MOTORLAB

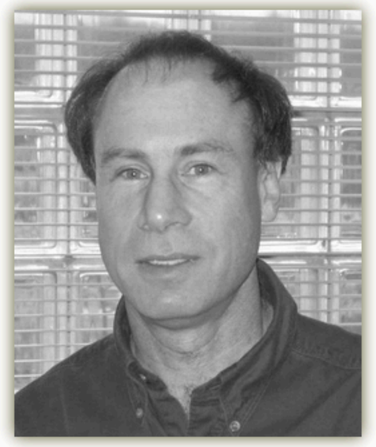
University of Pittsburgh

Image Caption

As a systems neurophysiology lab, we are interested in the way neural activity drives behavior. Our goal is to describe organizational principles of the time-varying relation between the firing rates of neurons and the behavior this activity generates.

Specifically, our research program centers on the relationship between cerebral cortical activity and arm movement. Over the last 25 years, we have found that there is a very good representation of the armis trajectory in the collective firing pattern of frontal cortical activity. This makes it possible to predict the detailed time course of arm, wrist and finger movement that contains many of the behavioral invariants that are characteristic of movement.

PEOPLE



Dr. Andrew Schwartz

Distinguished Professor of Neurobiology

Chair in Systems Neuroscience

Brain-Computer Interface Control of an Anthropomorphic Robotic Arm

Samuel T Clanton

CMU-RI-TR-11-21

July 21, 2011

The Robotics Institute
Carnegie Mellon University
Pittsburgh, PA 15213

Thesis Committee:
Andrew Schwartz, Chair
Nancy Pollard
George Stetten
Neville Hogan, Massachusetts Institute of Technology

Text size: ⊖ ⊕

Dr. Samuel Clanton

Physician

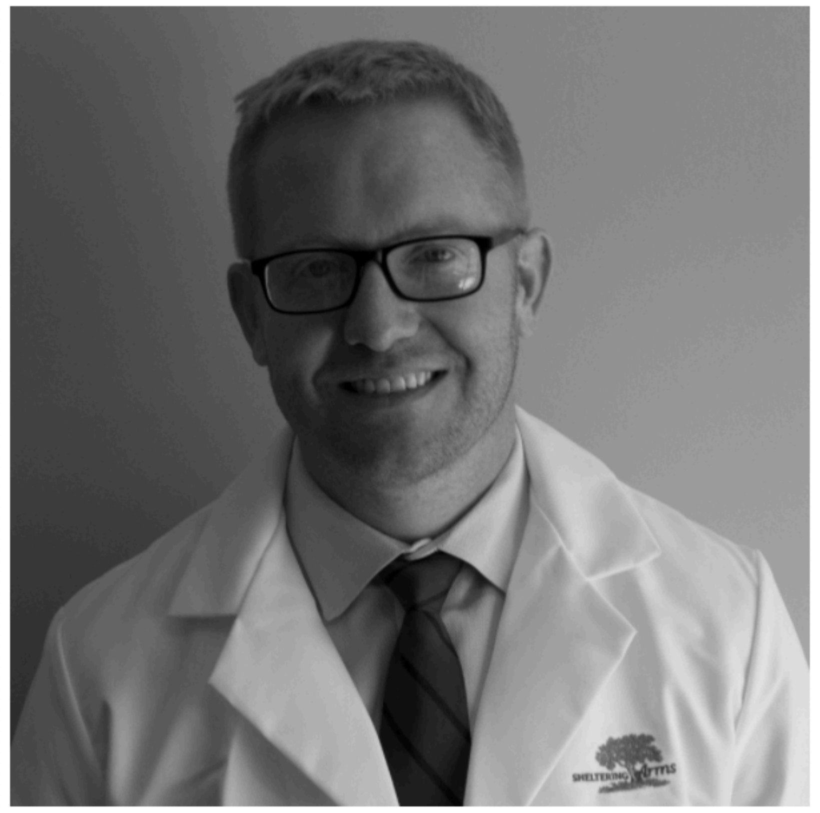
Home › Doctors & Psychologists › Dr. Samuel Clanton

Find a Therapist Become a Patient Refer a Patient Find a Doctor or Psychologist

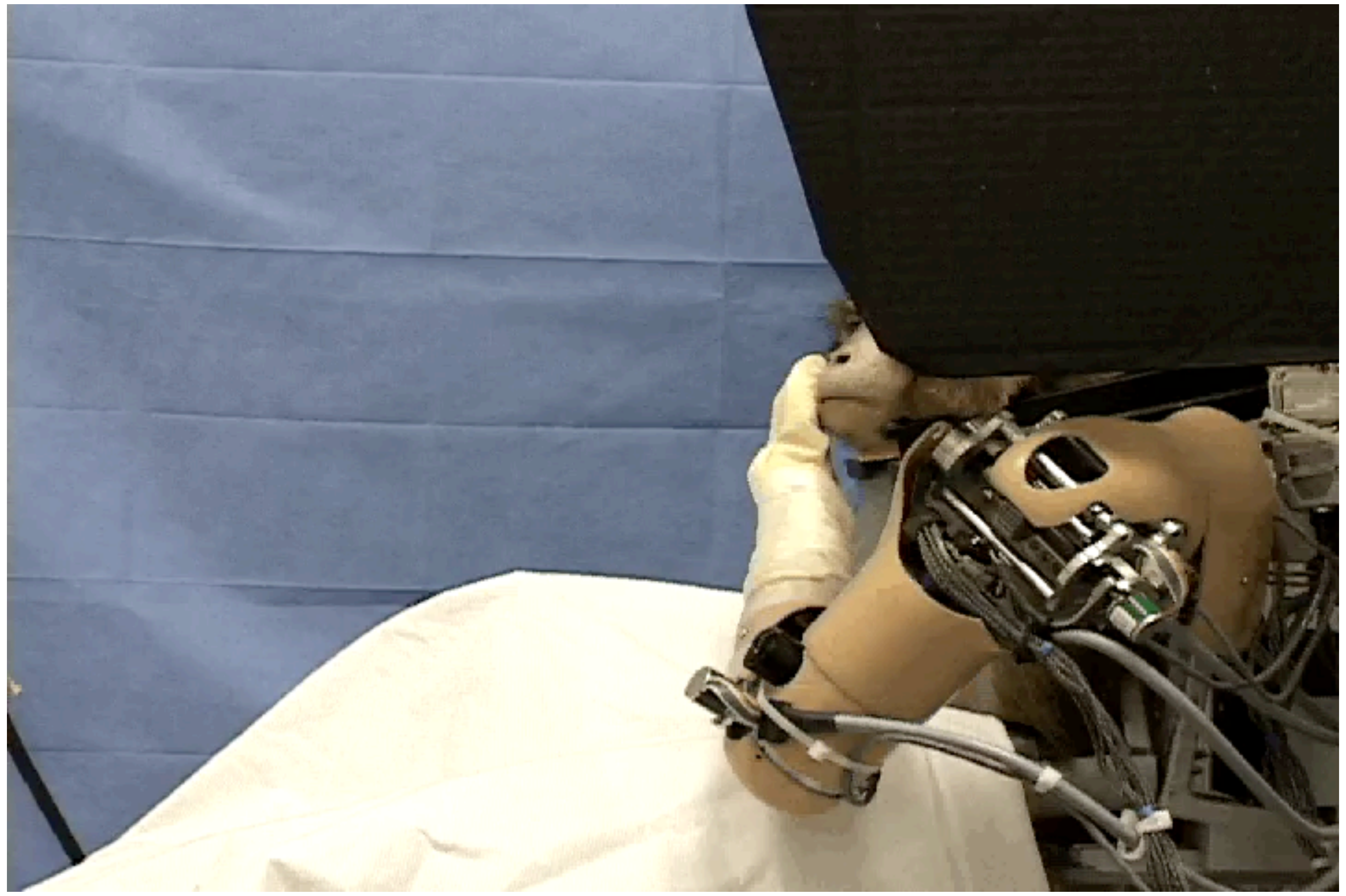
MAKE AN APPOINTMENT REQUEST INFORMATION

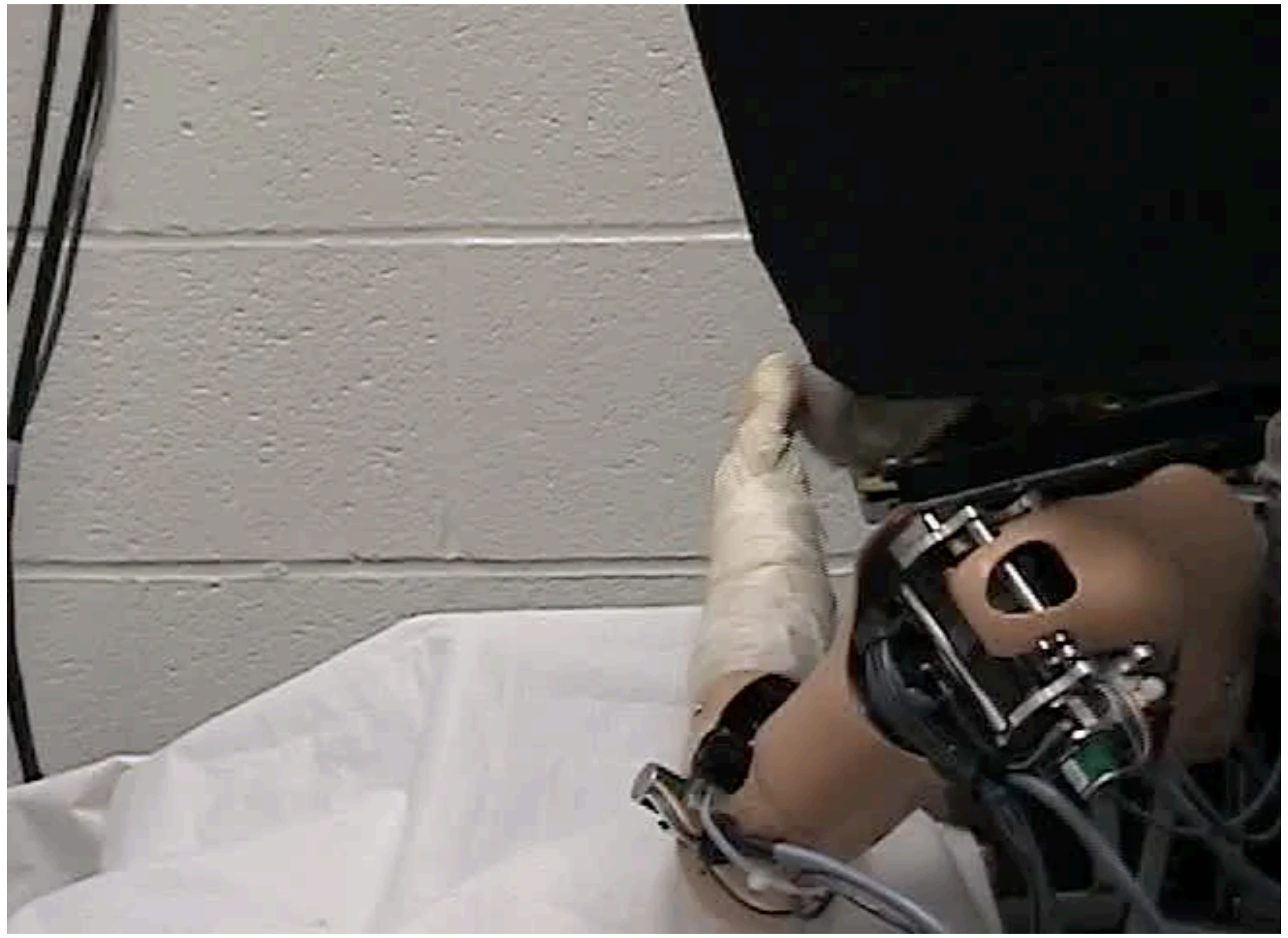
Dr. Samuel Clanton, MD, PhD, specializes in acquired brain injury and neurological rehabilitation. He received an undergraduate degree in biomedical engineering and computer science from Johns Hopkins University, a doctorate of philosophy in robotics from Carnegie Mellon, and a medical degree from University of Pittsburgh. He completed his physical medicine and rehabilitation residency at the Rehabilitation Institute of Chicago and a polytrauma/Brain Injury Fellowship at the Hunter Holmes McGuire Veterans Affairs Medical Center.

- Reynolds



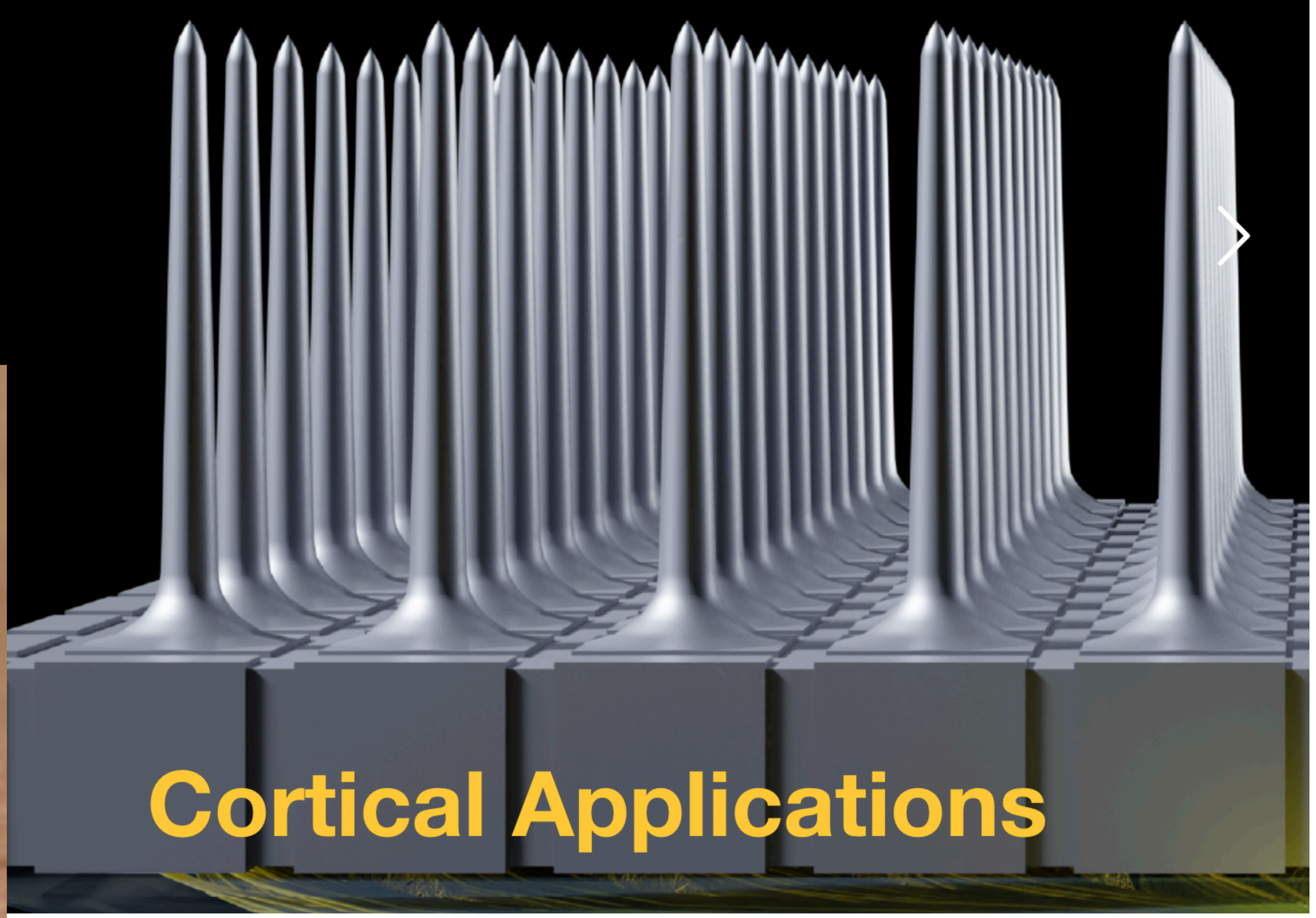
Dr. Samuel Clanton

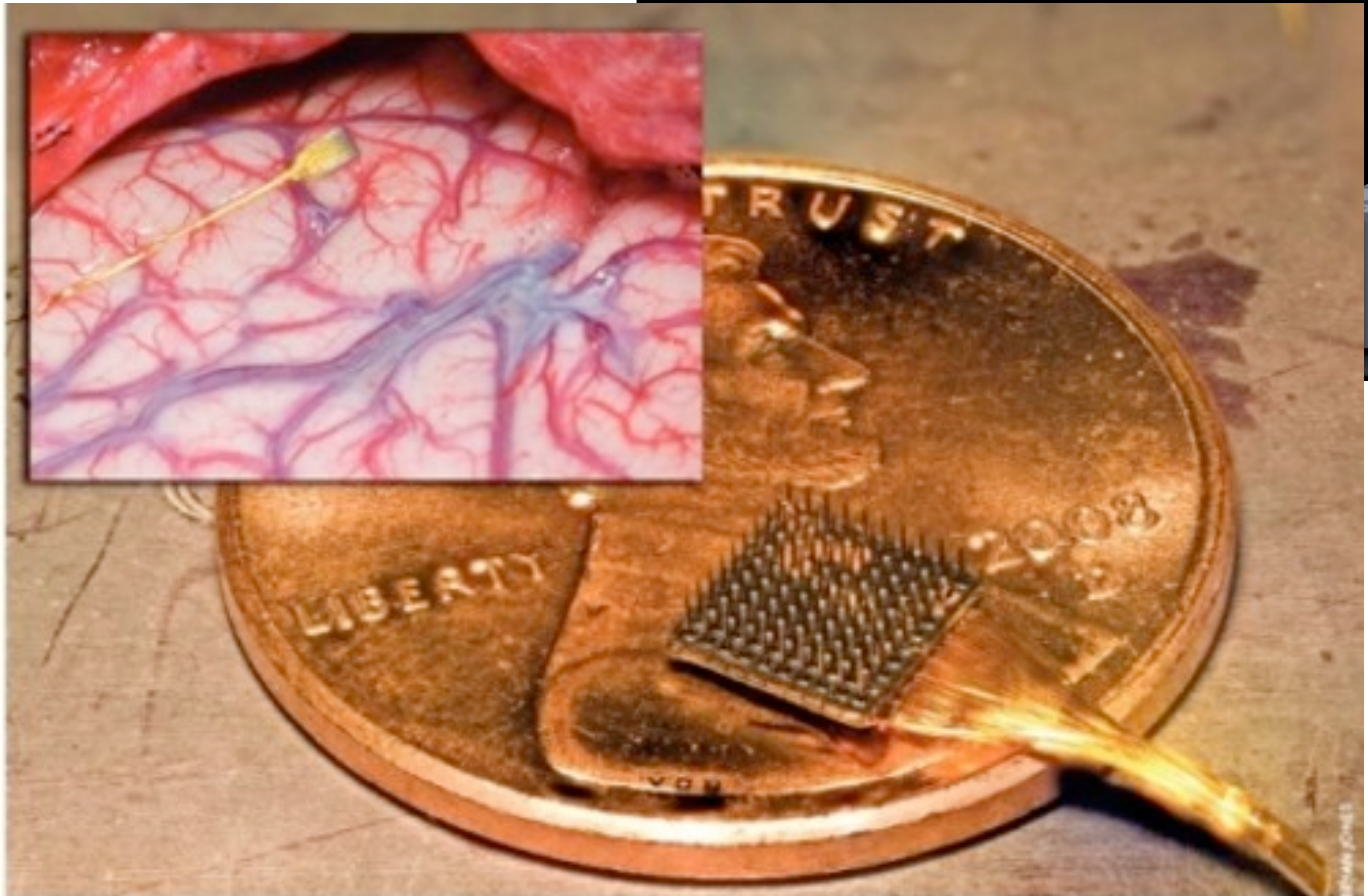


Utah Array™

The Utah Array is the industry benchmark for recording large populations of neurons. This patented microelectrode array has well-documented methods for obtaining stable and long-term neural recordings.





Population Vector Encoding

$$f = b_0 + b_x v_x + b_y v_y + b_z v_z$$

Translation only
f is square root firing rate of neuron
vx, vy, vz is translational velocity

$$f = b_0 + b_x v_x + b_y v_y + b_z v_z + b_{\theta x} v_{\theta x} + b_{\theta y} v_{\theta y} + b_{\theta z} v_{\theta z}$$

Translation and orientation

$$\boldsymbol{F}_{[t \times n]} = \boldsymbol{V}_{[t \times d]} \boldsymbol{B}_{[d \times n]}$$

Basic approach: take many observations f and solve for b vector
Each neuron's b-vector can be interpreted as a preferred direction

Population Vector Encoding

$$f = b_0 + b_x v_x + b_y v_y + b_z v_z$$

Basic approach: take many observations f and solve for b vector
Each neuron's b-vector can be interpreted as a preferred direction

$$\boldsymbol{F}_{[t\times n]} = \boldsymbol{V}_{[t\times d]}\boldsymbol{B}_{[d\times n]}$$

$$\boldsymbol{B} = \left(\boldsymbol{V}^{\mathrm{T}}\boldsymbol{V} + \lambda_1 {*} \boldsymbol{I}_{[d\times d]}\right)^{+}\boldsymbol{V}^{\mathrm{T}}\boldsymbol{F}$$

damped pseudoinverse

$$\boldsymbol{V}_{[t\times d]} = \boldsymbol{F}_{[t\times n]}\boldsymbol{W}_{[n\times d]}$$

$$\boldsymbol{W} = \left(B\Sigma_{[n\times n]}\ \boldsymbol{B}^{\mathrm{T}} + \lambda_2 {*} \boldsymbol{I}_{[d\times d]}\right)^{+}\boldsymbol{B}\ \boldsymbol{\Sigma}_{[n\times n]},$$

weighted damped pseudo inverse — it weights units that are more variable or carry less strong signals less

Assistance

Monkey controls subset of degrees of freedom

Velocities that do not move towards the target are attenuated

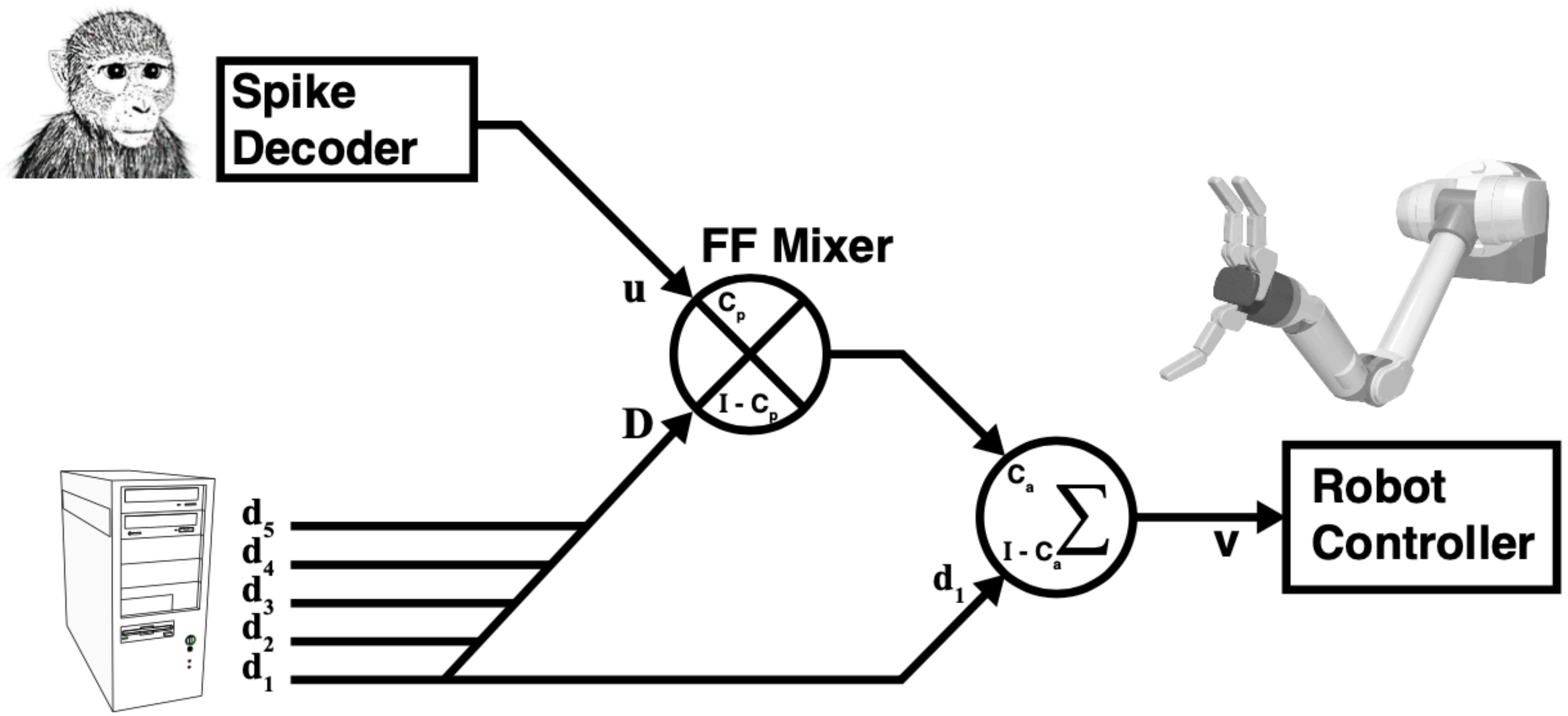


Figure 5.1: Schematic for the bimodal shared control system showing two layers of integration between BCI and automatically generated robot commands.

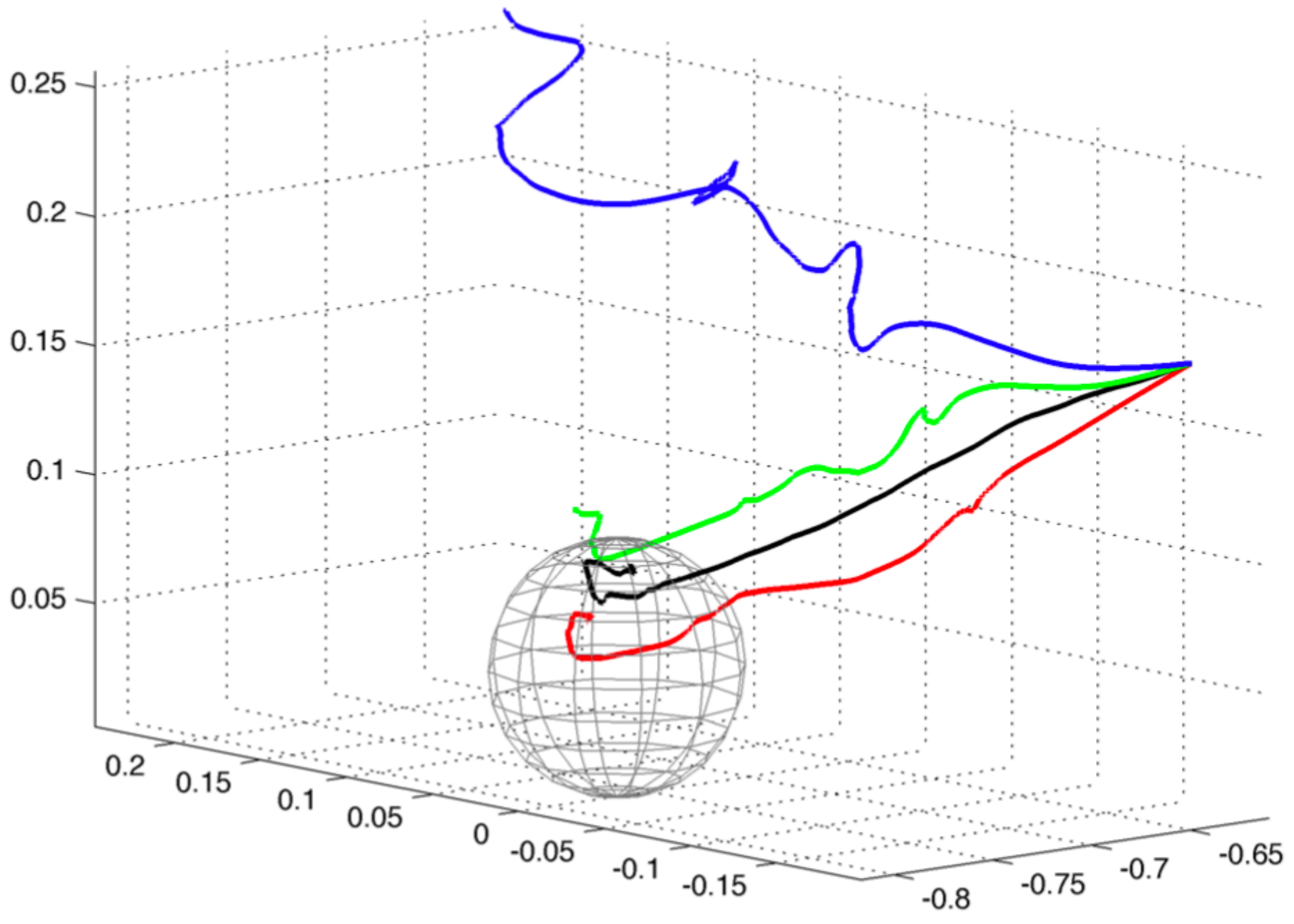


Figure 5.6: Results from simulation of a single control trial at different linear assistance c_p levels. Recorded brain-control commands were input into the BSC algorithm that output control commands at different levels of assistance. This output controlled the trajectory of a dynamic simulation of the prosthetic robot. Trials at $c_p = 1$ (blue), $c_p = 0.5$ (green) and $c_p = 0$ (red) are shown with the original recorded trajectory ($c_p \approx 0.4$, black). The linear control target region is denoted by the sphere.

IOP Publishing
Journal of Neural Engineering
J. Neural Eng. **12** (2015) 016011 (17pp)
doi:10.1088/1741-2560/12/1/016011

Ten-dimensional anthropomorphic arm control in a human brain–machine interface: difficulties, solutions, and limitations

B Wodlinger[1,2], **J E Downey**[2,3], **E C Tyler-Kabara**[1,3,4,5], **A B Schwartz**[1,2,3,5,6,7], **M L Boninger**[1,3,5,8] **and J L Collinger**[1,2,3,8]

[1] Department of Physical Medicine and Rehabilitation, University of Pittsburgh, Pittsburgh, PA, USA
[2] Center for the Neural Basis of Cognition, Pittsburgh, PA, USA
[3] Department of Bioengineering, University of Pittsburgh, Pittsburgh, PA, USA
[4] Department of Neurological Surgery, University of Pittsburgh, Pittsburgh, PA, USA
[5] McGowan Institute for Regenerative Medicine, University of Pittsburgh, Pittsburgh, PA, USA
[6] Systems Neuroscience Institute, University of Pittsburgh, Pittsburgh, PA, USA
[7] Department of Neurobiology, University of Pittsburgh, Pittsburgh, PA, USA
[8] Department of Veterans Affairs Medical Center, Pittsburgh, PA, USA

E-mail: collingr@pitt.edu

Received 21 March 2014, revised 3 November 2014
Accepted for publication 7 November 2014
Published 16 December 2014

CrossMark

Modular Prosthetic Limb

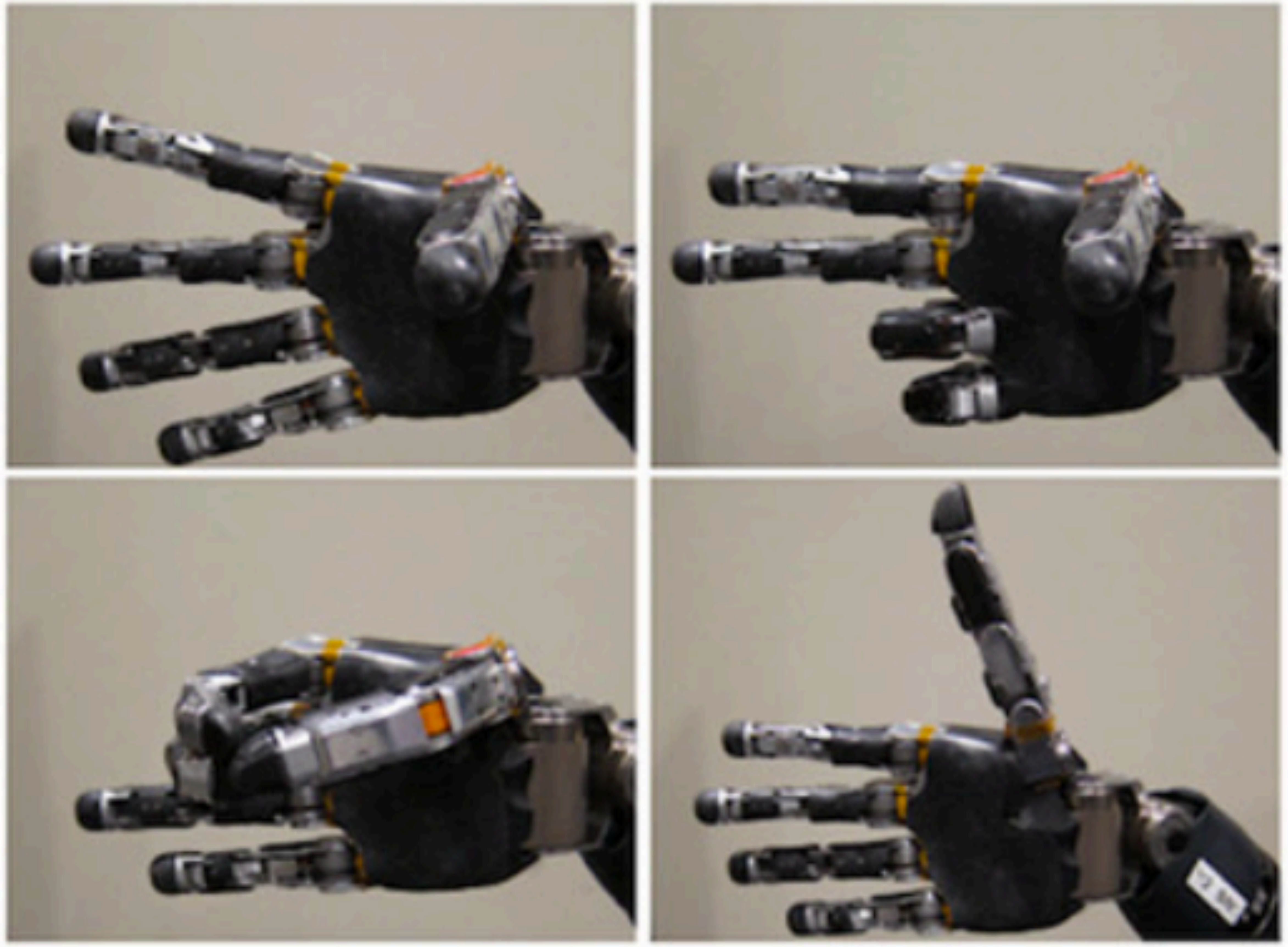
Capable of effectuating almost all of the movements as a human arm and hand and with more than 100 sensors in the hand and upper arm, the Modular Prosthetic Limb (MPL) is the world's most sophisticated upper-extremity prosthesis. There are currently ten MPLs being used for neurorehabilitation research across the United States.

The MPL features:

- Anthropomorphic (lifelike) form factor and appearance
- Human-like strength and dexterity
- High-resolution tactile and position sensing
- Neural interface for intuitive and natural closed-loop control

Population Vector Encoding - 10 dimensions

$$f = b_0 + b_x v_x + b_y v_y + b_z v_z + b_{\theta x} v_{\theta x} + b_{\theta y} v_{\theta y}$$
$$+ b_{\theta z} v_{\theta z} + b_{\mathrm{p}} v_{\mathrm{p}} + b_{\mathrm{s}} v_{\mathrm{s}} + b_{\mathrm{f}} v_{\mathrm{f}} + b_{\mathrm{t}} v_{\mathrm{t}},$$



Population Vector Encoding

Two rounds of decoding

(1) Watch robot and think about imitating motions

(2) Attempt motions while restricted to move forward and backwards along fixed path

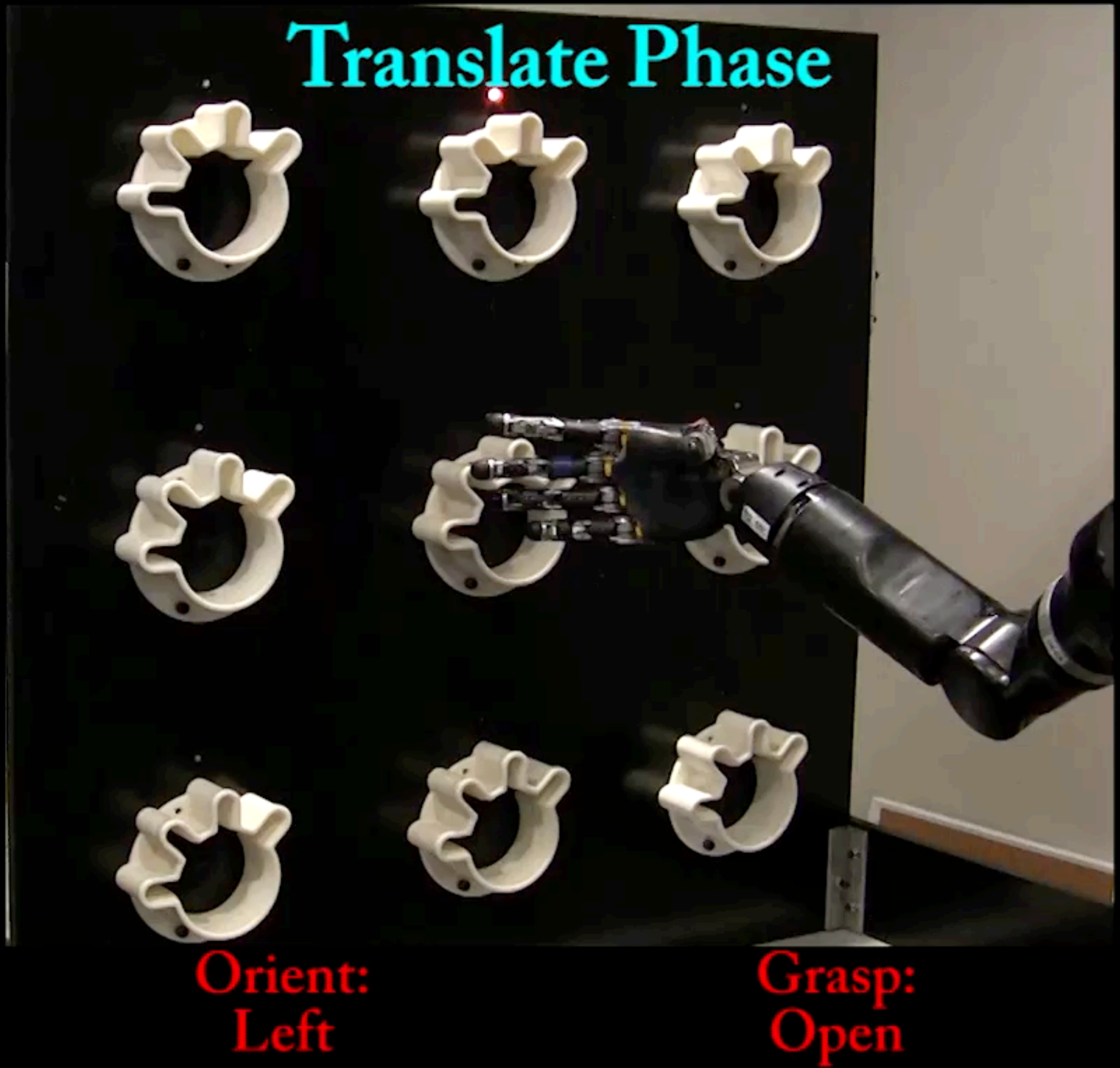
10-15 minutes of data collection in each phase

Table 1. Study timeline.

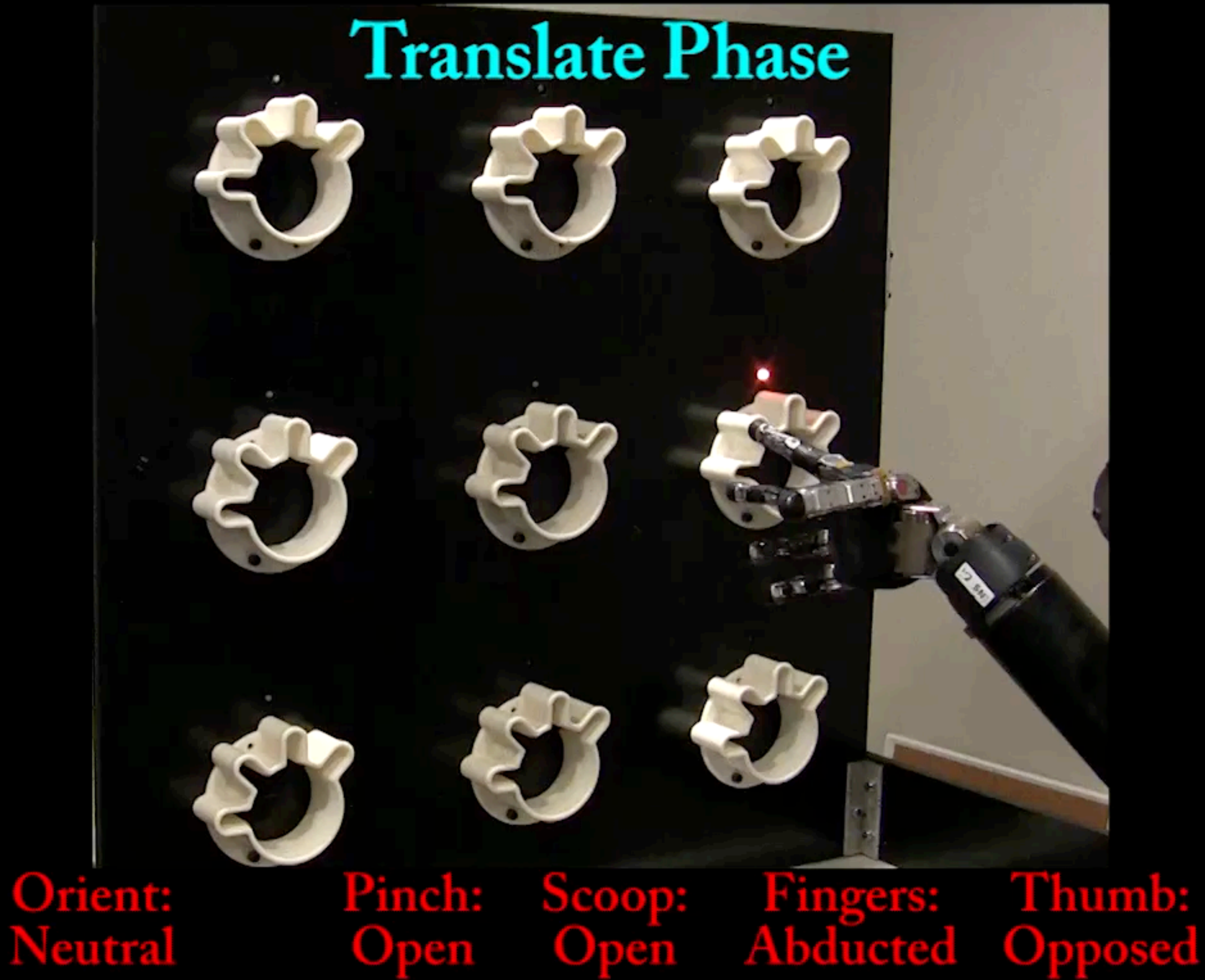
Study phases	7D from [3]	10D Study	10D Study	7D Paradigm Comparison Study
Days post-implant	32–95	119–189	192–236	266–280
Number of sessions	24	23	17	6
Calibration paradigm(s)	7D Sequence Task	10D Sequence Task	10D VR Object Task	7D VR Object Task, 7D Sequence Task, 7D VR Sequence Task
Testing paradigms	7D Sequence Task	10D Sequence Task	10D VR Object Task	7D Sequence Task
Testing conditions	Computer assisted and full brain control	Computer assisted and full brain control	Computer assisted only	Full brain control only
Functional evaluations (full brain control)	ARAT	none	ARAT	Box and Blocks-like task

ARAT: Action Research Arm Test.

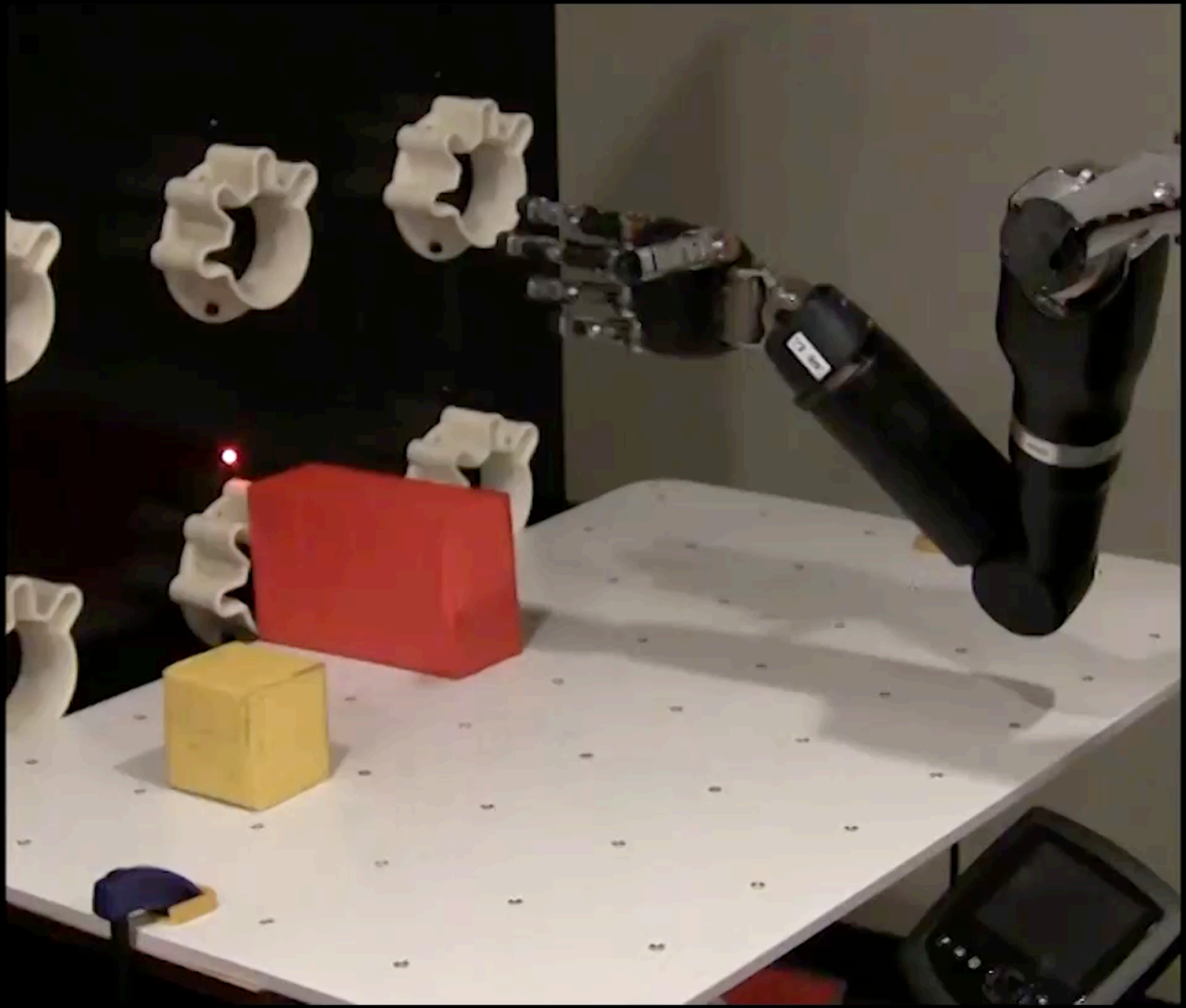
7D Sequence Task



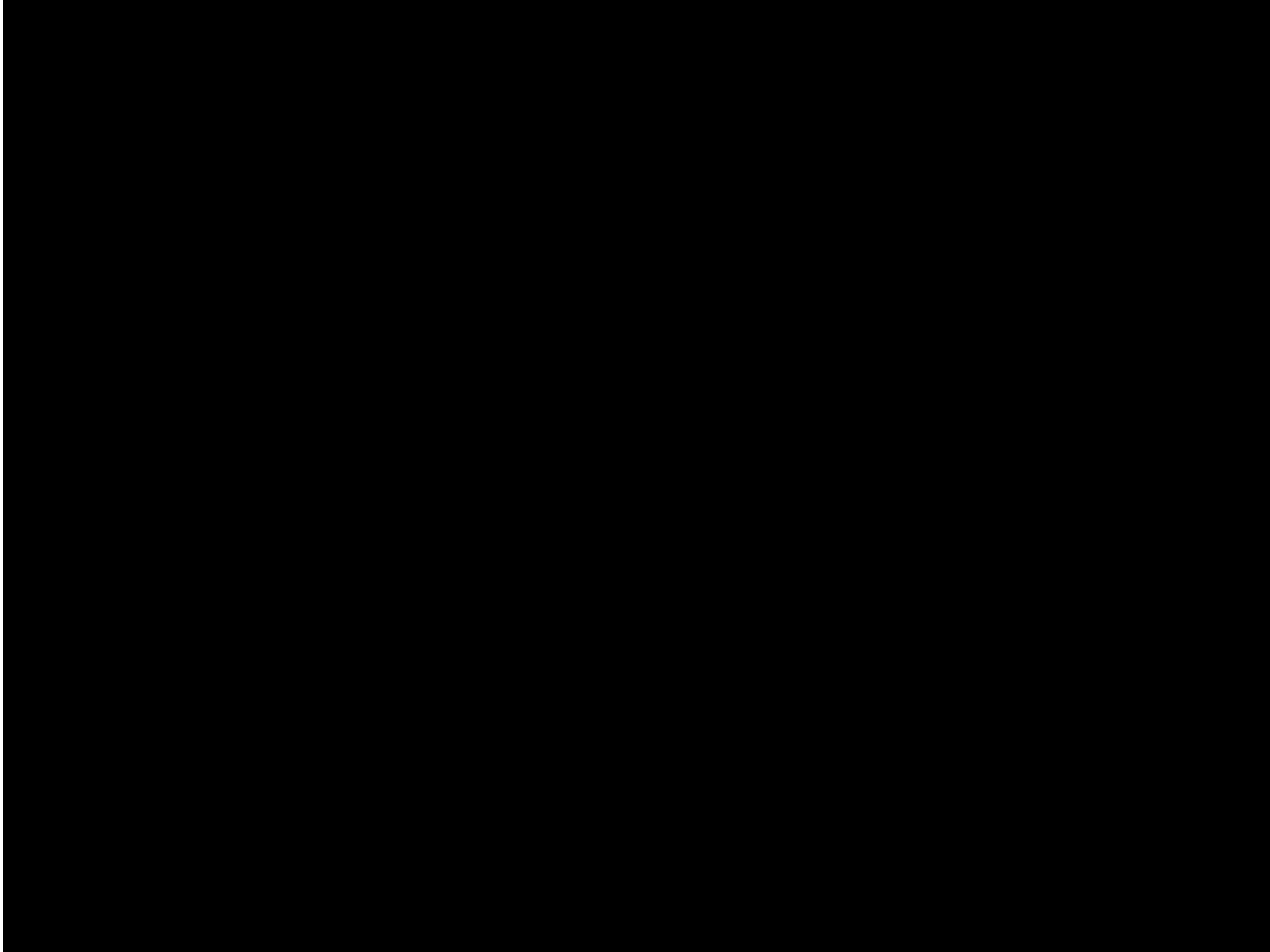
10D Sequence Task



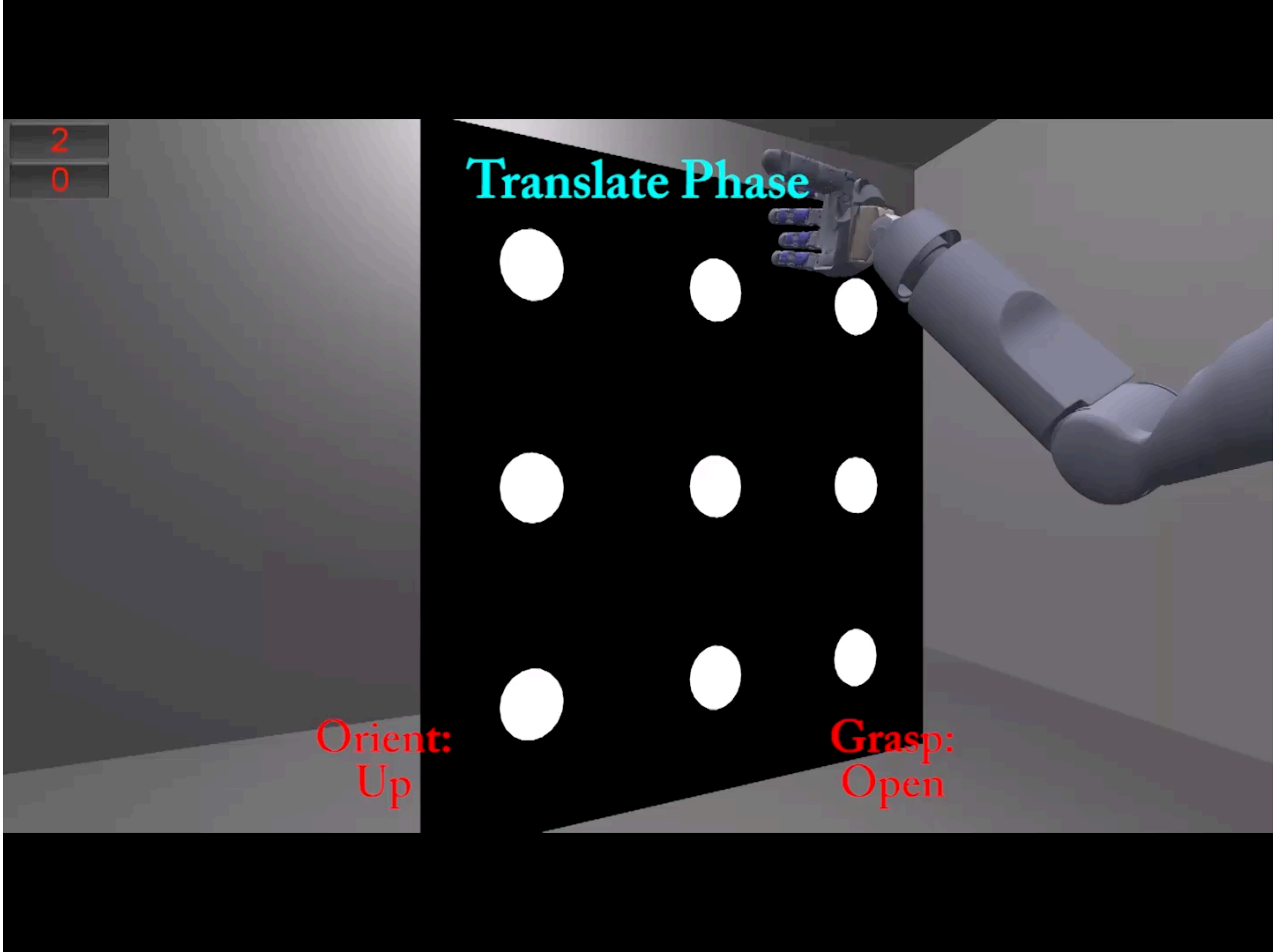
7D Comparison Experiments



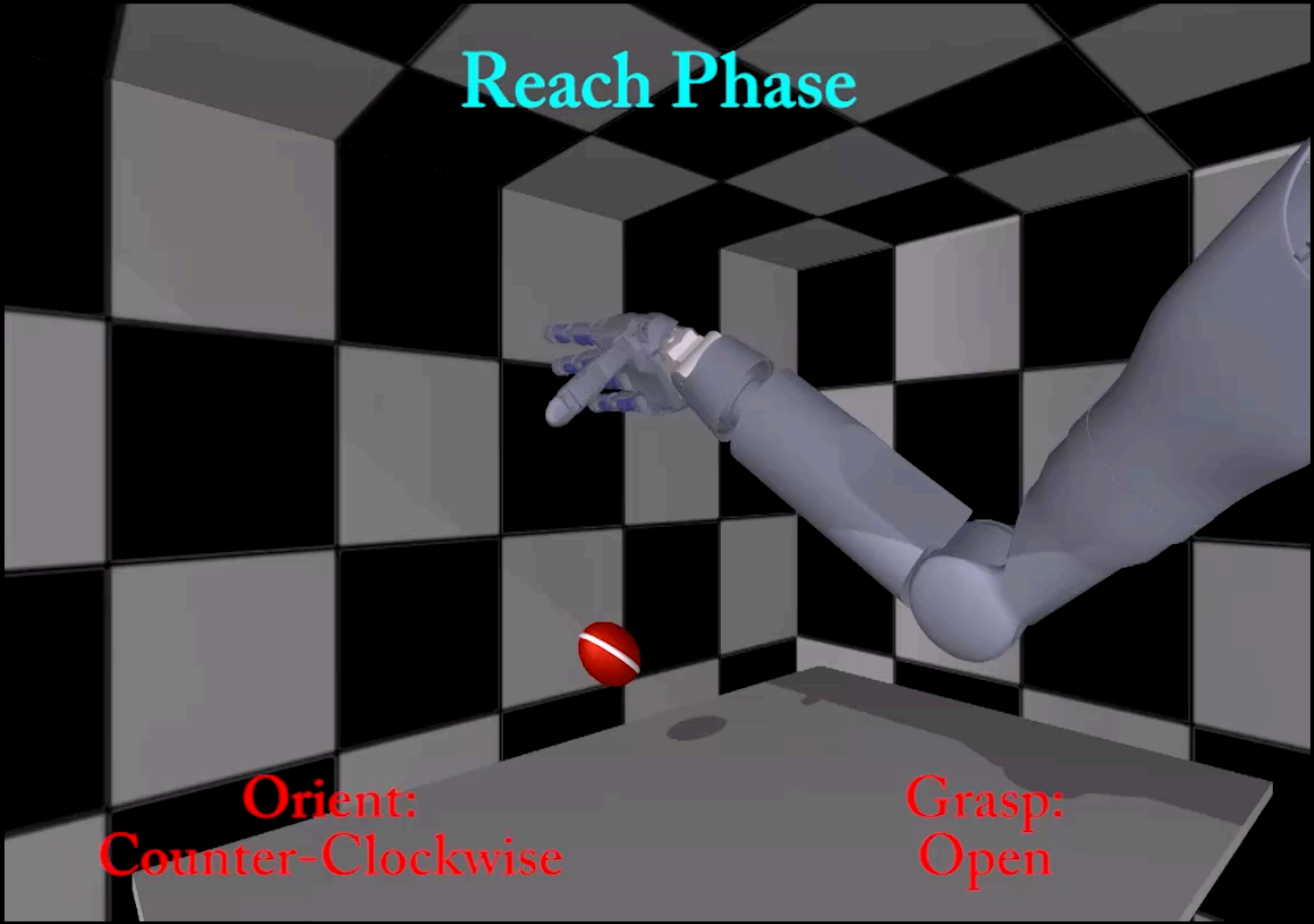
Early ARAT tests (prior to VR training)



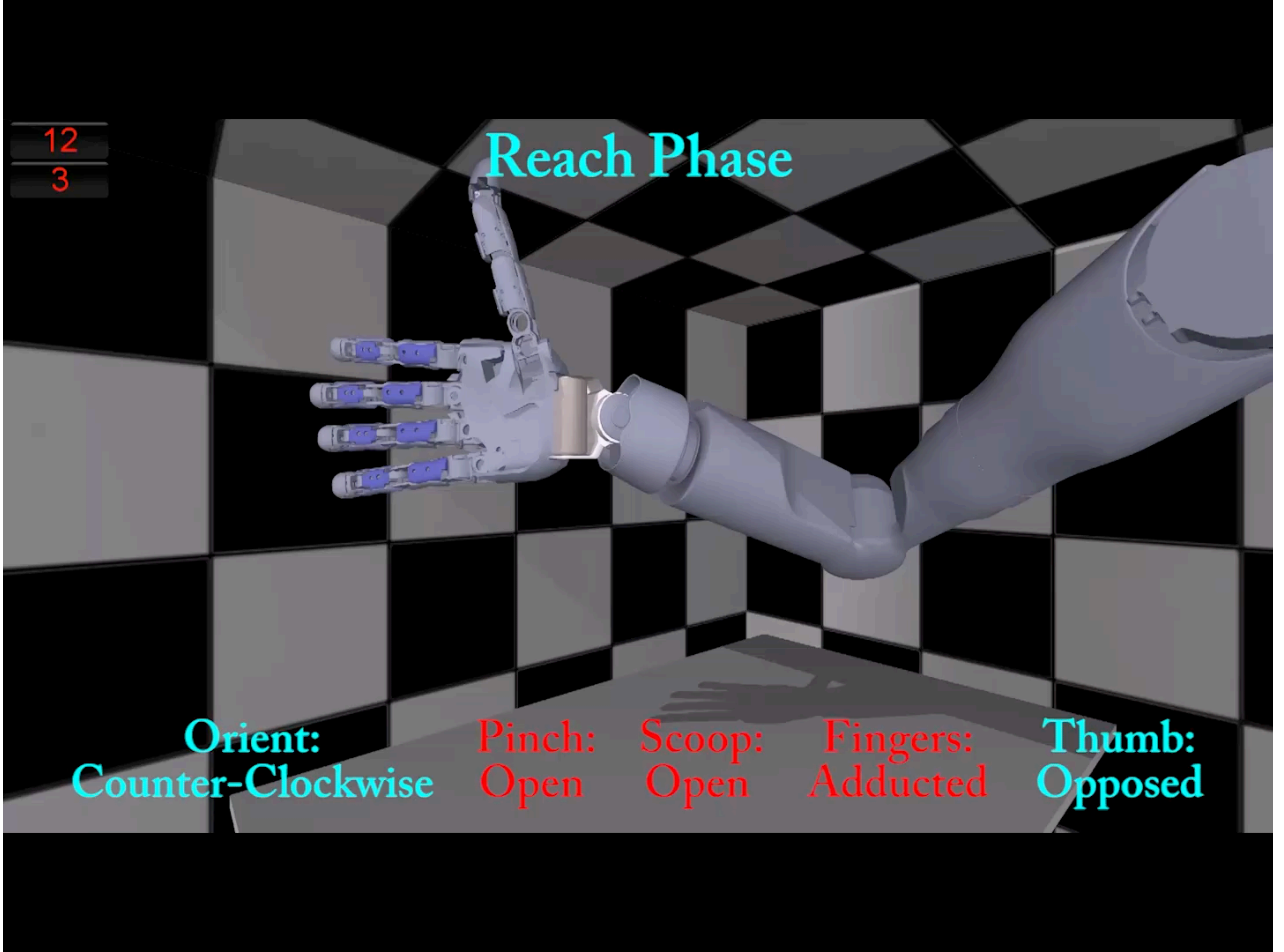
7D VR Sequence Task



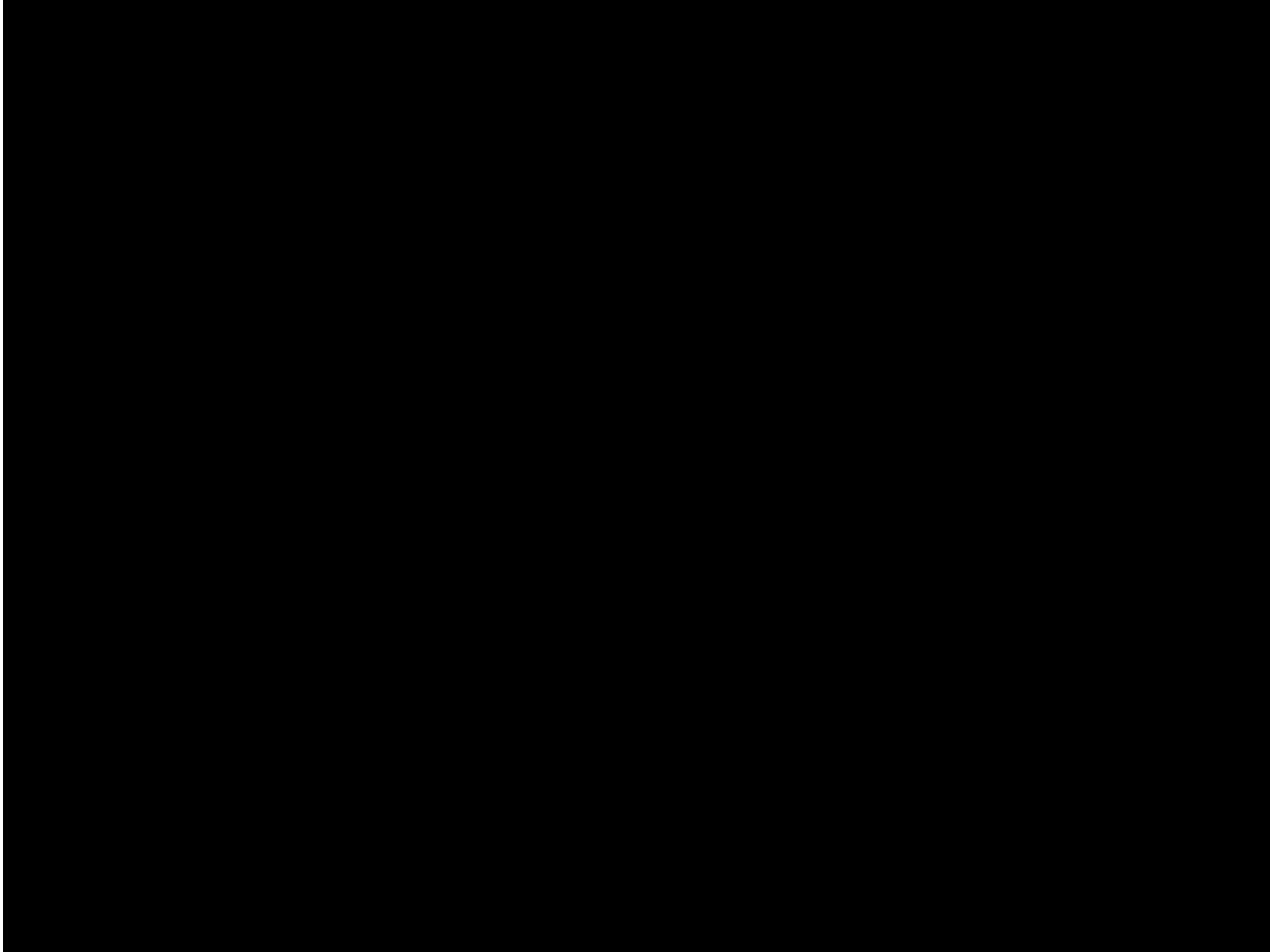
7D VR Object Task



10D VR Object Task



Later ARAT tests (after VR object training)



Some press

BRAIN-COMPUTER INTERFACE RESEARCH

UPMC Rehabilitation Institute and the University of Pittsburgh School of Medicine

Study participant Jan Scheuermann feeds herself

1) Nov. 28, 2012 - Chocolate bar
2) Nov. 30, 2012 - Chocolate bar
3) Nov. 30, 2012 - Chocolate truffle
4) Nov. 30, 2012 - String cheese
5) Nov. 30, 2012 - Red pepper

December 2012

TRT 05:27

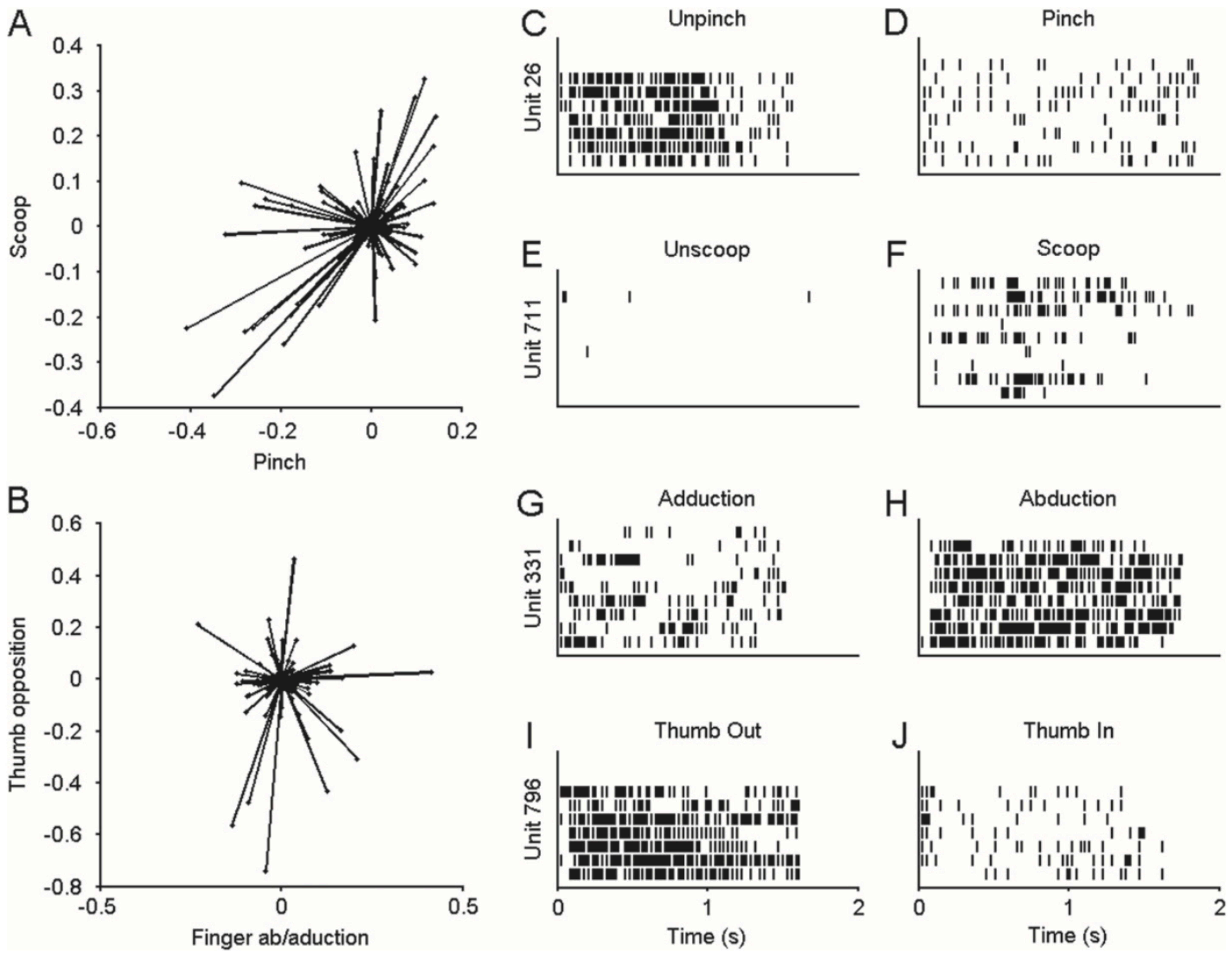


Figure 3. Neural tuning to hand shape in primary motor cortex. Data shown in this figure was based on 64 trials of observation activity collected during the 10D Sequence Task on day 179 post-implant. (A) Projection onto the Scoop-Pinch plane of preferred directions in 4D hand shape space. Each line represents a unit with the length indicating modulation depth. (B) Projection onto the thumb opposition–finger Ab/adduction plane of preferred directions in 4D hand shape space. A and B show that units had preferred directions that sampled the hand shape space although the depth of modulation of these units was variable. (C)–(J) Raster plots for single units showing response to positive and negative velocities along each dimension of hand shape space. Each row represents a single observation trial, where the command to move is given at $t = 0$. Each vertical line represents a single action potential from the unit listed on the *Y*-axis.

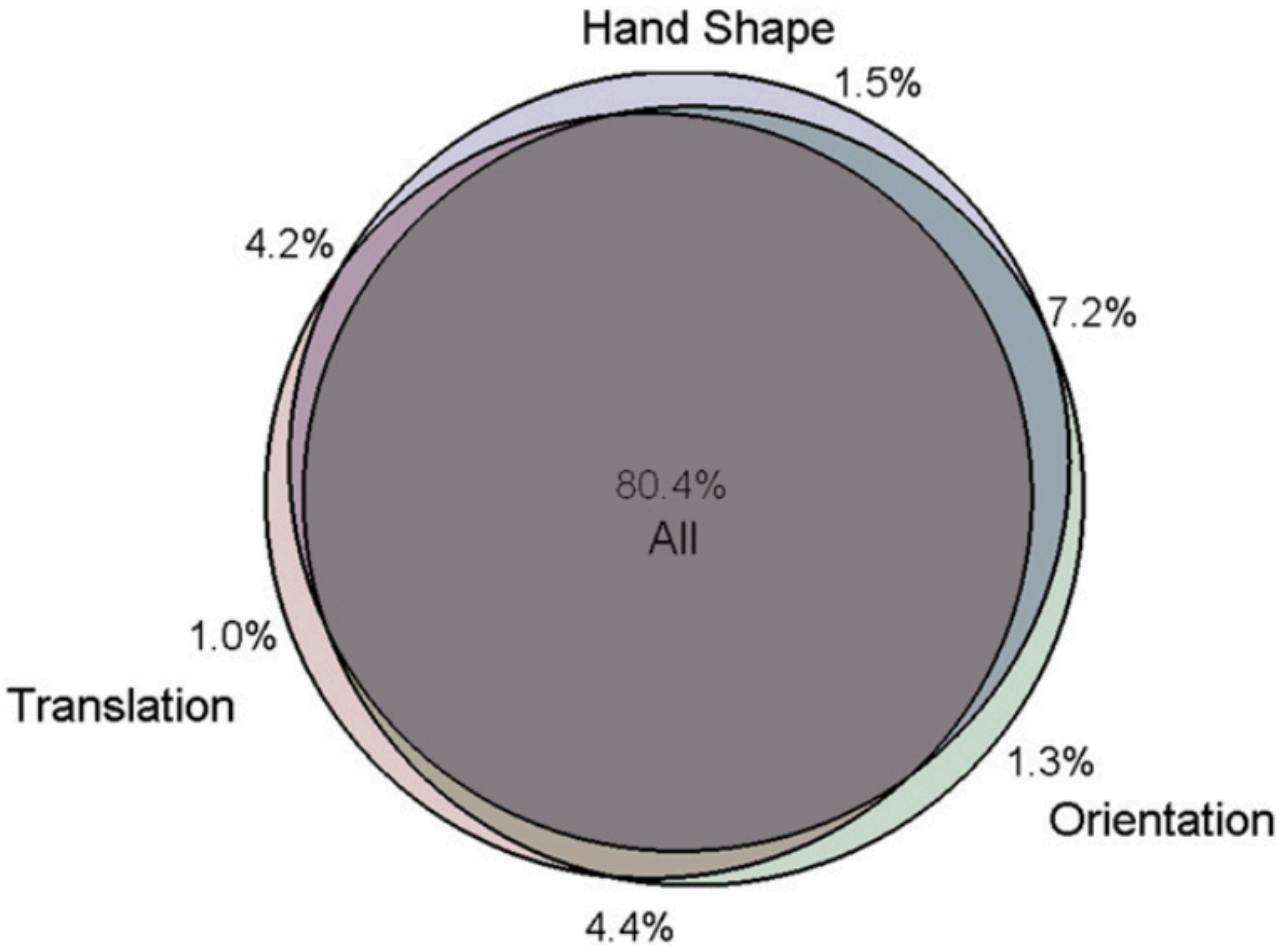
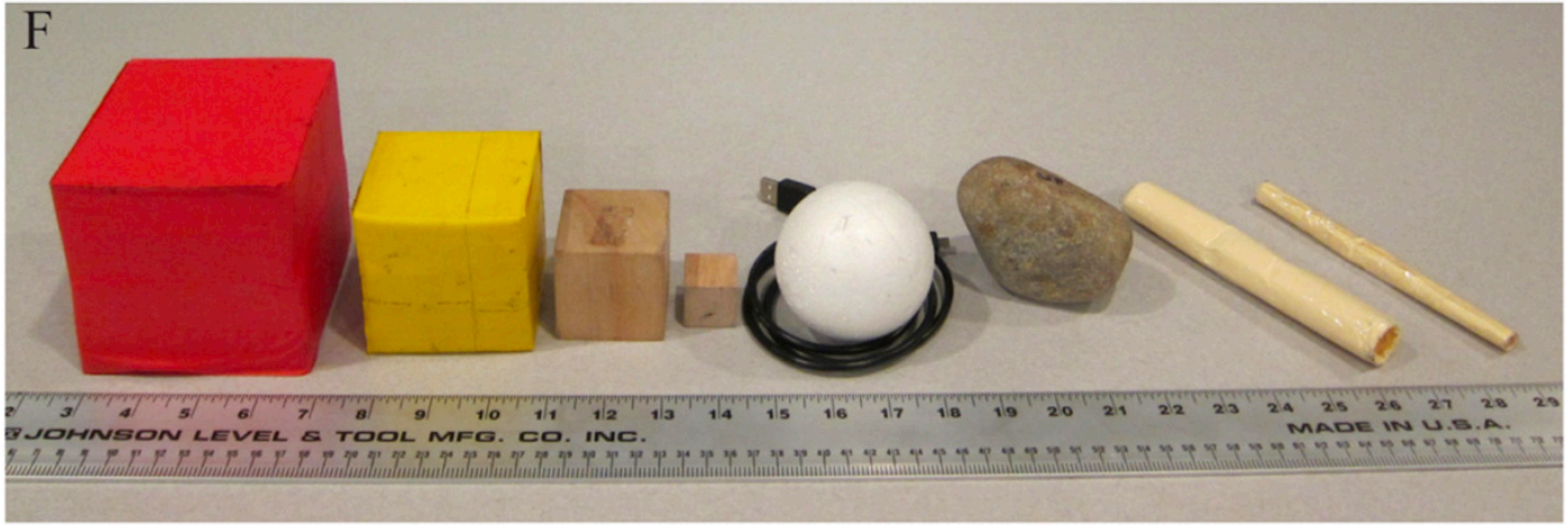


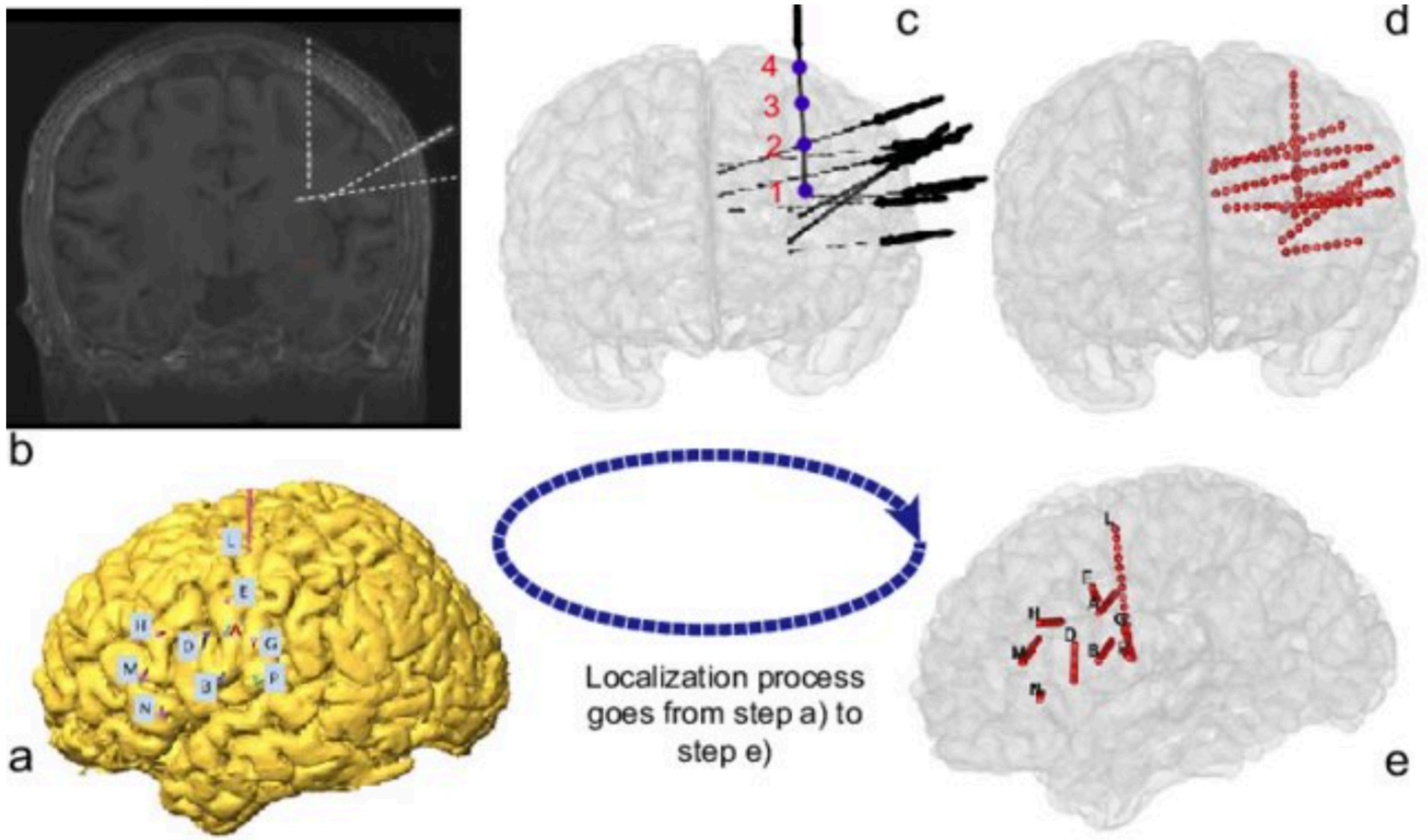
Figure 4. Venn diagram of the percentage of units significantly tuned to each domain or combination of domains over the 10D study duration. Most of the units (80.4%) recorded during this study have been significantly ($p < 0.05$) tuned to all three domains.



ARAT completion time during 10D control (s)											
Object	**Day 196**	**Day 199**	**Day 200**	**Day 203**	**Day 207**	**Day 210**	**Day 217**	**Day 220**	**Day 221**	**Day 228**	**Day 229**
1. Block, 10 cm cube	43.3	15.9	25.7	8.5	16.0	14.0	33.1	102.0	22.0	9.0	42.7
2. Block, 2.5 cm cube	12.6	13.3	13.1	—	13.2	43.6	—	70.0	—	56.5	—
3. Block, 5 cm cube	26.5	100.0	17.2	7.3	14.5	6.5	10.1	74.0	10.4	17.0	14.2
4. Block, 7.5 cm cube	40.7	12.6	10.5	7.0	11.6	5.8	14.0	12.0	7.0	10.4	41.9
5. Ball, 7.5 cm diameter	20.7	23.5	13.1	10.0	—	6.2	—	—	7.1	8.0	—
6. Stone, 10 cm × 2.5 cm × 1 cm	58.0	16.2	10.3	9.5	22.7	24.1	—	19.6	9.6	7.2	19.6
7. Pour water from glass to glass[a]	—	—	—	—	—	—	—	—	—	—	—
8. Tube, 2.5 cm × 16 cm	—	16.6	18.7	7.3	12.6	75.0	—	11.9	48.3	8.2	10.7
9. Tube, 1 cm × 16 cm	23.8	20.2	13.5	—	8.2	—	—	—	61.0	—	—
Average time/Item (s)	**32.2**	**27.3**	**15.3**	**8.3**	**14.1**	**25.0**	**19.1**	**48.3**	**23.6**	**16.6**	**25.8**
Total ARAT score	**16**	**17**	**17**	**15**	**16**	**16**	**12**	**15**	**16**	**16**	**14**

[a] Task 7 ‘Pour water from glass to glass’ was never fully completed during a scored session, but was attempted each day.

Alternative: SEEG electrodes



considered to be minimally invasive

Alternative: EEG (noninvasive)

Robotics and Autonomous Systems 116 (2019) 98–113

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

A service assistant combining autonomous robotics, flexible goal formulation, and deep-learning-based brain–computer interfacing

D. Kuhner [a,d,*,1], L.D.J. Fiederer [b,c,d,**,1], J. Aldinger [a,d,*,1], F. Burget [a,d,1], M. Völker [a,b,d,1], R.T. Schirrmeister [b,d], C. Do [a,d], J. Boedecker [a,d], B. Nebel [a,d], T. Ball [b,d], W. Burgard [a,d]

[a] Department of Computer Science, University of Freiburg, Germany
[b] Faculty of Medicine, University of Freiburg, Germany
[c] Faculty of Biology, University of Freiburg, Germany
[d] BrainLinks-BrainTools Cluster of Excellence, University of Freiburg, Germany

HIGHLIGHTS

- BCI-controlled autonomous robotic service assistant.
- First online brain–computer-interface using deep learning.
- Menu-driven language generation based on referring expressions.
- Modular ROS-based mobile robot interaction.
- Experimental evaluation with a real robot.

Alternative: EEG (noninvasive)