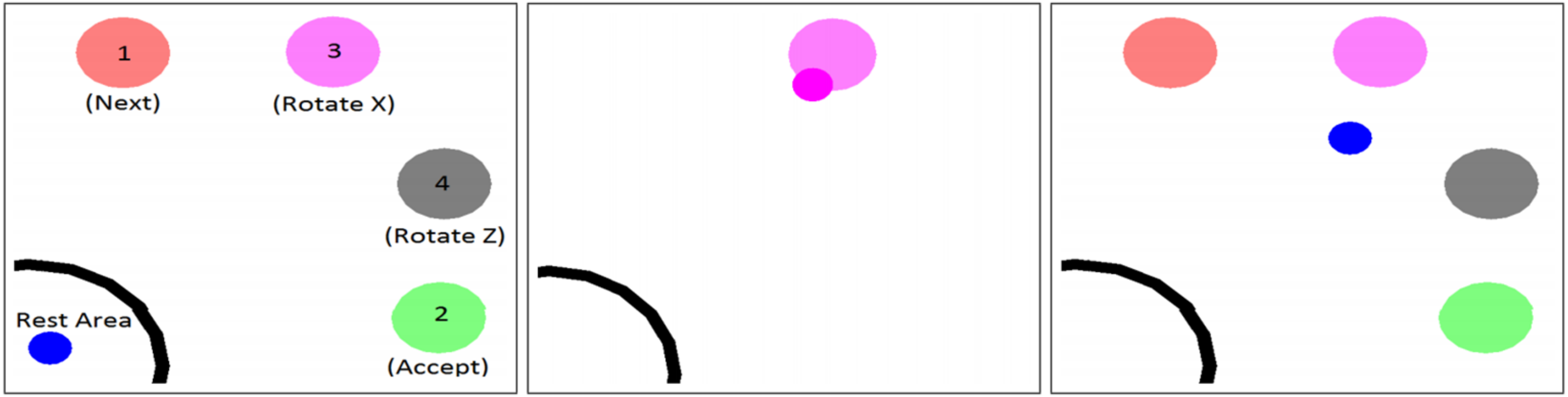
- EMG signal measured at a single recording site behind the ear.
  - Hairless
  - Facial muscle control SC injuries.

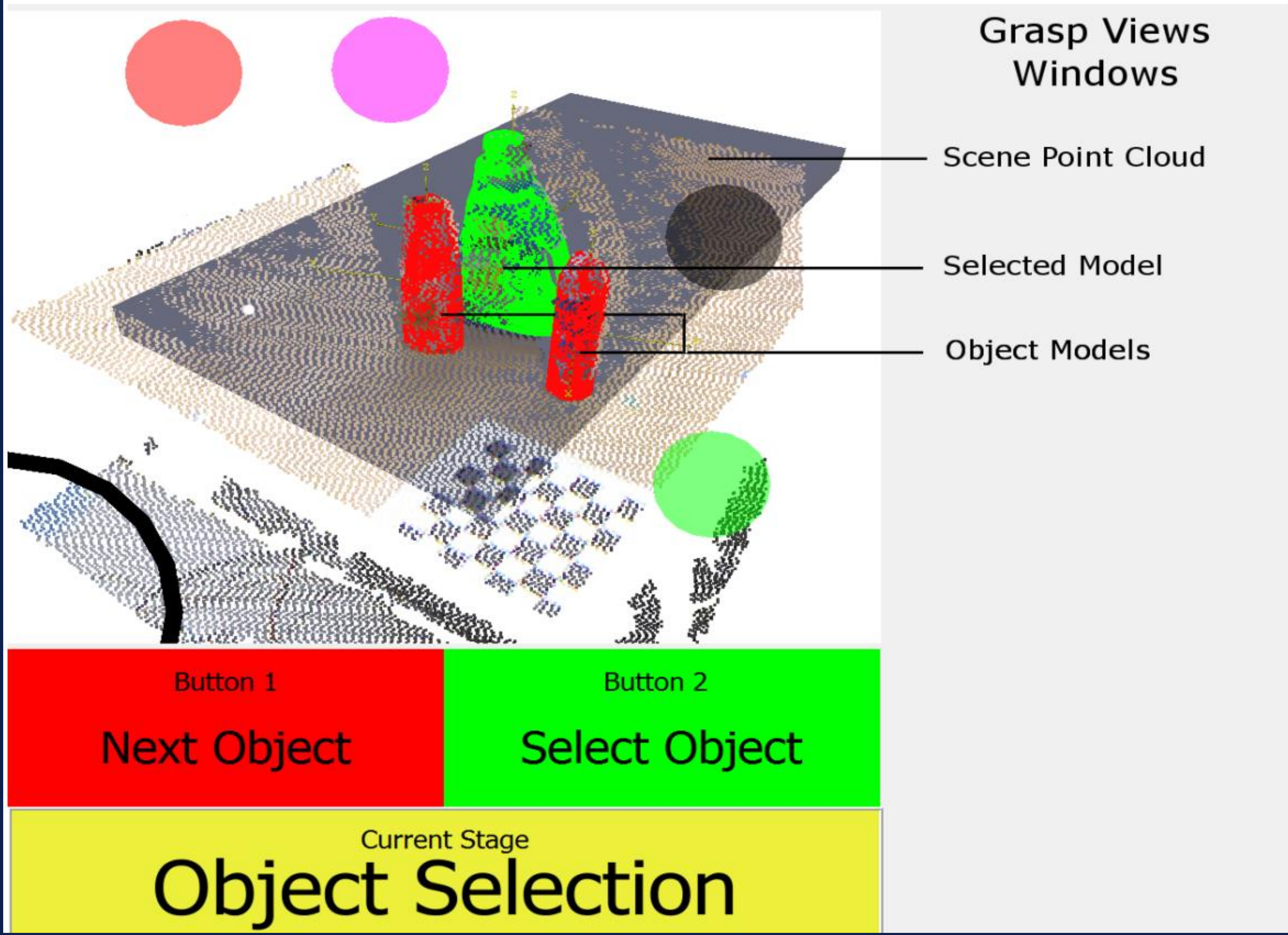
- Subjects are trained to generate 2 dimensions of control



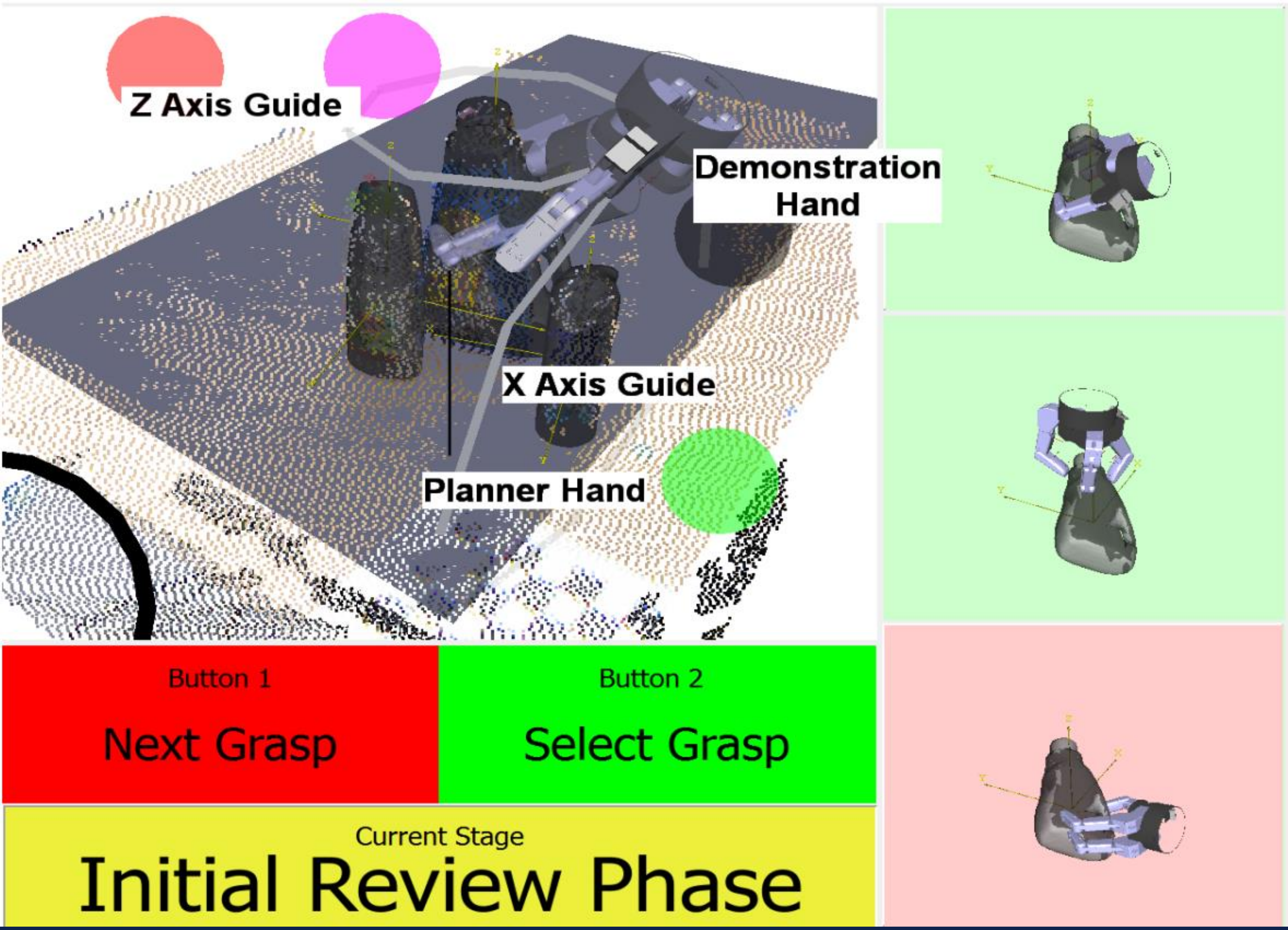
USING SEMG CONTROL

- 2D control is relatively fast, but somewhat inaccurate.
- Can handle center-out motions to targets
- These take the place of the gestures in the previous sections
  - Hitting the target selects the option, returning to rest activates it.



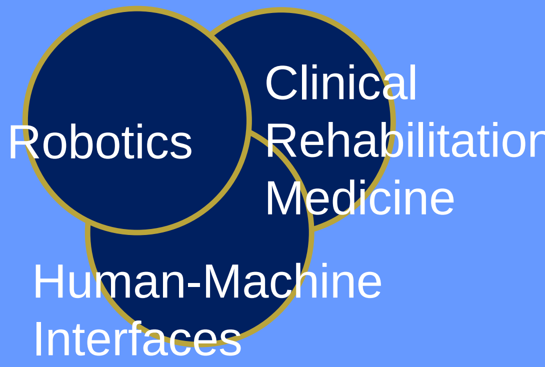


Grasp Views Windows
Scene Point Cloud
Selected Model
Object Models
Button 1
Next Object
Button 2
Select Object
Current Stage
Object Selection


Z Axis Guide
Demonstration Hand
X Axis Guide
Planner Hand
Button 1
Next Grasp
Button 2
Select Grasp
Current Stage
Initial Review Phase

Goal: Build clinically useful device

Spinal Cord Injured Subject (C3-C4) Manipulates Objects in New York City while Using Interface in Davis, California



- **Applicability to Different Medical Conditions**
- **Benefit vs. Frustration of Using Device**
- **Cognitive Load**
- **Interface Esthetics**
- **Learning Curves**
- **Neuromuscular Plasticity**
- **Portability**
- **Training Procedures**

Experiment: Impaired User, Davis CA, Grasping in Columbia Robotics Lab

Surface EMG recording

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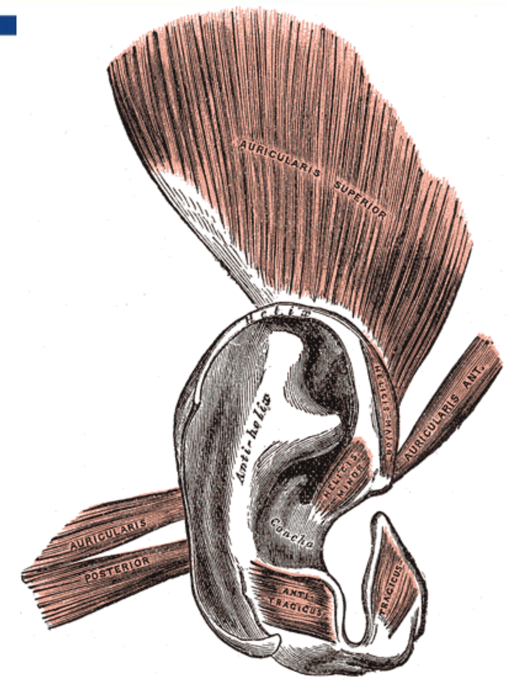
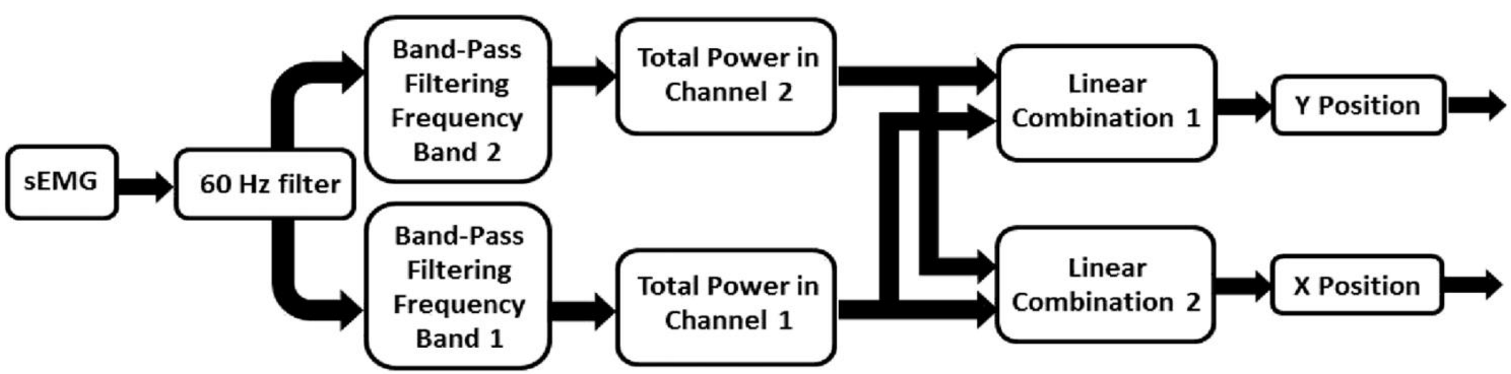
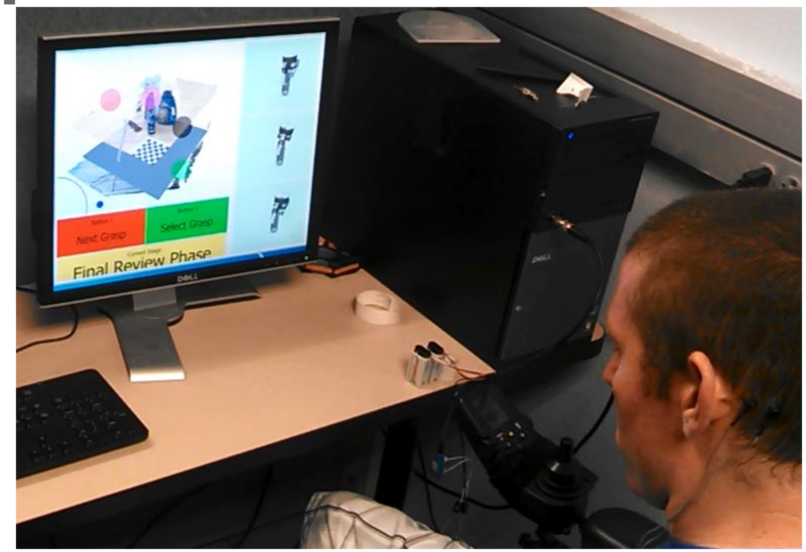
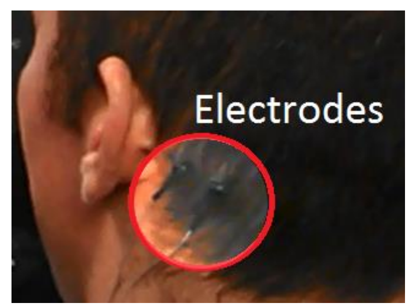




Human-in-the-Loop Grasping with Online and Offline Planning Using Noisy, Low Bandwidth Inputs

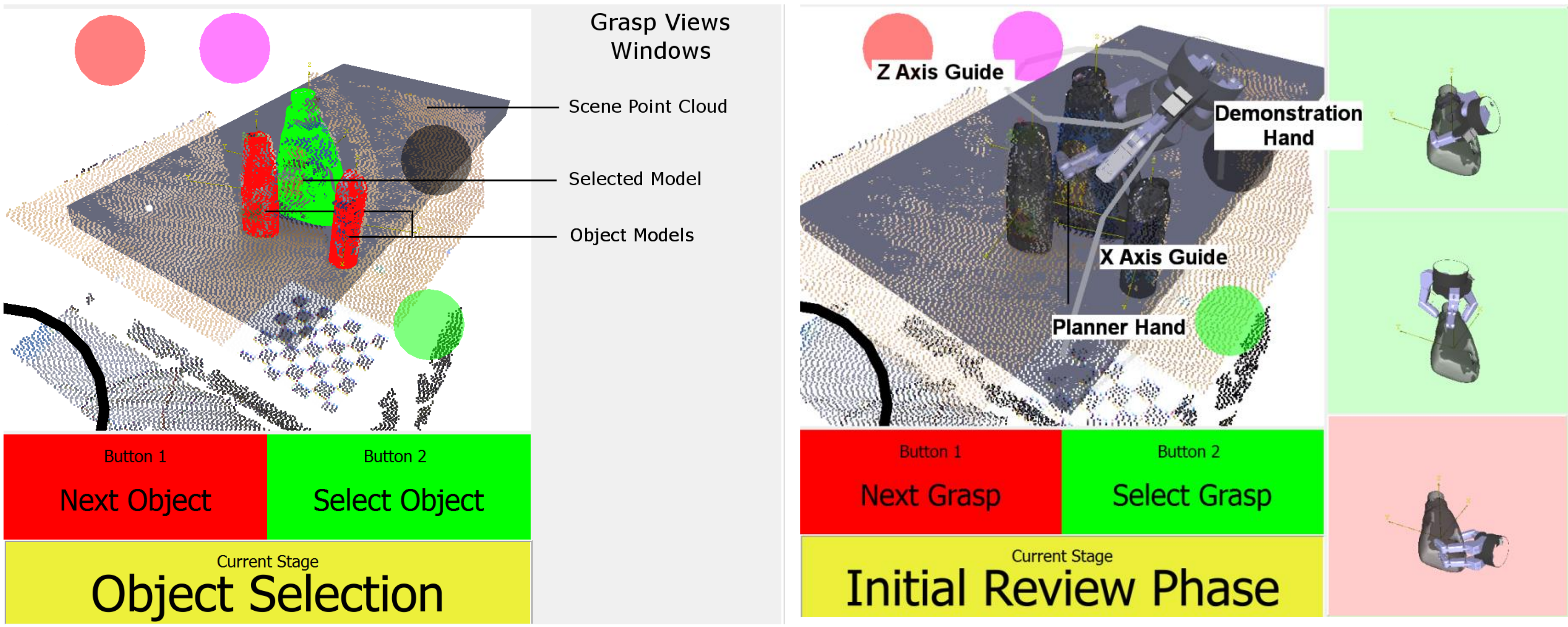
- Online shared control grasp planner [1]
- Offline Grasp Database [2]
- Integrated vision system [3]
- Novel behind the ear SEMG input device.[4]
- Human subject validation





[1] - Ciocarlie and Allen, "Hand posture subspaces for dexterous robotic grasping," IJRR
[2] - Goldfeder and Allen, "Data-Driven Grasping," *Autonomous Robots 31.1, 2011*
[3] - Papazov and Burschka, "An efficient ransac for 3d object recognition in noisy and occluded scene - ACCV 2011
[4] -S. Vernon and S. S. Joshi, "Brain-muscle-computer interface: mobile-phone prototype development and testing." IEEE Transactions Information Technology 2011.

Grasp Planning Interface



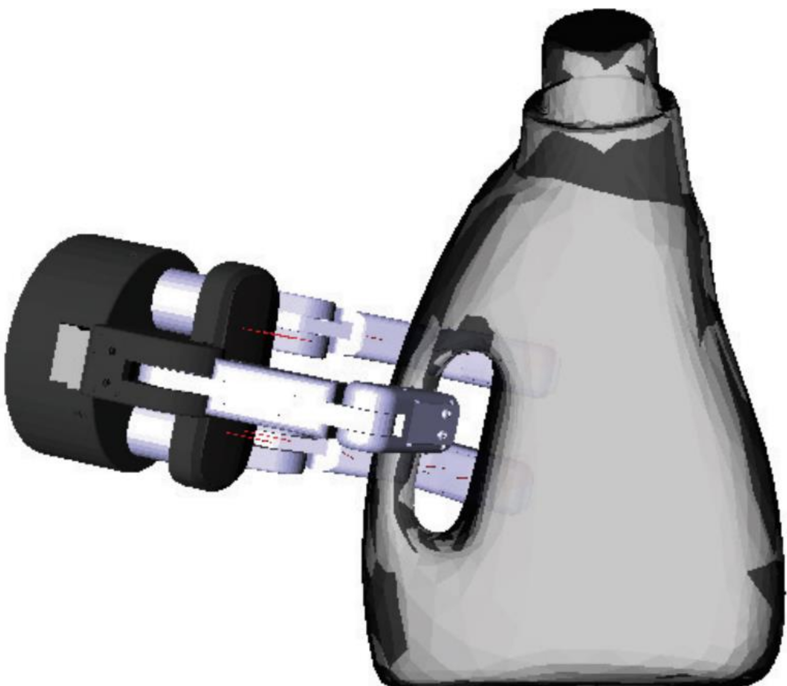
RESULTS

- Success feasible
- Selection very slow
- Cursor control noisy

Grasp	Time (s)	#Inputs	#Timeouts	Mistaken Selections
Detergent 1	564	14	14	2
Detergent 2	609	9	50	0
Shaving Gel	910	12	11	1

INCORPORATING PREPLANNED GRASPS

- Seed database with Offline Eigengrasp Planner
  - Run planner starting in each direction for each object
  - Take best grasp from each direction
- Grasps with special semantic meaning can be manually encoded
  - i.e. handle grasps
  - Automated generation of these is hard



HANDLING NOVEL OBJECTS

- The vision system will align the closest object that it can find.
- Grasping only requires local alignment.
- Users can rerun vision system until alignment is good at the right part.

SUBJECT VALIDATION

- 5 Subjects
- 3 Objects
  - Flashlight, Detergent Bottle, Novel juice bottle
- Known objects
  - 2 Grasp Directions,
    - Top, Side
  - 3 Attempts
- 5 grasp attempts on novel object

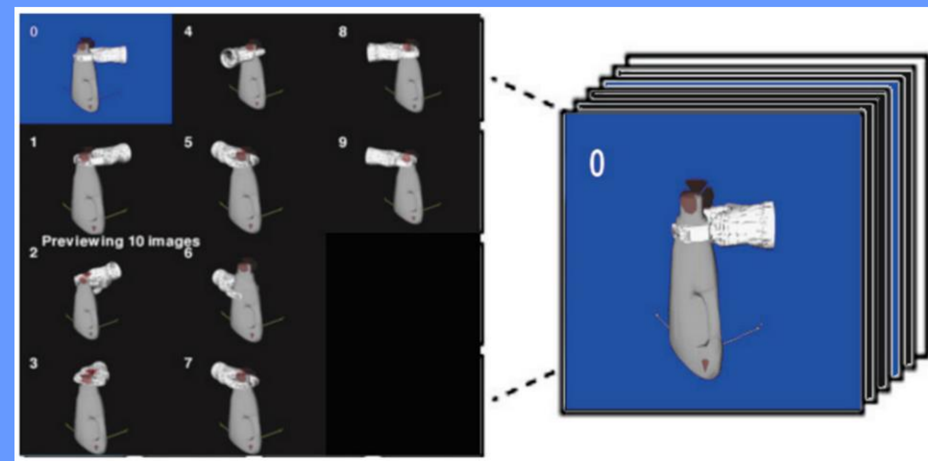
Grasp	Subject	Success	Time
Detergent Bottle Top	1	Yes	75
	2	Yes	53
	3	No	45
	4	No	122
	5	Yes	135
	Mean	60%	86
Detergent Bottle Side	1	No	66
	2	Yes	40
	3	Yes	52
	4	Yes	80
	5	Yes	85
	Mean	80%	64
Detergent Bottle Open Choice	1	Yes	50
	2	Yes	57
	3	Yes	53
	4	Yes	135
	5	Yes	128
	Mean	100%	85
Shampoo Bottle Top	1	Yes	151
	2	Yes	72
	3	Yes	60
	4	No	126
	5	No	104
	Mean	60%	102
Shampoo Bottle Side	1	Yes	134
	2	Yes	95
	3	Yes	132
	4	Yes	164
	5	Yes	143
	Mean	100%	133

Grasp	Subject	Success	Time
Shampoo Bottle Open Choice	1	Yes	93
	2	Yes	121
	3	Yes	63
	4	Yes	95
	5	Yes	117
	Mean	100%	98
Shaving Gel Top	1	No	83
	2	No	123
	3	Yes	112
	4	No	139
	5	Yes	97
	Mean	60%	111
Shaving Gel Side	1	Yes	65
	2	Yes	52
	3	Yes	57
	4	Yes	88
	5	Yes	92
	Mean	100%	71
Shaving Gel Open Choice	1	No	73
	2	Yes	59
	3	Yes	76
	4	Yes	81
	5	Yes	85
	Mean	80%	75
Average Perfor- mance	1	66%	87
	2	88%	75
	3	88%	72
	4	77%	114
	5	88%	109
	Mean	82%	92

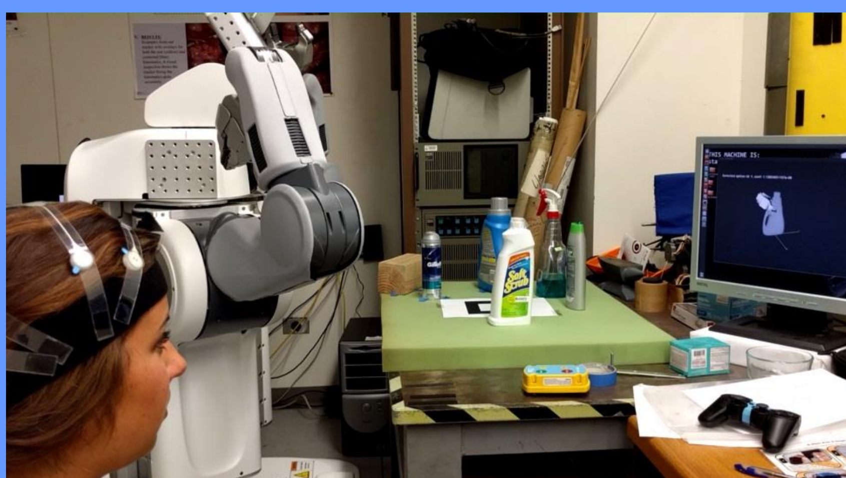
Grasping amidst Clutter

EEG Based Grasping

Rapid Serial Visual Presentation



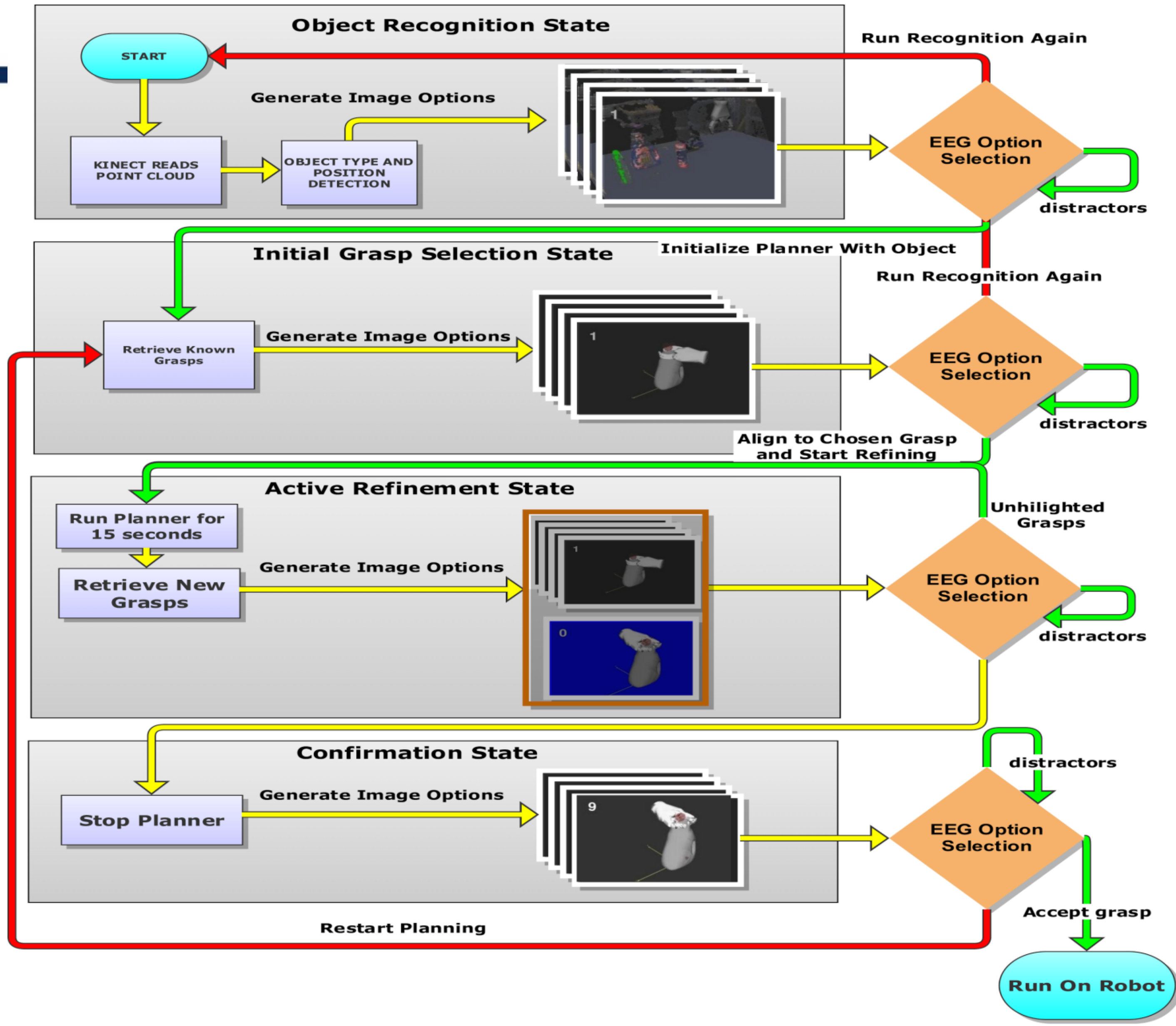
Review Panes for Grasp Selection



PR 2: Cluttered scene, 5 subjects

MICO Arm:, 3 subjects, 3 objects, 3 grasps

Rapid Serial Visual Presentation Paradigm



CLASSIFYING THE INTEREST SIGNAL

Eight electrodes captured (x)
Divided into 100 ms epochs
100 ms to 1200 ms post presentation
Interest measure is a weight linear combination over all electrodes over all bins.

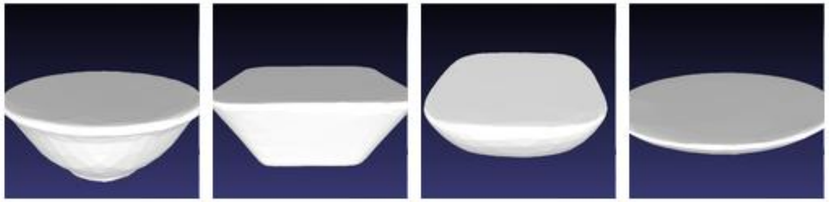
$$y_{sn} = \sum_i w_i x_{in} \qquad y = \sum_n v_n y_{sn}$$

CLASSIFIER TRAINING

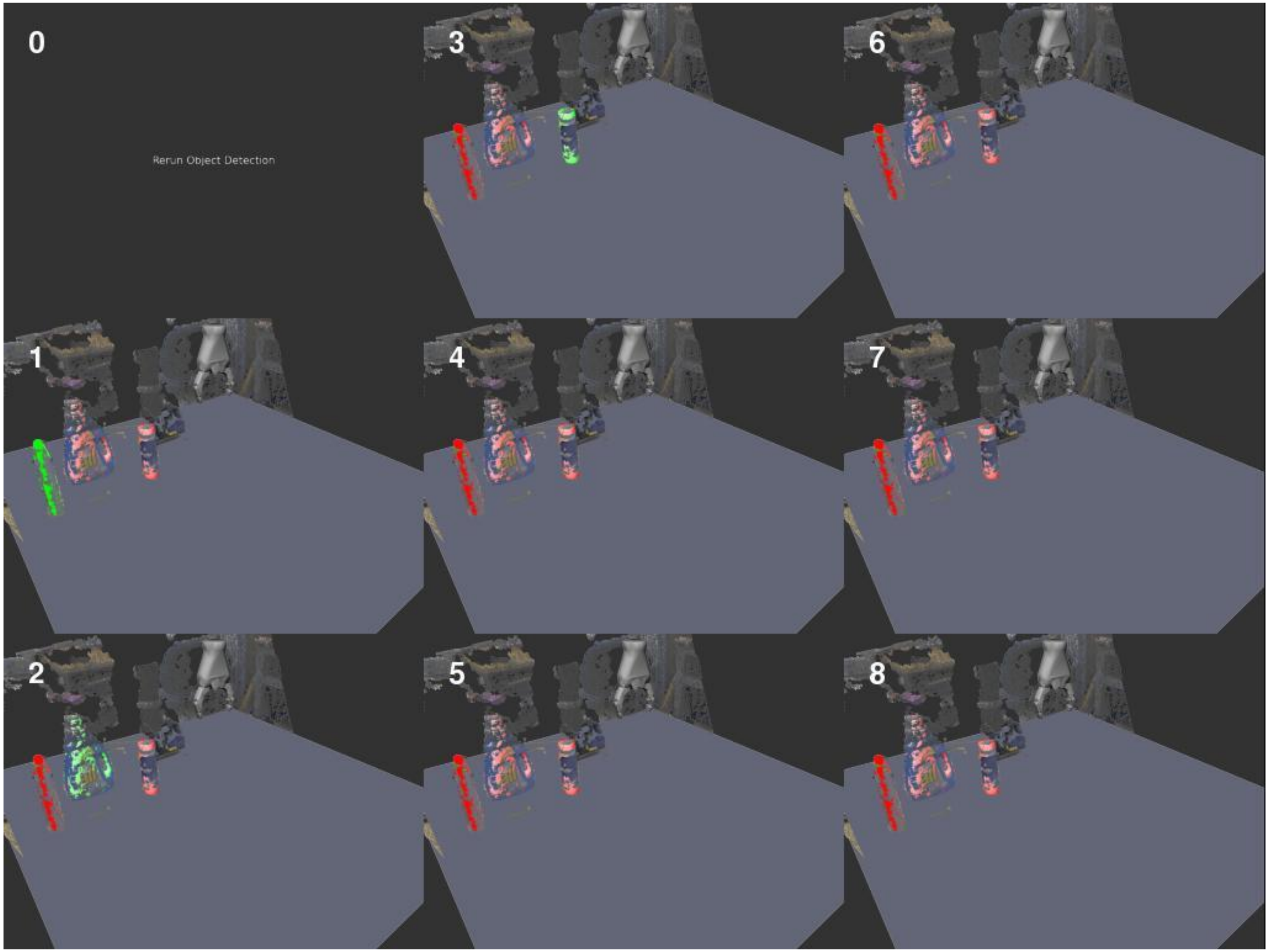
Object class selection task

Find the bowls

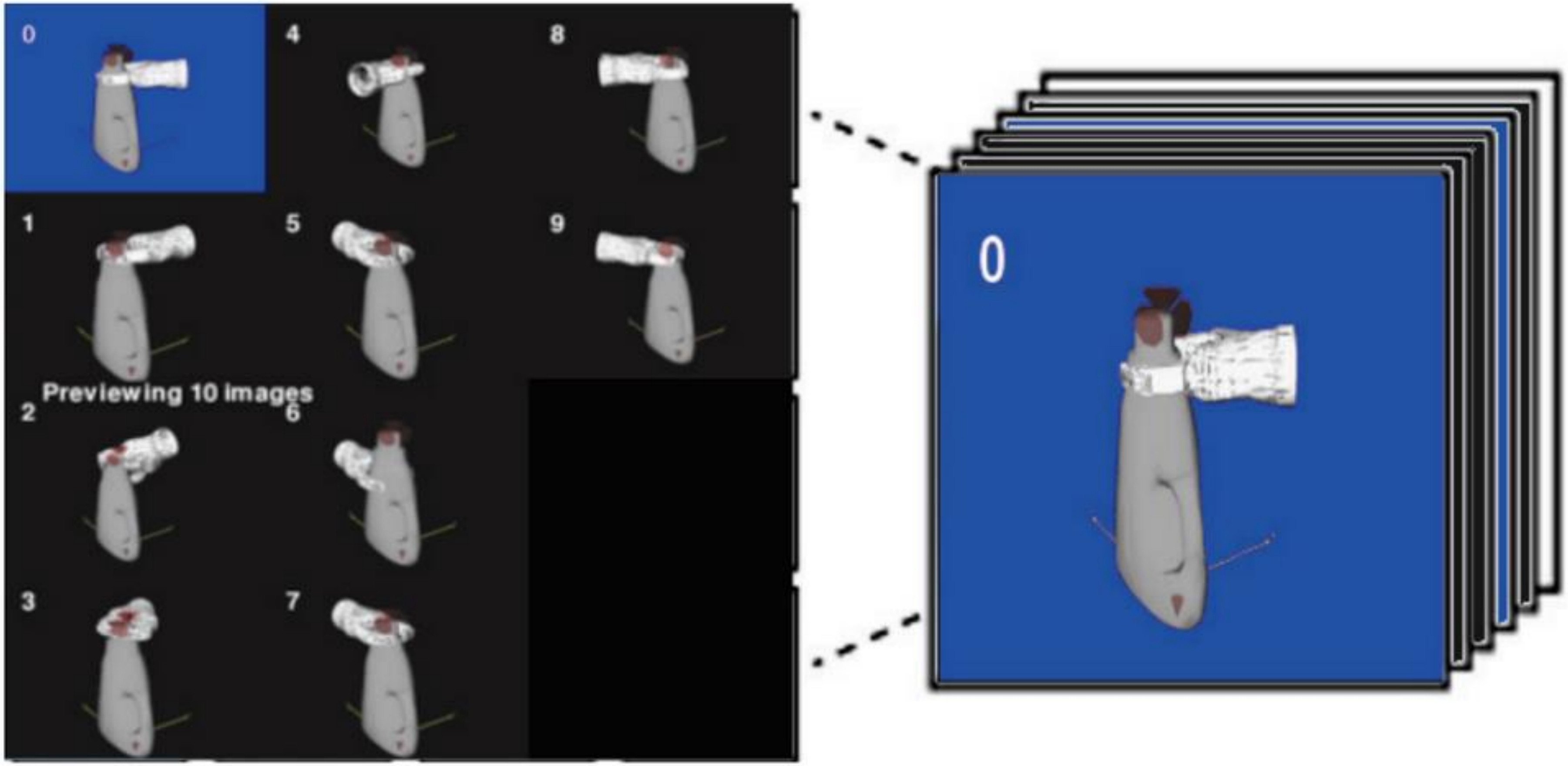
38 distractors, 2 target images



REVIEW PANES (OBJECT SELECTION)



REVIEW PANES (GRASP SELECTION)



EEG Grasping

Grasping with your brain:

A brain-computer interface for fast grasp selection

Robert Ying, Jonathan Weisz, and Peter K. Allen
Columbia University Robotics Group

RESULTS

100% success rate
Grasps took between 2 and 4.5 minutes.
Speeds comparable to self guided selection using sEMG

Grasp	Subject	Misselections	Refinement Iterations	Time(s)
Detergent Bottle Top	1	0	1	120
	2	2	3	150
	3	1	2	135
Detergent Bottle Side	1	0	1	120
	2	1	2	135
	3	0	1	120
Detergent Bottle Choice	1	0	10	270
	2	0	2	135
	3	3	5	180
Shampoo Bottle Top	1	0	1	135
	2	0	1	120
	3	0	1	150
Shampoo Bottle Side	1	0	1	120
	2	1	1	135
	3	0	2	135
Shampoo Bottle Choice	1	1	1	210
	2	1	3	120
	3	0	1	150
Shaving Gel Top	1	0	2	180
	2	1	1	120
	3	0	2	135
Shaving Gel Side	1	1	2	135
	2	0	1	120
	3	0	2	150
Shaving Gel Choice	1	0	2	120
	2	0	1	120
	3	0	2	180

CONCLUSIONS

Some subjects required small adaptions

Calibration procedure may be necessary

Subjects were able to understand how to use the system pretty quickly.

Combination of both approaches?

RSVP to filter.

sEMG to chose.