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Model for closed-loop neuroprosthetic operation

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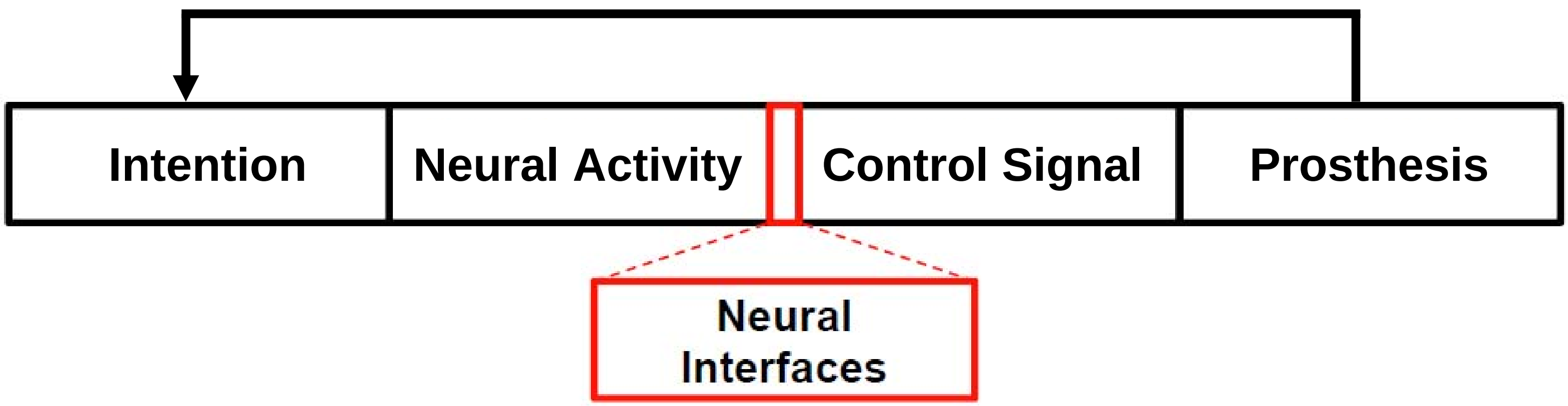
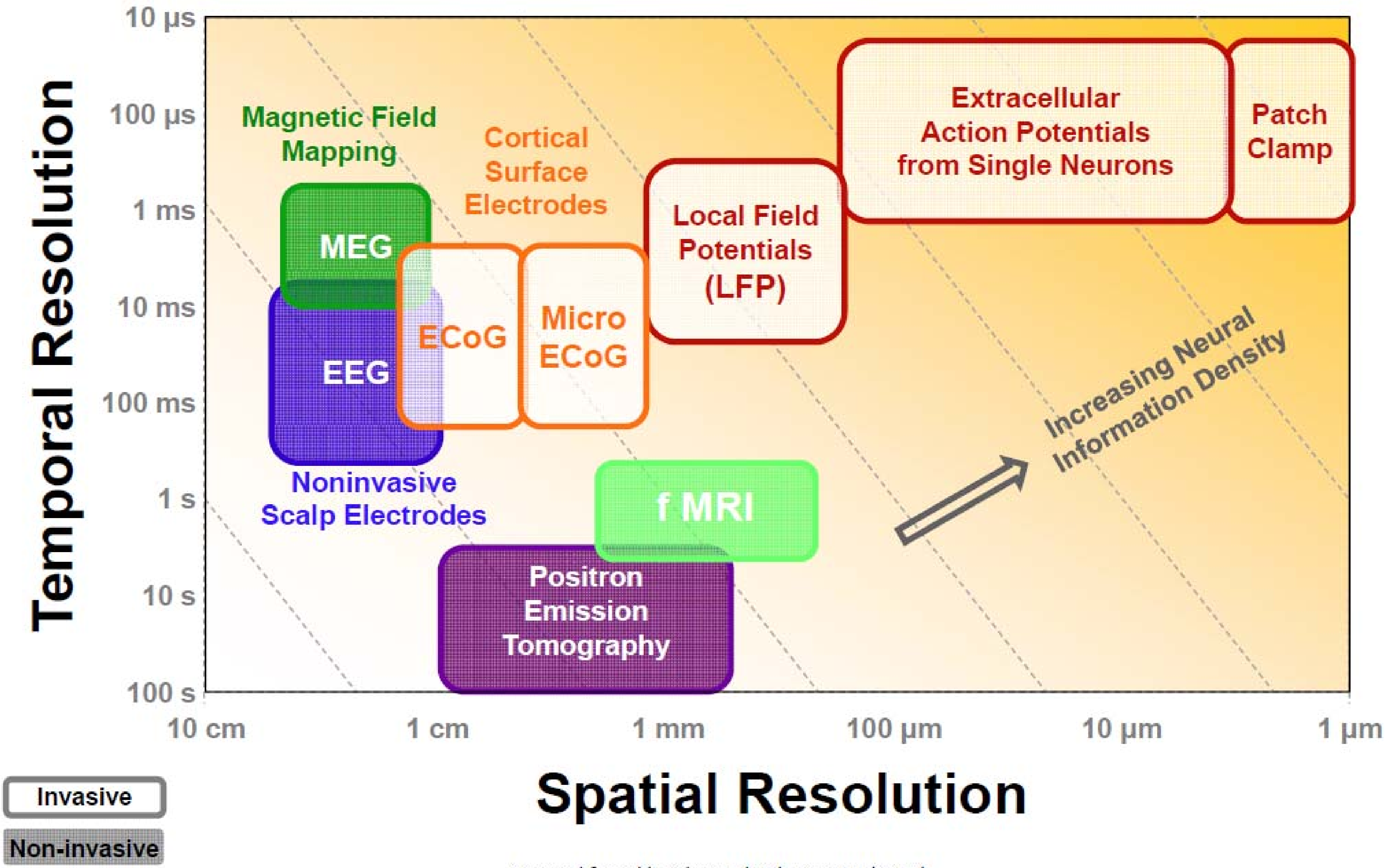
State of Investment and Research in Neuroscience



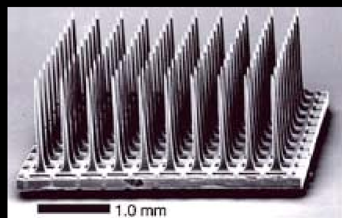
Advances in prosthesis technology have far exceeded all neural interface technologies.

Neural Activity is Measured at Various Scales

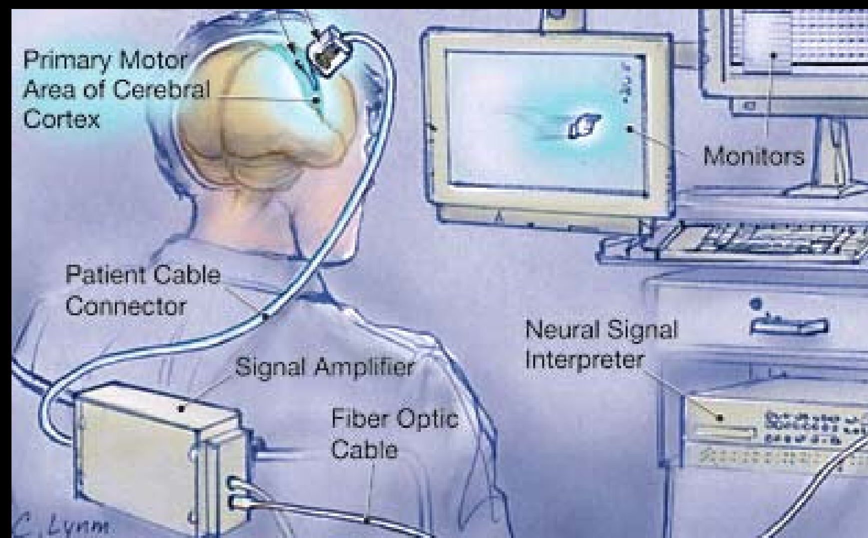


Approved for public release; distribution is unlimited.

Brain-computer interface (BCI) for cursor control

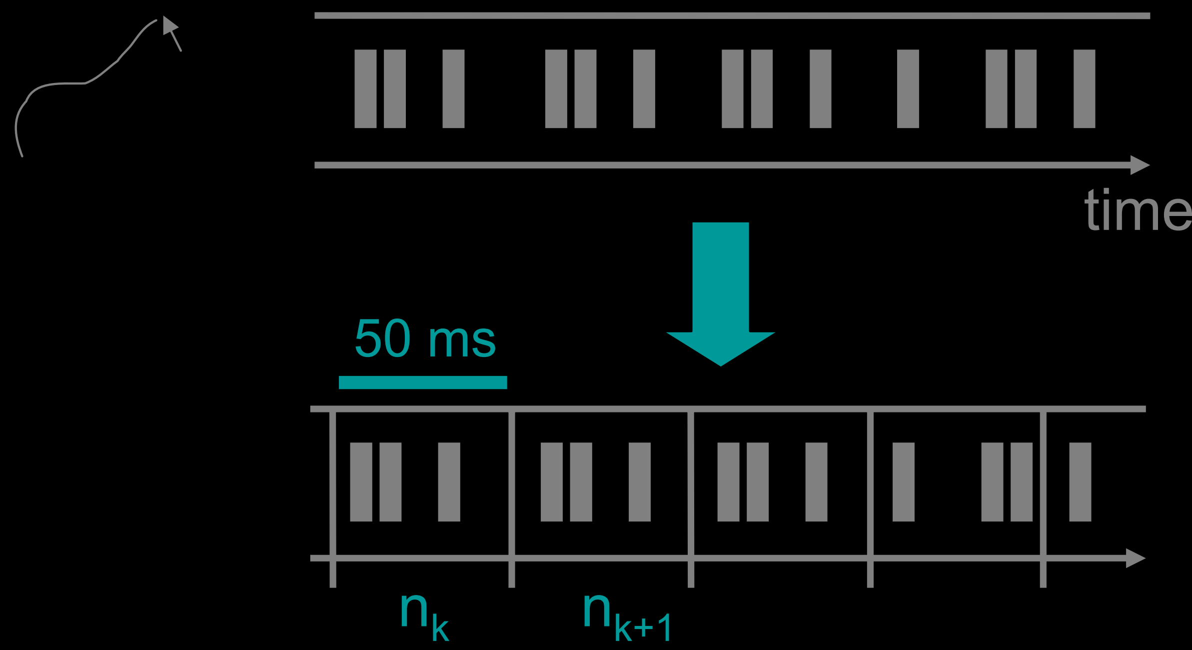


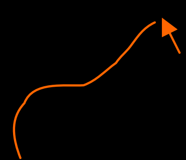
sensory feedback



neural signal decoder

BCI neural decoding with linear regression





$$\begin{bmatrix} \text{x-position} \\ \text{y-position} \end{bmatrix} = A \begin{bmatrix} | & | & & | \\ n_k & n_{k-1} & \cdots & n_{k-20} \\ | & | & & | \end{bmatrix}$$

L. Srinivasan, ls2@nsplab.org, 2/16/2012

BCI neural decoding: state space approach

k	time step *k*
n_k	# spikes
x_k	cursor position
H_k	history of spikes

Observation (neural signal) model

$$p(n_k \mid x_k, H_k)$$

State-space (human intention) model

$$p(x_k \mid x_{k-1})$$

Neural signal decoder

$$p(x_{k-1} \mid H_k) \xrightarrow{n_k} p(x_k \mid n_k, H_k)$$

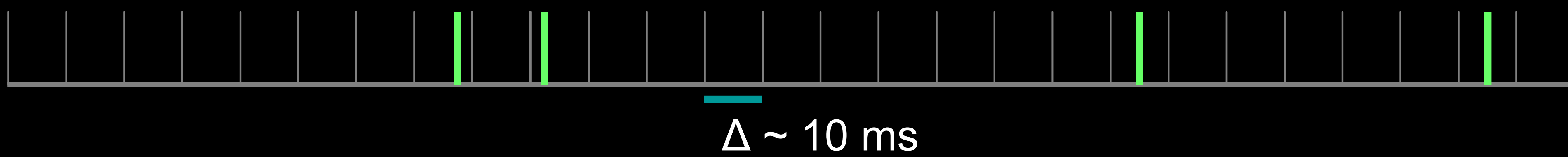
Srinivasan, et. al, "General Purpose Filter Design for Neuroprosthetic Devices," *Journal of Neurophysiology*, 2007

Modeling spikes: point process likelihood

k	time step *k*
n_k	# spikes
x_k	cursor position
H_k	history of spikes

Observation (neural signal) model

$$p(n_k \mid x_k, H_k)$$



Conditional intensity function,

$$\lambda(x_k \mid \mathbf{H}_k)$$

defines the observation density

$$p(n_k \mid \mathbf{x}_k, \mathbf{H}_k) \approx (\lambda(\mathbf{x}_k \mid \mathbf{H}_k)\Delta)^{n_k} e^{-\lambda(\mathbf{x}_k \mid H_k)\Delta}$$

Eden, Srinivasan, Sarma, "Neural Signal Processing Tutorial II",
Short Course - Society for Neuroscience, 2008

Summary of Decoding Methods

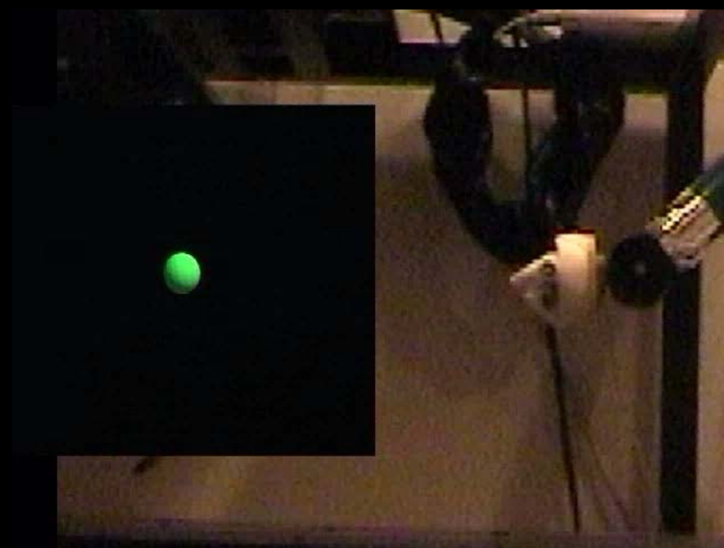
- Linear Mappings
  - Population vector algorithm (PVA)
  - Linear regression
- Recursive Bayesian Estimation
  - Kalman filter
  - Approximate point process filters

Neural signal decoder

$$p(x_{k-1} \mid H_k) \xrightarrow{n_k} p(x_k \mid n_k, H_k)$$

BCI neural decoding: variants of linear regression

L. Hochberg, et. al, *Nature*, 2006



D. Taylor, et. al, *Science*, 2002

Open-loop versus closed-loop testing

open-loop

Intention → Neural Activity → Decode → Control Signal → Prosthesis

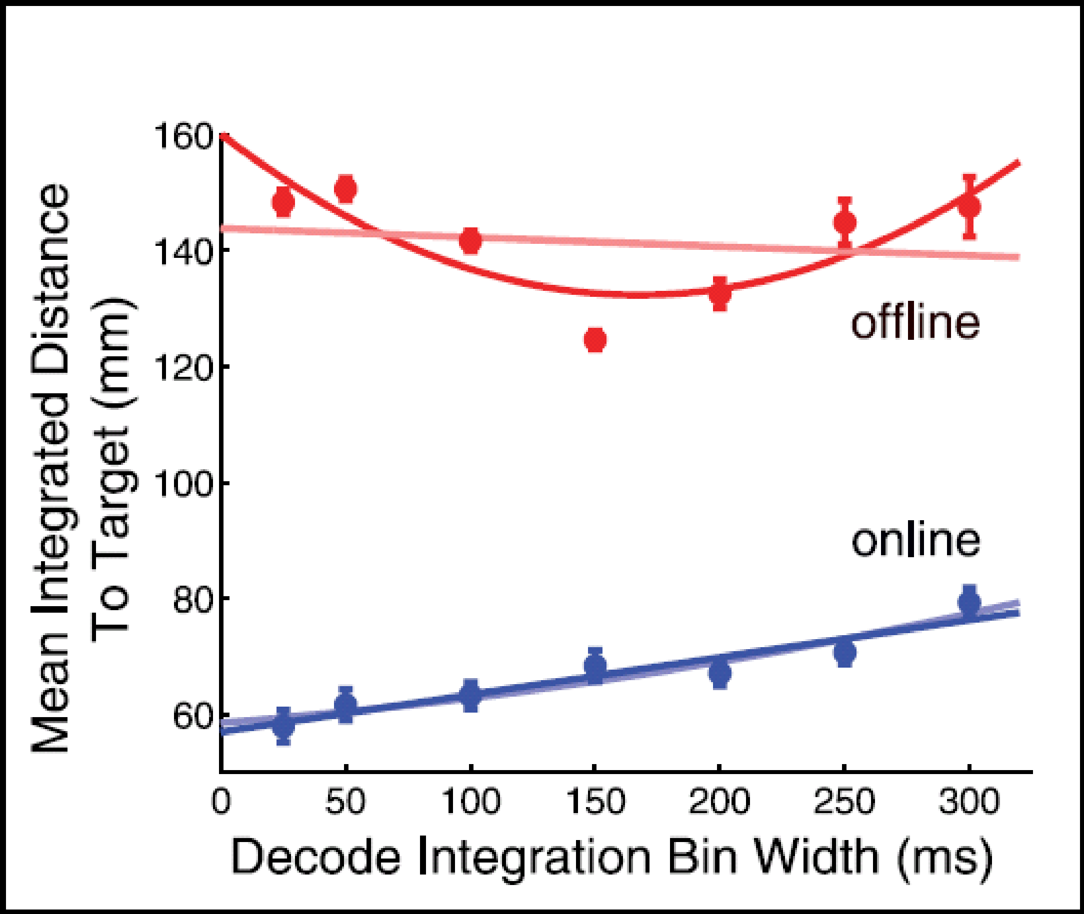
closed-loop

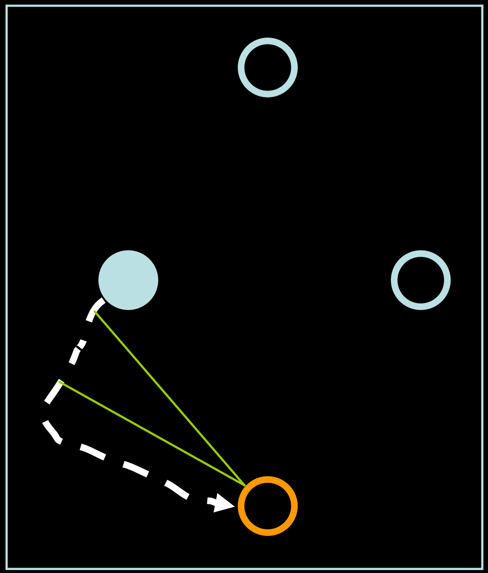
Sensory Feedback

Intention → Neural Activity → Decode → Control Signal → Prosthesis

Four closed-loop (CL) phenomena

(1) CL error lower than OL

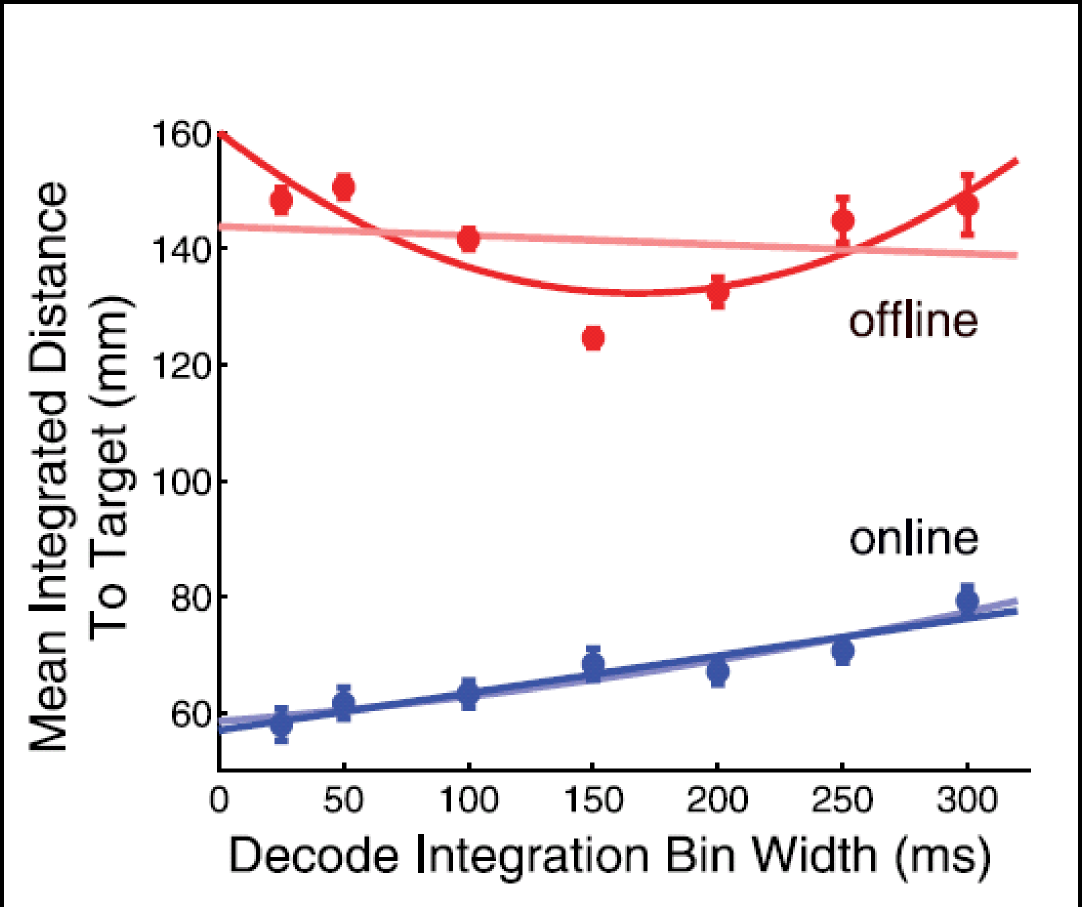


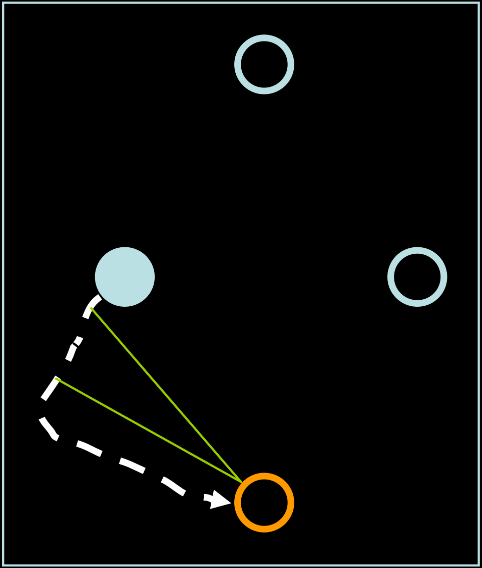


Cunningham & Shenoy, *J. Neurophys.*, 2010

Four closed-loop (CL) phenomena

(1) CL error lower than OL
(2) CL error grows with binwidth

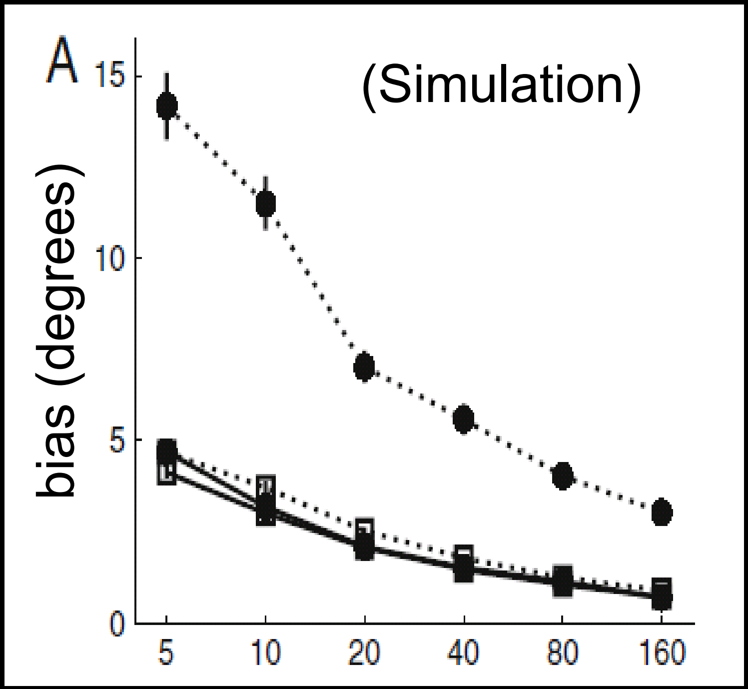


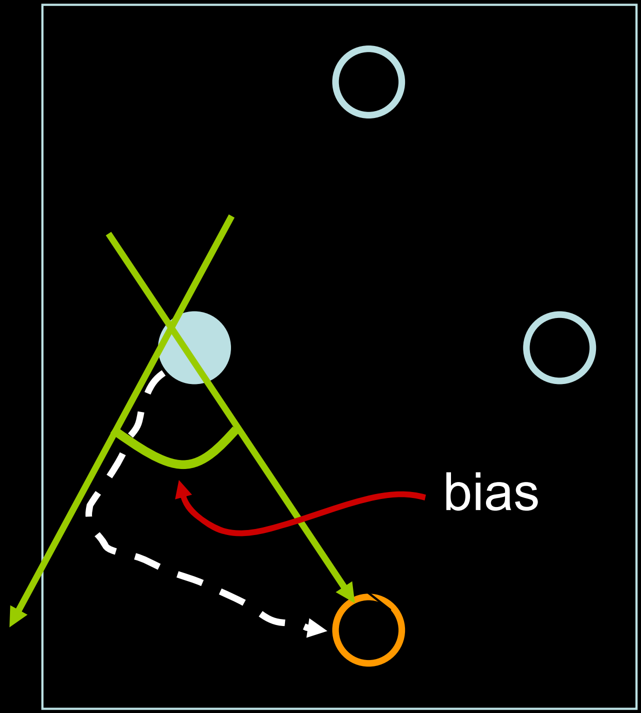


Cunningham & Shenoy, *J. Neurophys.*, 2010

Four closed-loop (CL) phenomena

(3) CL bias less than OL

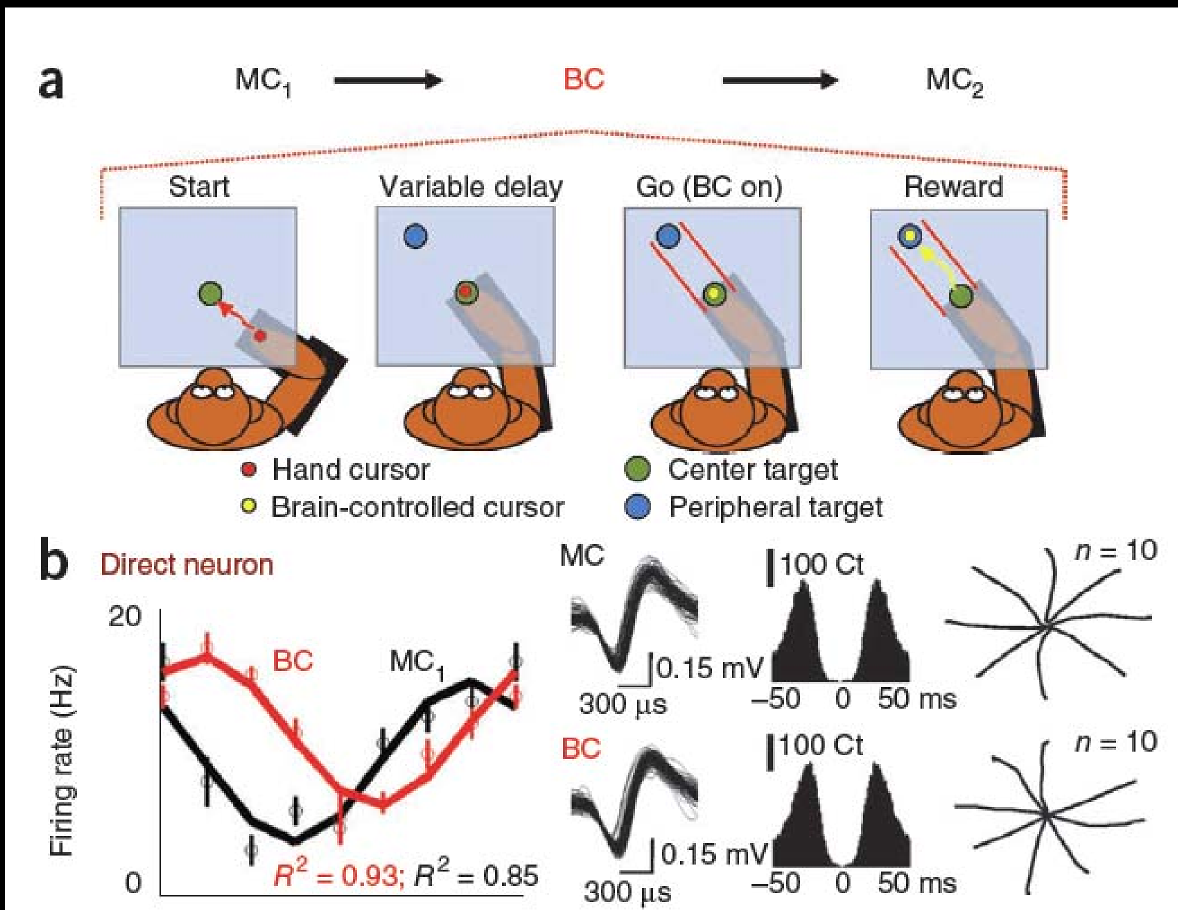




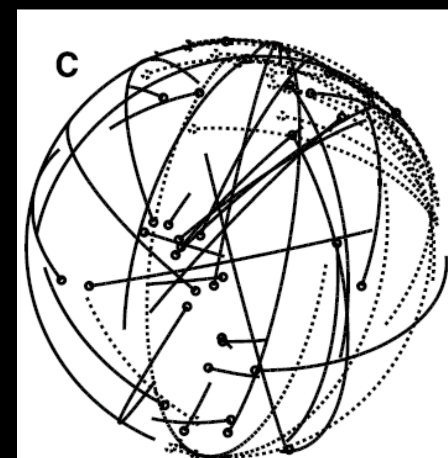
Chase, Schwartz, Kass, “Bias, optimal linear estimation, and the differences between open-loop simulation and closed-loop performance of spiking-based brain-computer interface algorithms” (Neural Networks, 2009)

Four closed-loop (CL) phenomena

(4) Tuning curves shift between OL and CL

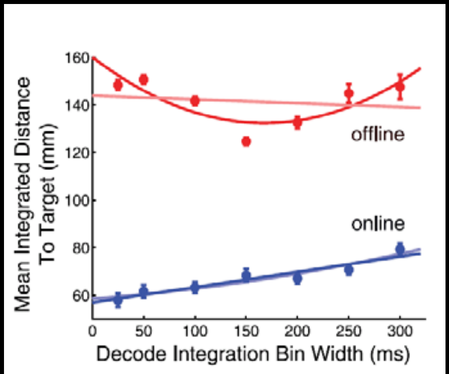


Ganguly and Carmena, “Reversible large-scale modification of cortical networks during neuroprosthetic control” (Nature Neurosci 2011).



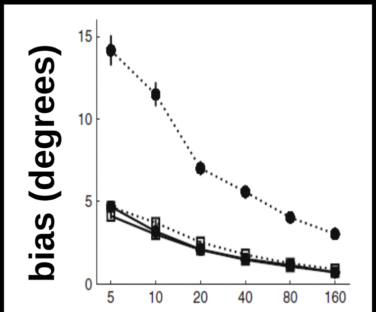
Taylor, Helms-Tillery, Schwartz, “Direct Cortical Control of 3D Neuroprosthetic Devices” (Science 2002).

Summary: open-loop (OL) vs. closed-loop (CL)

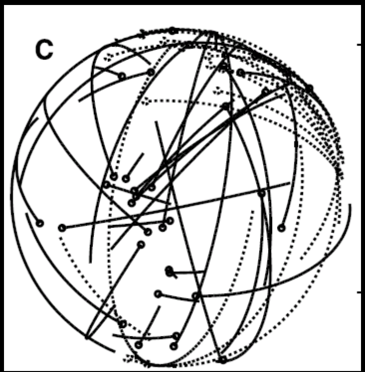


(1) CL error lower than OL

(2) CL error grows with binwidth



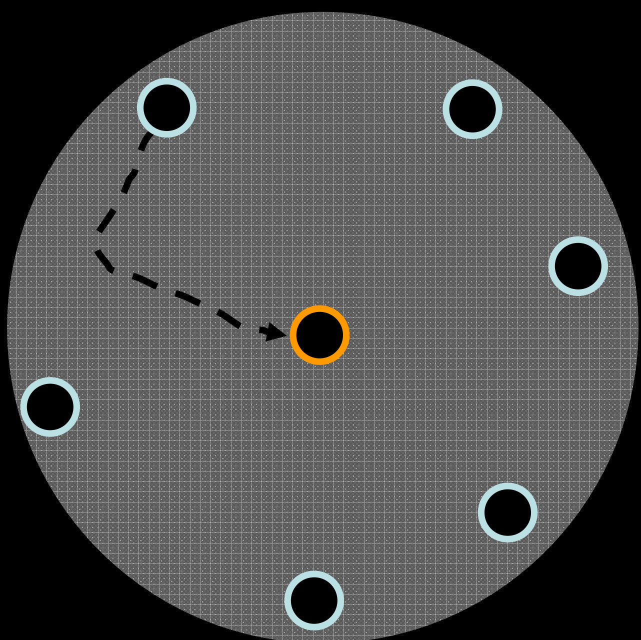
(3) CL bias less than OL

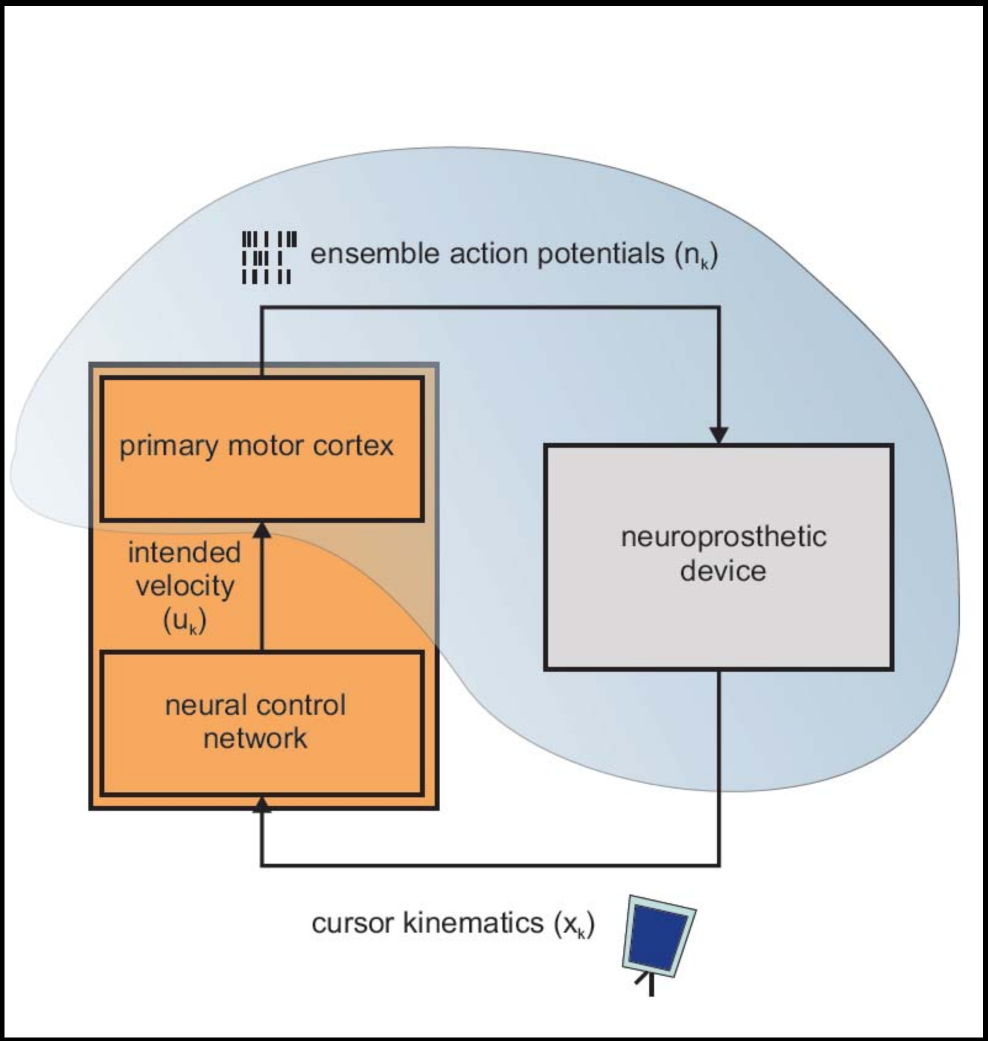


(4) Tuning curves shift between OL and CL

Model for closed-loop neuroprosthetic operation

Reach task





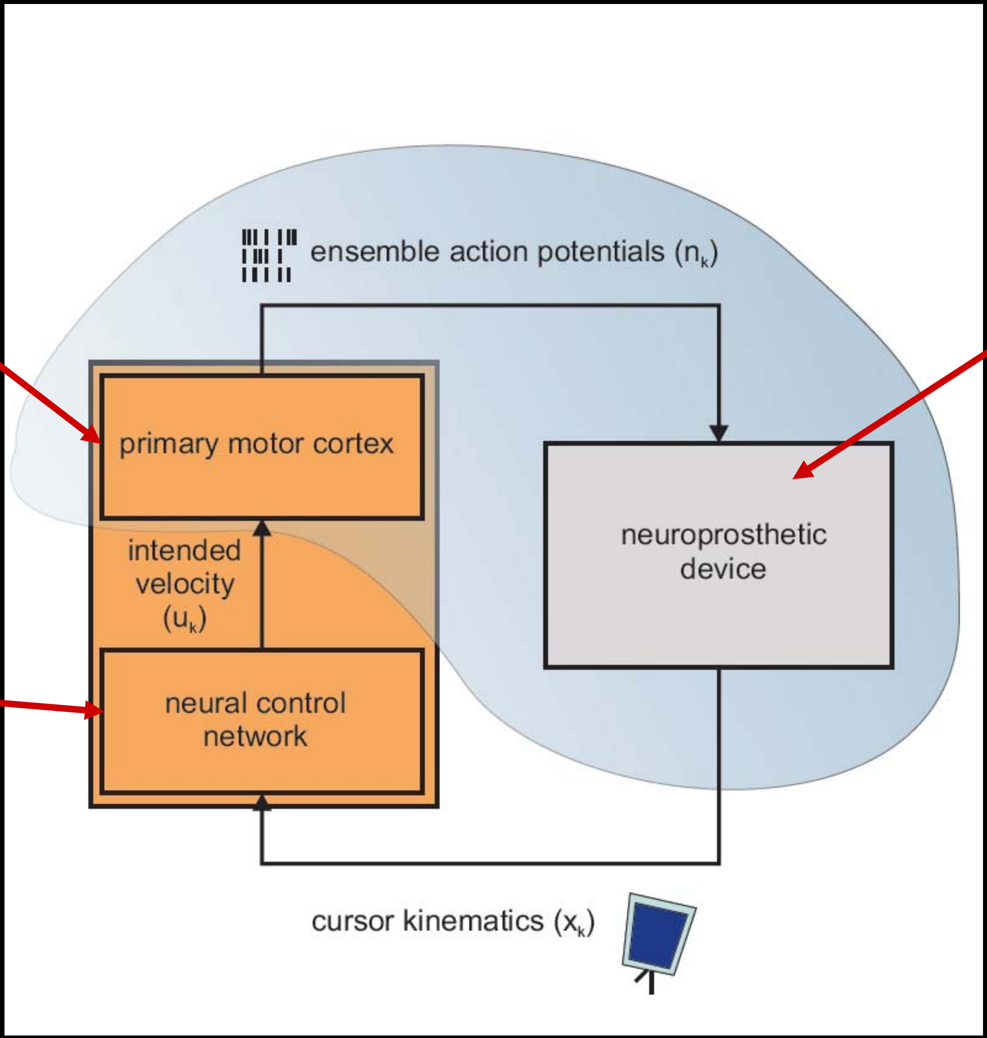
Model for closed-loop neuroprosthetic operation

$$\lambda_k^i = b_i \cdot v_k + c_i$$

point process model

linear quadratic controller

$$u_k = Lx_k$$



Kalman filter

L. Srinivasan, ls2@nsplab.org, 2/16/2012

Components of the LQR neural control network

1 state to control

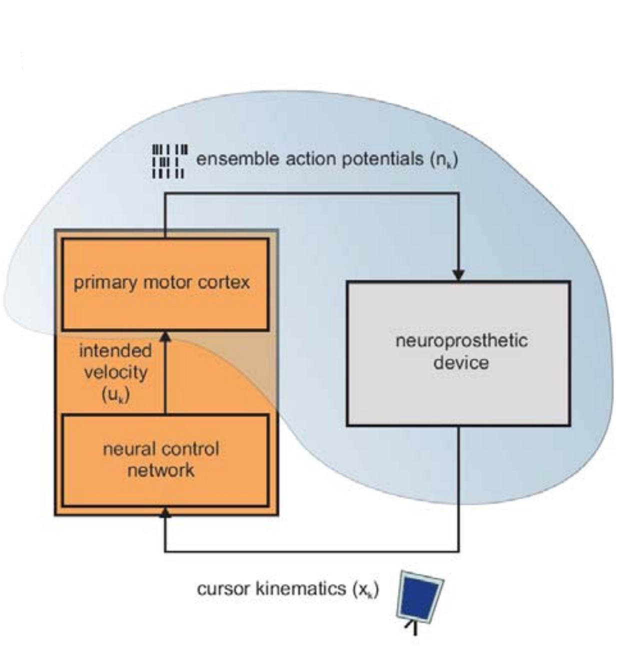
$$x_k = \begin{pmatrix} p_x & p_y & v_x & v_y & 1 \end{pmatrix}^T$$

2D cursor position, velocity

2 linear, time-invariant plant model

$$x_{k+1} = Ax_k + \varepsilon_k$$

Cascaded effect of:
steady-state Kalman filter
and motor neuron output



3 Quadratic cost

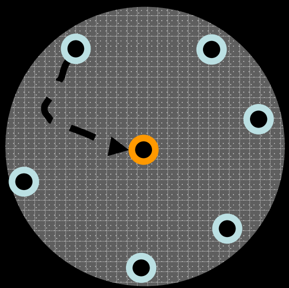
$\sum$
Squared distance to origin
Square of cursor speed
Square of intended cursor speed

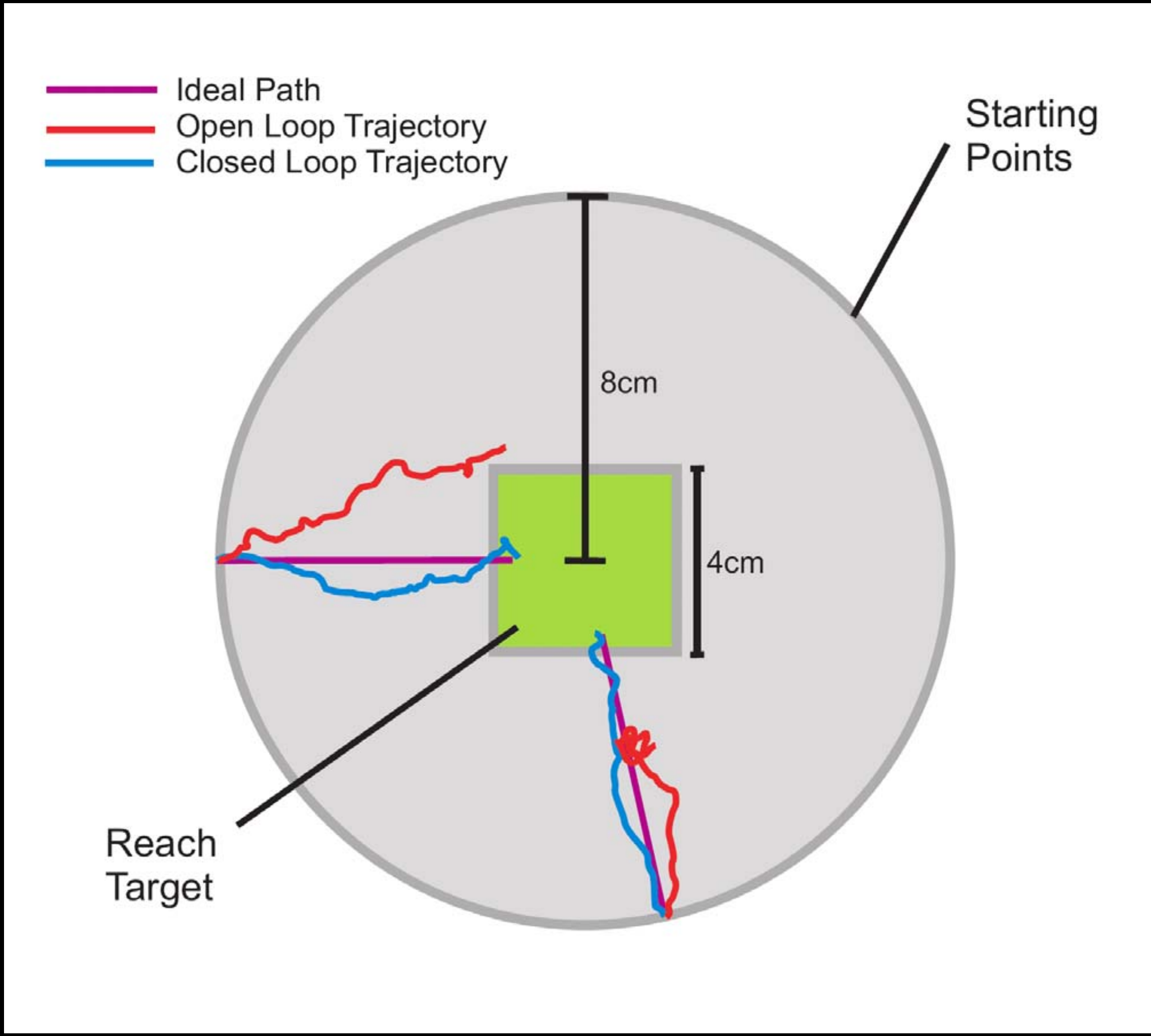
Book Reference: Bertsekas, Dynamic Programming and Optimal Control

4 control policy

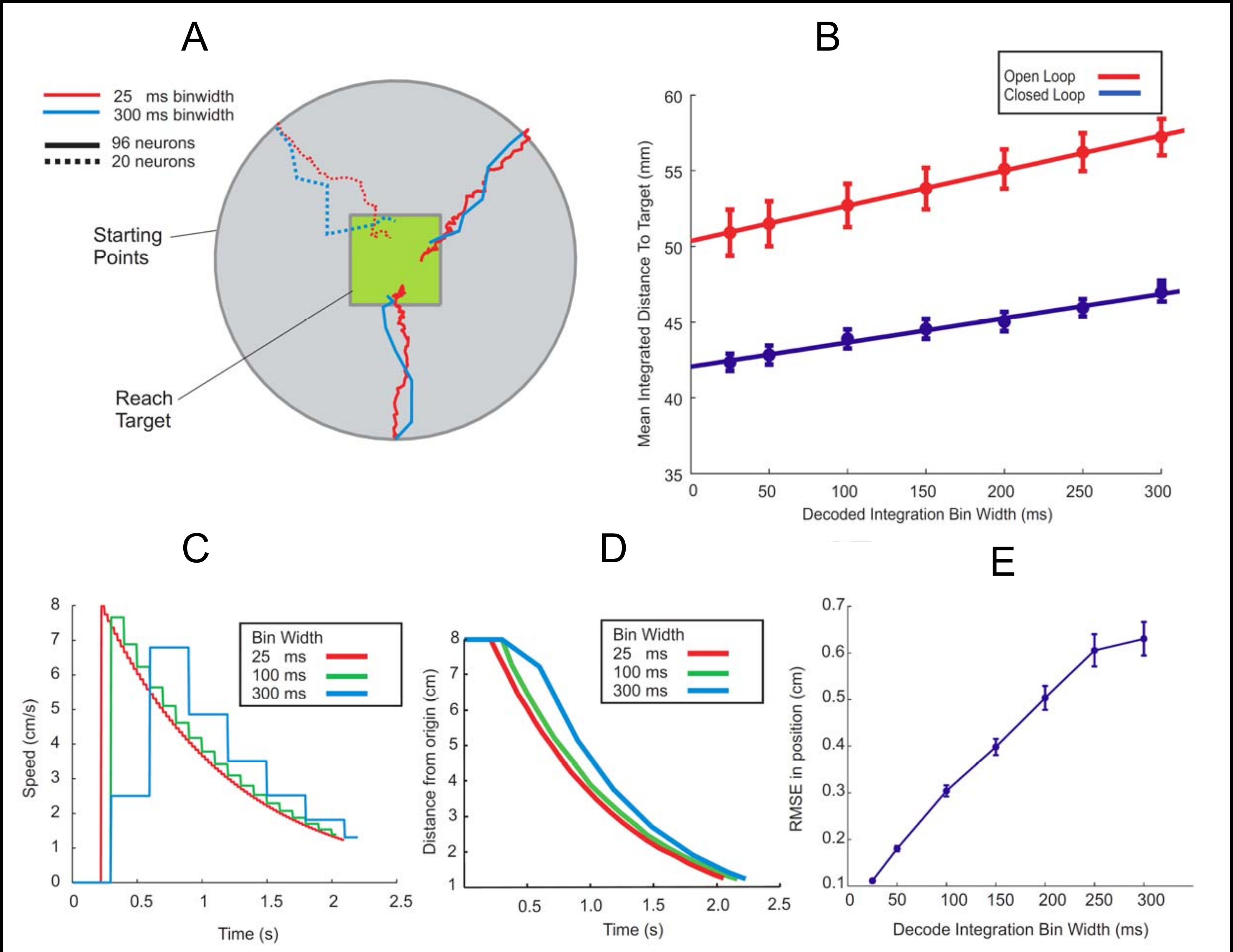
$$u_k = Lx_k$$

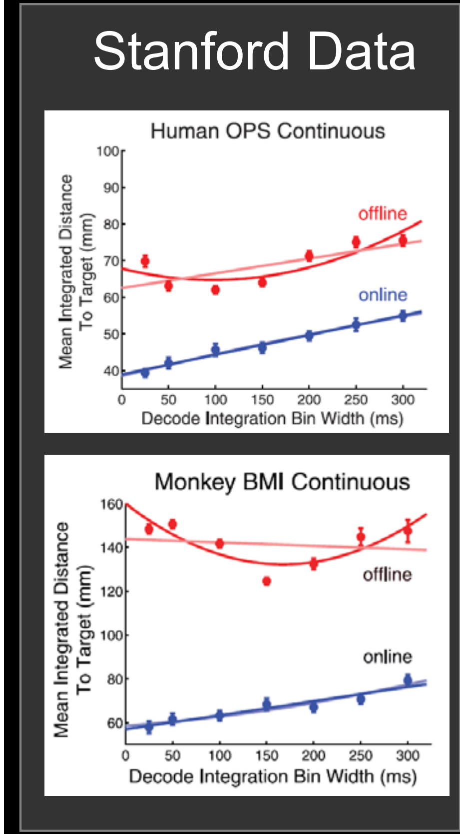
Reaching task





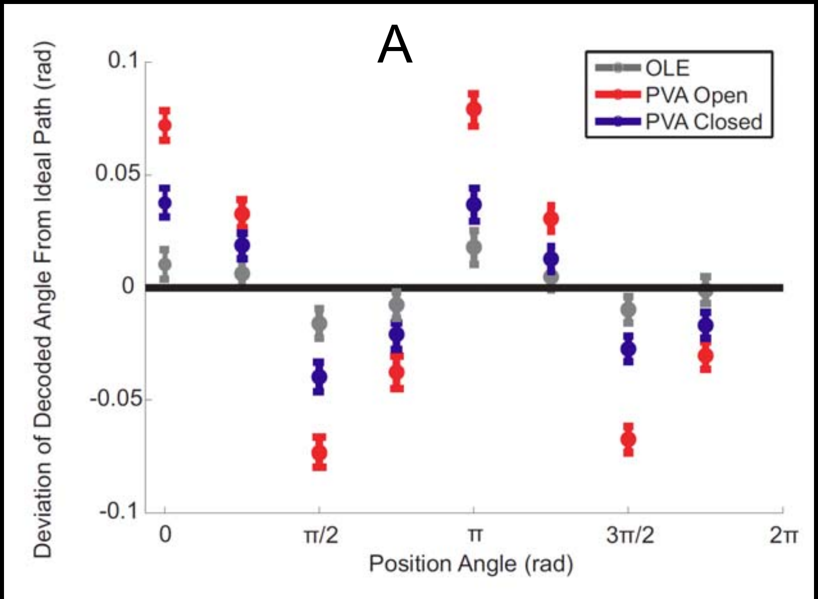
Performance versus bin width



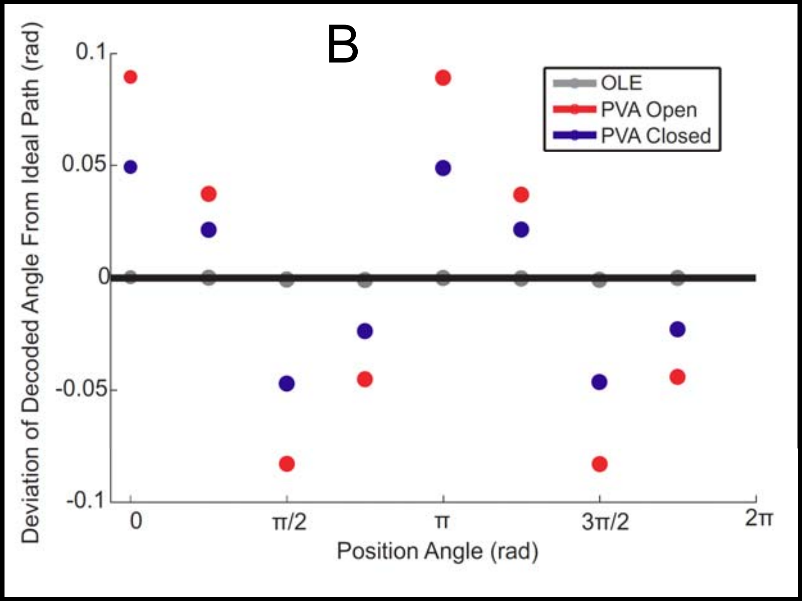


Bias correction in closed-loop

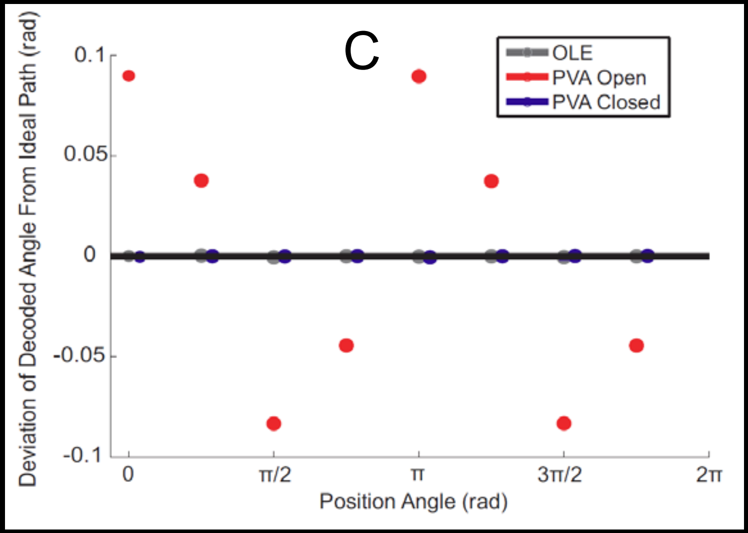
Original model



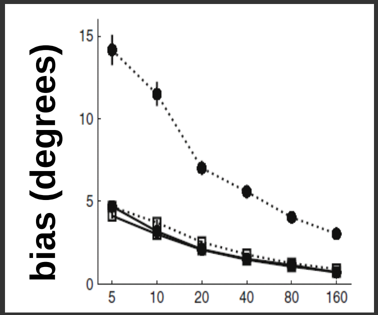
Gaussian neural signals



Zero cost on controller



CMU/U.Pitt. Data



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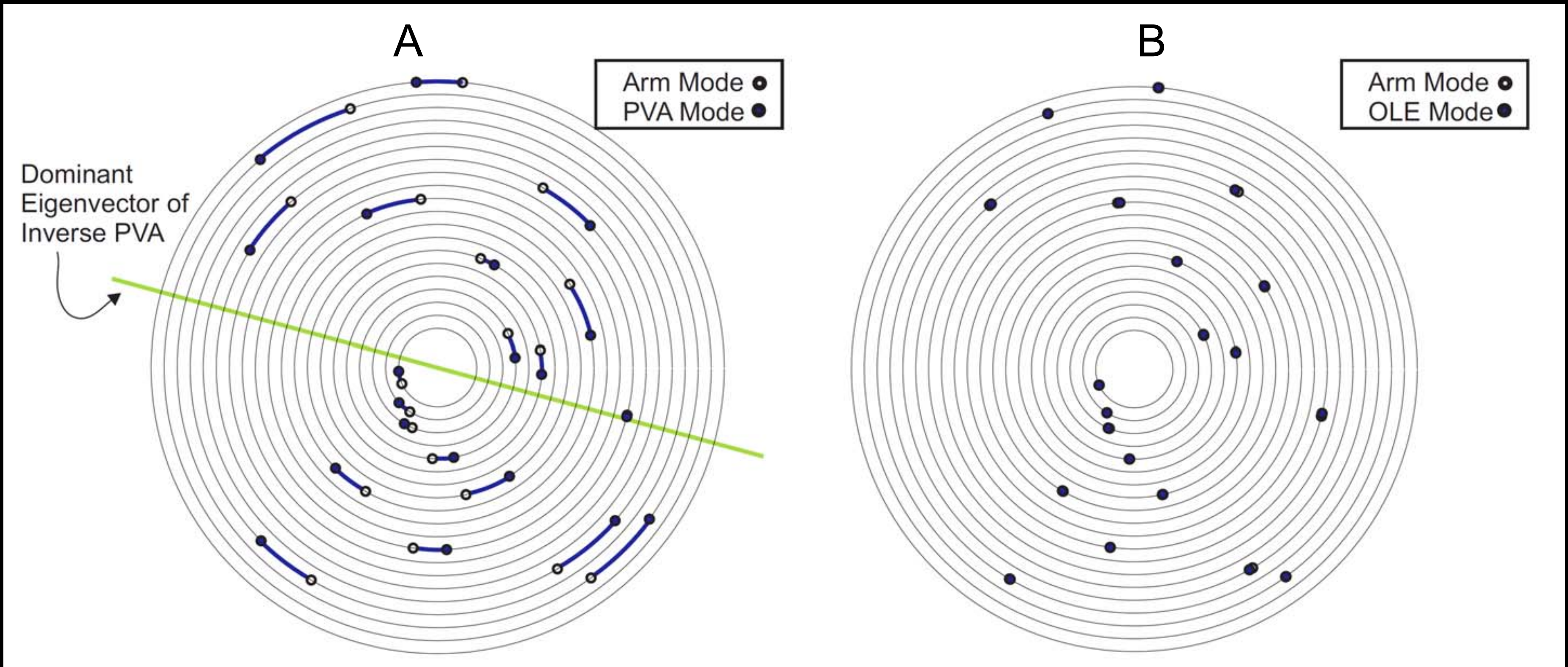
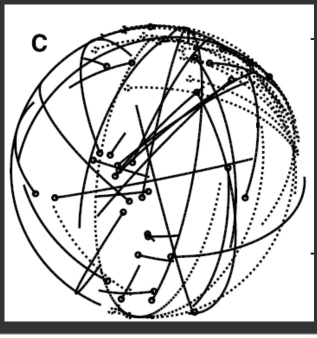
Arm v. BMI operation: instant tuning curve shift

Arm vs. PVA control **Arm vs. OLE control**



UCSF, U.Pitt Data

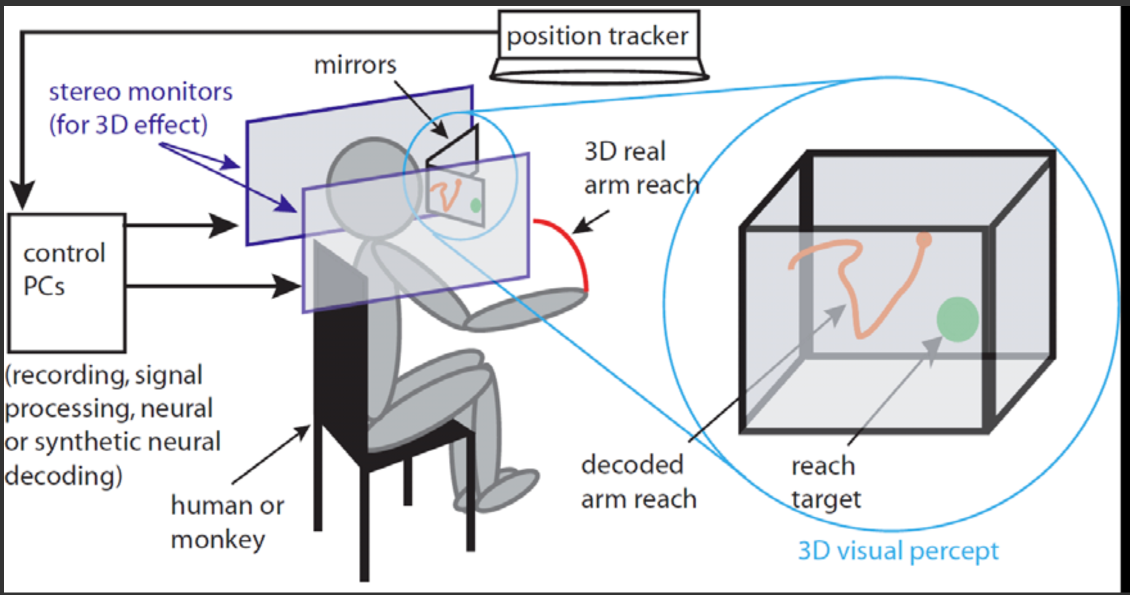


Model Insights

- Binwidth-dependent performance is intrinsic to discrete time control, even under perfect neural decoding
- Brain incurs energetic cost associated with compensating decoder bias
- Tuning curve shifts reflect the brain's implementation of a new control policy

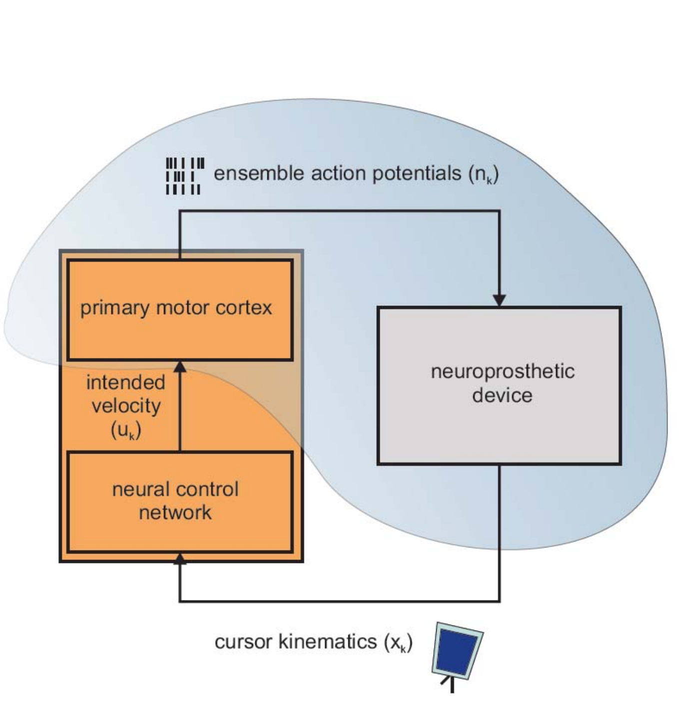
Model as Closed-Loop Simulator

Human-based closed-loop simulator



[Stanford] Cunningham and Shenoy, “A Closed-Loop Human Simulator for Investigating the Role of Feedback-Control in Brain-Machine Interfaces” (J. Neurophys., 2010)

In silico closed-loop simulator



Lagang & Srinivasan, under review

Acknowledgments

- American Heart Association
- UCLA Radiology

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