Cognitive Control Signals for Neural Prosthetics

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EE599e

Presenter: Jeff Cole

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Sensory-motor pathway broken with paralysis

The neural prosthetic system would record the plans to make movements from cortex, interpret these neural signals, and use them to operate external devices.

Motivation

- Previous research focus:

    Extracting hand trajectories by recording signals primarily from the motor cortex.

- This paper:

    Can higher level "goal-of-movement" signals be decoded from the parietal reach region (PRR) instead?

Overview of Experiment

Higher level signals related to goals of movement were decoded from monkeys and used to position cursors on a computer screen without the animals emitting any motor behavior.
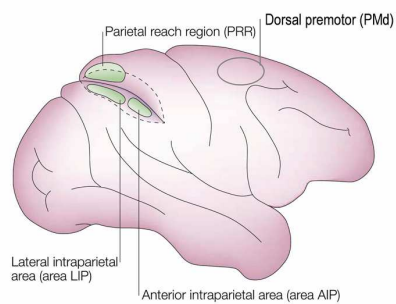
Experimental Setup

- 3 Monkeys
- Electrodes were implanted at points along the major pathway for visually guided movement

Pathway for visually guided motor behavior
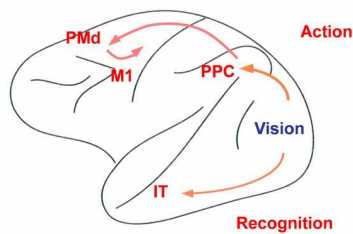
Experimental Setup

Adopted from Y. Cohen and R. Andersen, Nature Reviews Neuroscience, 2002. Please obtain permission."
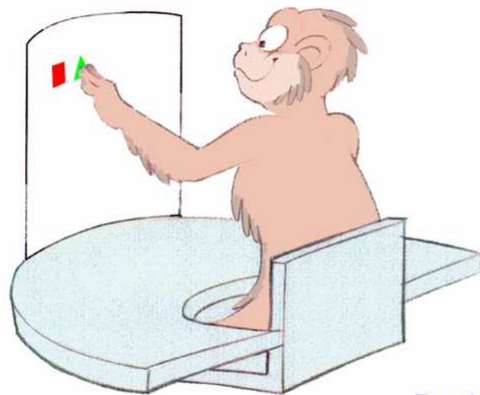
64 electrodes in MIP (a component of PRR)

32 electrodes in PMd

Actually this paper covers two (separate) experiments
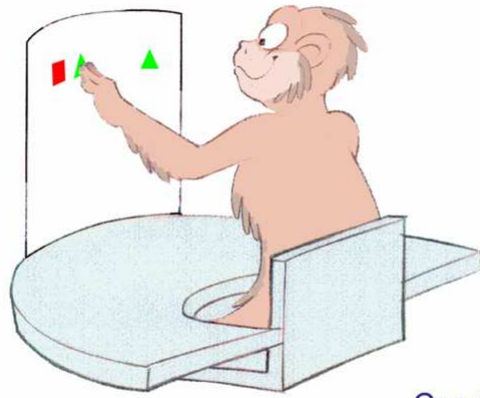
- For the first experiment:

   Perform both reaching (motor) tasks
   and thinking (goal planning) tasks
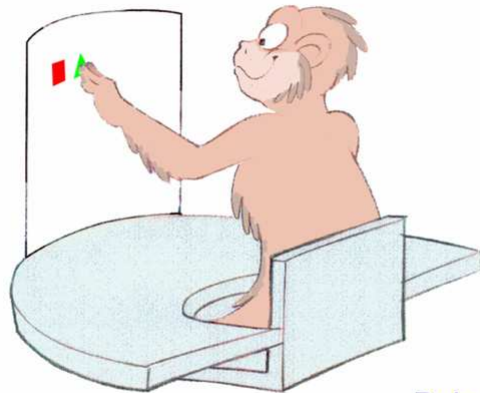   and record neural response.

Reach Trials Task

Begin Trial

Reach Trials Task
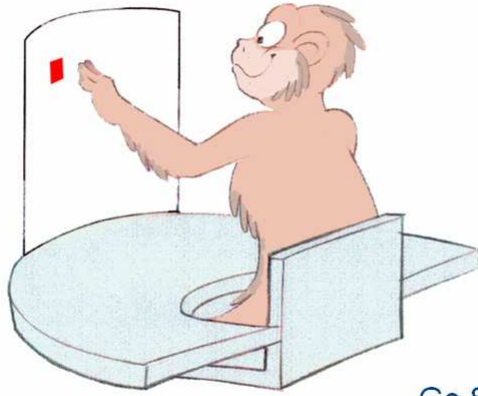

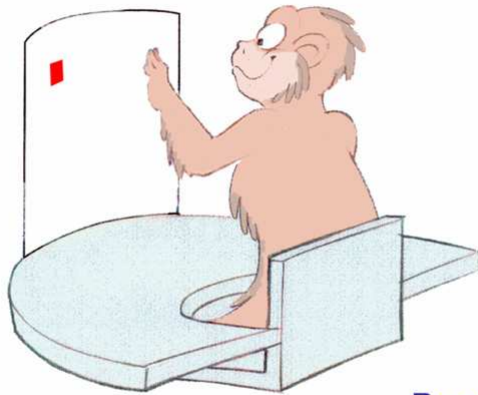Cue location

Reach Trials Task

Delay Period

Wait for 1.2 to 1.8 seconds (memory period)
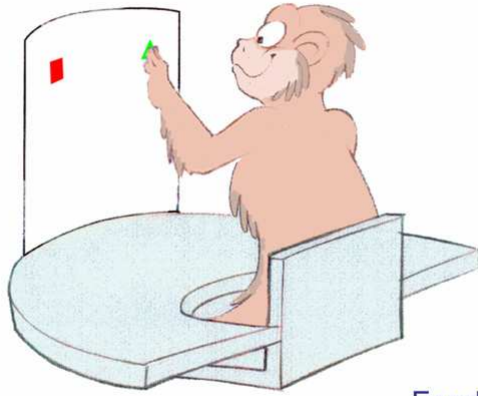
Reach Trials Task

Go Signal

Reach Trials Task

Reach

Reach Trials Task

Feedback

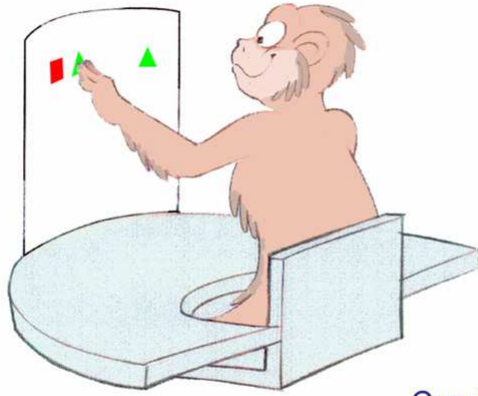Successful reach trials were added to a database to be used for brain trials
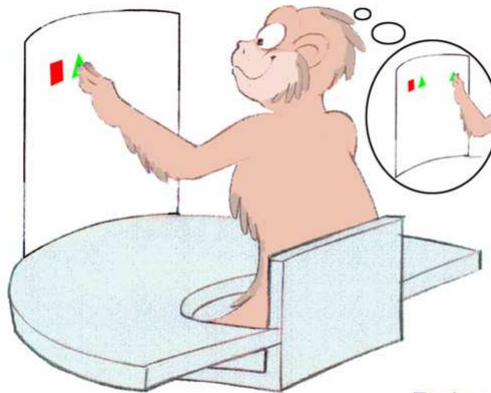
Brain Trials Task
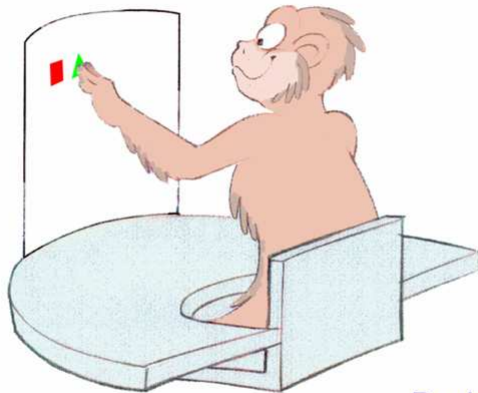
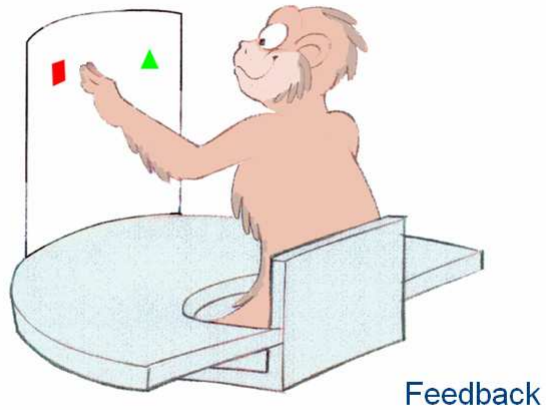Begin Trial

Brain Trials Task

Cue location

Brain Trials Task
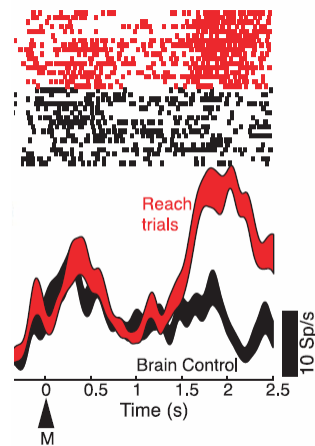
Delay Period

Brain Trials Task

Feedback

Neural Activity

Comparison of neural activity during Reach and brain control trials

M is the start of the memory period
SP is short for "spikes"

Reach trials

10 Sp/s

Brain Control

Time (s)

M

Using 8 neurons →

C
Overall % correct = 64.4%
Percent correct
4 Targets
Trial number

← Using 8 neurons
Overall % correct = 63.6%
6 Targets
Trial number

Using 16 neurons →

D
Overall % correct = 67.5%
Percent correct
8 Targets
Trial Number

← Using N neurons
and offline training
Number of Neurons
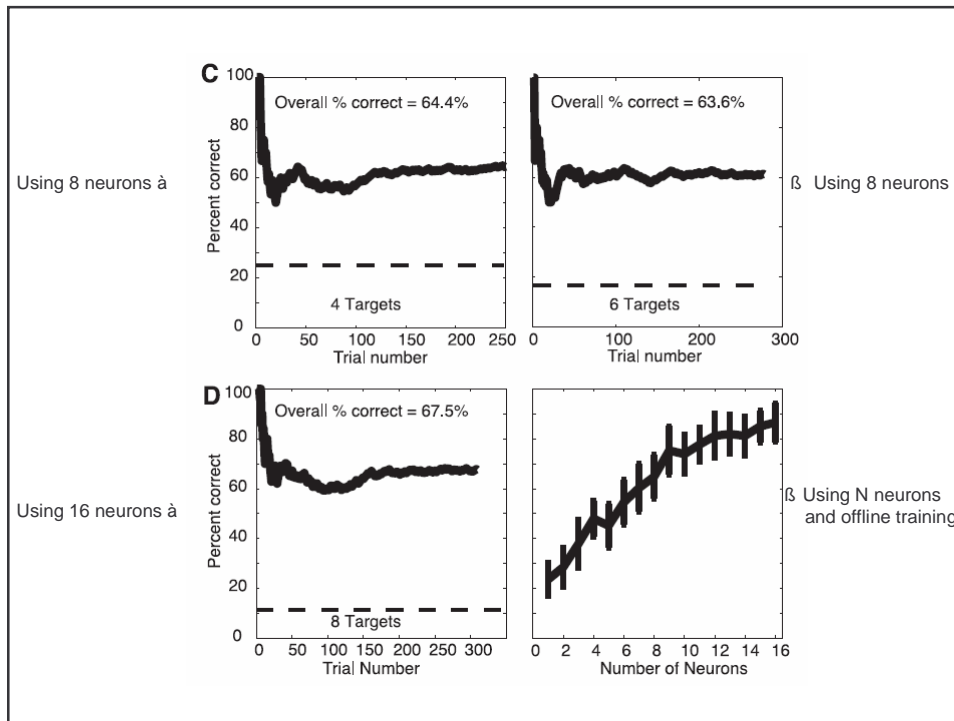
Mean (standard deviation)
success rates across all sessions

		Monkey S	NS	Monkey C	NS	Monkey O	NS
Parietal Cortex	4 Targets	45.0 (10.5)	62	34.2 (5.0)	81	43.2 (17.1)	13
	5 Targets	48.1 (7.3)	10	30.6 (2.9)	7	59.3 (0.2)	2
	6 Targets	37.1 (11.1)	10	25.6 (5.8)	2	31.2 (14.7)	6
Premotor Cortex	* 4 Targets	75.2	1				
	* 8 Targets	68.2 (1.3)	2				

Is this surprising to anyone else?

Only 1 session of premotor cortex
Yielded almost twice the success rate.

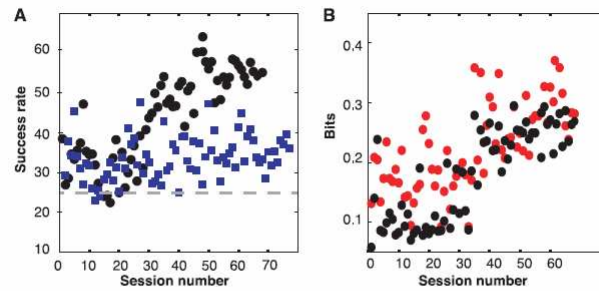Fig. 2. (A) Overall success rates for decoding movement intention from four possible target positions. Black circles, monkey S; blue squares, monkey C. The number of brain control trials varied from 250 to 1100 trials. (B) The mean mutual information of the cells from monkey S, whose activity was used to build the database (red) and perform the brain control task (black), is depicted for all 68 sessions. For each session, a selection of cells was chosen on the basis of significant tuning. These cells were then used in the brain control trials. The mutual information of these cells was calculated for the 120 reach trials and the subsequent 120 brain control trials.

Conclusions

- Increasing the number of cells will result in very fast and accurate online decodes
- Significant improvements were shown over the course of weeks

Actually this paper covers two (separate) experiments

- For the second experiment:

    Can the expected value (reward) also be decoded from PRR activity?
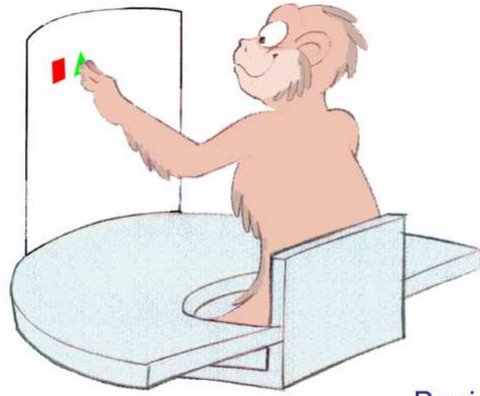
    Reward variables: amount, probability or type

Setup

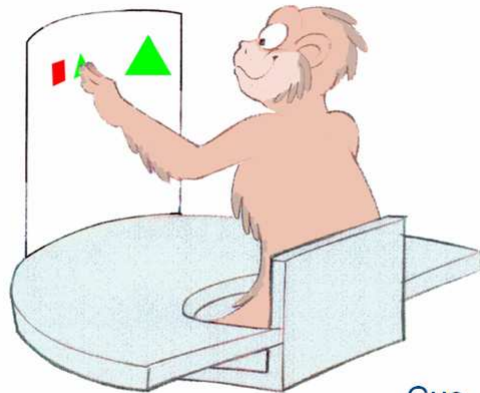- Same as previous experiment except:

    Cue target size indicated the amount, probability or type of reward
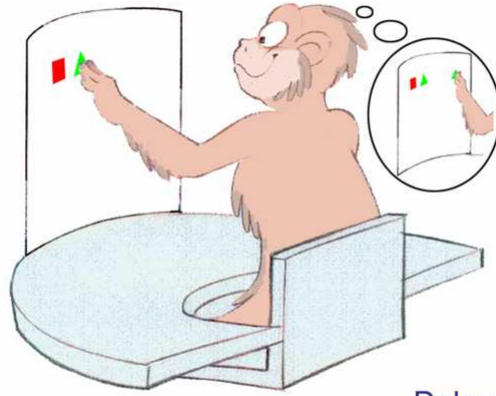
Reward Variable Trials Task
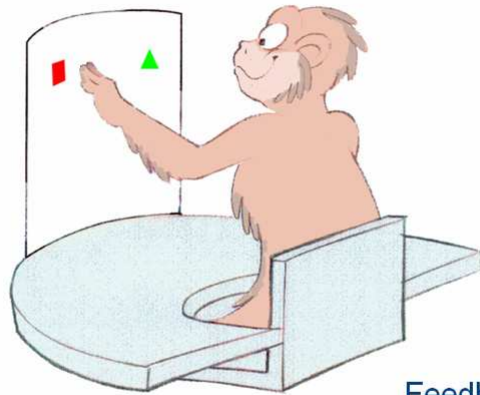

Begin Trial

Reward Variable Trials Task

Cue
Size indicates
type, prob, or amount
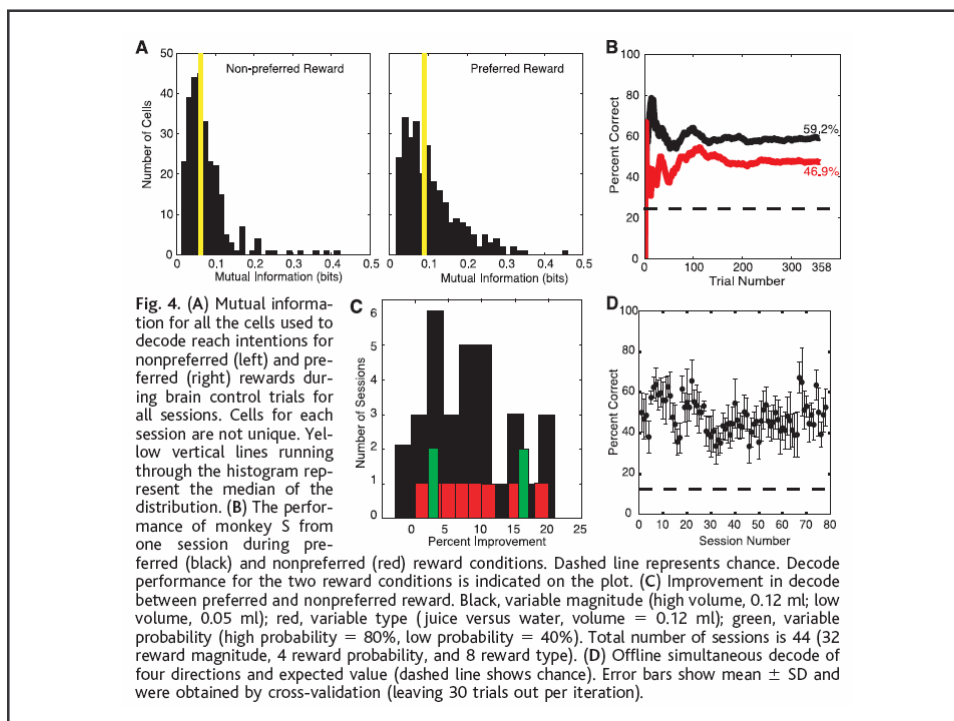of reward

Reward Variable Trials Task

Delay Period

Reward Variable Trials Task

Feedback

Fig. 3. (A) Response of a neuron during brain control trials in which reward type was varied; orange juice (black) versus water (red) and (B) its tuning curve. Rasters are aligned to the onset of the memory period. The direction of the intended reach that elicited the responses is written on the figure. Vertical lines superimposed on the PSTH enclose the 900-ms memory segment used to calculate the tuning curves and the duration of the neural activity used to decode reach intention during brain control trials. Volume of juice and water was the same (0.12 ml).

Fig. 4. (A) Mutual information for all the cells used to decode reach intentions for nonpreferred (left) and preferred (right) rewards during brain control trials for all sessions. Cells for each session are not unique. Yellow vertical lines running through the histogram represent the median of the distribution. (B) The performance of monkey S from one session during preferred (black) and nonpreferred (red) reward conditions. Dashed line represents chance. Decode performance for the two reward conditions is indicated on the plot. (C) Improvement in decode between preferred and nonpreferred reward. Black, variable magnitude (high volume, 0.12 ml; low volume, 0.05 ml); red, variable type (juice versus water, volume = 0.12 ml); green, variable probability (high probability = 80%, low probability = 40%). Total number of sessions is 44 (32 reward magnitude, 4 reward probability, and 8 reward type). (D) Offline simultaneous decode of four directions and expected value (dashed line shows chance). Error bars show mean ± SD and were obtained by cross-validation (leaving 30 trials out per iteration).

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Analysis

- The expectation of a high reward value increased the successful online decode of goals by up to 21%

- The preferred reward carried more information than trials ending in non-preferred rewards.

- "The results of this study show that the goal signal can be used as a source of prosthetic control."

Question for the class

- Does this analysis follow logically and conclusively from the data?

- Essentially they showed that monkeys will perform tasks better when the rewards are better.

- And they concluded that they had successfully decoded the type of reward, size of reward, and probability of reward using PRR neural activity.

- Couldn't we also conclude that the monkeys just try harder, or pay more attention when they know there is more payoff for their efforts?

Their rebuttal to the question I just posed:

"The increased activity is unlikely to be due to attention, given that no increase to the expected delivery of the non-preferred reward was recorded when it was averse."

Apparently they tried using saline instead of water and showed that the response to the saline was similar to the response of the water (neutral)

"Reaction time is significantly smaller for the preferred reward condition. This enhanced motor performance is consistent with increased motivation."

Summary of Paper

- Setup: Electrode arrays were placed in the PRR of monkey brains. The monkeys were then shown targets and an attempt was made to extract their high-level goals rather than their intended hand trajectories by looking at whether neural activity increased during the one second interval after the target was shown.

- Results: Over time and with more neurons sampled, the monkeys performed the tasks better and their neural activity was greatly increased when the reward was preferred

- Conclusion: Both goals and preferences can be read from neural activity and then used by neural prosthetics to perform desired tasks

Learning to Control a Brain-Machine Interface for Reaching and Grasping by Primates

J. M. Carmena, M. A. Lebedev, R. E. Crist, J. E. O'Doherty, D. M. Santucci, D. F. Dimitrov, P. G. Patil, C. S. Henriquez, M. A. L. Nicolelis

EE599e

Presenter: Jeff Cole

4/12/06

Overview

- Paper presents results from a series of long-term studies in macaque monkeys.
- Demonstrates ability of the same ensemble of cells in closed-loop mode to control two distinct movements of a robotic arm: reaching and grasping

Electrode Placement

- Multiple arrays containing 16-64 micro-wires each were implanted in several frontal and parietal cortical areas:
  - » Dorsal premotor cortex (PMd)
  - » Supplementary motor area (SMA)
  - » Primary motor cortex (M1)
  - » Primary somatosensory cortex (S1)
  - » Medial intrparietal area (MIP)

- Total of 96 in Monkey 1
- Total of 320 in Monkey 2
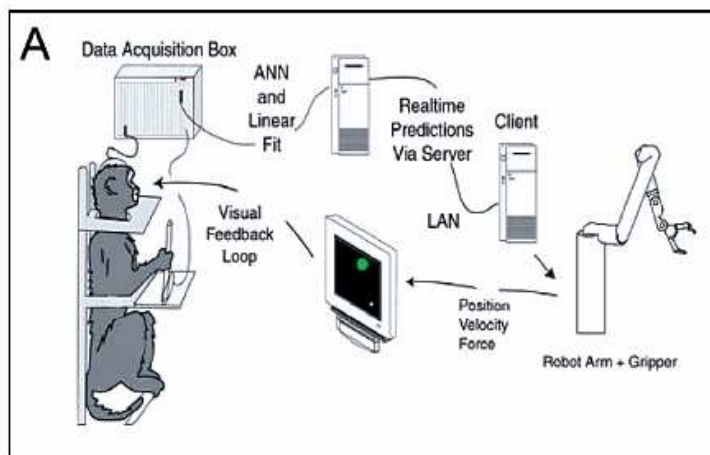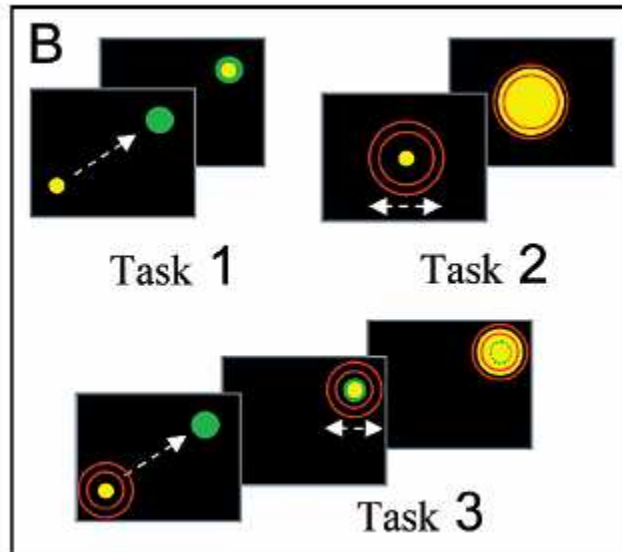
Linear Model

- Hand position, velocity, and gripping force were modeled as a weighted linear combination of neuronal activity using a multidimensional linear regression (Wiener Filter)
- Several alternative decoding algorithms were tested offline, including a Kalman filter, normalized least-mean squares filter, and an artificial neural-network. But none of these methods could consistently outperform the Wiener Filter.
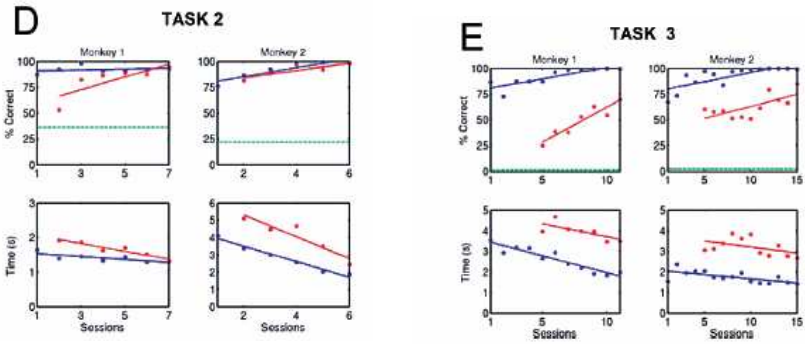
Real Time prediction of Motor Parameters

- Firing rates were sampled using 100 ms bins and 10 bins preceding a given point in time were used for training the model and predicting with it.
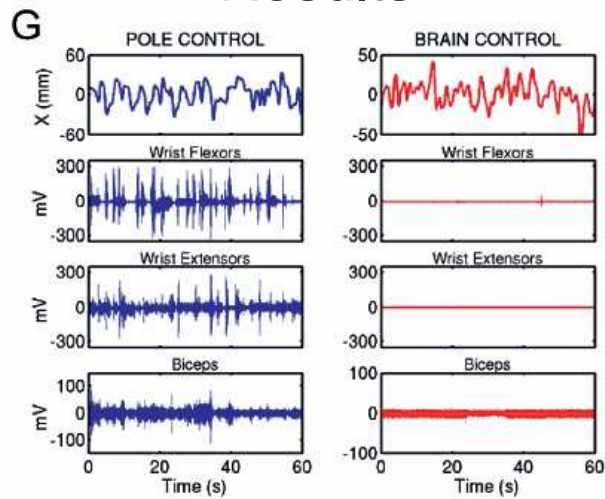- Models were trained with 10 minutes of data and tested by applying them to subsequent records
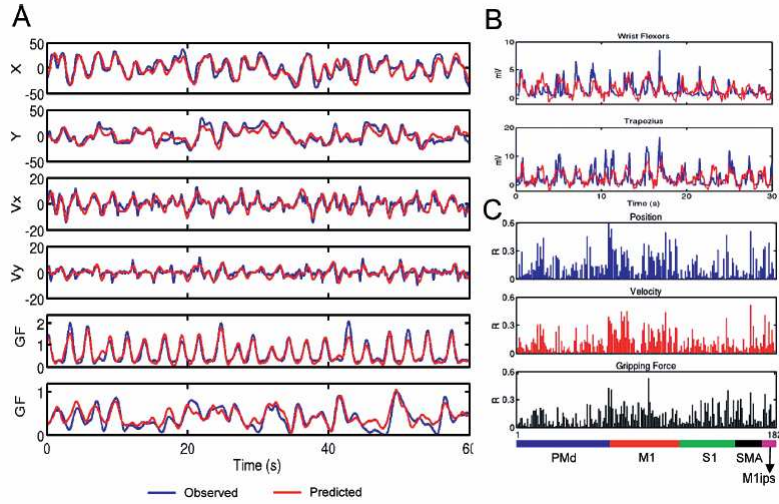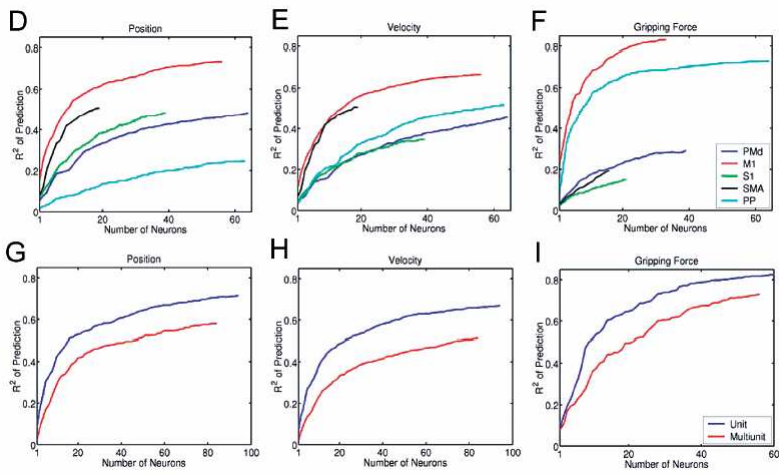
Results
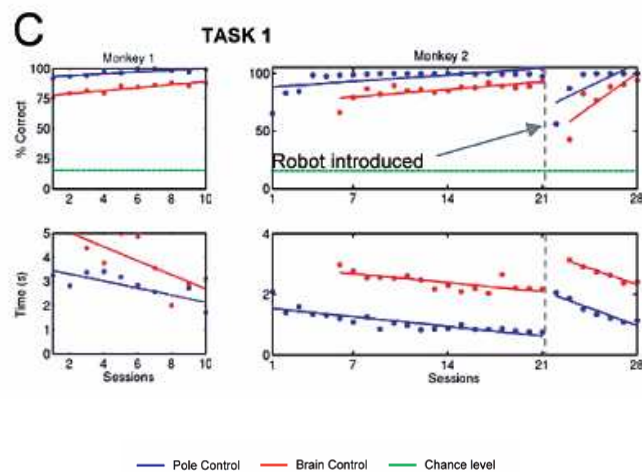
Results

Results

Results

Results

Some Highlights from paper

- Key novel feature: the introduction of the robot equipped with a gripper into the control loop of the BMIc after the animals had learned the task

- The presence of continuous visual feedback helped to stabilize model performance

- Increasing the size of neuronal population improved quality of prediction

Some Highlights from paper

- Although all cortical areas surveyed contained information about any given motor parameter, for each area, different numbers of neurons were required to achieve the same level of prediction

- Analysis revealed that predictions of any motor parameter based on combined neural ensemble activity were far superior to those obtained based only on the mean and contribution of single neurons

Summary / Conclusions

Reliable, long-term operation of a BMIc was achieved by extracting multiple motor parameters from several frontopariental neural ensembles

Monkeys learned to reach and grasp virtual objects with a robot even in the absence of overt arm movements

Summary / Conclusions

Performance was possible because large populations of neurons from multiple cortical areas were sampled. Thus large ensembles are preferable for efficient control of BMI

This is consistent with the notion that motor programming and execution are represented in a highly distributed fashion across frontal and pariental areas and that each of these areas contains neurons that represent multiple motor parameters.