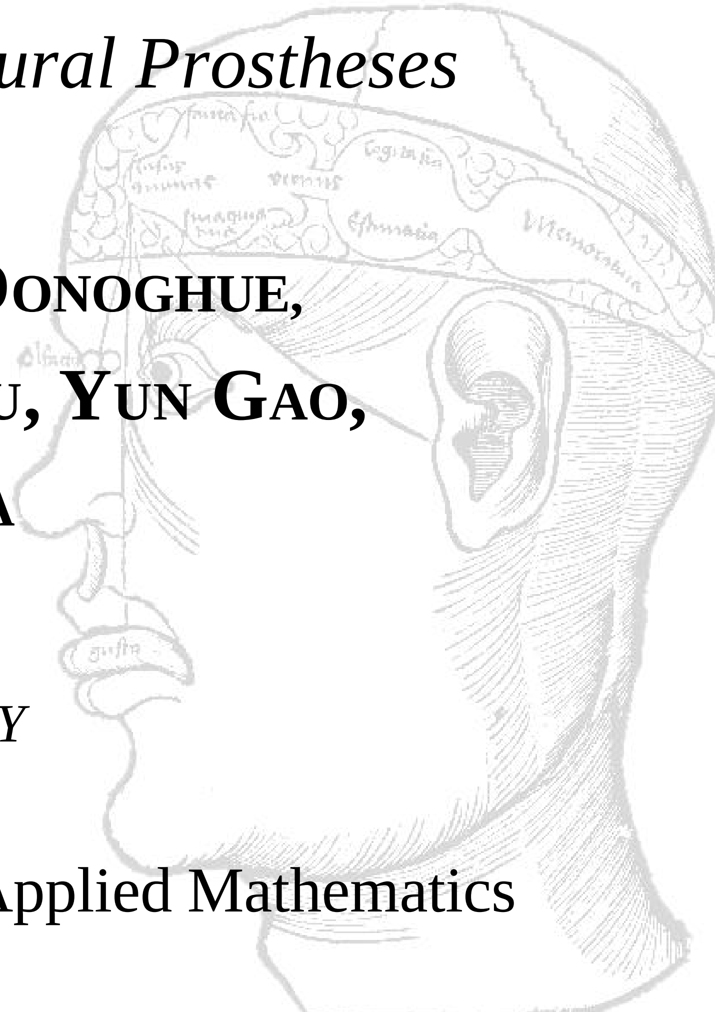
Models of Neural Coding in Motor Cortex

And Their Application to Neural Prostheses



MICHAEL BLACK, JOHN DONOGHUE,

ELIE BIENENSTOCK, WEI WU, YUN GAO,

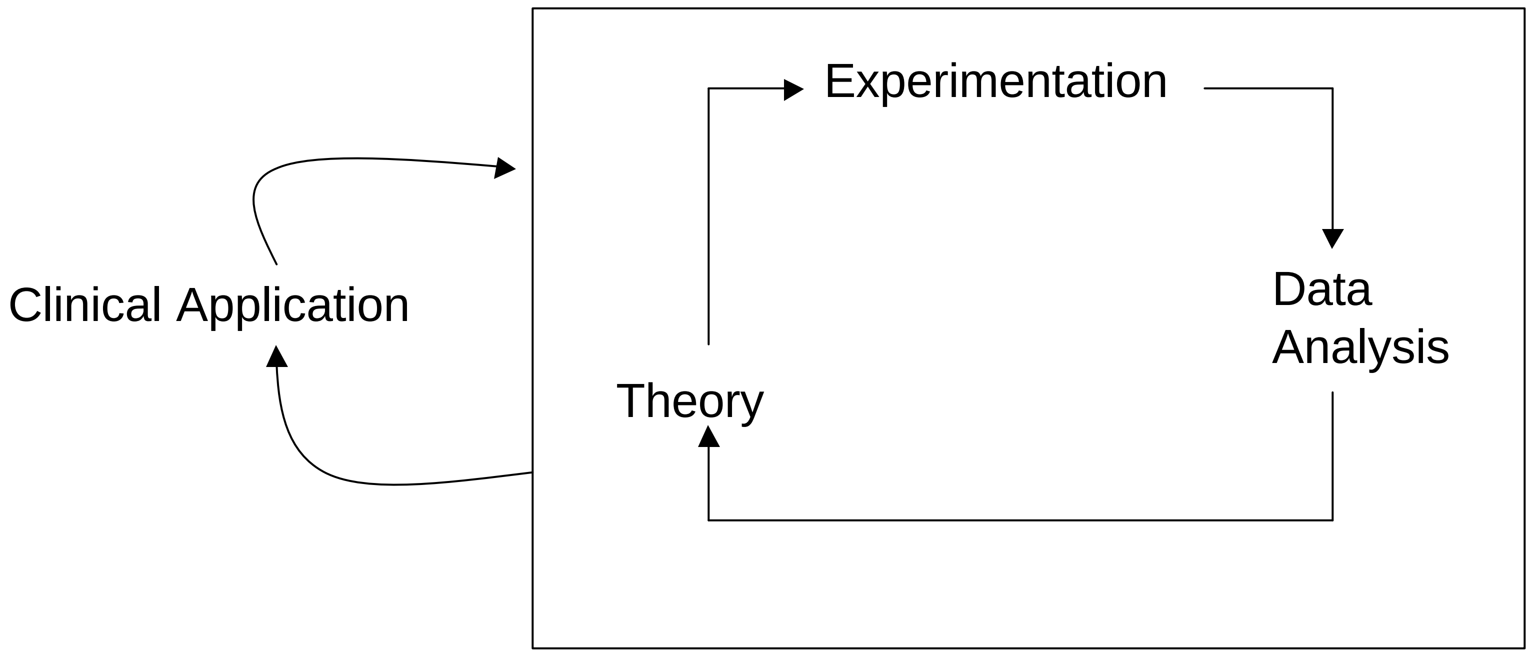
MIJAIL SERRUYA

BROWN UNIVERSITY

Computer Science   Neuroscience   Applied Mathematics

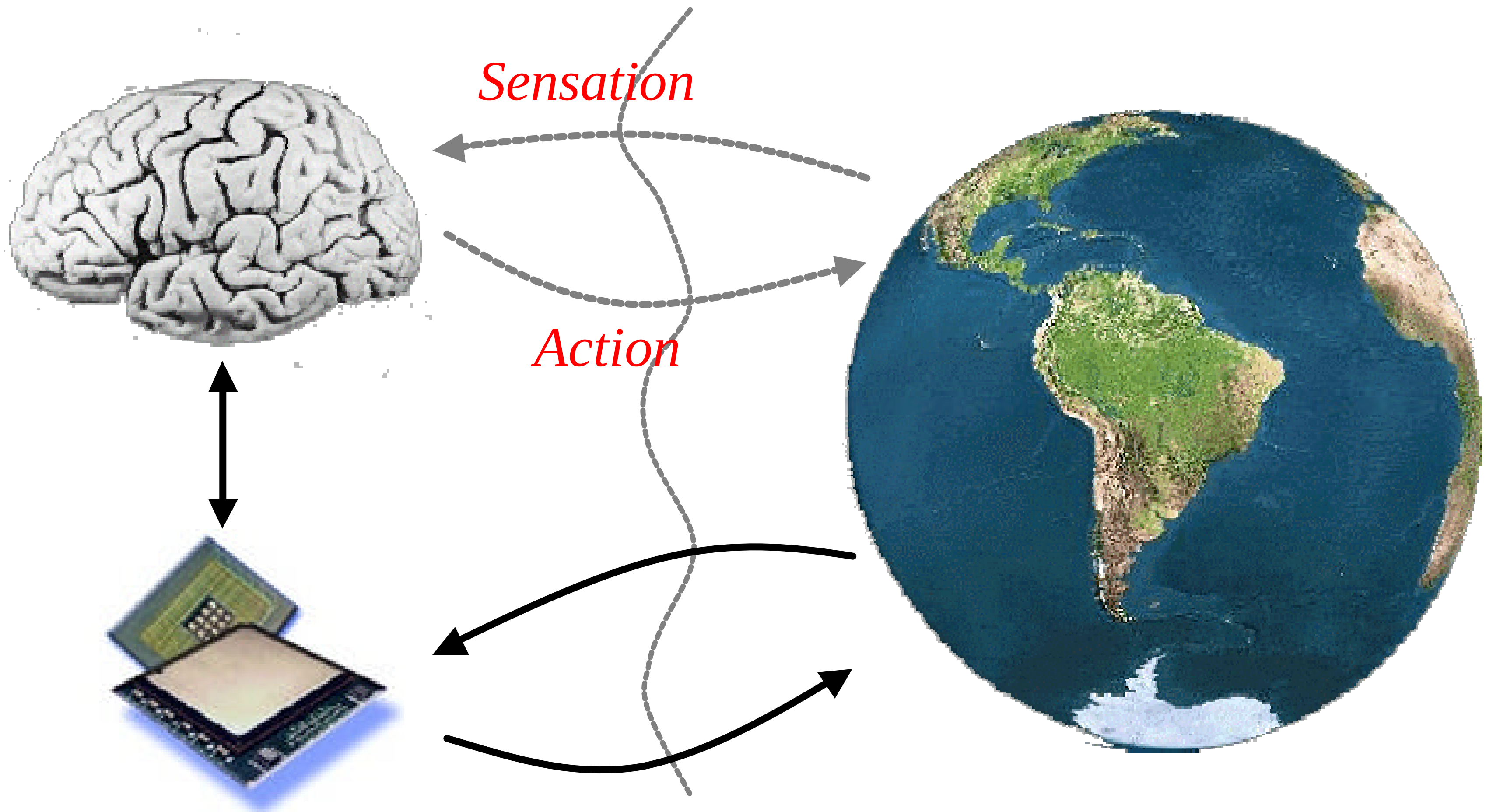
EMERY'S OVERVIEW

My approximation of what Emery said:



Balance and exploit basic science, engineering, and clinical goals.

NEURAL PROSTHESIS



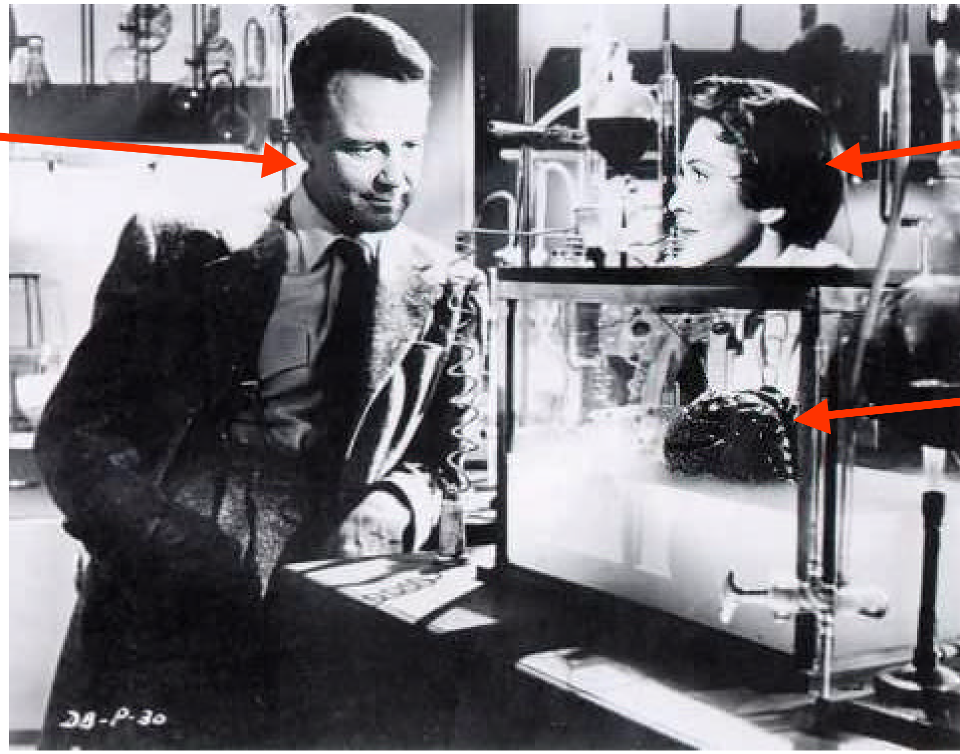
THE LINK SEPARATED

* Stroke (e.g. in brain stem).
* Spinal cord injuries
  Approximately 200,000 cases in the USA
  11,000 new cases/year
  Fifty-six percent in 16 to 30 year age group
  0.7% Recover
* Amyotrophic Lateral Sclerosis (ALS or Lou Gehrig's disease)
  20,000 cases with 5,000 new cases/year
* Multiple Sclerosis
* Blindness
* Hearing impairment

Brain-Machine Interfaces

“Mad” scientist

Nancy Davis (Reagan)

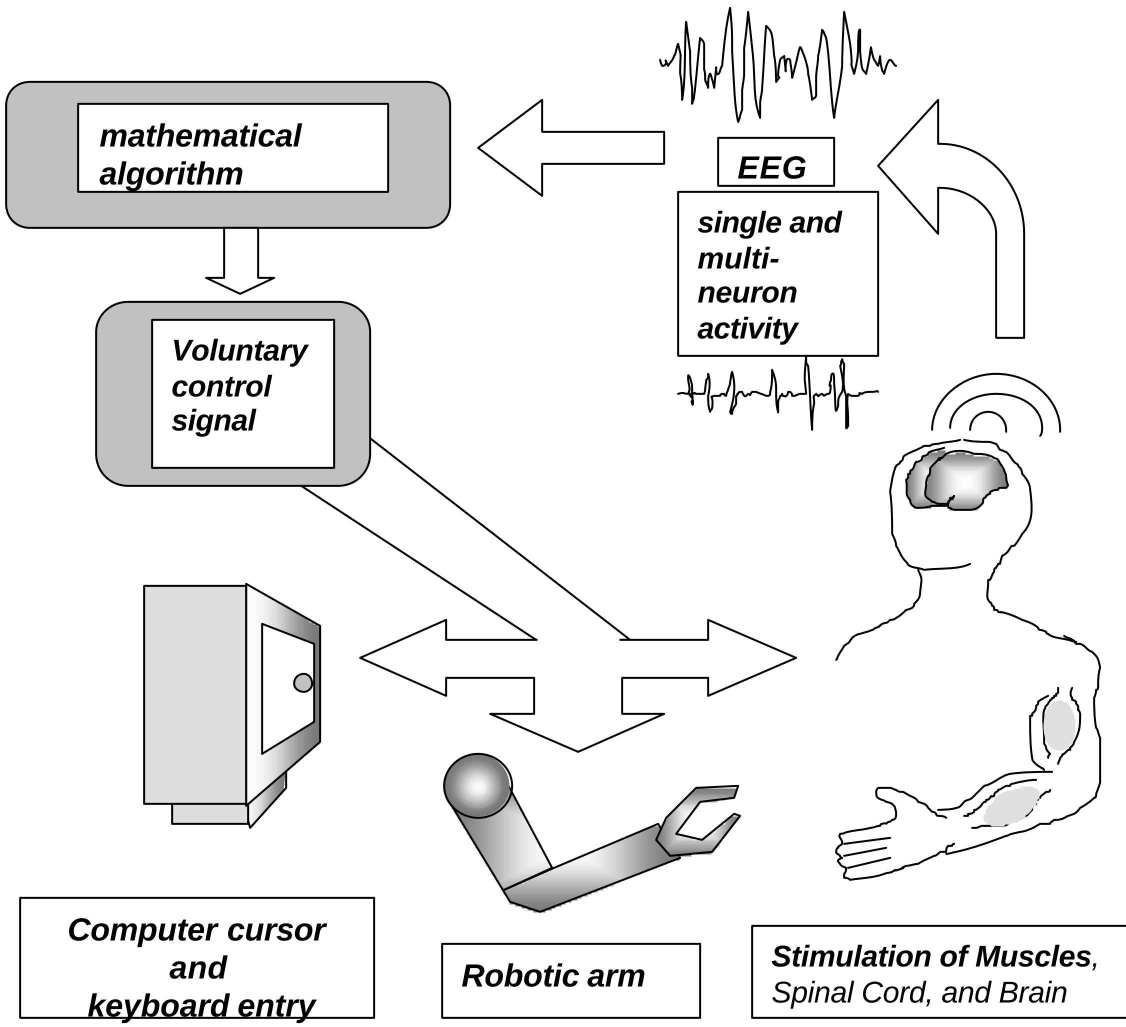


Brain

“If I could find … a ***code*** *which* ***translates*** *the relation between the reading of the encephalograph and the mental image …the brain could* ***communicate*** *with me.”*

“Donovan’s Brain”, Curt Siodmak, 1942

A Neural Prosthesis



Focus on central rather than peripheral nervous system.

Source: Mijail Serruya

KEY QUESTIONS

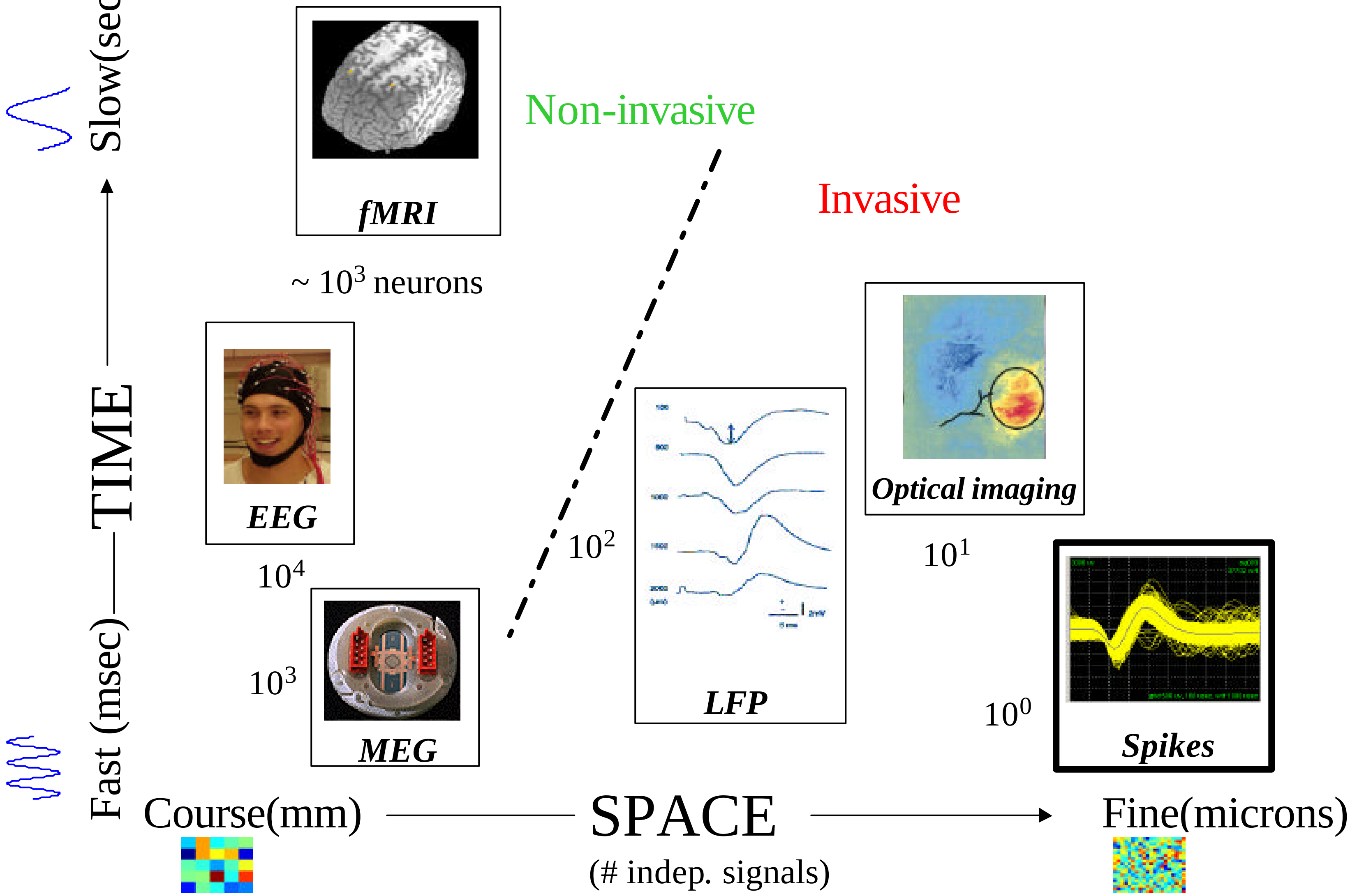
1. **Measurement**: What can we measure? From where? How?

2. **Encoding**: How is information represented in the brain?

3. **Decoding**: What algorithms can we use to infer the internal "state" of the brain?

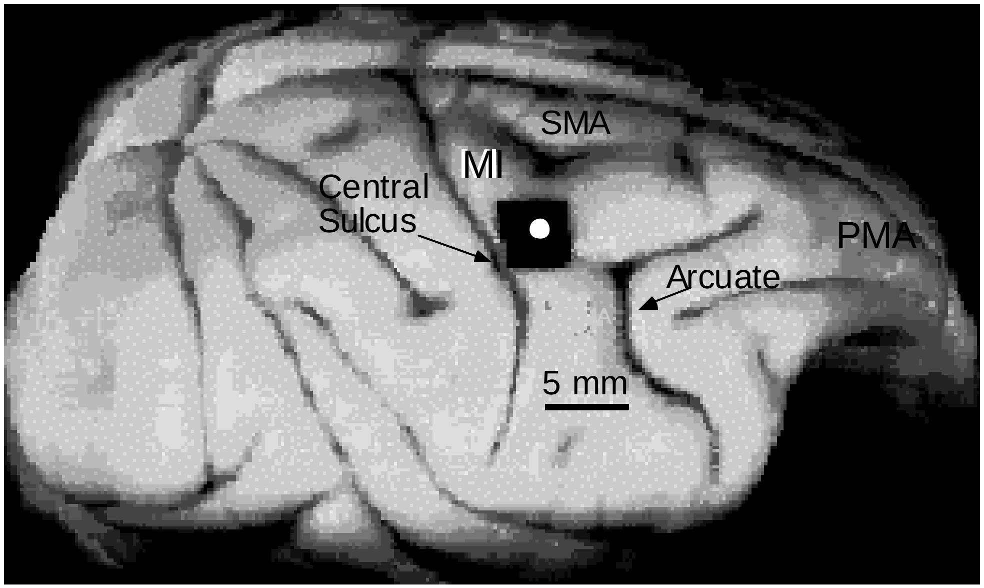
4. **Interface**: How can we build practical interfaces and train people to use them?

SENSING THE BRAIN



Source: Matt Fellows

IMPLANT AREA

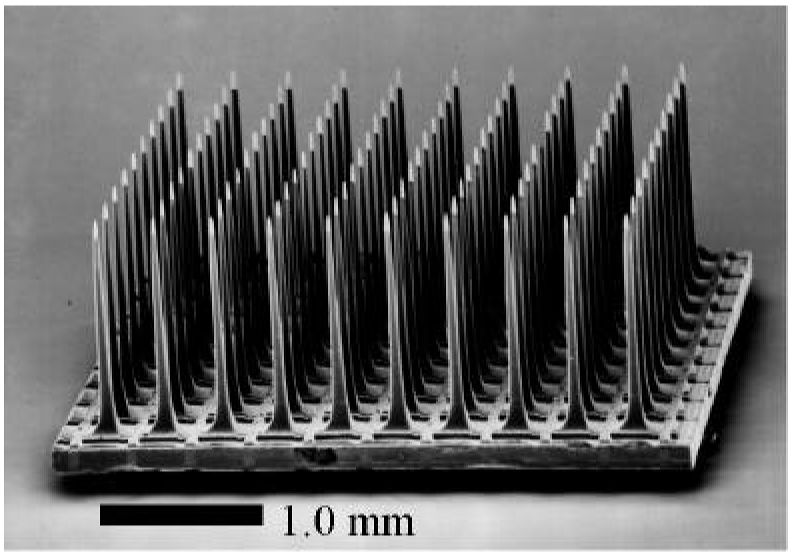


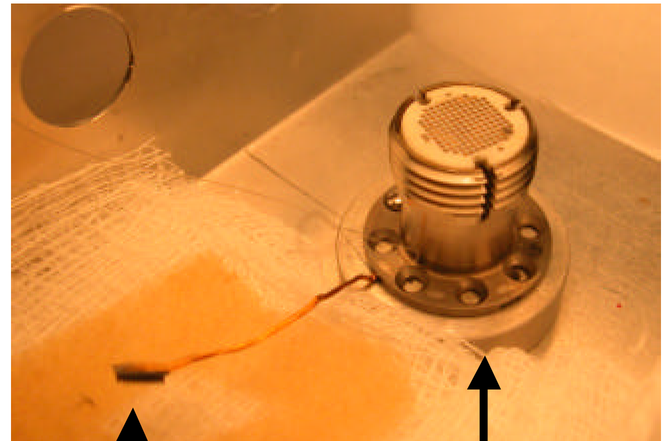
MI arm area of motor cortex.

* firing rates of cells correlated with hand motion (velocity, position, acceleration?)
* accessible
* *hypothesis*: natural for controlling motion of a prosthesis.

NEURAL IMPLANT

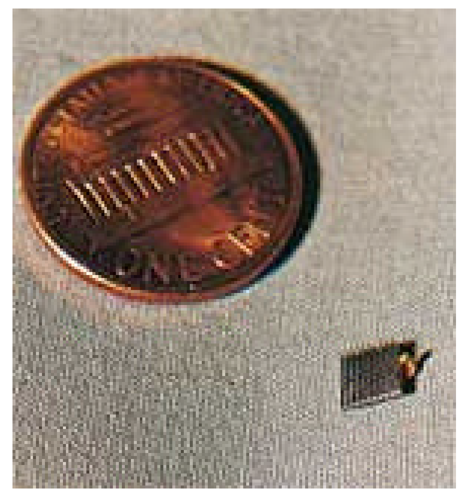
Bionic Technologies:





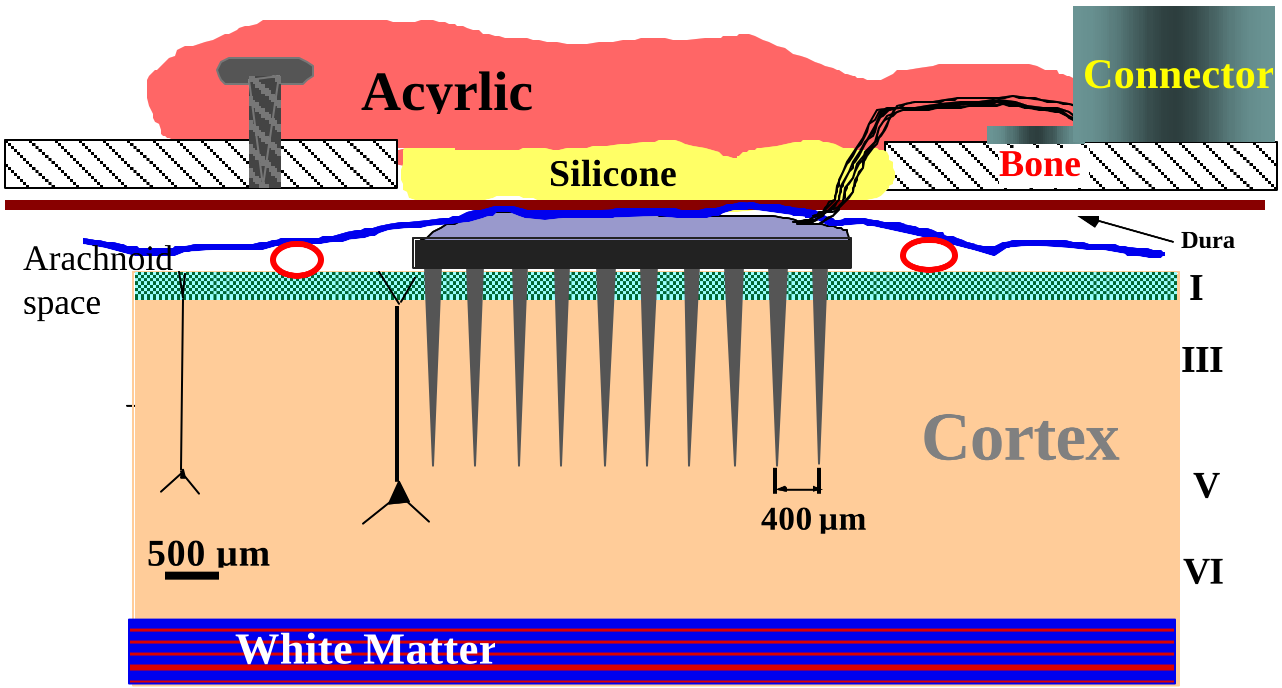
Electrode array

Neural connector



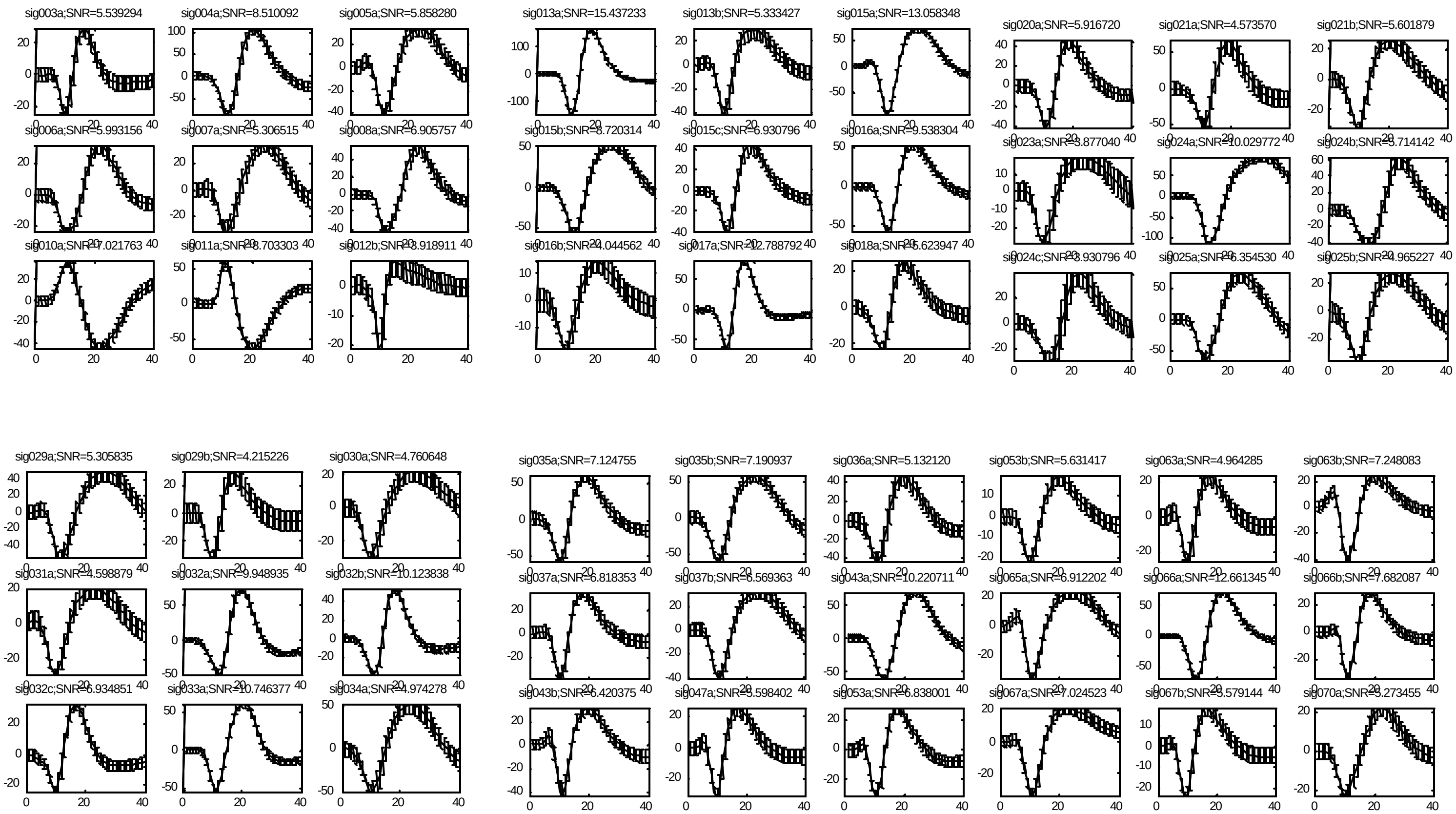
100 electrodes,
400µm separation
4x4 mm

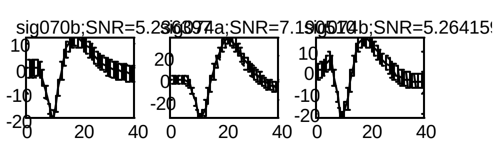
NEURAL IMPLANT



Chronically implanted.
Stable recording for 2-3 years (not necessarily same cells every day).
Spikes as well as local field potentials.
Take what you get.

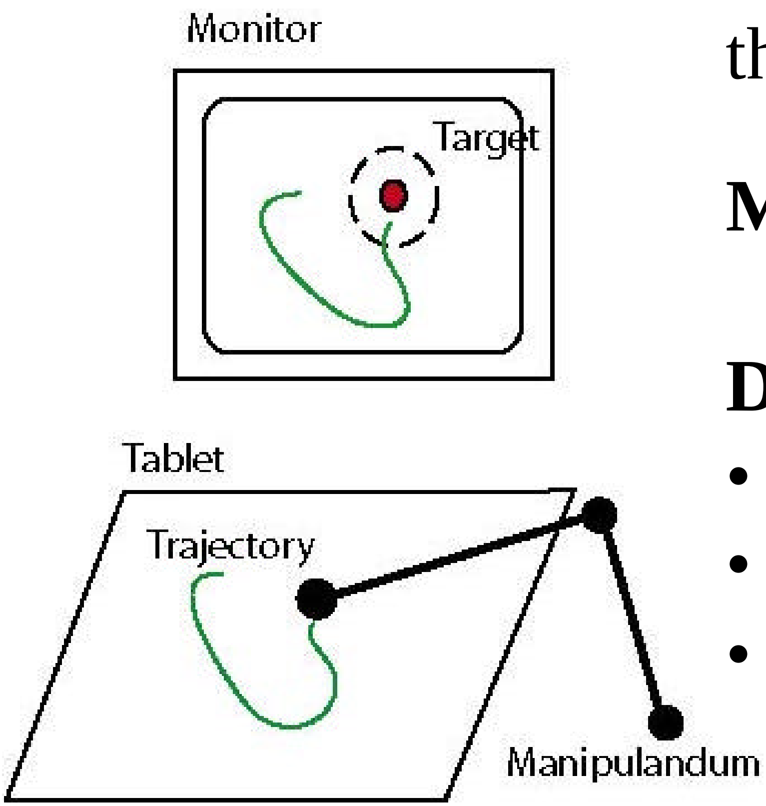
EXAMPLE RESPONSES





Latest Results with NeuroPort: 200 neurons from two arrays.

“PINBALL” TASK

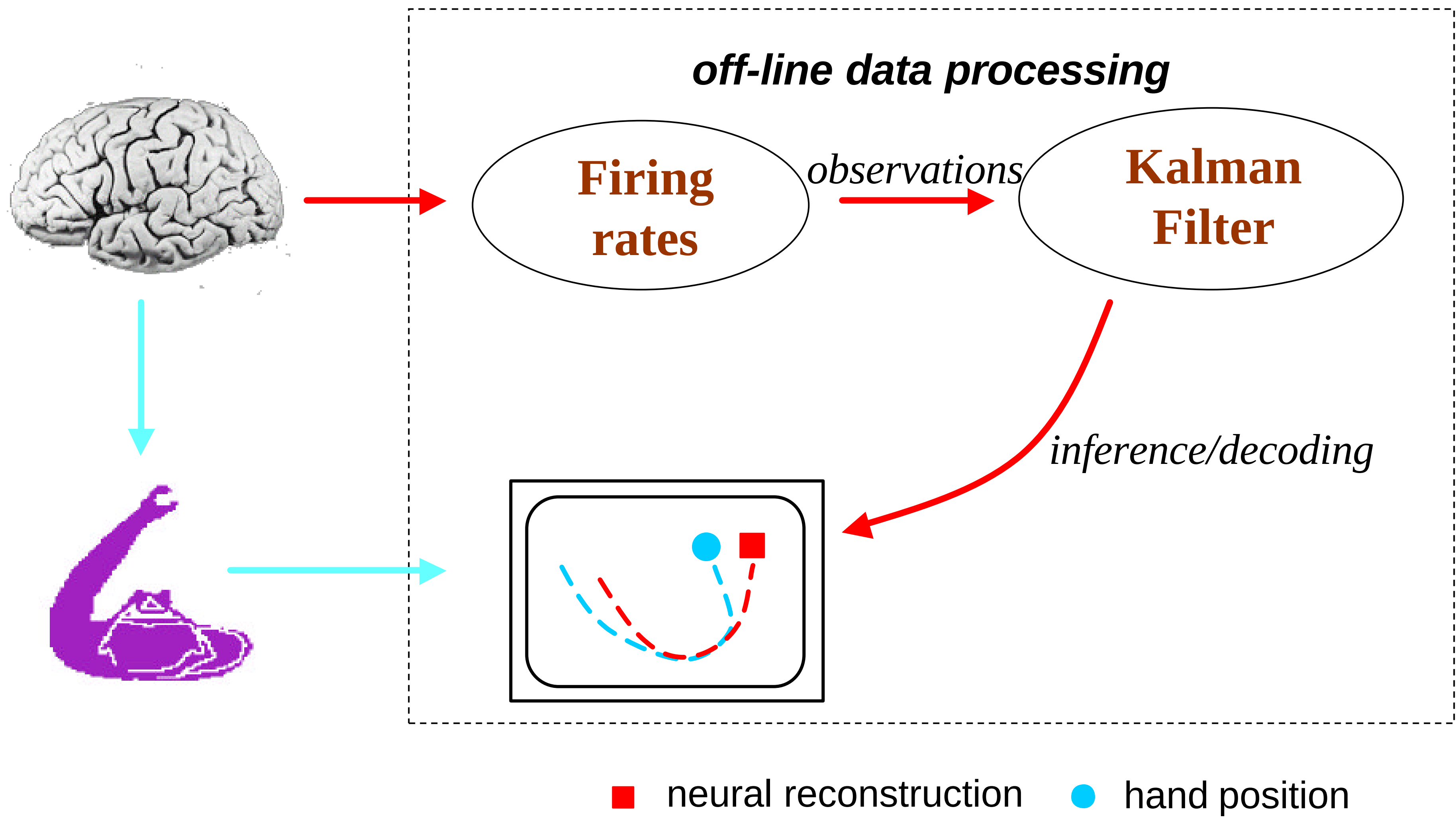


Task: Hit random targets on the screen.

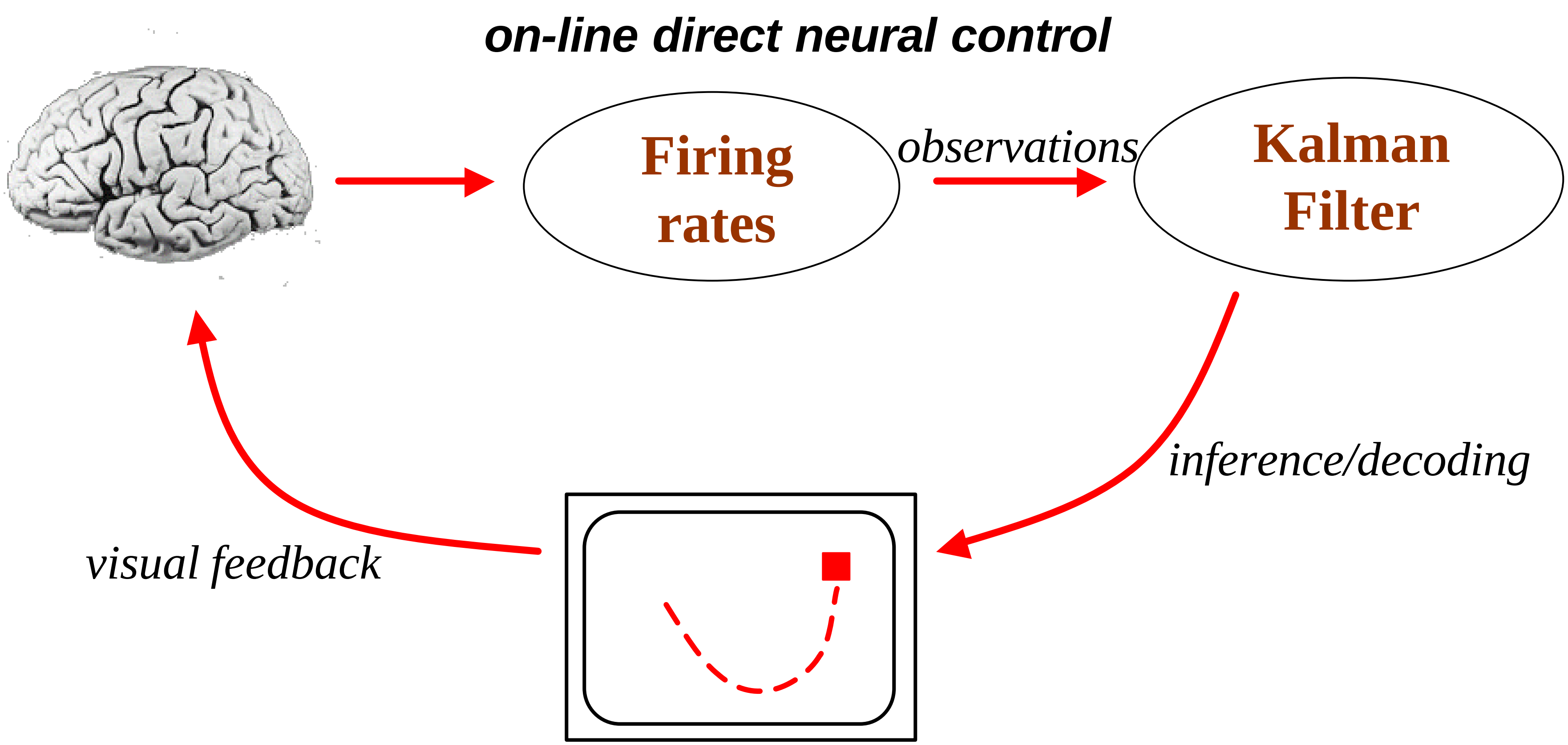
Motions: fast, unconstrained

Data (4.5 minutes)**:**
- Position (Velocity, Acceleration)
- 1.5 minutes needed for training
- Firing rate (42 cells, non-overlapping 70ms bins)

EXPERIMENAL PARADIGM



CLOSED-LOOP CONTROL



■ neural reconstruction

Generative Model

Encoding:

$$\vec{z}_k = f_1(\vec{x}_k) + \vec{q}_k$$

$$\vec{x}_k = f_2(\vec{x}_{k-1}) + \vec{w}_k$$

noise (e.g. Normal or Poisson)

neural firing rate of N=42 cells in M=70ms

behavior (e.g. hand position, velocity, acceleration)

ENCODING

Cosine tuning (Georgopoulos et al ’82). Single cell:

$$z_k = h_0 + h_x \sin(q_k) + h_y \cos(q_k)$$

q_k = hand direction at time k

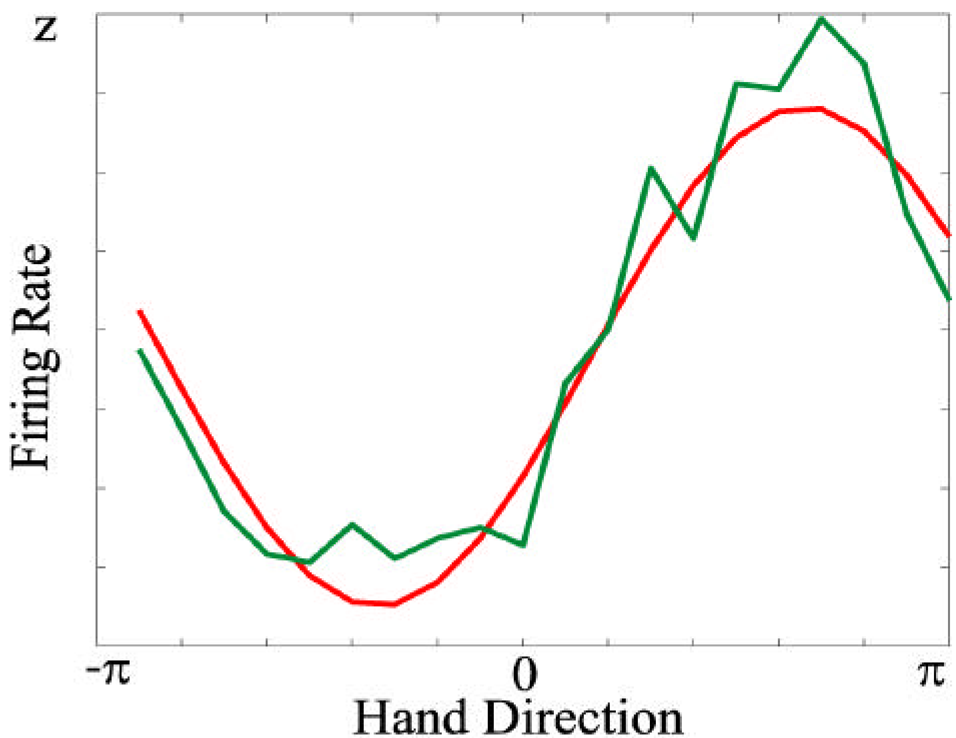
Not sufficient for continuous control.

Speed?

Position?

Acceleration?

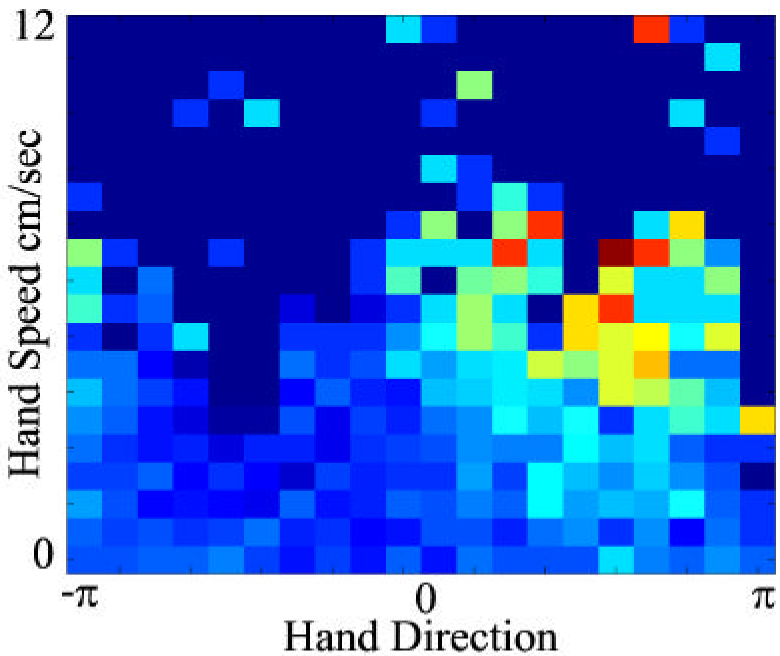
Noise model?

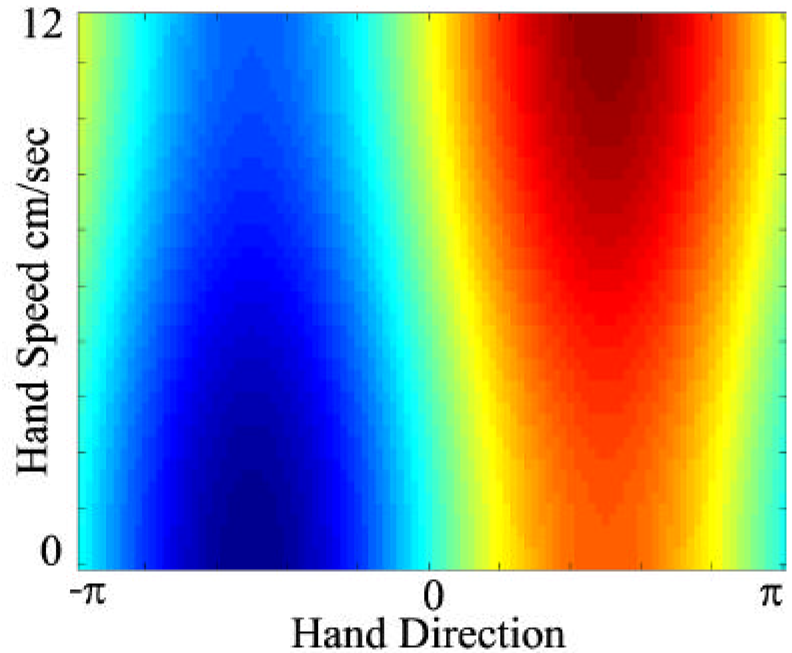


ENCODING

Moran & Schwartz ('99):

$$
\begin{aligned}
z_k &= s_k(h_0 + h_x \sin(q_k) + h_y \cos(q_k)) \\
&= h_1 + h_x v_{x,k} + h_y v_{y,k} \quad \text{(\textit{Linear} in velocity).}
\end{aligned}
$$

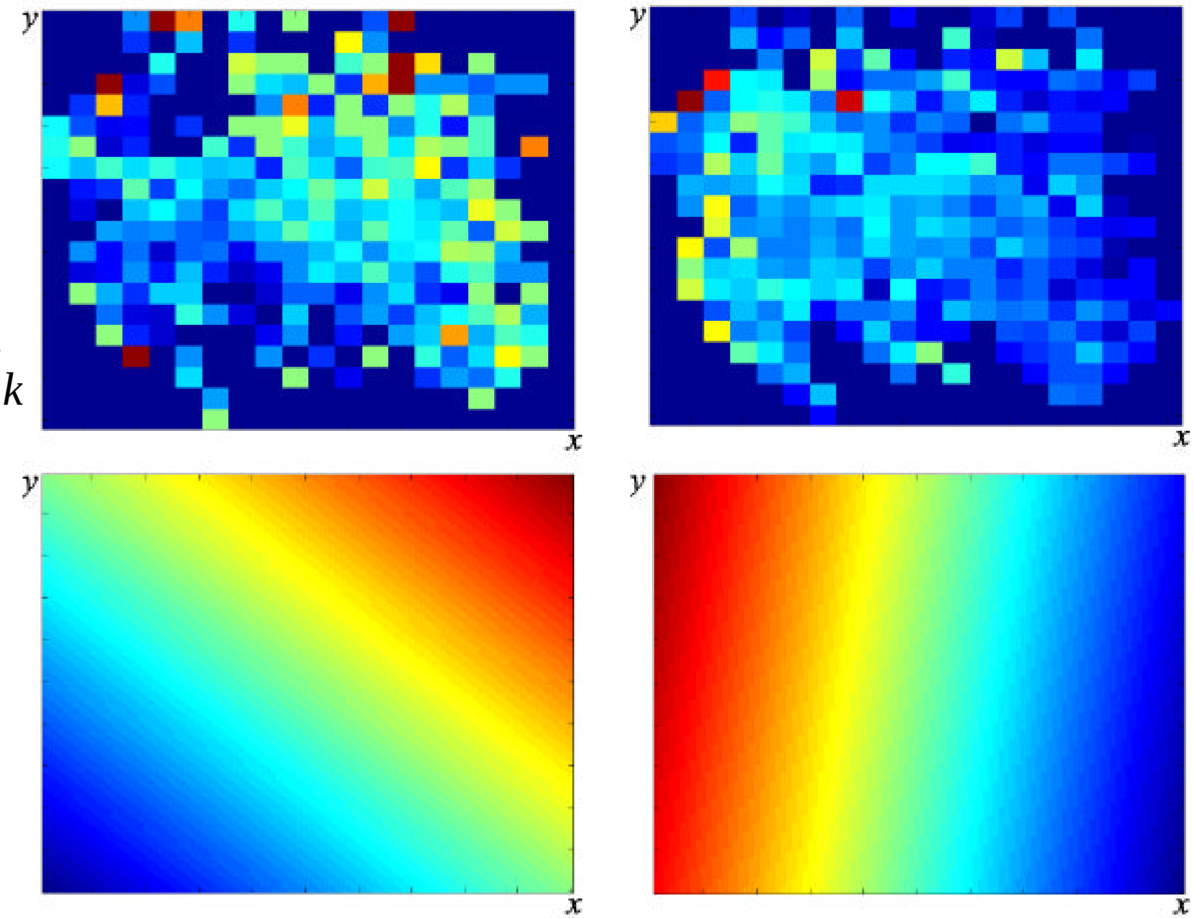




ENCODING

Linear encoding of position

$$z_k = b_0 + b_x x_k + b_y y_k$$



ENCODING SUMMARY

* Firing rate is approximately linearly related to hand position and velocity.

* Linear models relating firing to accleration, jerk, snap, … also improve the encoding but with diminishing returns.

* Firing rates of cells are not conditionally independent (need to model the correlations) [Hatsopoulos et al ’98].

DECODING

• Georgopoulos et al. (1986) • Taylor et al. (2002)	Population Vector (only velocity)
• Zhang et al (1998) • Brown et al. (1998)	“two step Bayes” Recursive Bayesian (hippocampal place cells)
• Wessberg et al.(2000) • Gao et al. (2002) • Principe et al (2002)	Linear filter, ANN Particle filter ad hoc Kalman model
• Serruya et al.(2002)	Linear filter (position) (closed loop)

DECODING MODEL

* sound probabilistic framework.
* make explicit our assumptions about the data and noise.
* indicate the uncertainty of the estimate.
* requires a small amount of “training” data.
* provide on-line estimation of hand position with short delay (within 200ms).
* more accurate estimates than previous methods (population vectors or linear filters).

GENERATIVE MODEL

Observation Equation:

system state vector

$$\begin{pmatrix} x_k \\ y_k \\ v_{x_k} \\ v_{y_k} \\ a_{x_k} \\ a_{y_k} \end{pmatrix}$$

firing rate vector (sqrt)

$$\begin{pmatrix} z_k^1 \\ z_k^2 \\ \vdots \\ z_k^{42} \end{pmatrix}$$

$$\vec{z}_k = H \vec{x}_k + \vec{q}_k$$

42 X 6 matrix

42 X 42 matrix

$$\vec{q}_k \sim N(0, Q)$$

$$k = 0, 1, 2, \cdots$$

System Equation:

$$\vec{x}_{k+1} = A \vec{x}_k + \vec{w}_k$$

6 X 6 matrix

6 X 6 matrix

$$\vec{w}_k \sim N(0, W)$$

$$k = 0, 1, 2, \cdots$$

OPTIMAL "LAG"

Measurement Equation

Firing precedes motion:

* Uniform: lag j time steps (1 time step = 70ms)

$$\vec{z}_{k-j} = H\ \vec{x}_k + \vec{q}_k \qquad j = 0,1,2,3,4$$

* Non-uniform: lag $(j_1, j_2, \cdots, j_{42})$ time steps

TRAINING

$$H = \underset{H}{\operatorname{argmin}} \sum_k \| \vec{z}_k - H\vec{x}_k \|^2$$

$$A = \underset{A}{\operatorname{argmin}} \sum_k \| \vec{x}_{k+1} - A\vec{x}_k \|^2$$

$$\begin{aligned} Q &= \mathbf{cov}(\{\vec{z}_k - H\vec{x}_k\}_k) \\ &= (\mathbf{z} - H\mathbf{x})(\mathbf{z} - H\mathbf{x})^{\mathrm{T}} \end{aligned}$$

$$\begin{aligned} W &= \mathbf{cov}(\{\vec{x}_{k+1} - A\vec{x}_k\}_k) \\ &= (\mathbf{x}_{k+1} - A\mathbf{x}_k)(\mathbf{x}_{k+1} - A\mathbf{x}_k)^{\mathrm{T}} \end{aligned}$$

Centralize the training data, such that

$$\mathrm{E}(\{\vec{z}_k\}) = 0, \quad \mathrm{E}(\{\vec{x}_k\}) = 0$$

Bayesian Inference

Infer behavior from firing.

p(behavior at k | firing up to k) =

$$p(\vec{x}_k \mid \vec{Z}_k) = k \; p(\vec{z}_k \mid \vec{x}_k) \; p(\vec{x}_k \mid \vec{Z}_{k-1})$$

likelihood

prior

observation model

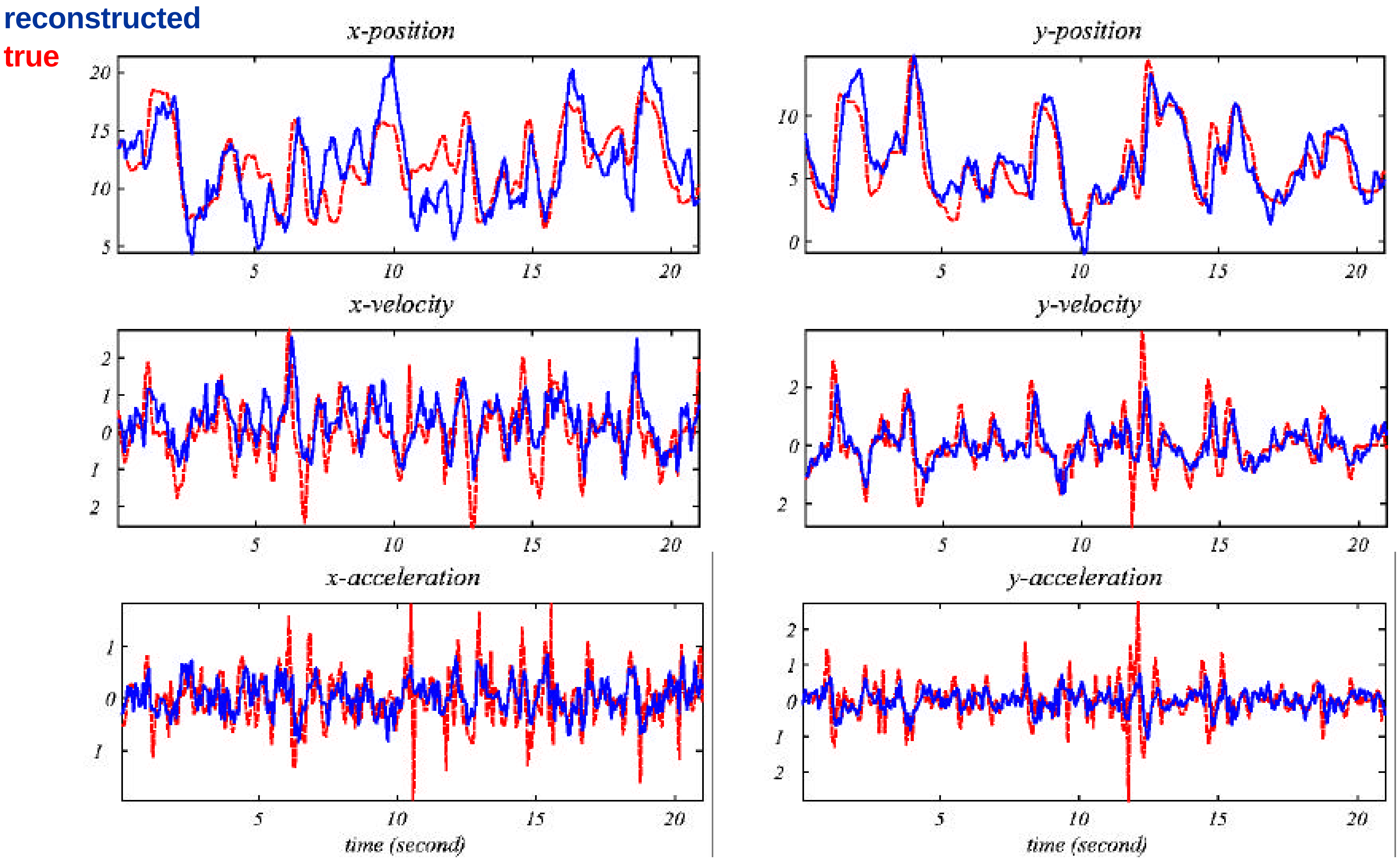
$$\vec{z}_k \sim ?\; (H\,\vec{x}_k,\, Q)$$

$$p(\vec{x}_k \mid \vec{Z}_{k-1}) = \int p(\vec{x}_k \mid \vec{x}_{k-1})\; p(\vec{x}_{k-1} \mid \vec{Z}_{k-1})\, d\vec{x}_{k-1}$$

$$\vec{x}_k \sim N\,(A\vec{x}_{k-1}, W) \qquad N\,(\hat{\vec{x}}_{k-1}, P_{k-1})$$

system model

RECONSTRUCTION (TEST DATA)

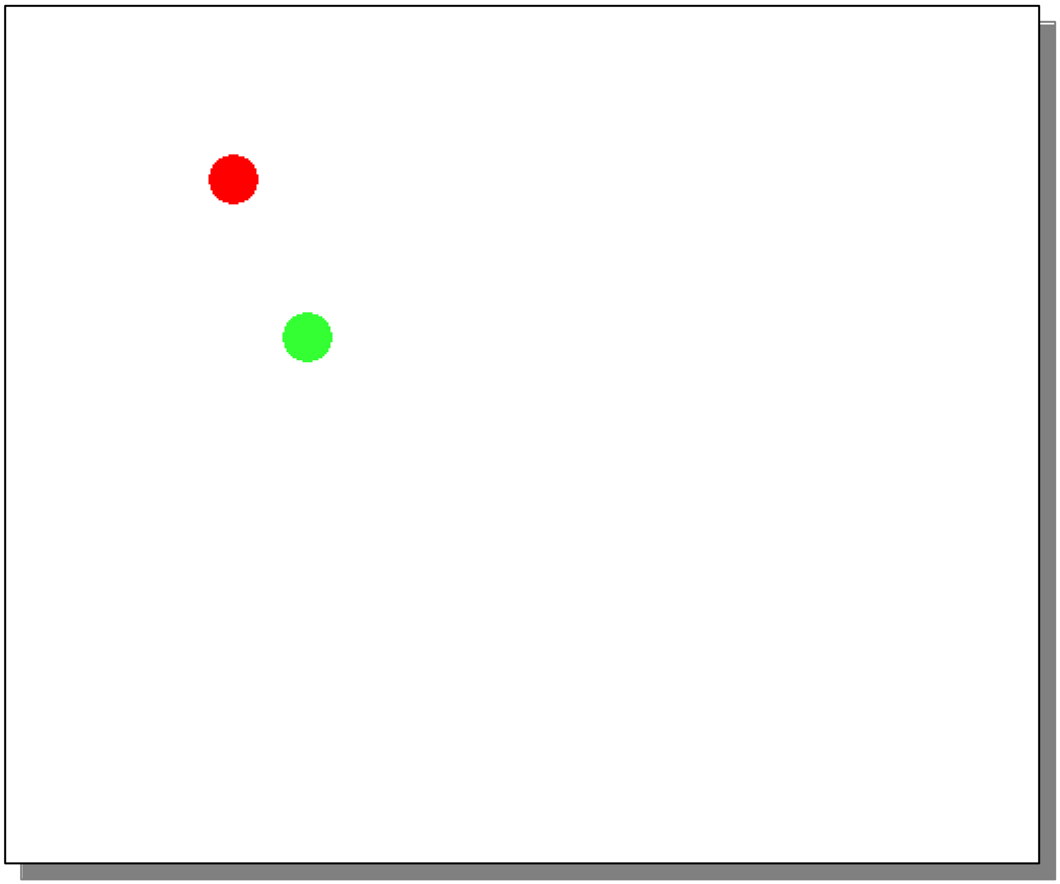


RECONSTRUCTION AND LAG

Methods	CC (x, y)	MSE (cm^2)
Kalman (0ms lag)	(0.77, 0.91)	6.96
Kalman (70ms lag)	(0.79, 0.93)	6.67
Kalman (140ms lag)	**(0.81, 0.93)**	**6.09**
Kalman (210ms lag)	(0.81, 0.89)	6.98
Kalman (280ms lag)	(0.76, 0.82)	8.91
Kalman (non-uniform)	(0.82, 0.93)	5.24

Note: MSE approx 7.2 with diagonal covariance (conditional independence)

Closed Loop Neural Control



Target

Neural control

Linear filters
built on-line.

Mijail Serruya

BEYOND LINEAR GAUSSIAN

Generalized Linear Models (GLM).

$$h_k = H\vec{x}_k = g(m_k)$$

Natural log for Poisson

$$m_k = g^{-1}(H\vec{x}_k)$$

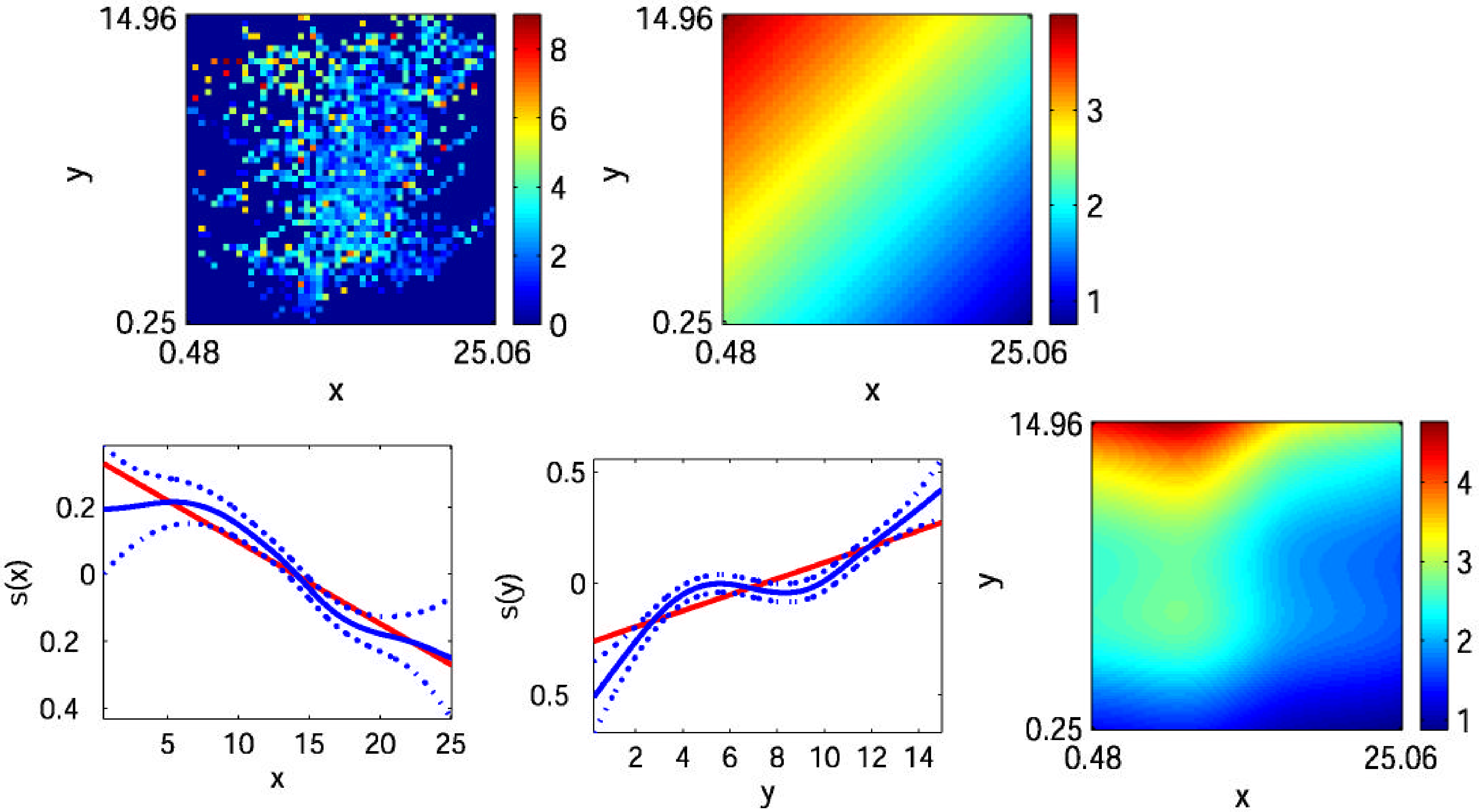
$$z_k \sim N(g^{-1}(H\vec{x}_k), \mathbf{Q})$$

Generalized Additive Model (GAM).

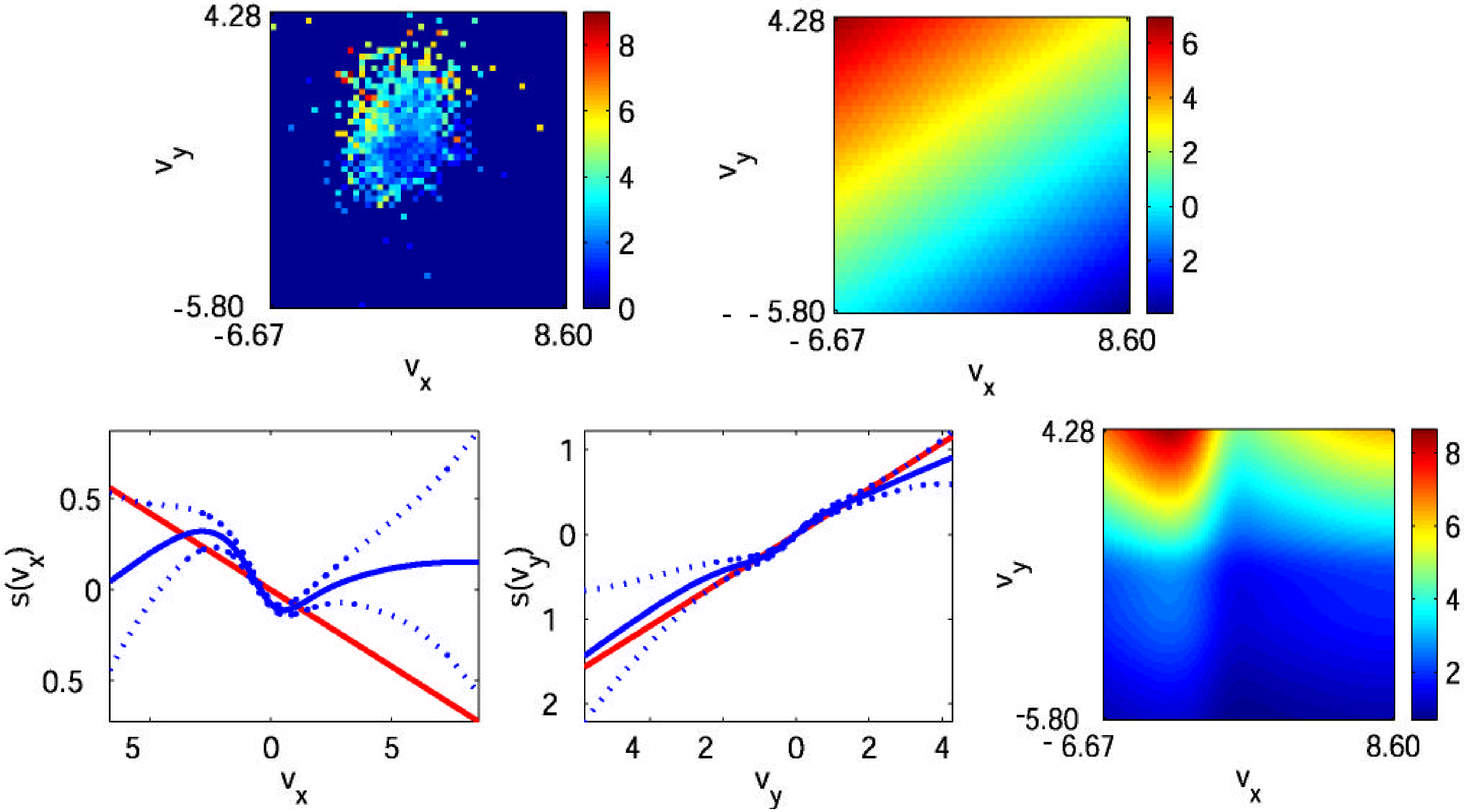
$$h_k = g(m_k) = \sum_i s_i(x_{k,i})$$

4th order splines.

GAM of Position



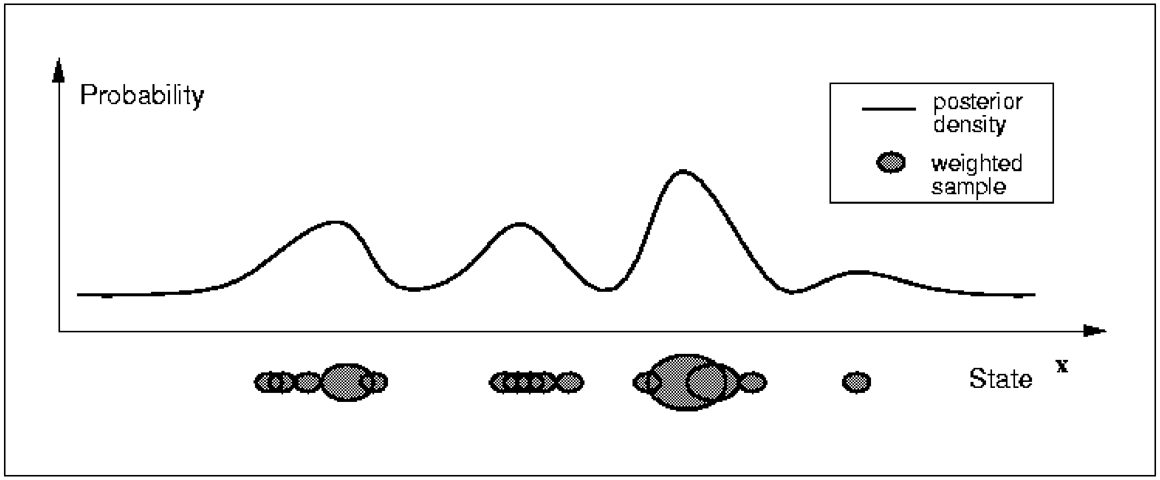
GAM of Velocity



FACTORED SAMPLING

Non-Gaussian Posterior:

- non-Gaussian or non-linear likelihood
- non-linear temporal prior



Isard & Blake '96

Particle set = $\{\vec{x}_k^{(i)}, p^{(i)}\},\ i = 1..N$

PARTICLE FILTER

Posterior $p(\vec{x}_{k-1} \mid \vec{Z}_{k-1})$

sample

Temporal dynamics

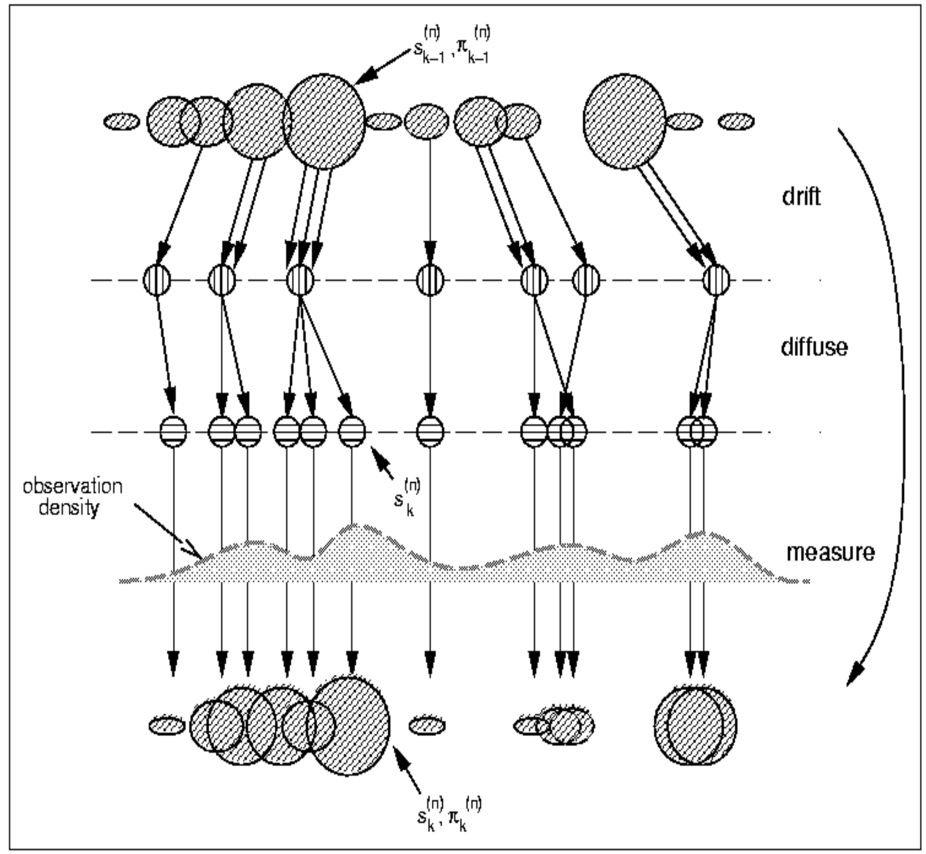
$p(\vec{x}_k \mid \vec{x}_{k-1})$

sample

Likelihood $p(\vec{z}_k \mid \vec{x}_k)$

normalize

Posterior $p(\vec{x}_k \mid \vec{Z}_k)$



Isard & Blake '96

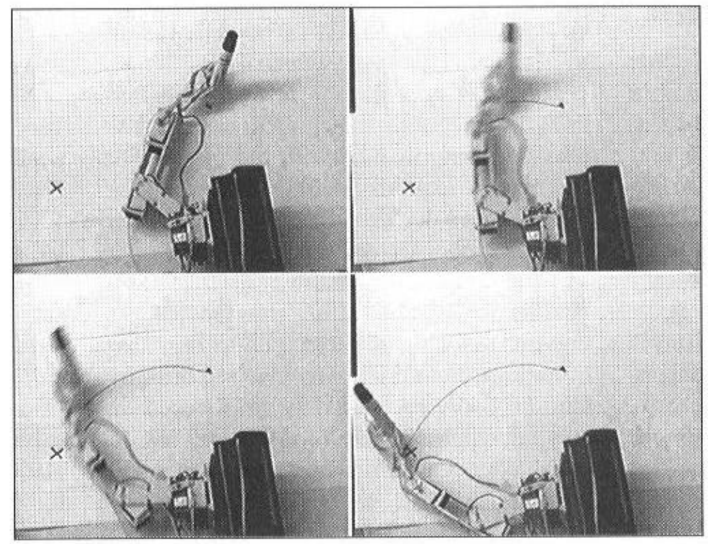
DECODING ACCURACY

Method	MSE	x cc	y cc
LGM (indep)	7.17	0.8	0.92
GLM (indep)	6.36	0.79	0.89
LGM (full cov)	6.13	0.81	0.93
GAM (indep)	6.04	0.84	0.9

QUESTIONS AT THE INTERFACE

* training paralyzed subjects

* controlling "unnatural" devices
    • cursors
    • robotic arms, hands.
    • mobile robots



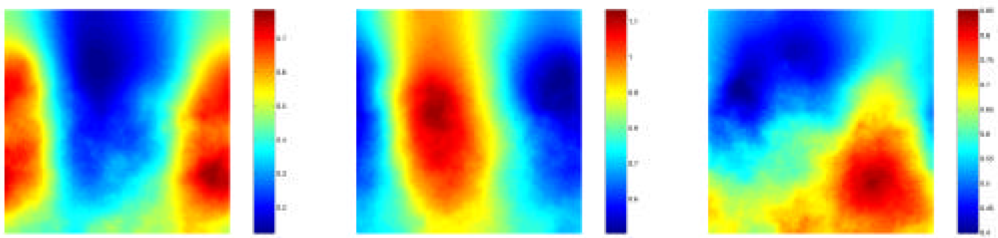
* controlling multiple devices
    - switching contexts
    - adaptation

* Where should the computation take place (brain or computer)?

* What level of autonomous control/perception is needed?

CURRENT/FUTURE WORK

* 3D motion and joint angles.
* Incorporating local field potentials.
* Non-parametric tuning functions



* Recognizing patterns of motion (gestures).
* Plasticity.
* Robot control (service robots, semi-autonomous).
* Recording from multiple brain areas.

SUMMARY

* Firing rate of MI cells is approximately linearly related to position, velocity, and acceleration of the hand.

* Modeling the full covariance matrix is important for decoding.

- independent Gaussian or independent Poisson does worse

* The Kalman filter is optimal if the model is linear and the noise is Gaussian.

- the firing can be made approximately Gaussian.

* Useful estimates of hand motion can be derived from only 42 cells and a 1.5 minutes of training data

- cursor control suggests a neural prosthesis may be practical

CONCLUSIONS

We are on the verge of having *biologically-embedded* hybrid neural-computer systems.

In animal models we have demonstrated continuous 2D cursor control and limited robotic control.

The work opens opportunities to study

* how the brain represents and processes information
* computational models of biological control
* novel hybrid control systems
* new robotic systems and prostheses

THANKS

M. Fellows, *Neuroscience*

D. Sheinberg, *Neuroscience*

N. Hatsopoulos, *Neuroscience*

W. Patterson, *Engineering*

A. Nurmikko, *Engineering*

G. Friehs, *Brown Medical School*

S. Geman, *Division of Applied Mathematics*

D. Mumford, *Division of Applied Mathematics*

L. Paninski, *NYU, Center for Neural Science*

S. Shoham, *Princeton*

Support:

National Science Foundation, ITR Program.

The Keck Foundation

The National Institutes of Health