



Moving by Thinking: Towards a Cortical Neural Prosthetic

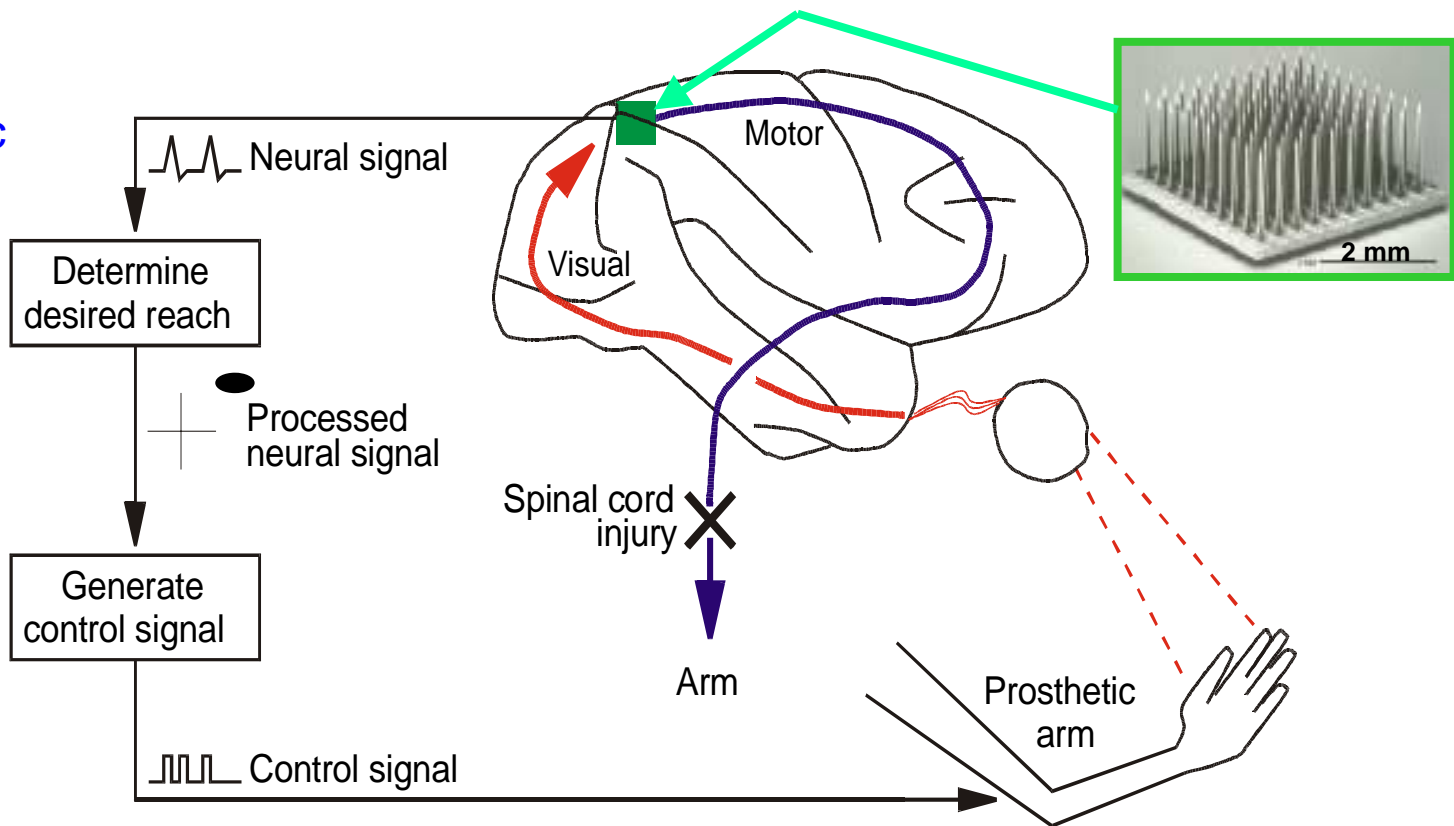


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Proposed Cortical Prosthetic System



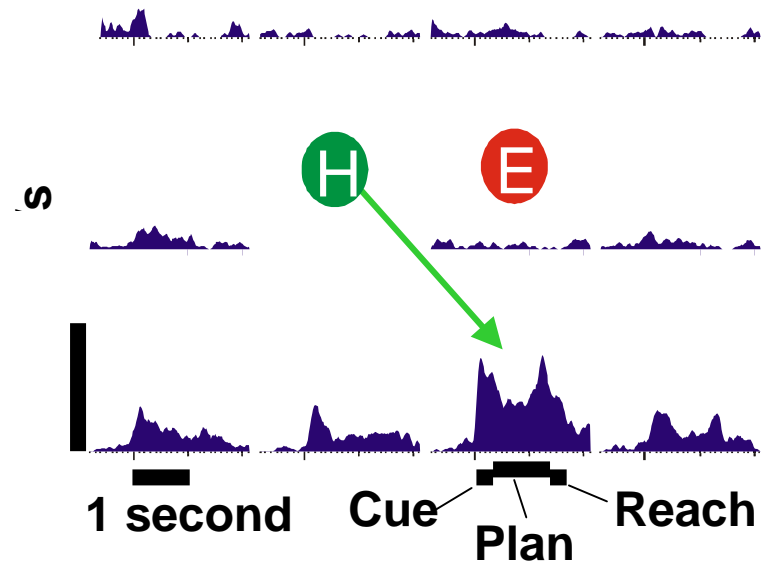
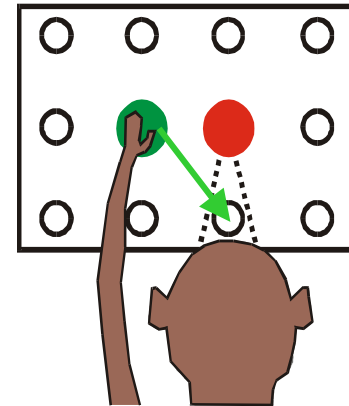
Potential Advantages of PRR Neurons for Prosthetic Systems

PRR neurons encode:

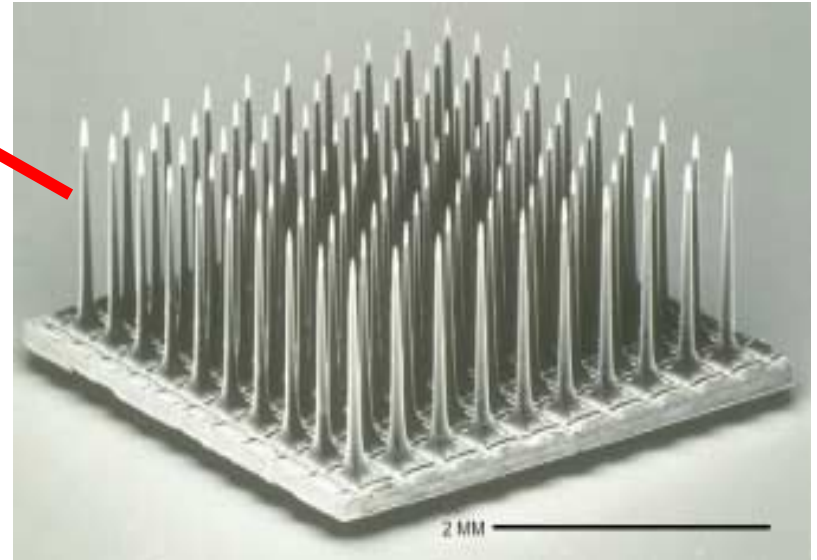
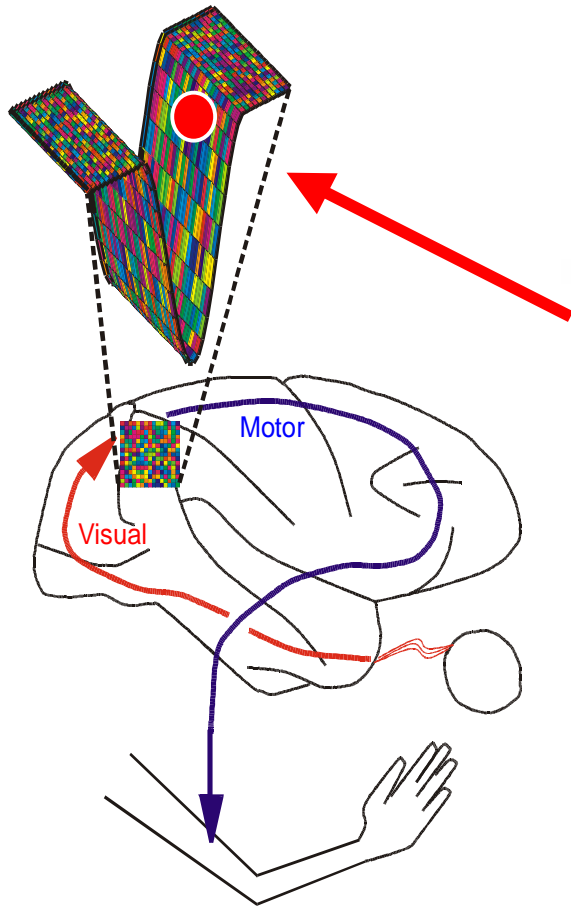
- The plan to reach to a target
- The plan for the upcoming reach
- The plan with respect to the eyes

PRR neurons may:

- not encode muscle forces
- reorganize little following injury
- adapt quickly to calibrate the system



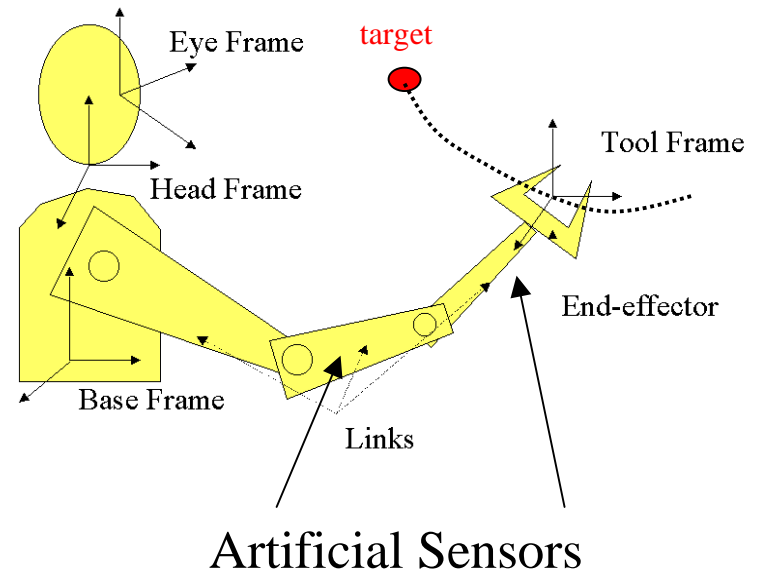
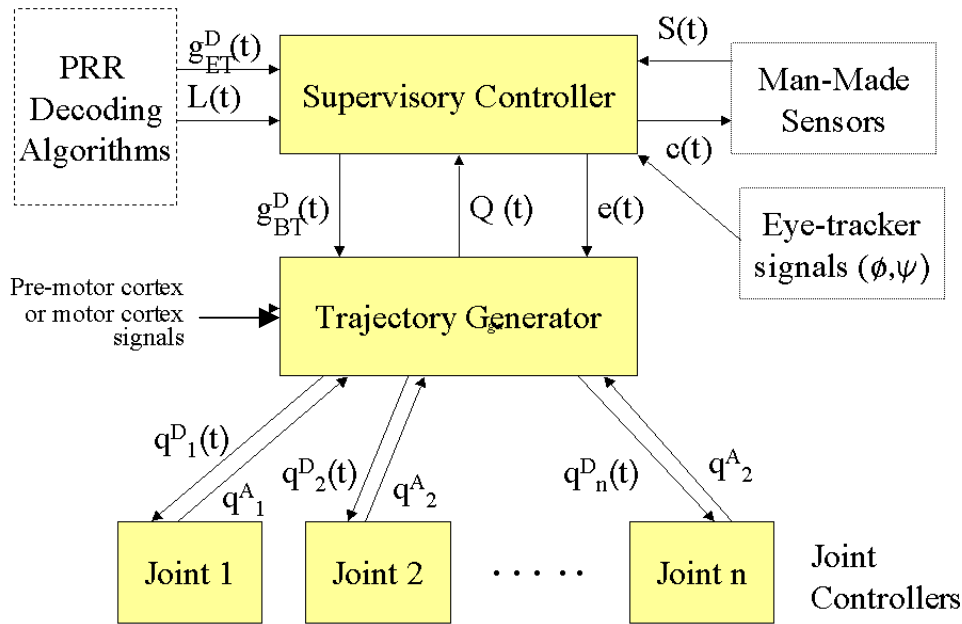
Recording from Many Neurons: Chronic Electrode Array in PRR



Courtesy Bionic Tech.

Courtesy Bionic
Tech.

Arm Control Systems



Key variables

- intended reach location
- intentional and cognitive mind state
- external sensor variables

Key Challenges and Research Agenda

1) What *control signals* can be decoded?

- arm reach direction
- “logical” variables corresponding to intent
 - Target/no target, go, scrub, replan, path sequence, via point

2) Best decode method: accuracy, robustness, SNR?

3) How many neural signals needed?

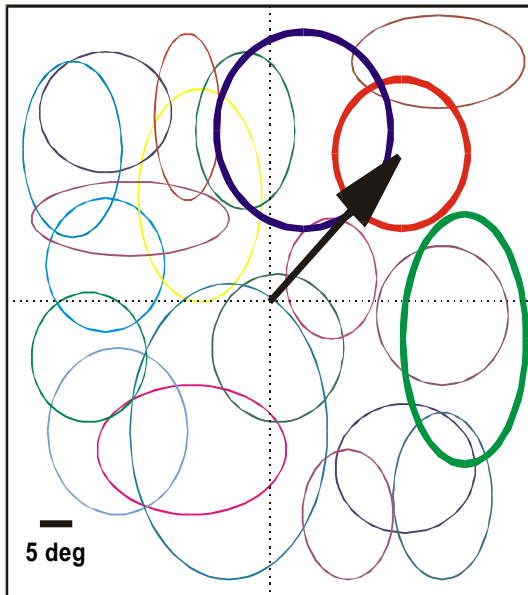
4) Construct a dynamic model of human intent?

5) Adaptive Algorithms?

6) System latency?

7) Safe arm control algorithms? (incorporating external sensors?)

Estimating the Planned Reach Direction



PRR receptive fields span workspace.

Complete set of reaches: $P(n|x)$

Neuron 1



Neuron 2



Neuron 3

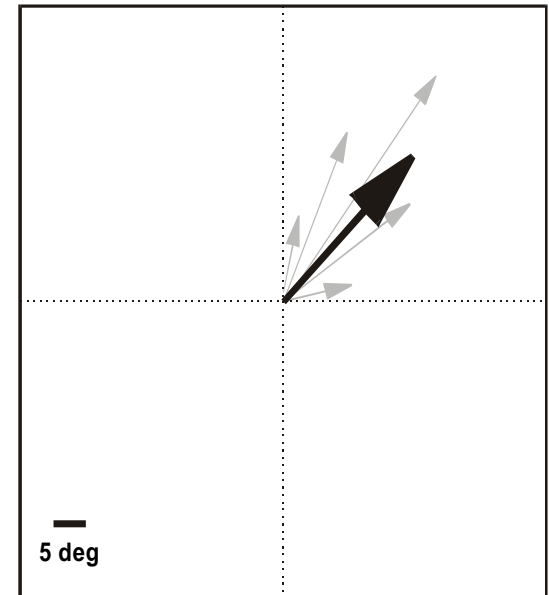


Time →



For any given reach...

... measure spike trains: n



Calculate probability of all reaches:

$$P(x|n) P(n) = P(n|x) P(x)$$

Select most probable: $\max (P(x|n))$

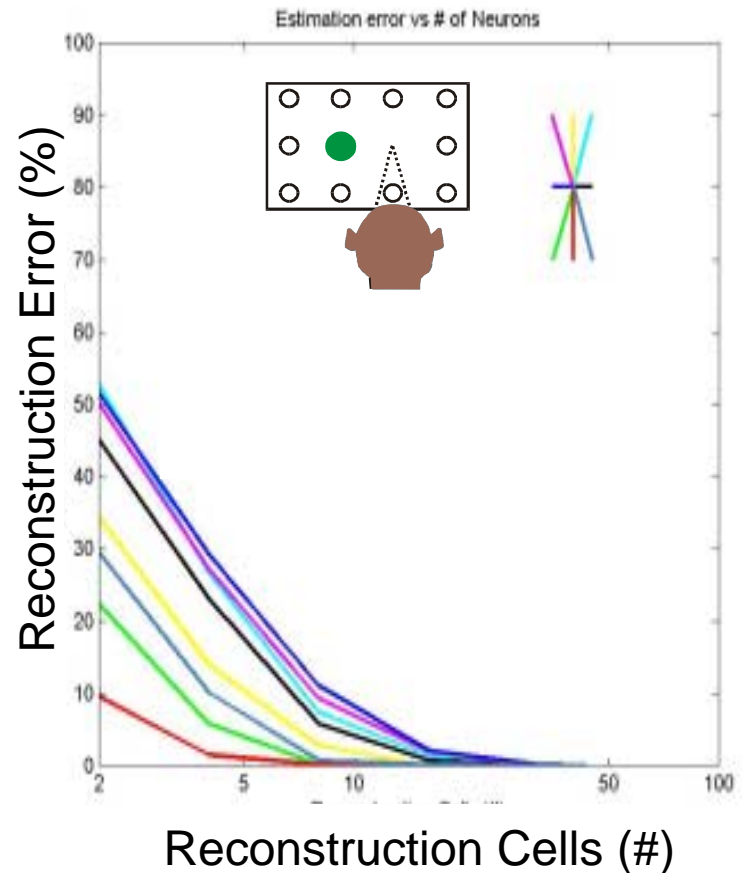
Reconstruction Performance

Reach tuning in 49 PRR neurons

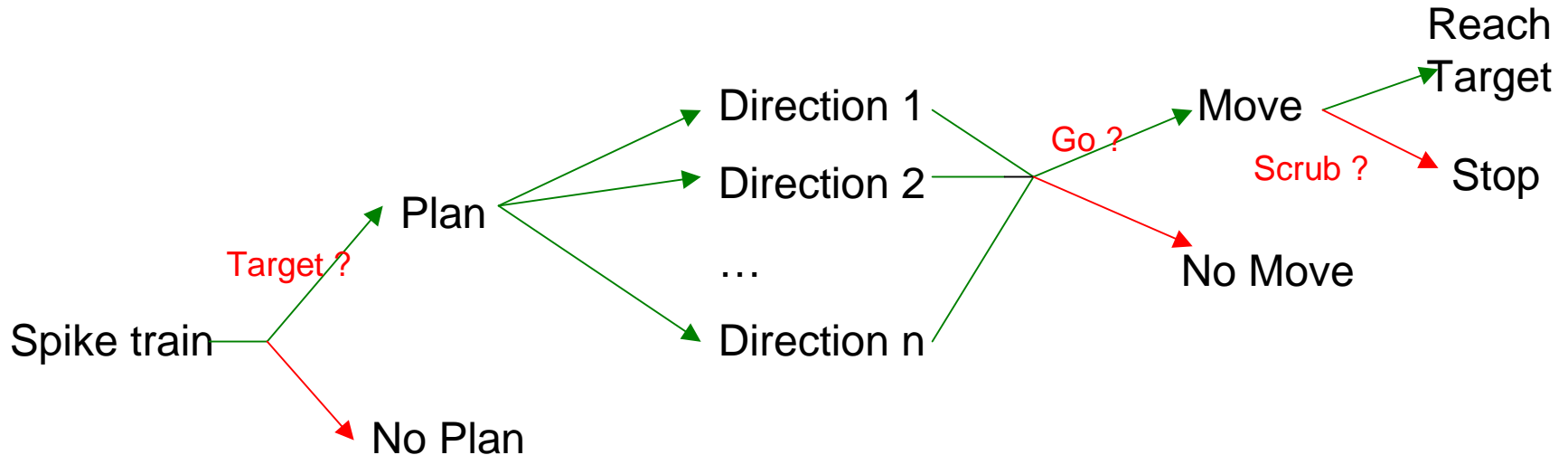


Neurons recorded one at a time
(Monkey CKY)

Error vs. Population Size



Decoding Logical Signals

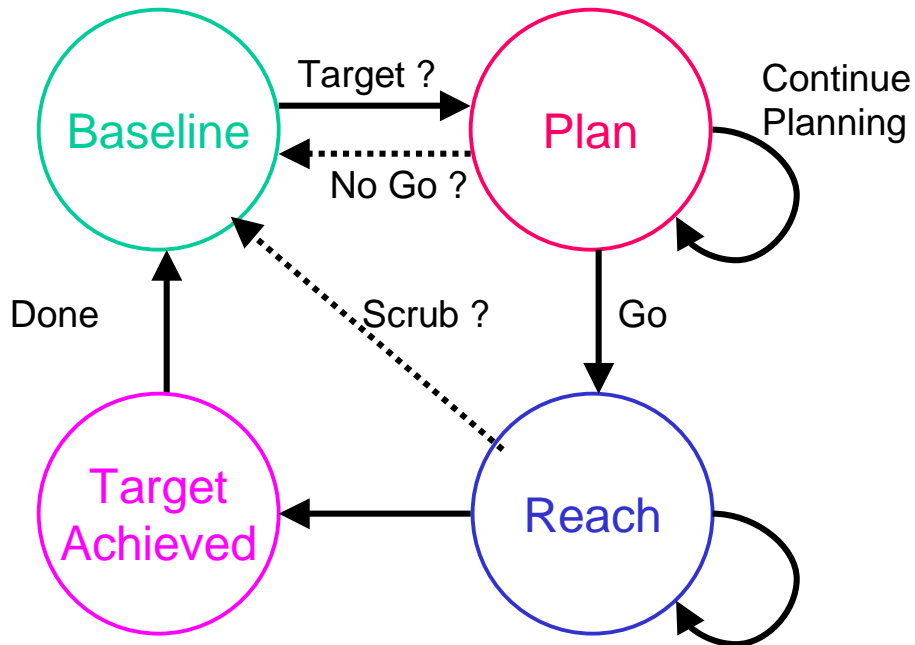


Planning involves a sequence of logical decisions

Decoding logical states and transitions is key to:

- accurate decoding of reach
- purposeful and effective control of prosthetic

Simple Finite State Machine (FSM) model



Logical planning sequence can be idealized as a FSM (this one is crude). Need to:

- Detect transitions
- Determine current State

Logical Decoding can be added to current framework

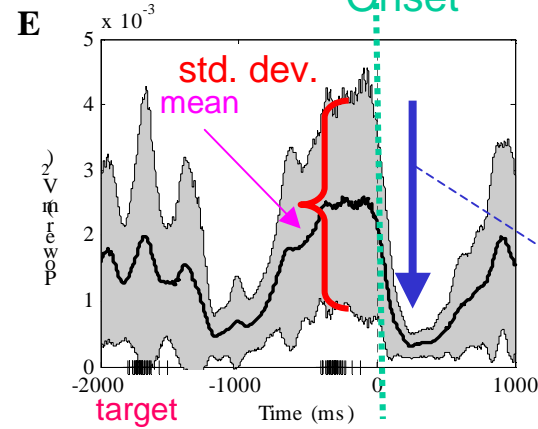
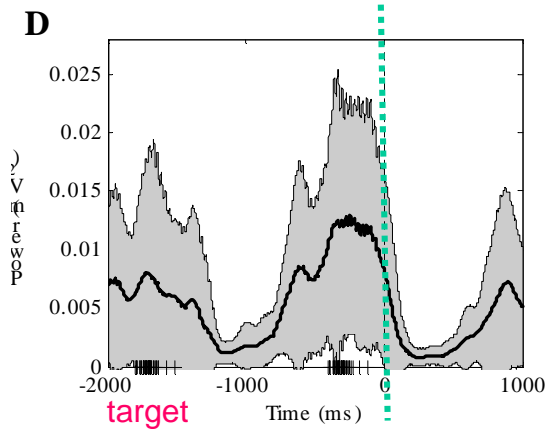
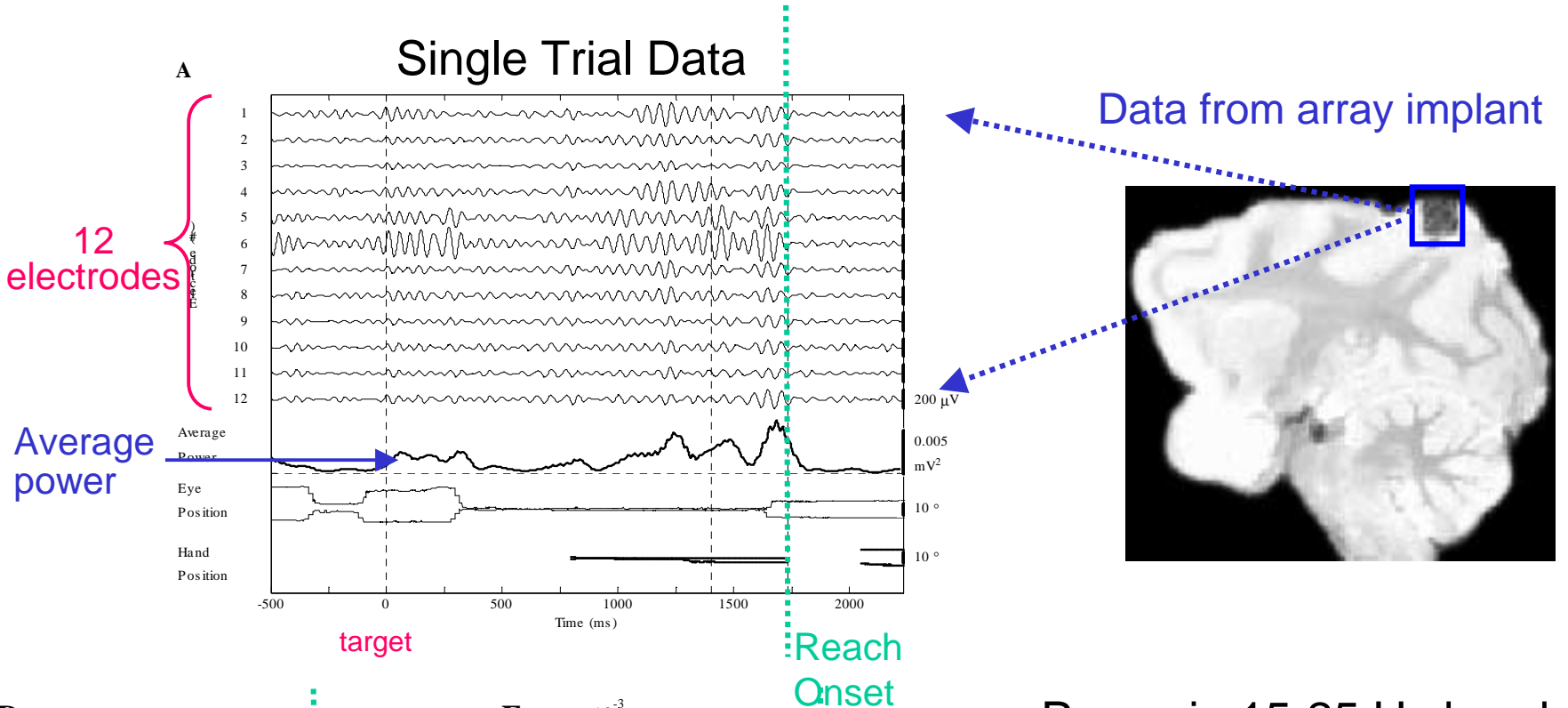
$$P(\xi | \nu) = \frac{P(\xi)P(\nu | \xi)}{P(\nu)}$$

- $\xi =$
- Reach Direction &
 - Target/No Target Logic Condition &
 - Move/No Move Condition
 - ...

During this period we have

- demonstrated *target*, *go* decoding
- shown how very simple FSM model can improve decoding

A "Go" Signal in the LFP



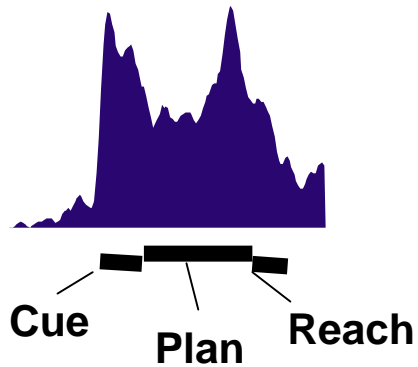
Power in 15-25 Hz band

- averaged over channels
- average over trials

“Naïve” Classification of State Evolution

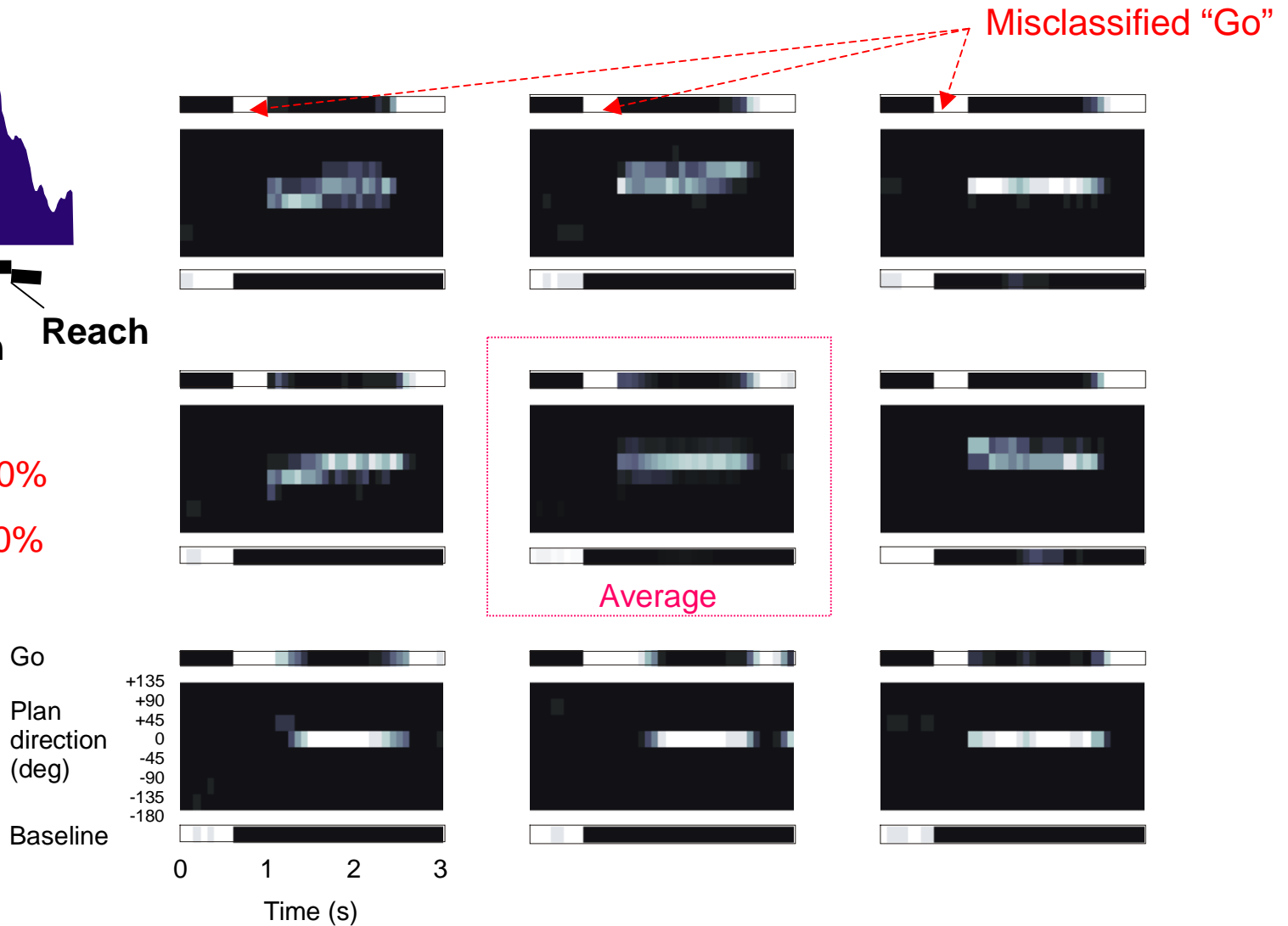
(i.e., decoding without benefit of FSM model)

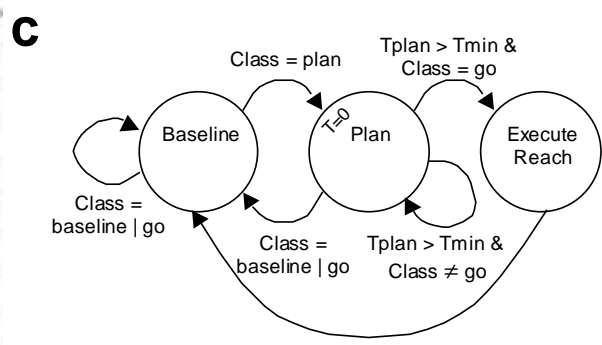
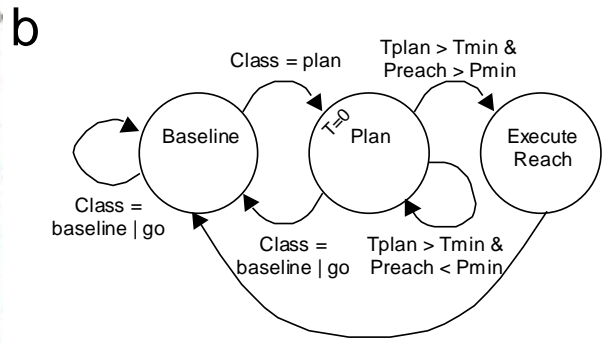
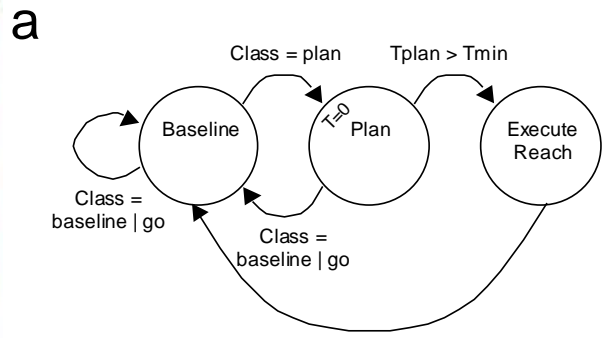
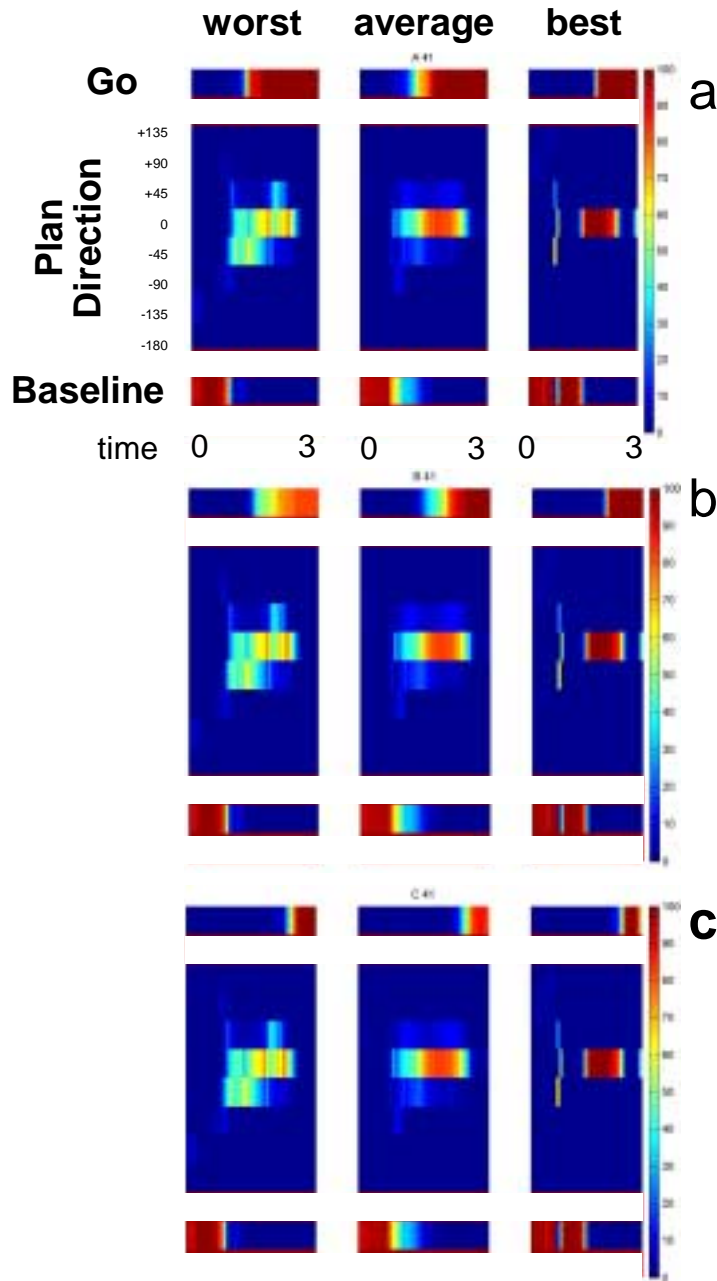
(250 msec windows)



White = 100%

Black = 0%



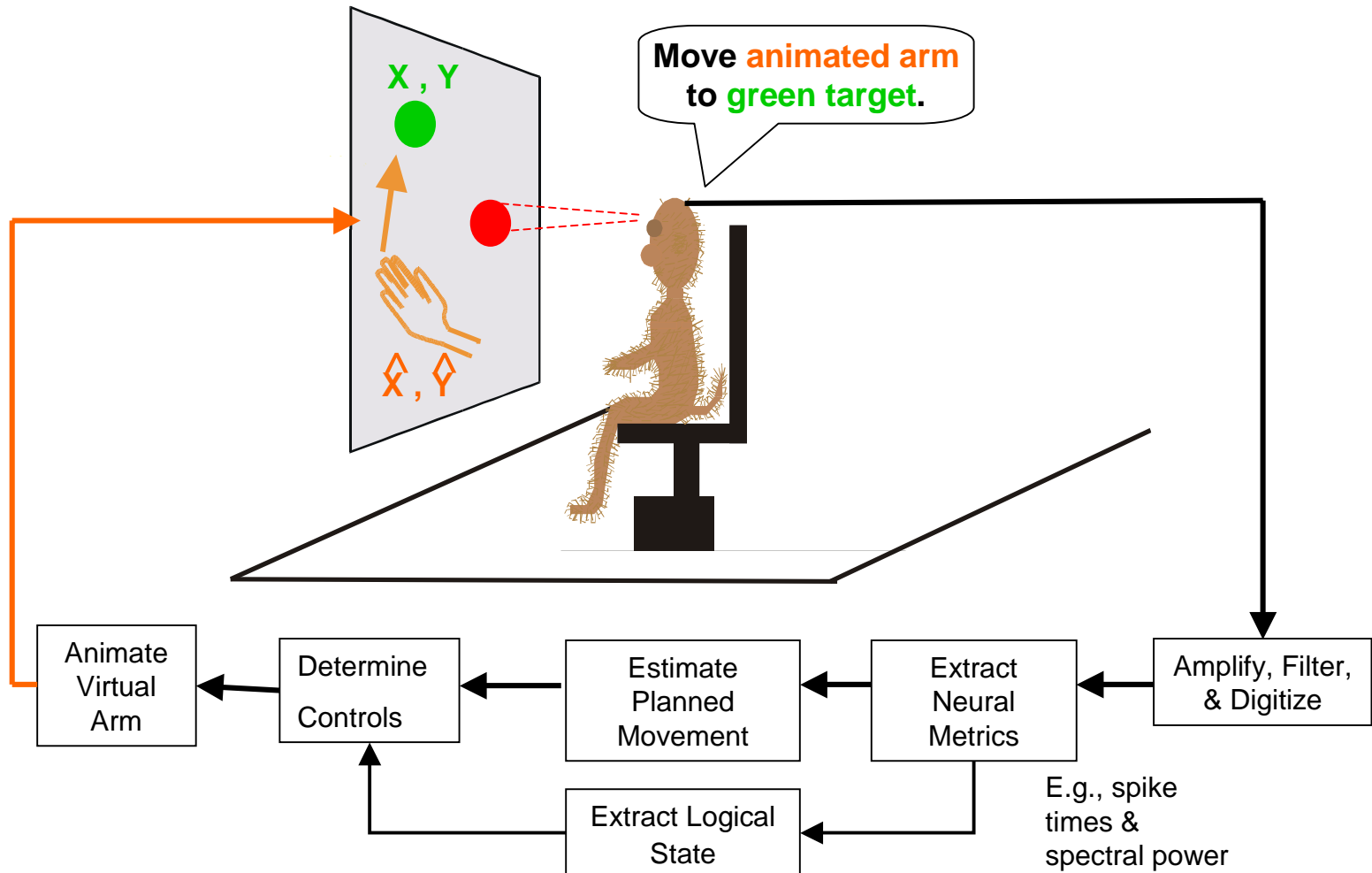


State Prediction Performance for different FSM models

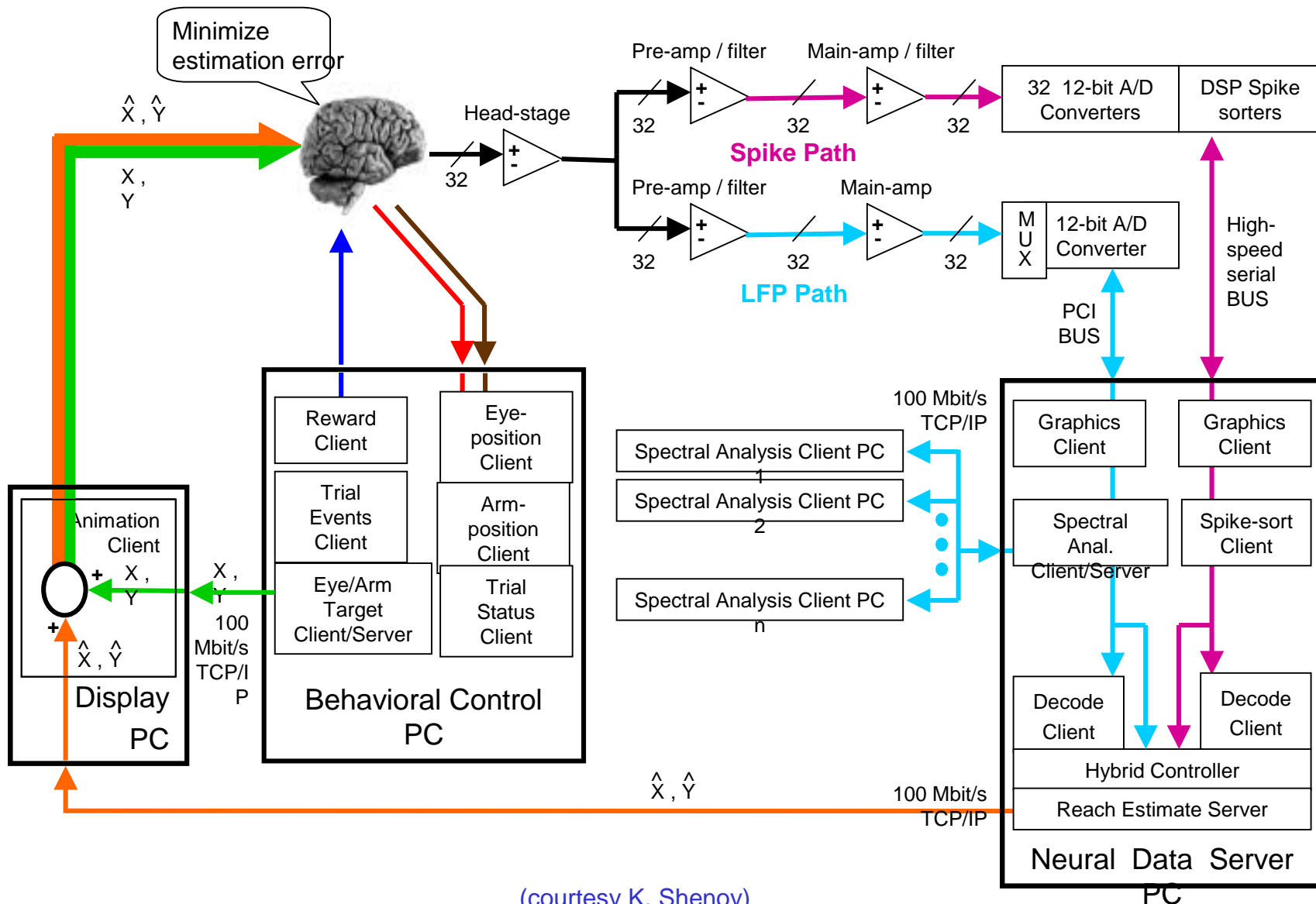
(250 msec windows)

Moral: performance improves with better FSM models

Prosthetic-System Testbed: Physical Setup



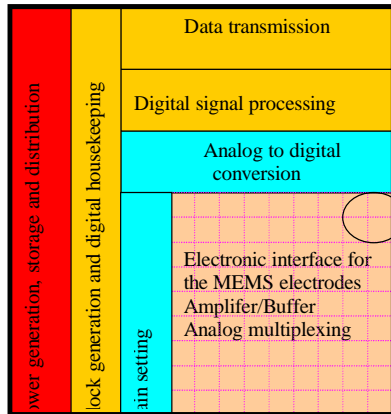
Prosthetic-System Testbed Architecture



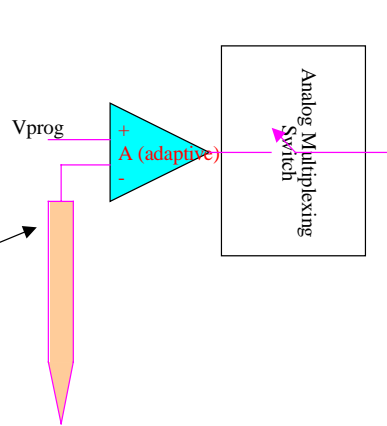
(courtesy K. Shenoy)

Future Integrated/Implantable Systems

(M. Mojaridi et. al, JPL)



neuro-prosthetic system diagram



electronic electrode interface

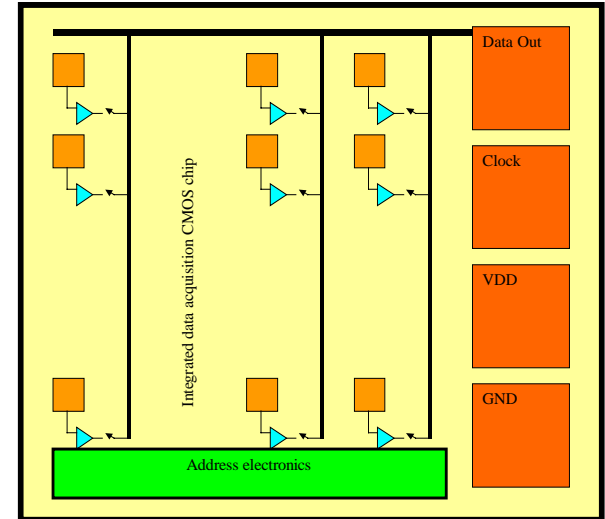
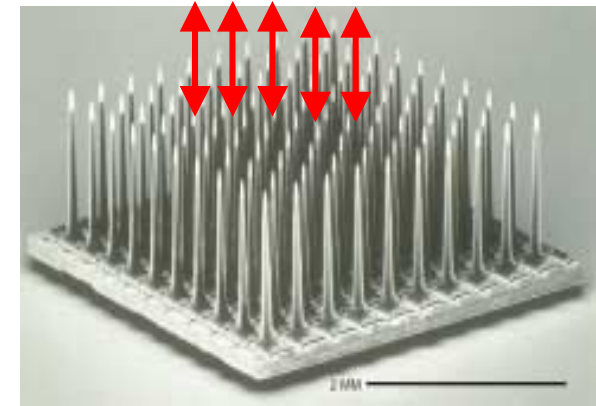
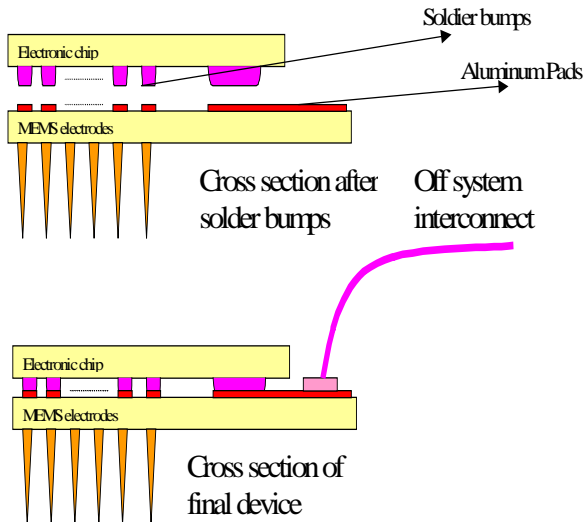
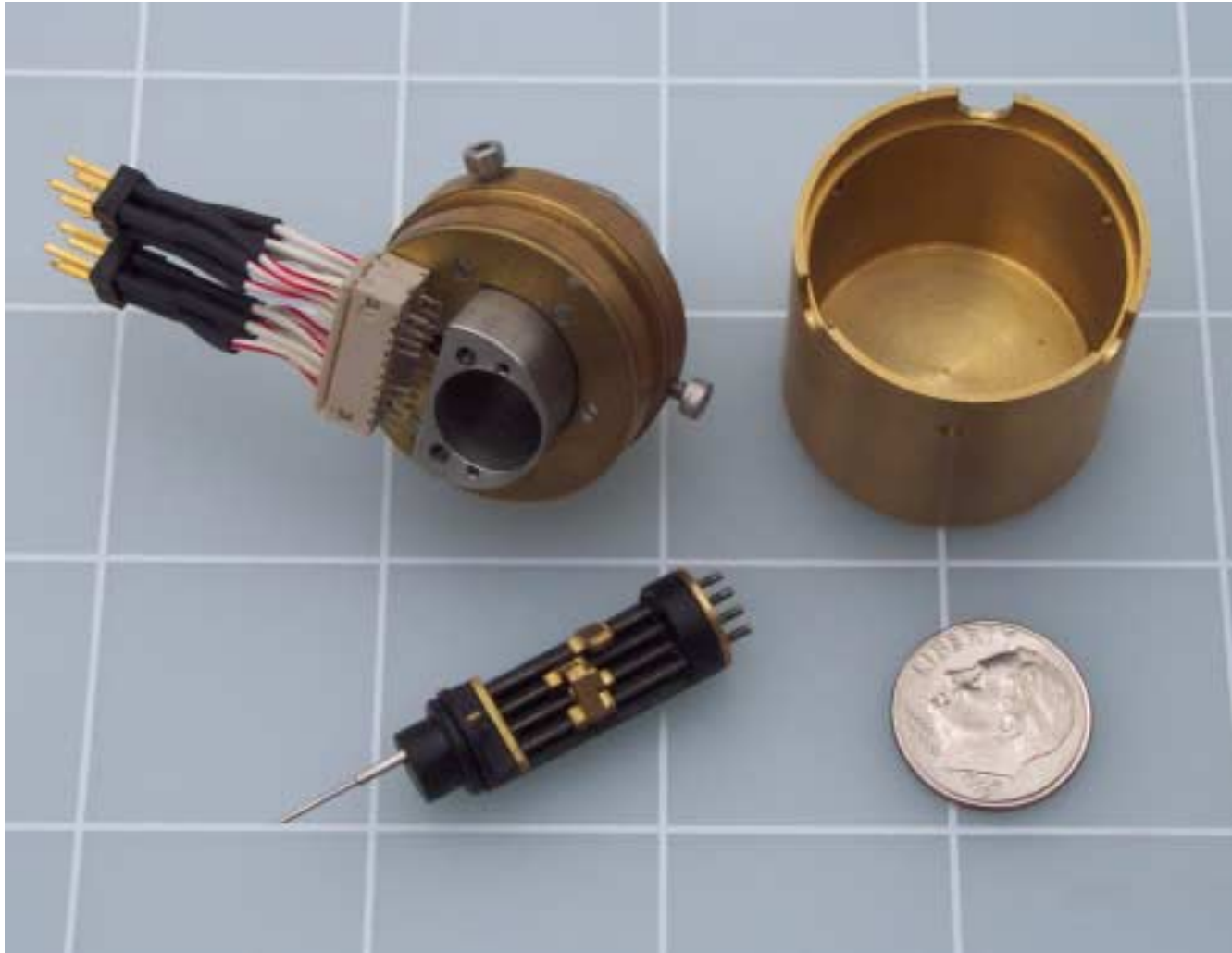


Diagram of neuro prosthetic data acquisition system



Movable Tetrode Arrays



Generalization

Future implantable human sensors will

- measure many signals in parallel
- have wireless telemetry
- have low-power on-board processing circuitry
- be able to continually adjust their geometry (via miniature on-board actuators) to optimize signal quality

CNSE/Lee have expertise in MEMS, wireless, low-power VLSI, sensor processign