Architectures and Algorithms for Brain Machine Interfaces

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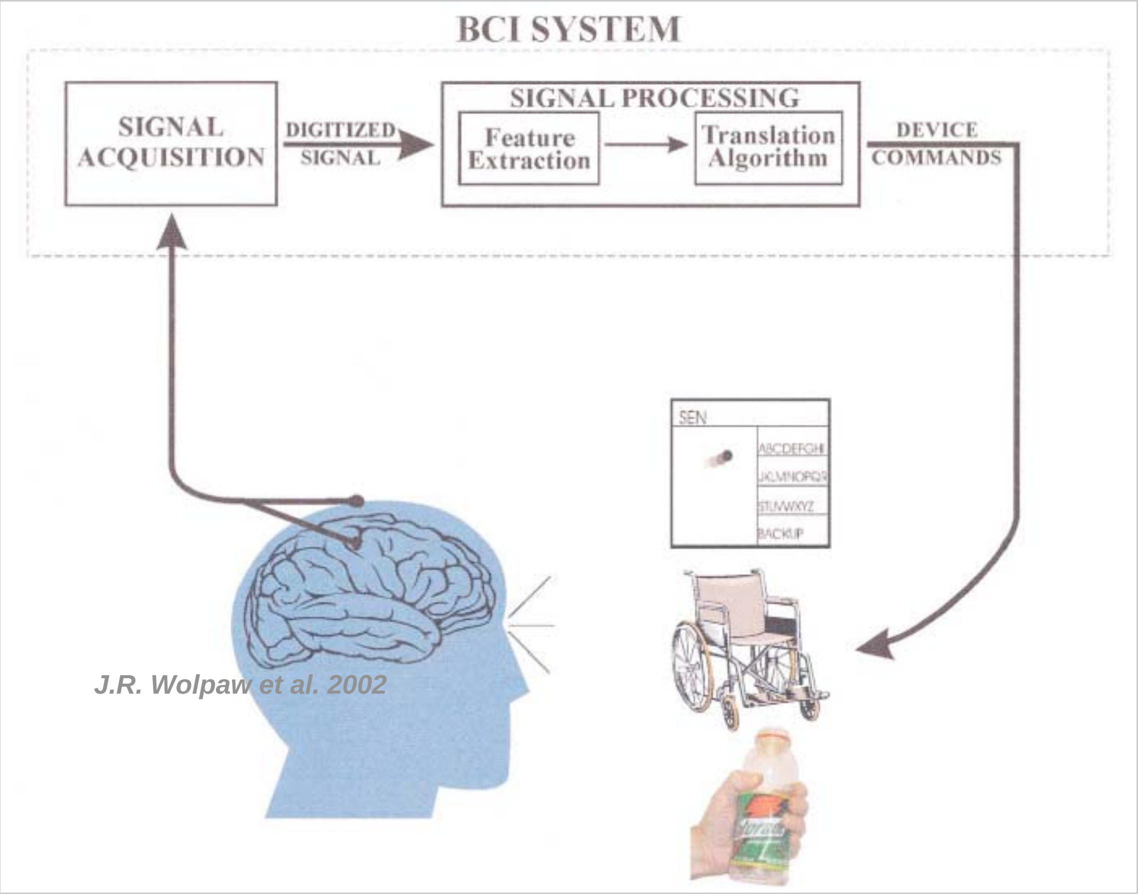
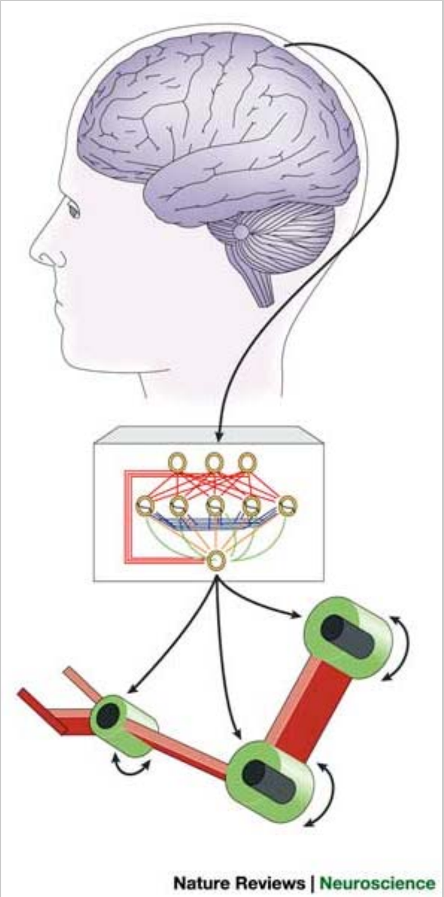
Current Architectures

BCI and BMI bypass the brain's normal peripheral nerves pathways.





Great progress was achieved in the last 10 years, BUT…. the channel bandwidth is way too low ~ 25 bits/minute (BCI) ~180 bits/minute (BMI)

BMI lessons learned

Present systems are **signal translators** and have several deficiencies.

Current decoding methods use kinematic training signals - not available in the paralyzed

I/O models cannot contend with new tasks without retraining. Subjects must change their brain activity!

There is no reason to limit the role of BMIs to passive decoders.

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WTEC Panel Report on

INTERNATIONAL ASSESSMENT OF RESEARCH AND DEVELOPMENT IN BRAIN-COMPUTER INTERFACES

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Greg A. Gerhardt
Dennis J. McFarland
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BMI lessons learned

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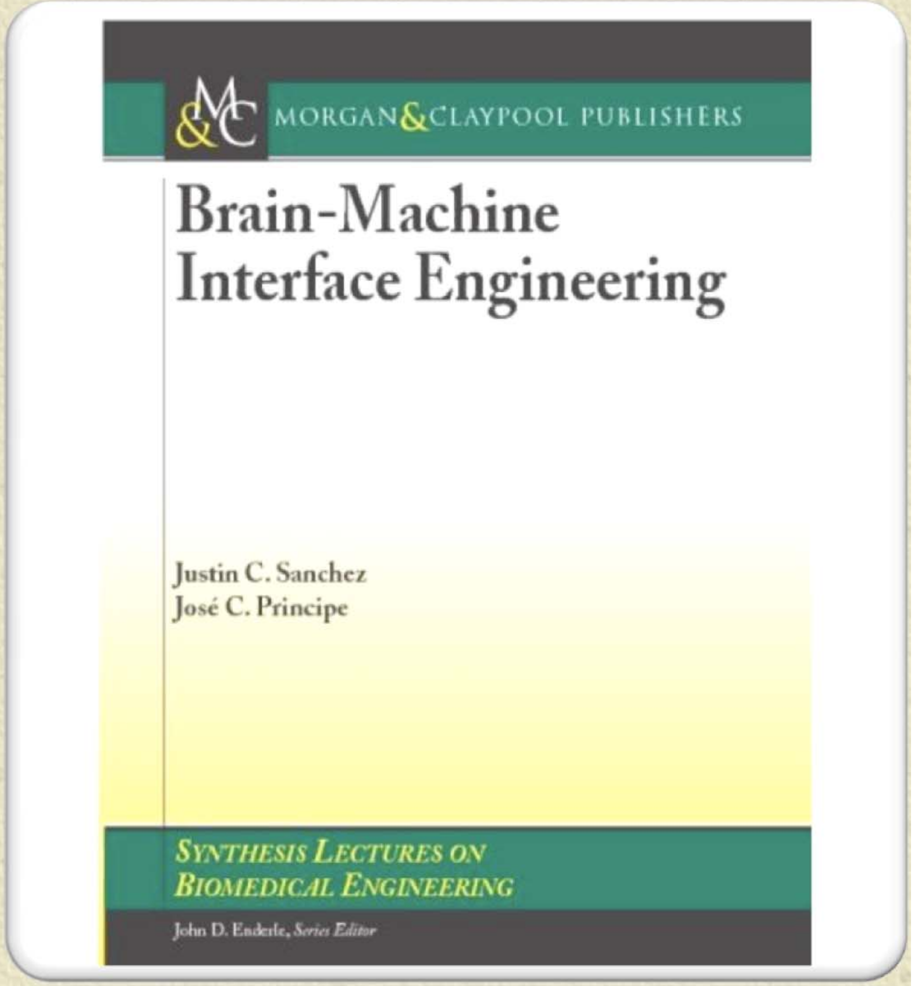


Grand Challenges

1- How to improve the channel bandwidth?

- *More neurons, but 3.26 dB per neuron (Nicolelis)*
- *Better Algorithms, but the literature shows that one should not hope for miracles!*
- *Multiscale, (EEG/ECoG, LFPs, spikes) neural centric signal processing.*

- *Perhaps all of the above will be needed.*

Multiscale Neural Signal Processing+ Modeling

Develop new algorithms with a nested hierarchy for quantifying neural population dynamics.

Least Invasive

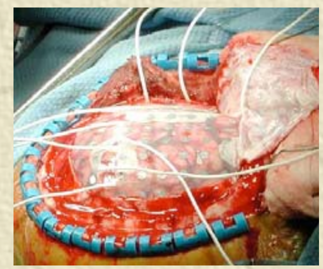
EEG

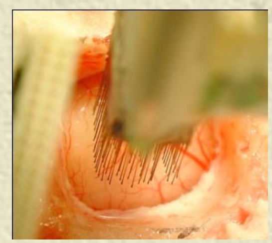
ECoG

Microelectrodes

LFP+SPIKES

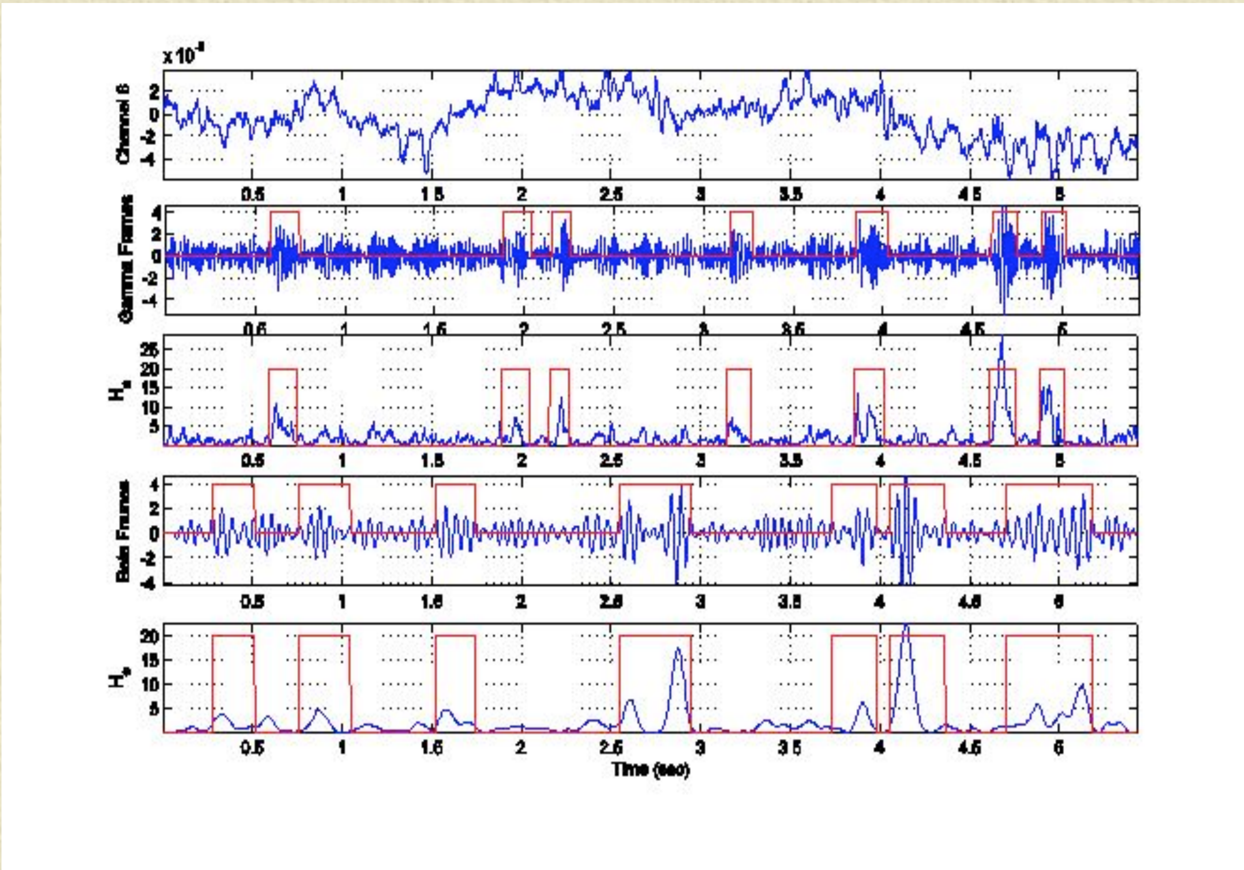
Highest Resolution





Warning: be careful with the Fourier transform

I- Understand EEG/ECOG Spontaneous Activity On-line Detection of Perceptual Frames



Beta /Gamma Frames

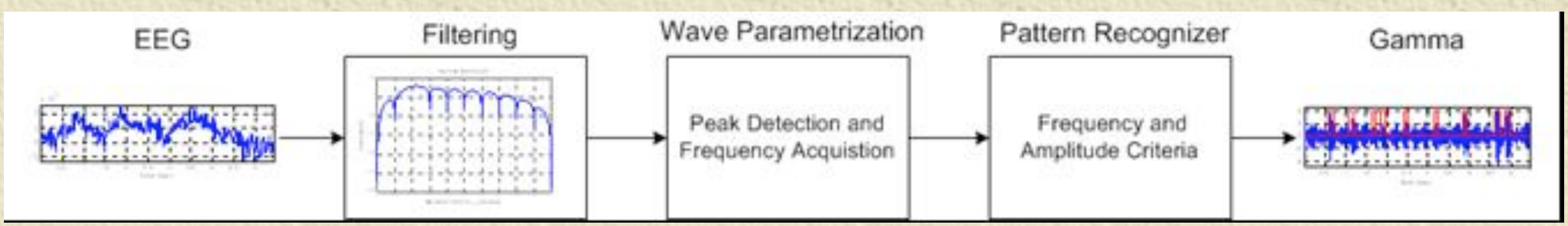
- Pragmatic Information (**Walter Freeman**)

$$H_e(t) = \frac{1}{N}\sum_{i=1}^{N}\frac{\left\|X_i(t)\right\|^2}{\left\|X_i(t)-X_i(t-1)\right\|}$$

$$X_i(t) = x_i(t) + j\cdot H\{x_i(t)\}$$

H{.} Hilbert Transform

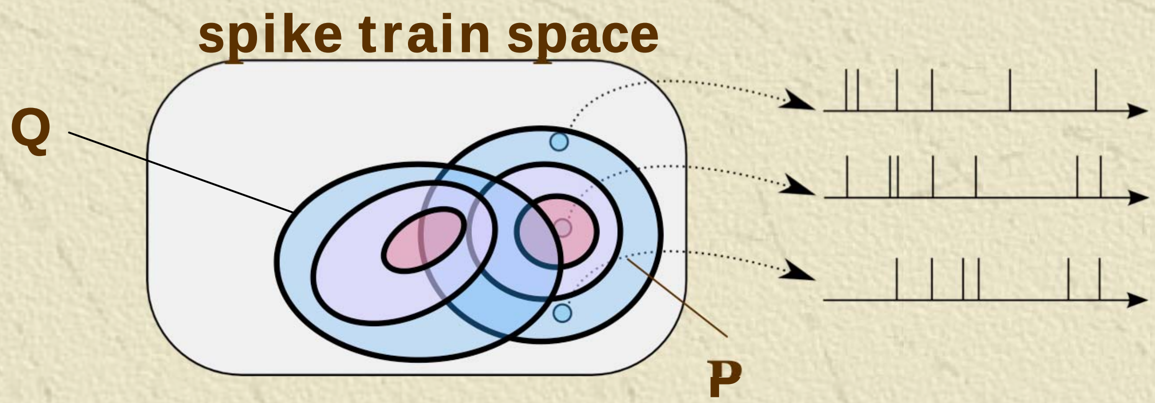
- Our pattern recognizer matches them well



I-Definition of Spike Trains

Point process describes stochastically a sequence of events occurring in time

A spike train is **a realization** of a point process



- The probability measure over the spike train space defines a point process
- Advantage: Spike trains naturally create a sparse representation
- Disadvantage: The theory of point processes is difficult.

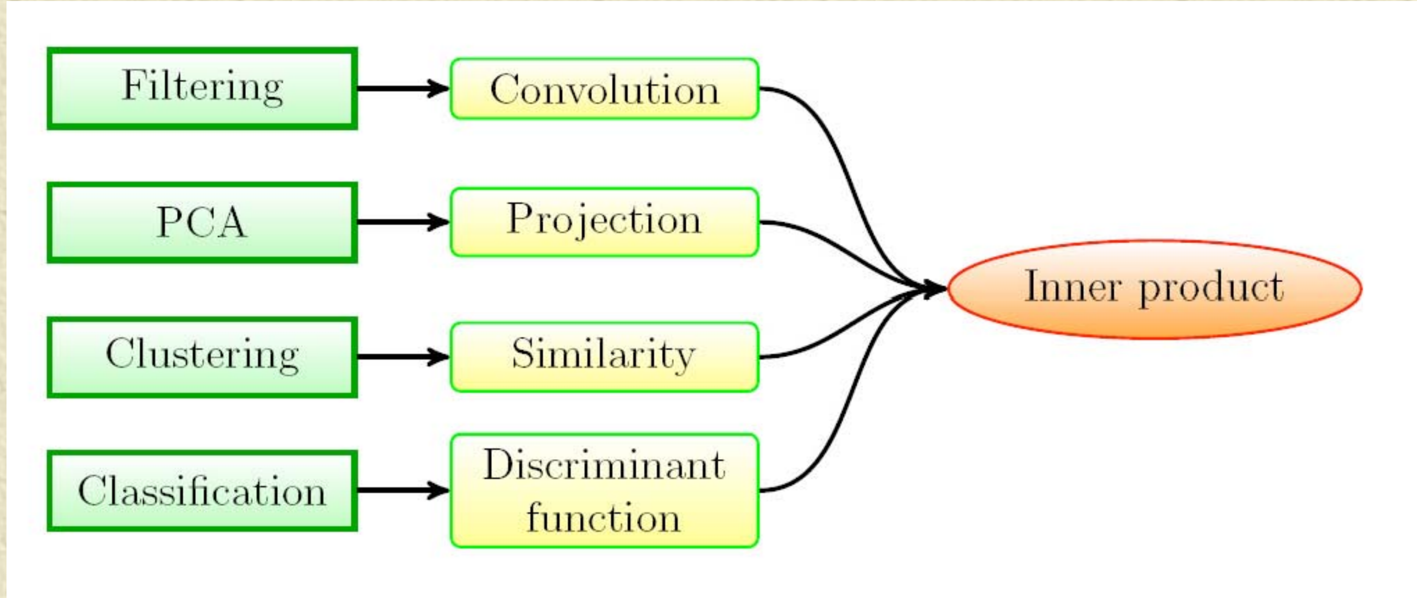
I-Requirements for signal processing with spike trains

	topology	metric	linear structure	norm	inner product	
Metric space	O	O				**k-Nearest Neighbor algorithm**
Banach space	O	O	O	O		**k-means algorithm**
Hilbert space	O	O	O	O	O	**Support Vector Machine, Least squares, PCA, CCA, …**
Point processes?	?	?	?	?	?	

Most signal processing algorithms operate in Hilbert space.

What to do: binning (that is easy and explores the sparseness), but it only **captures the full information** contained in the spike train structure in very restricted cases (Poisson).

I- Inner Product: The fundamental operator for signal processing



How can we do it?

We have defined a Reproducing Kernel Hilbert Space (RKHS) to provide the mathematical structure to perform signal processing with spike trains.

Paiva, et al Neural Computation, 2008

I- Cross-intensity kernels

- Given two point processes p_i, p_j, define the inner product between their conditional intensity functions

$$\lambda(t \mid H_t) = \lim_{\Delta t \to 0} \frac{\Pr\{\text{event in}[t, t + \Delta t) \mid H_t\}}{\Delta \text{t}}$$

$$I(p_i, p_j) = \left\langle \lambda_{p_i}(t \mid H_t^i), \lambda_{p_j}(t \mid H_t^j) \right\rangle_{L_2(T)}$$

$$= E\left[\int_T \lambda_{p_i}(t \mid H_t^i) \lambda_{p_j}(t \mid H_t^j) dt\right]$$

- This yields a family of cross-intensity (CI) kernels, in terms of the model imposed on the point process history, H_t.

I- Kernel Examples

- Memoryless CI (mCI) kernel: For the Poisson process the inner product simplifies to

$$I(p_i, p_j) = \int_T \lambda_{p_i}(t)\lambda_{p_j}(t)dt$$

This is the simplest of the CI kernels.

- Nonlinear cross-intensity (nCI) kernel:

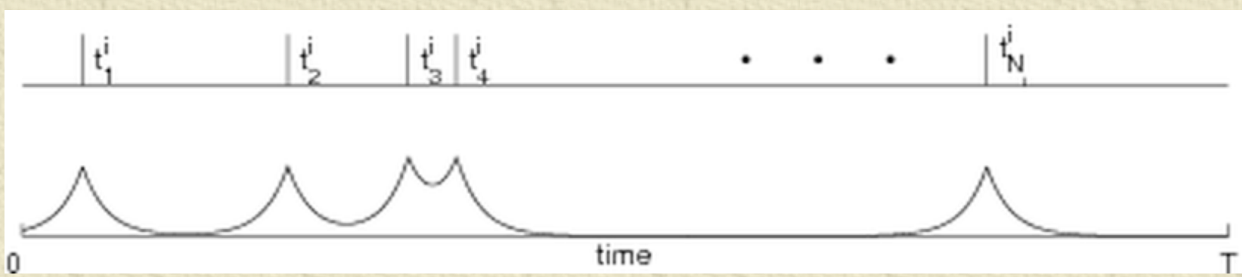
$$I_\sigma^*(p_i, p_j) = \int_T \kappa_\sigma(\lambda_{p_i}(t), \lambda_{p_j}(t))dt$$

with κ_σ a symmetric positive definite kernel, which is sensitive to nonlinear couplings in the time structure of the intensity functions (such as in renewal processes).

I- Estimation of the mCI kernel

- One needs to estimate the intensity function.
- Simplest approach is kernel smoothing: Places a smoothing function (e.g. exponential) at each event location,

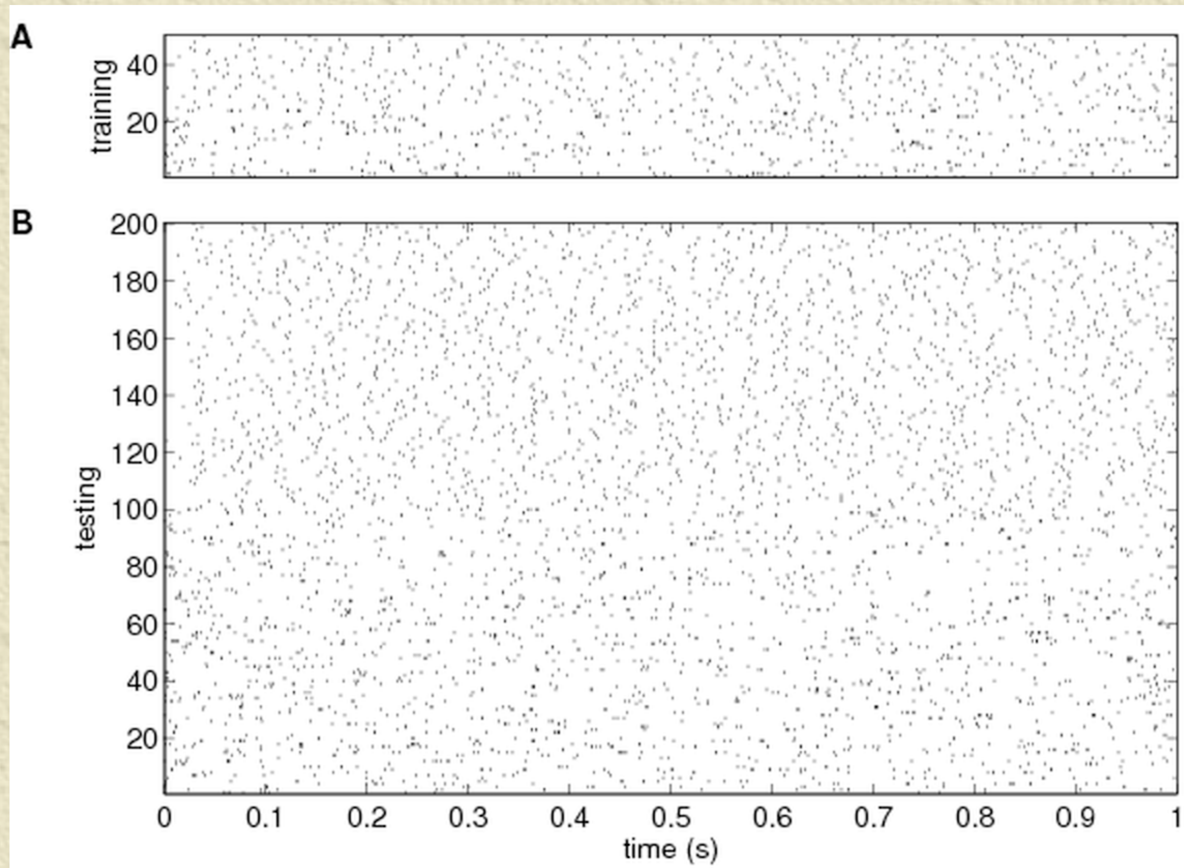
$$\hat{\lambda}_{p_i}(t) = \sum_{m=1}^{N_i} h(t - t_m^i)$$



- Shows clearly the difference between spike timing and rate methods (window size).

I- PCA of Renewal Process Structure

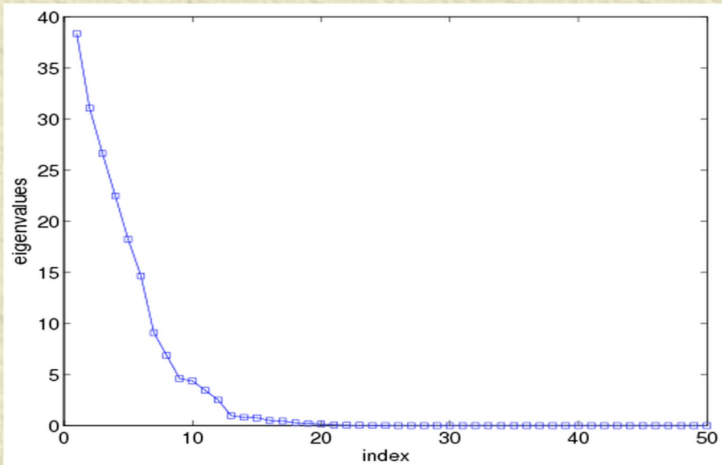
Dataset

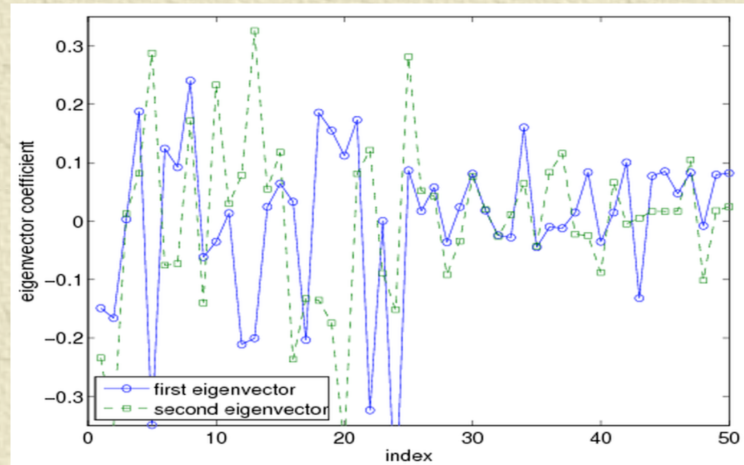


I- PCA of Renewal Process Structure

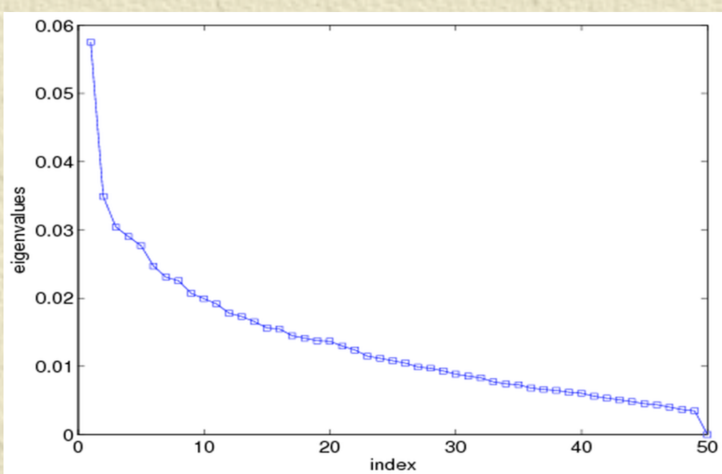
Eigenvalues and eigenvectors of ST structure

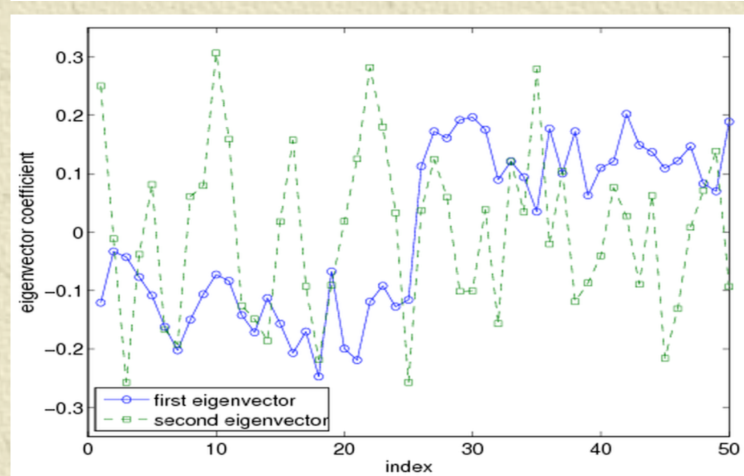
mCI kernel





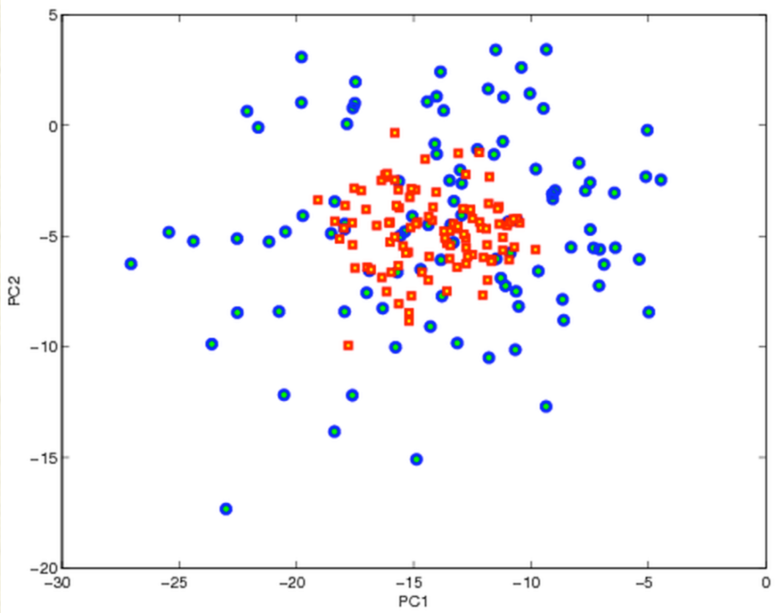
nCI kernel

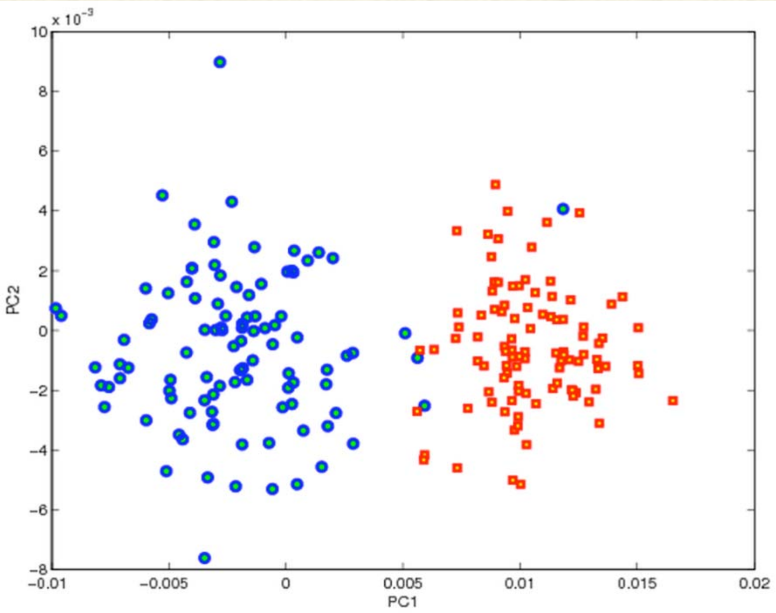




I- PCA of renewal processes

Projection of testing dataset





mCI kernel

nCI kernel

II- Kernel induced divergences

$$\mathcal{D}_K(P,Q) = \iint K(x,y)\,\mathrm{d}\mu(x)\,\mathrm{d}\mu(y)$$

$$\mu = P - Q$$

- If K is a strictly positive definite function on spike trains, D_K is a divergence, i.e. it captures full statistics.

$$\sum_{i=1}^{N_P}\sum_{j=1}^{N_P} K(x_i,x_j) - 2\sum_{i=1}^{N_P}\sum_{j=1}^{N_Q} K(x_i,y_j) + \sum_{i=1}^{N_Q}\sum_{j=1}^{N_Q} K(y_i,y_j)$$

II- Statistical Inference with Kernel Divergence

Hypothesis testing	• Change point detection, non-stationarity detection, plasticity detection
Goodness of fit	• Model fitting
Neural coding	• Classification error bound • Coding capacity in the presence of constraints and noise
Dependence	• Functional connectivity
Conditional dependence	• Causality, functional connectivity

Park and Principe, ICASSP 2010

Grand Challenges

1- How to Improve the Channel Bandwidth?

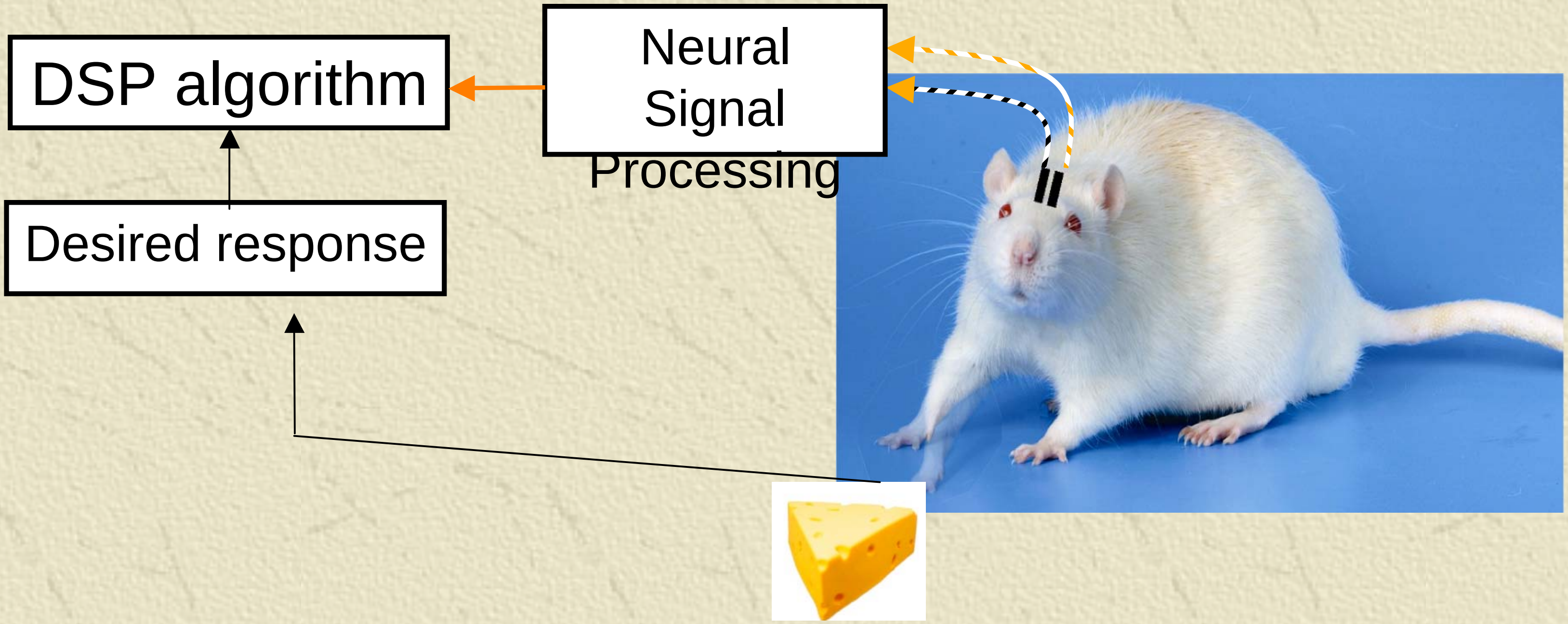
Neural centric signal processing

2- How to learn online the decoding without kinematic variables?

Decoding is a necessary first step. But it can be improved. Novel BMI architectures – Symbiotic BMIs

- *Allows for novel ways of cooperative adaptation and learning to expand the universe of brain decoders*
- *Capitalizes on the engineering knowledge of optimal control and computational intelligence*

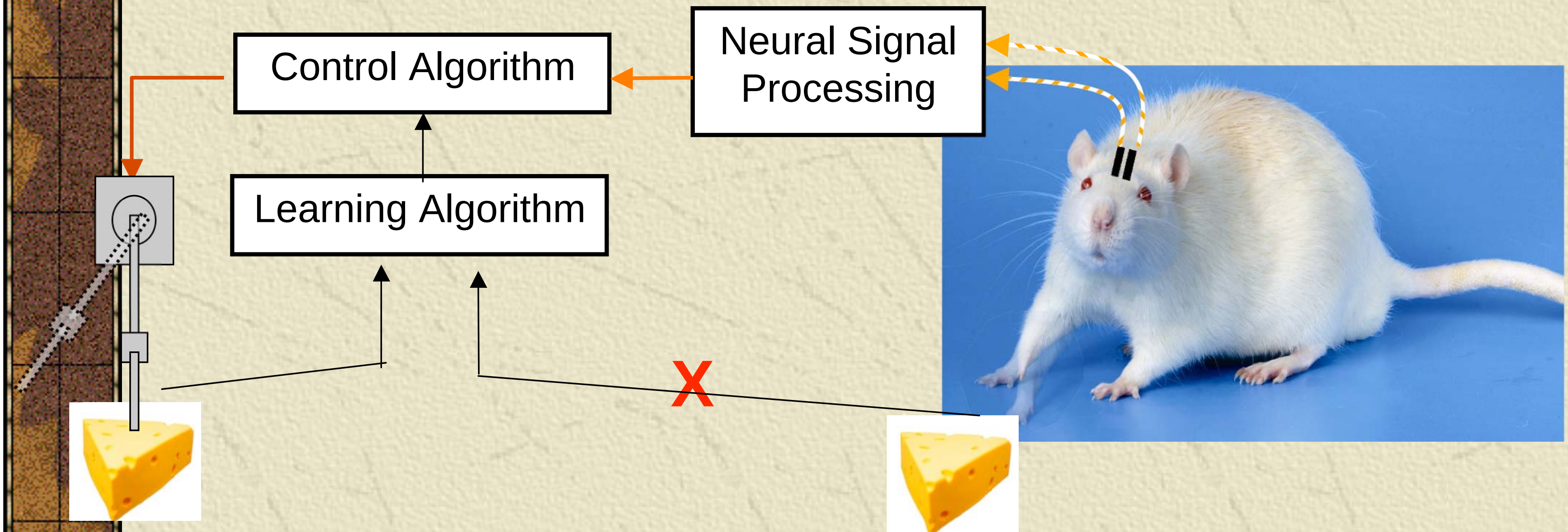
A Paradigm Shift for BMIs!



During training the user actions create a desired response to the DSP algorithm.

During testing the DSP algorithm creates an approximation to the desired response.

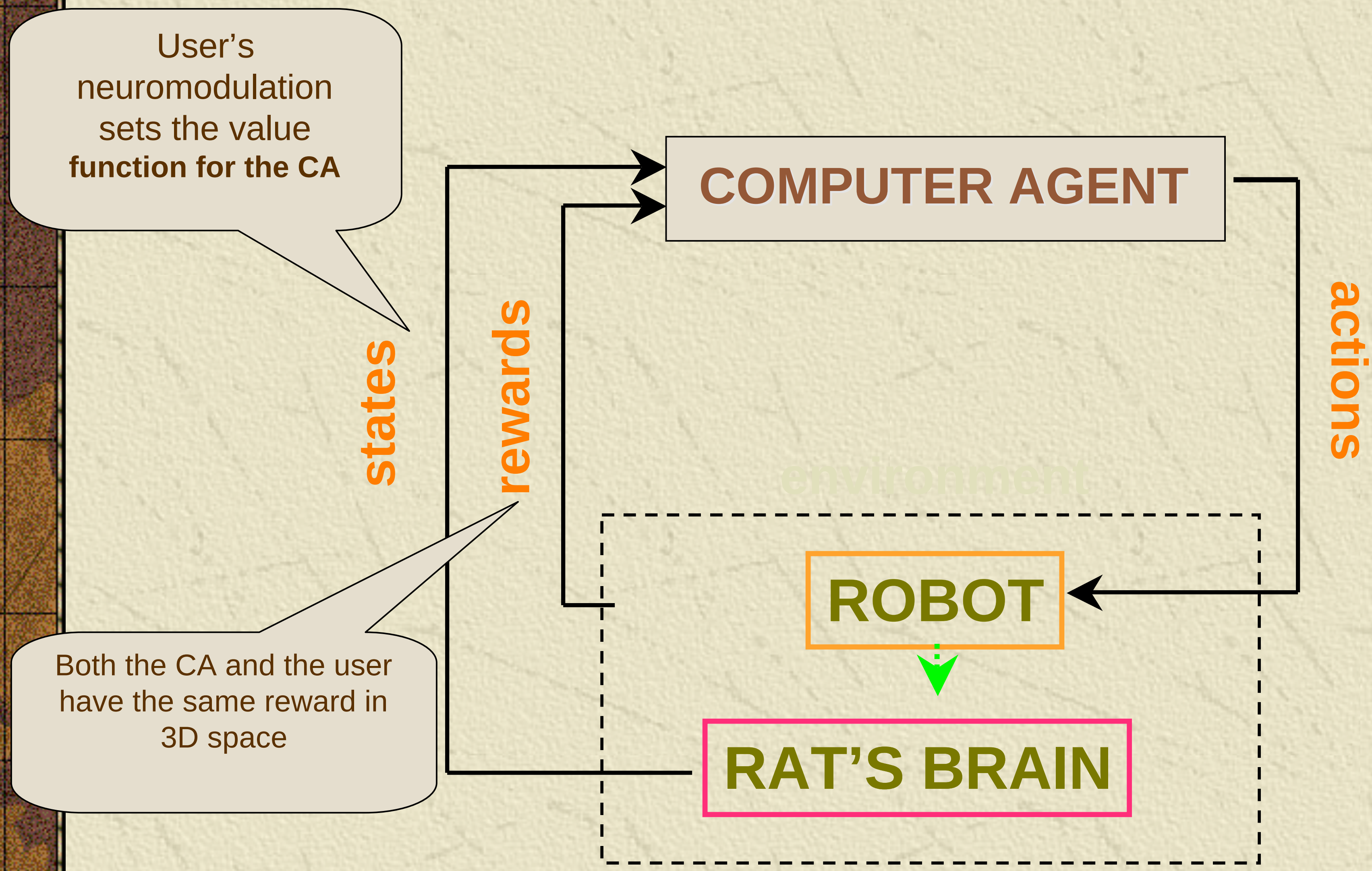
A Paradigm Shift for BMIs!



The control algorithm learns through reinforcement to achieve common goals in the environment.

Shared control with user to enhance learning in multiple scenarios and acquire *the net benefits of behavioral, computational, and physiological strategies*

S-BMI involves TWO intelligent agents in a cooperative dialogue!!!



Features of Symbiotic BMI

- Both systems adapt in close loop in a very tight coupling between brain activity and computer agent CA (CA states are specified by brain activity).
- User must incorporate the CA in its world representation
- CA must decode brain activity to evaluate its actions.
- This architecture implements a symbiotic biological-computer system.
- First Generation:

Reinforcement Learning

(biological plausible)

Closed-Loop RLBMI (top view)

Functional levers

Non-functional levers

Robot workspace in rat visual field of view.

BLUE – Robot

GREEN - Lever

Top-view of the rat behavioral cage.

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Novel BMI architectures – Symbiotic BMIs

3 – Funding

I would hope that NIH creates **a new Study Section** *for neuro prosthetics (CNS/PNS) to capitalize on the critical mass, knowledge, vitality and vision of this group of researchers*

Team

Jack DiGiovanna - BME

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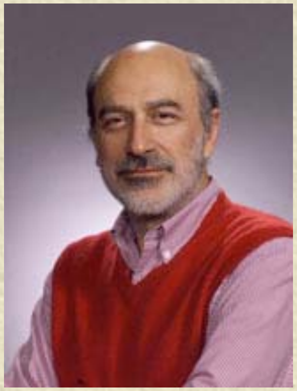

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