BCI/BMI research for Neural Prosthesis

(or Brain to Hand
Or Decoding Dexterity)

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Revolutionizing Prosthesis
DARPA RP 2009 Grand Challenge

S. Harshbarger
and
JHU/Applied
Physics Lab
Team

BCI: Brain Computer Interface

BMI: Brain Machine Interface

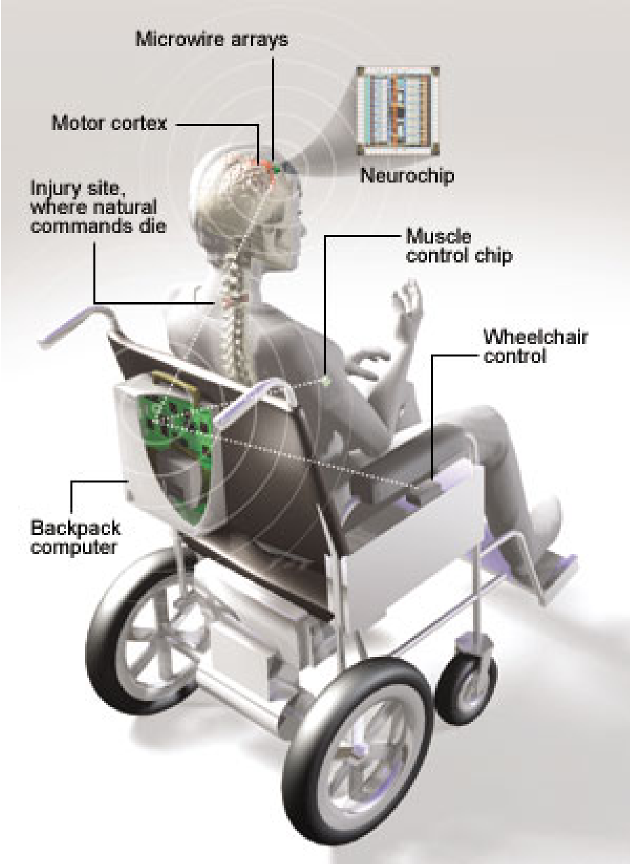
Motivation for BCI/BMI Research

rebuilding instead of repairing

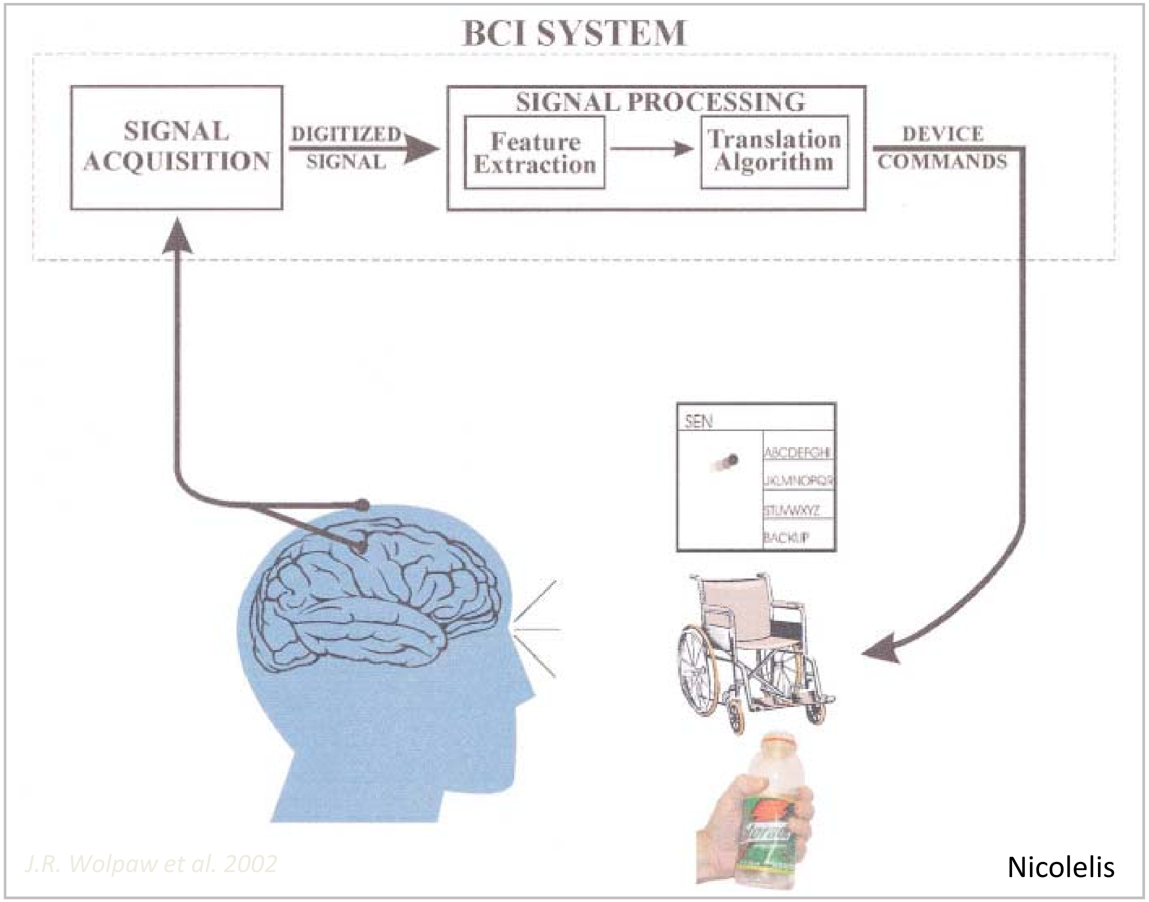
In USA, more than 200,000 patients live with the motor sequelae (consequences) of serious injury. There are two ways to help them restore some motor function:

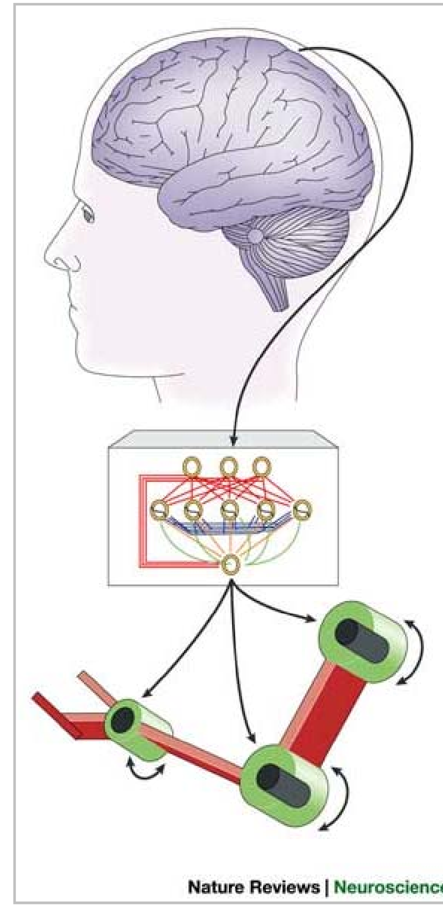
- Repair the damaged nerve axons
- **Build neuroprosthetic device**

Not a natural way, but a imitation



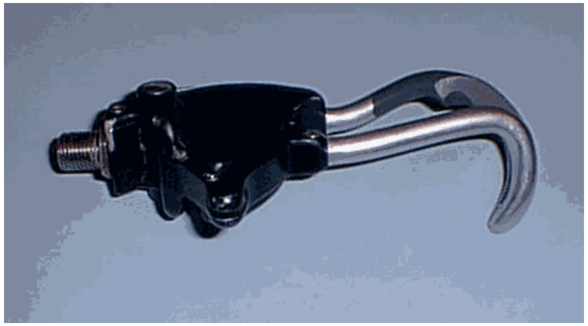
Nicolelis, 2001

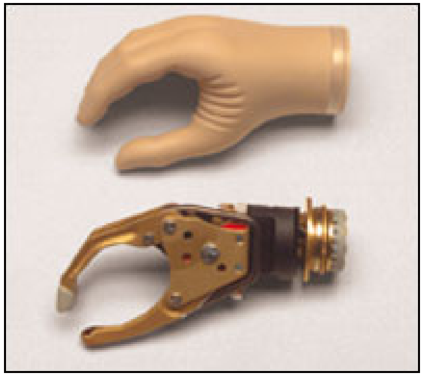




BCI (BMI) **bypasses the brain's normal pathways of peripheral nerves and muscles**

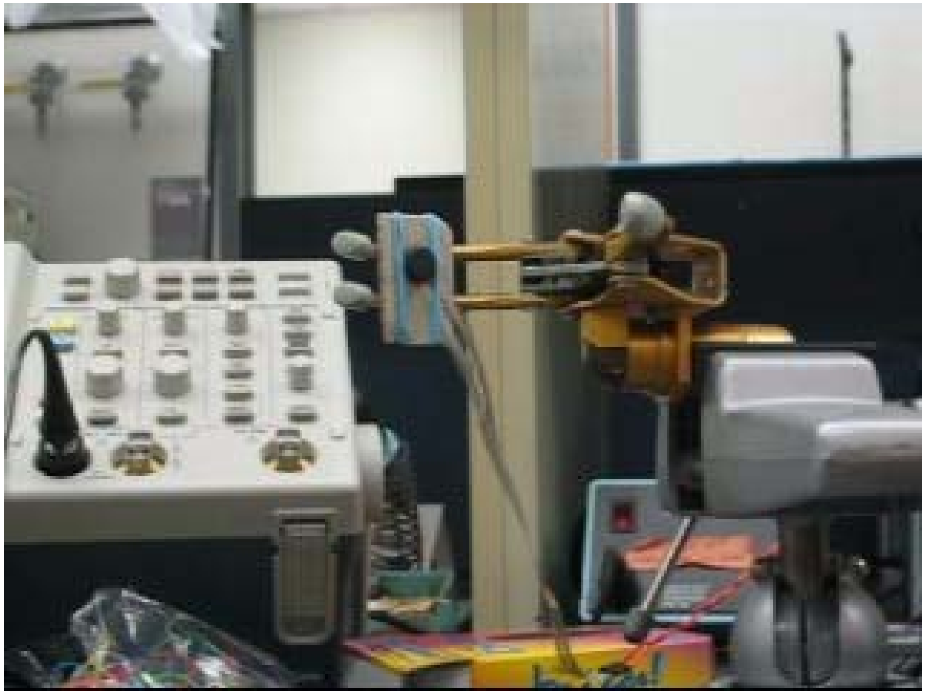
Prostheses



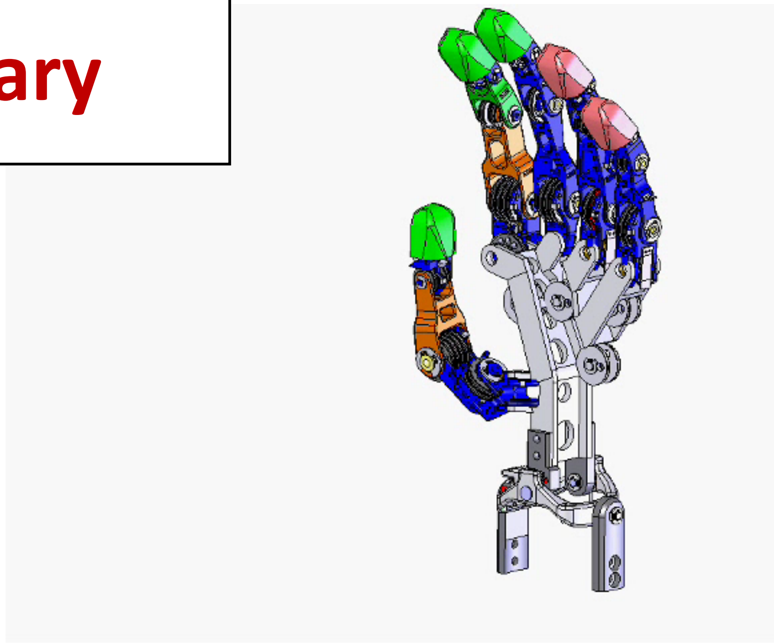


Commercially available prosthetics from otto bock

Present Prosthetic Hands/Claws



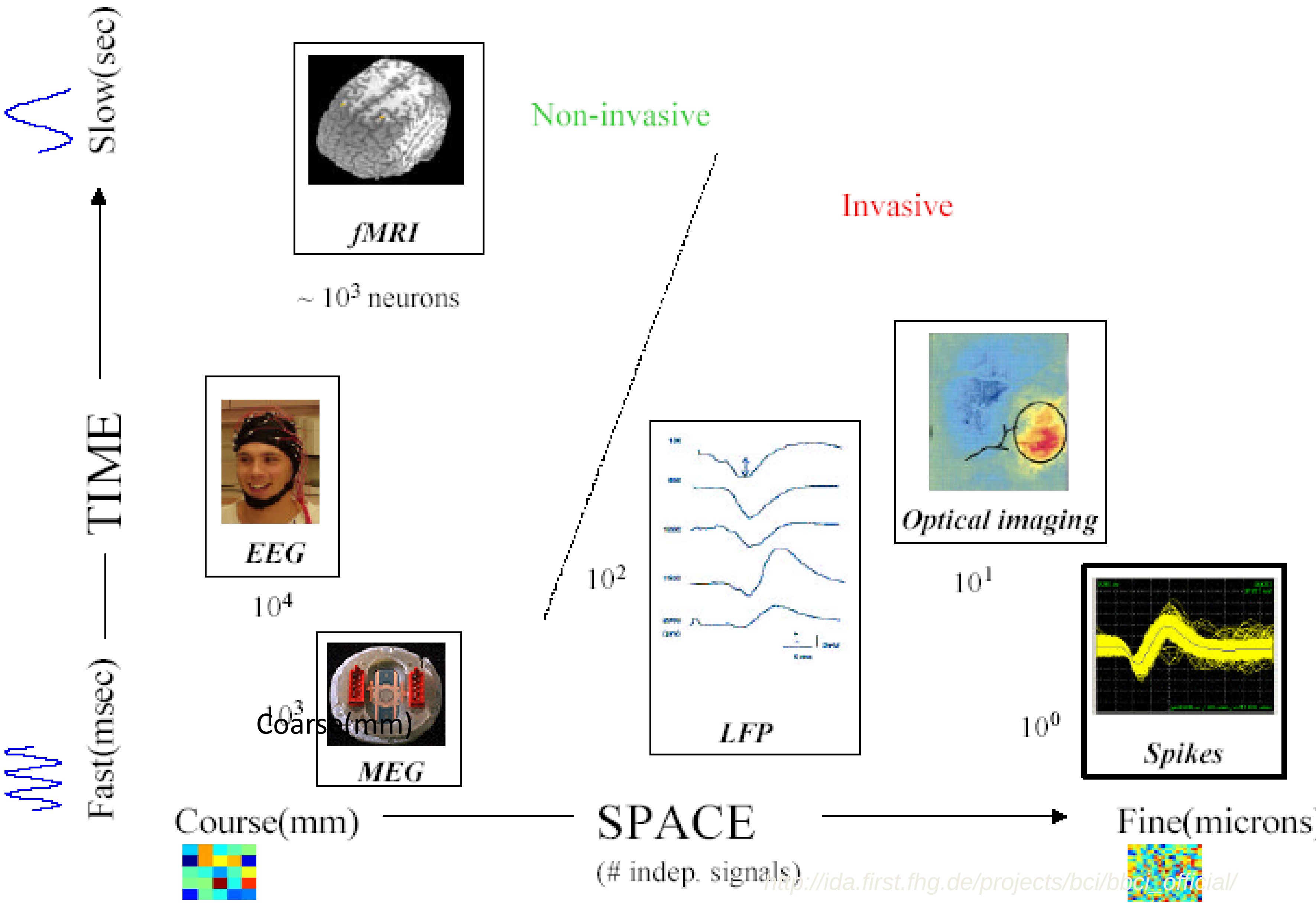
State of the Art Prosthetic Hand Development – Revolutionary Prosthetics Program



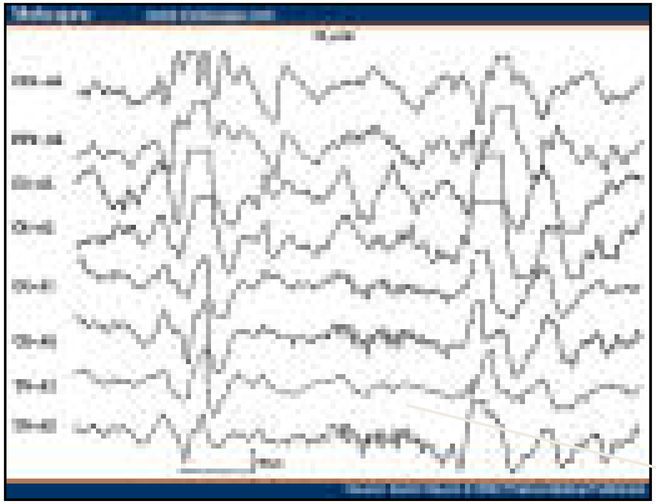
“Michelangelo Hand” – developed by Otto Bock

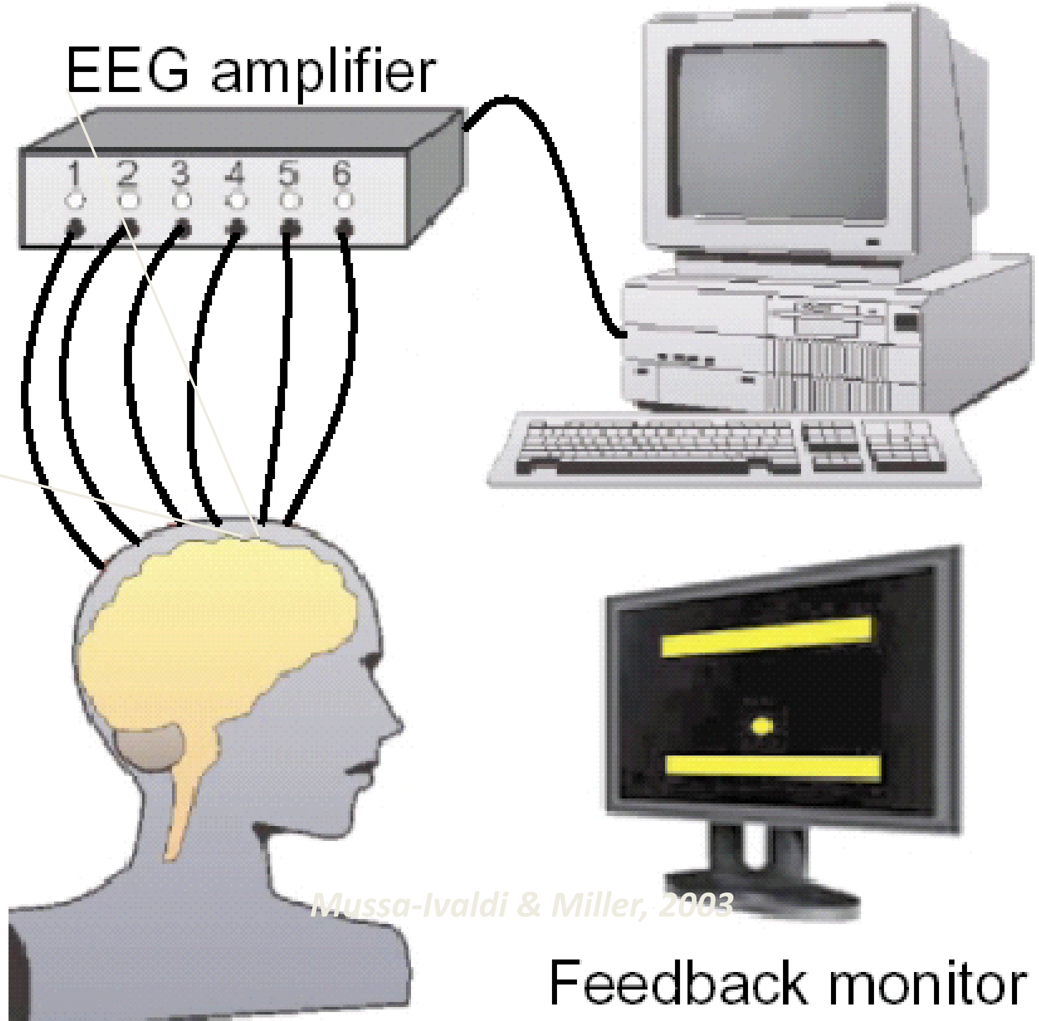
- Weight = 400 g
- Speed of opening = 408 mm/sec
- Grip force = 120 N (27 lbsf)
- Width of opening = 102 mm (4”)
  - Powered by Lithium-Ion battery within the Dynamic Arm. Sufficient capacity to operate for 18 hours of usual everyday activities

Spatial and Temporal Scales of Neural Signals



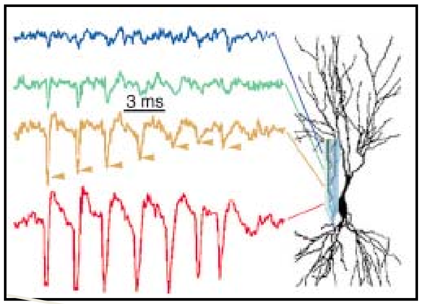
Nonivasive: EEG based BCI

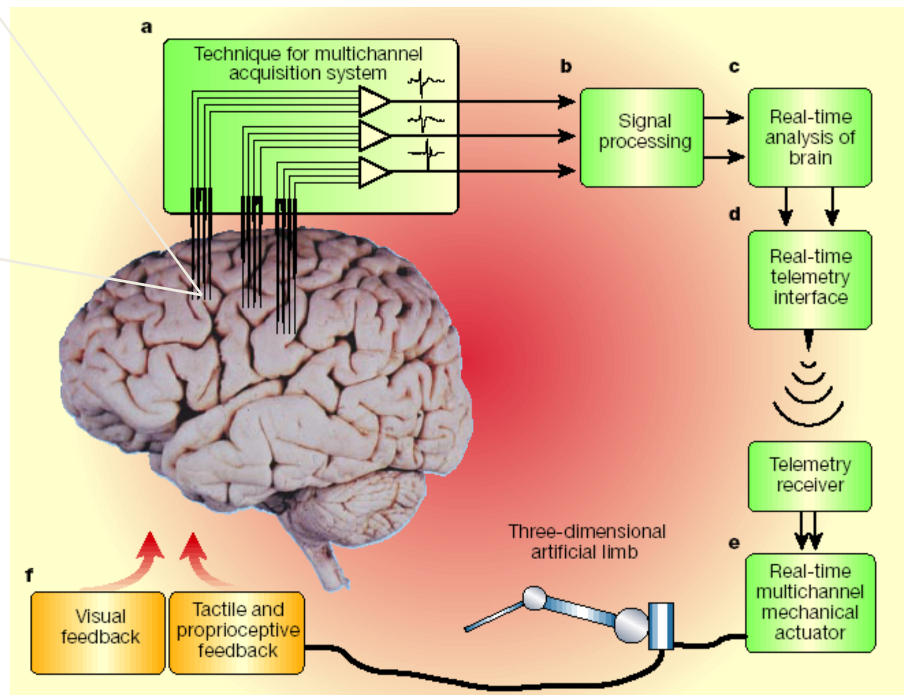




- non-invasive
- promising for some therapies
- time-consuming
- not suitable for precise control

Neuron Spike based BMI

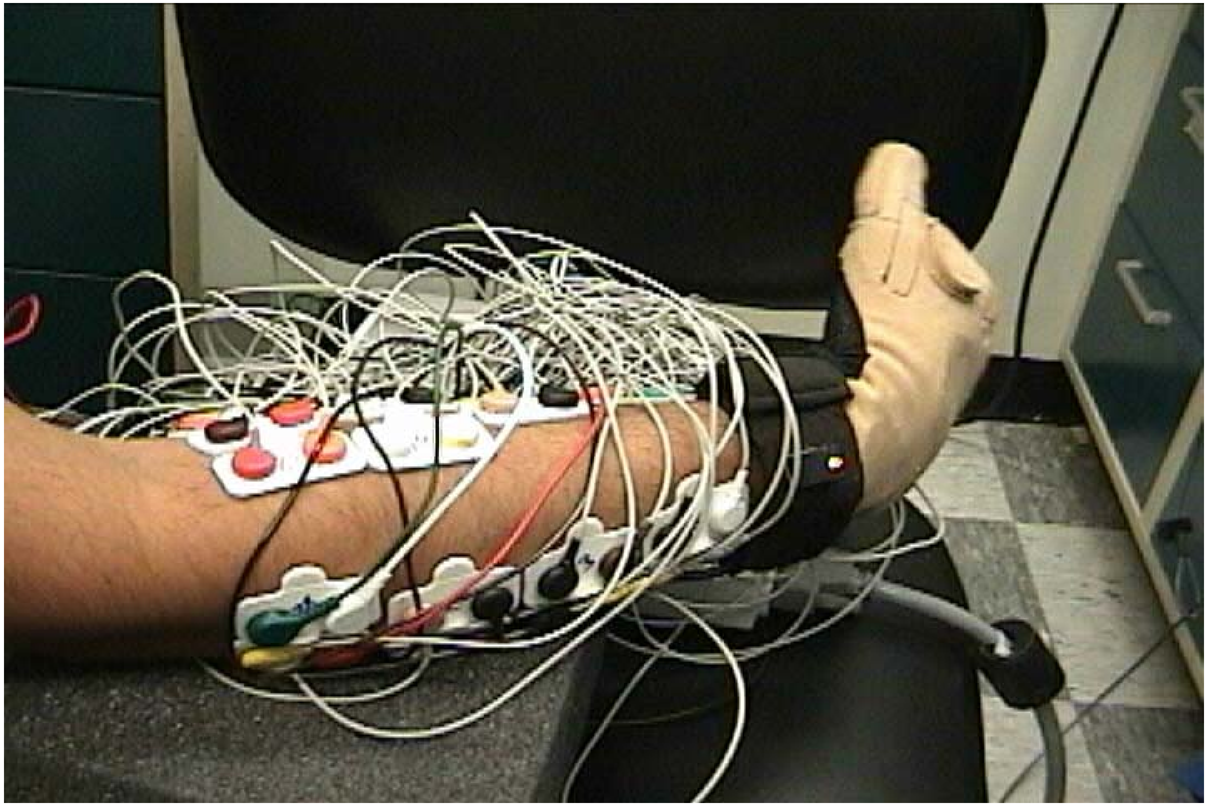




Nicolelis, 2001

- high speed real time control
- precise control of movement
- invasive
- high risk for clinical application

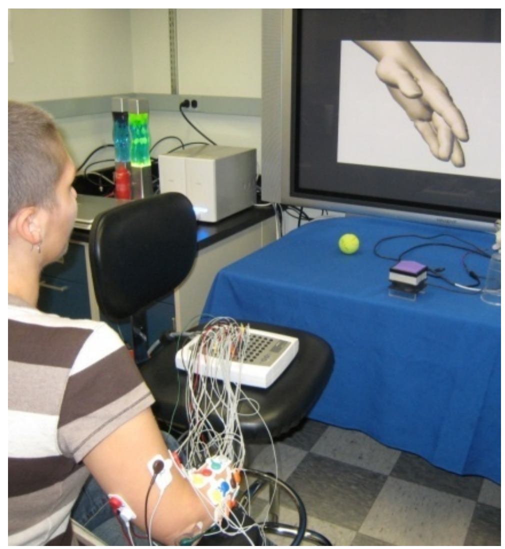
Part I: Muscle Conrtol of Prosthesis

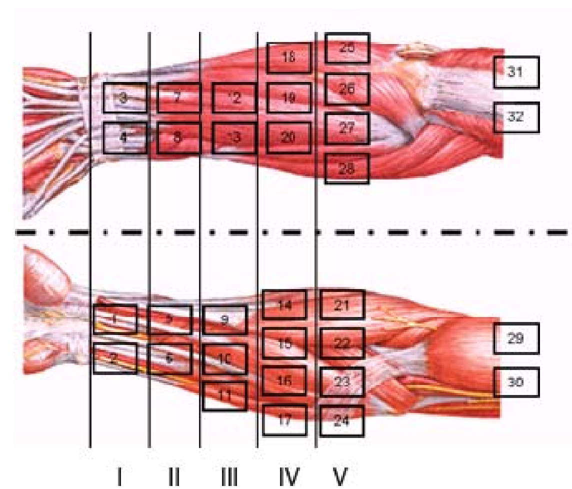


With F. Tenore, R. Smith, D. Huberdeau, M. Parmar, R. McLaren, R. Etienne-Cummings

Experimental protocol

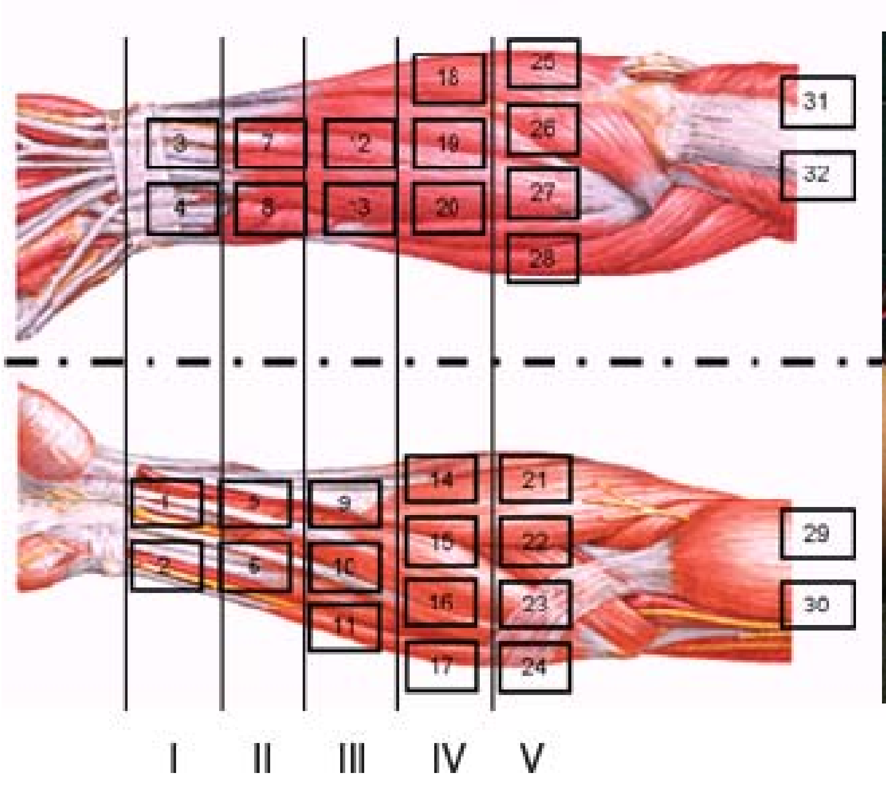
- Acquisition of non-invasive surface EMG signals from arm
- Data gathered from healthy adults and amputees

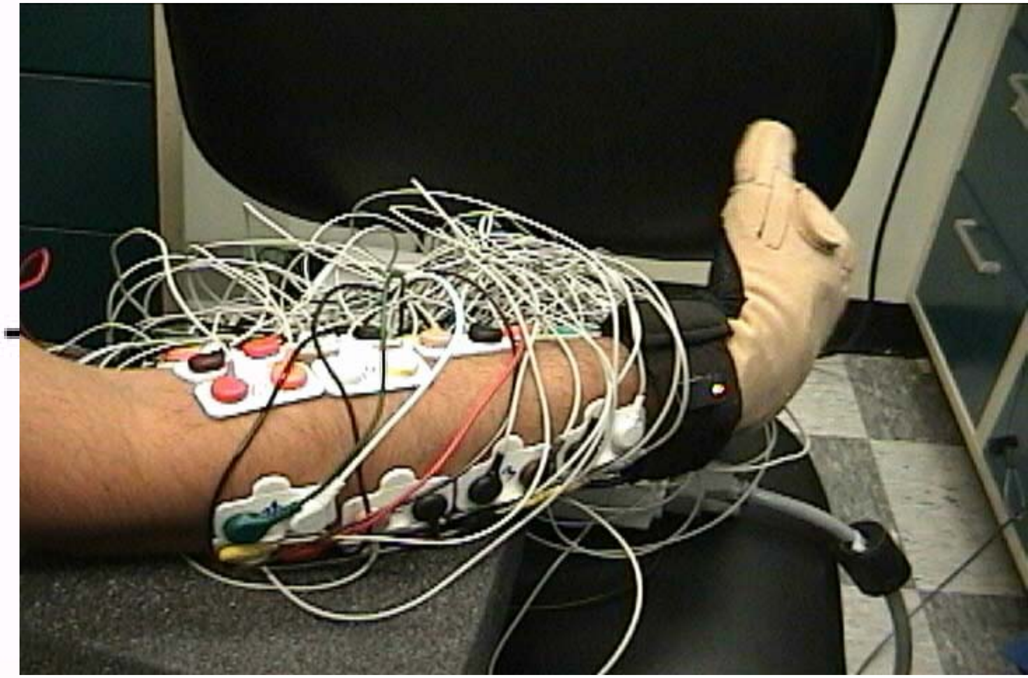




F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, N. V. Thakor, 2007. **Towards the Control of Individual Fingers of a Prosthetic Hand Using Surface EMG Signals***. Proc EMBC, 2007*.

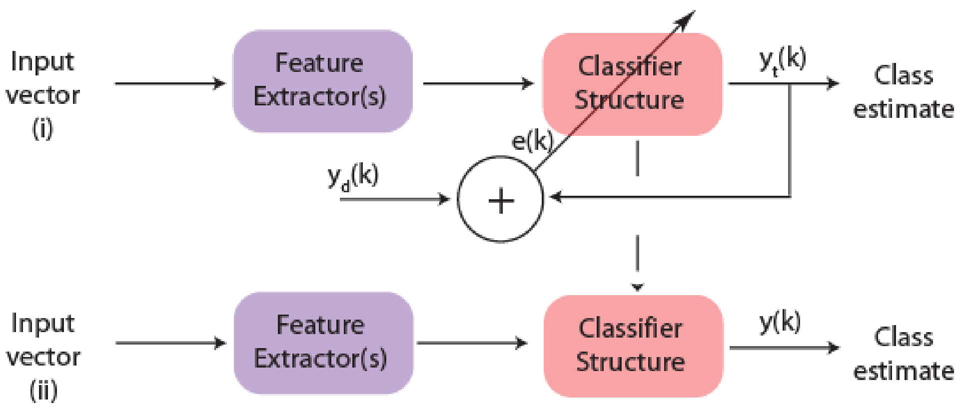
Experimental Setup

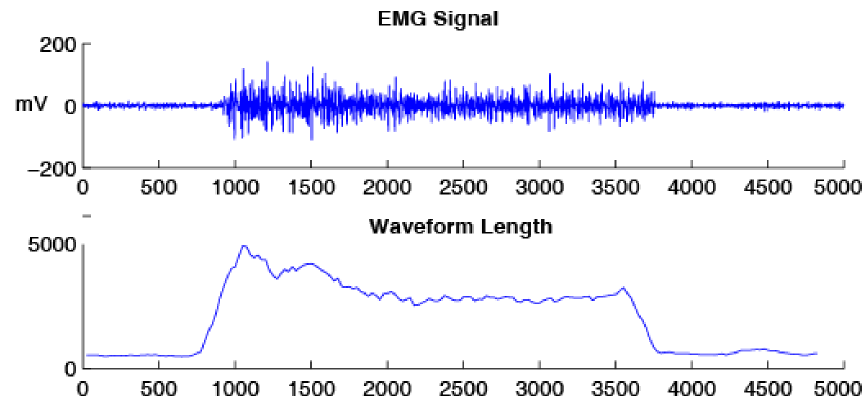




Decoding movements

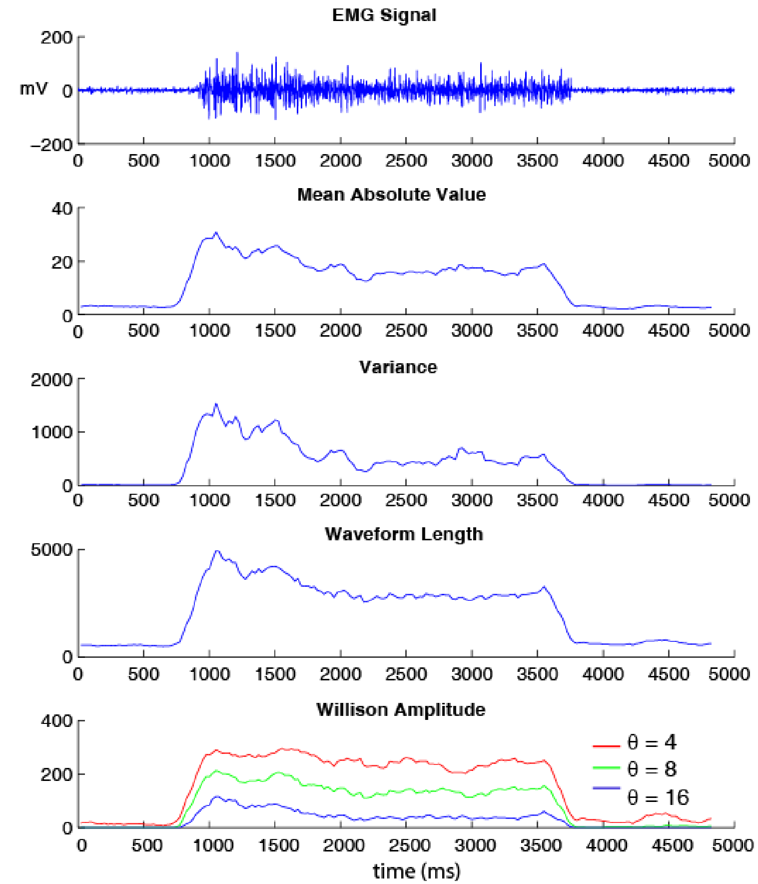
- Extraction of EMG features
- Multilayer neural networks
- Implementation in virtual model

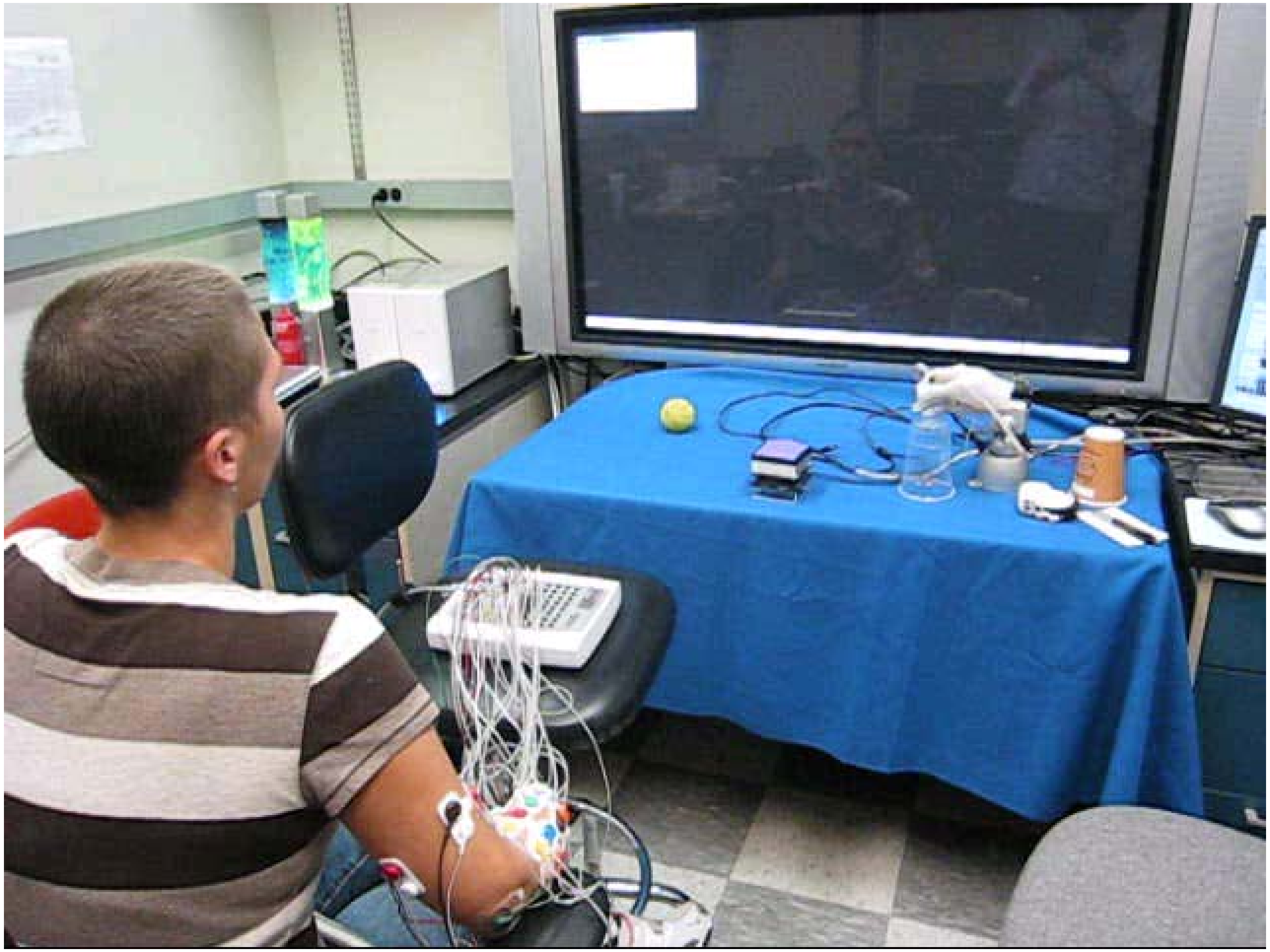




Feature Extraction: Time Domain Features

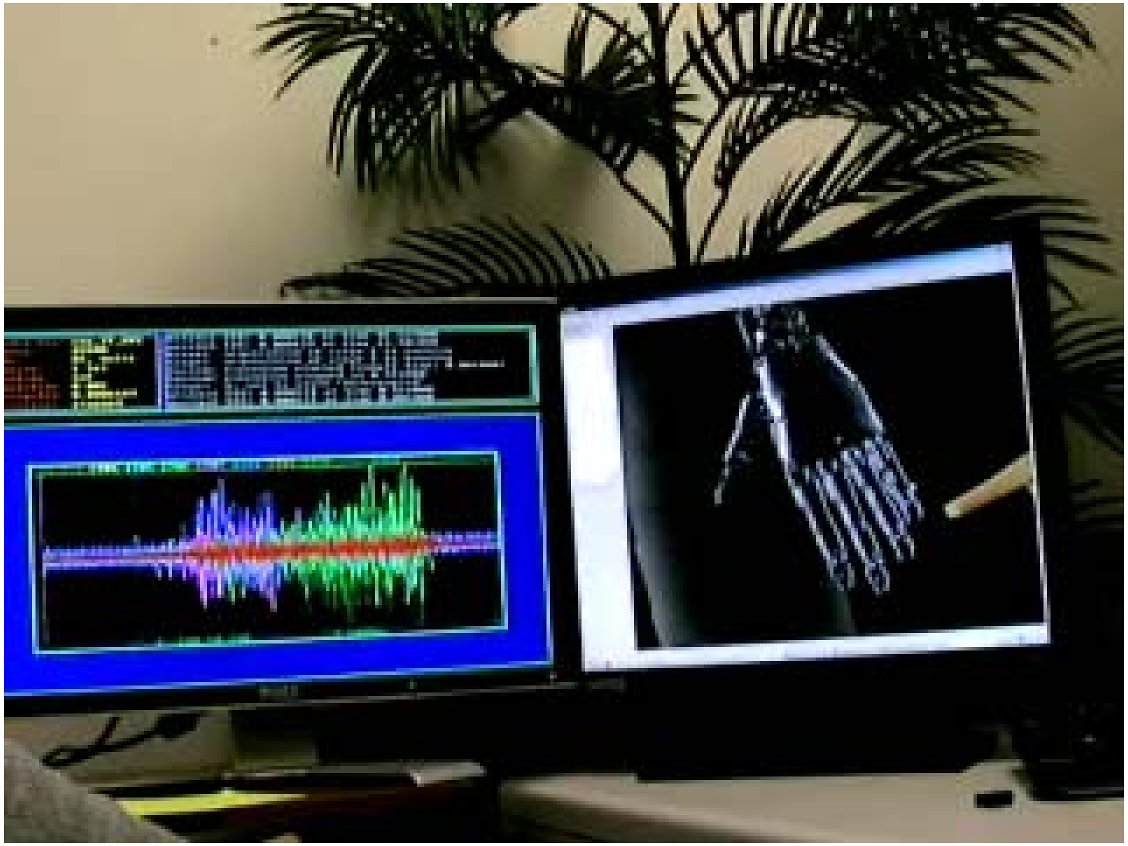
- Four features examined:
  - Mean absolute value: [redacted]
  - Variance: [redacted]
  - Waveform length: [redacted]
  - Willison Amplitude: [redacted]





Open Loop Decoding in Virtual Integrated Environment

- Open loop processing in VIE allows visualization of algorithm functionality

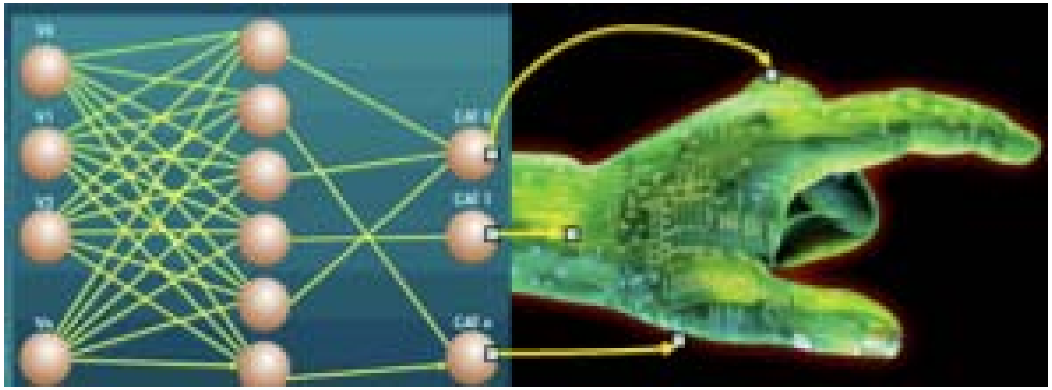


Toward Continuous Position Decoding

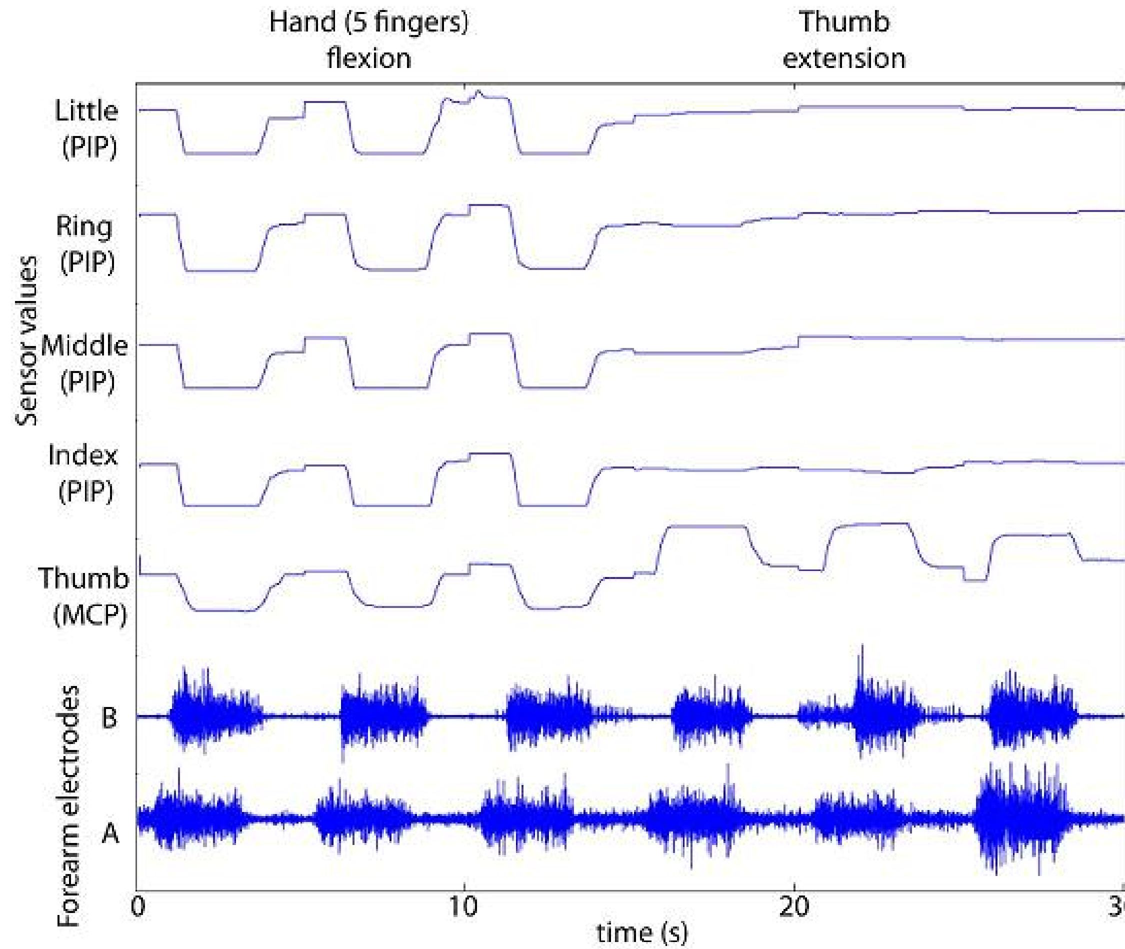
- Current focus on classifying limited number of movements e.g. index flexion, wrist abduction
- With aid of tracking systems, e.g. CyberGlove, decoding of continuous range of positions

Methods: Neural Network

- A feed-forward neural network was constructed
  - Hidden layer neurons ~ Tan sigmoid transfer function
  - Output neurons ~ Pure linear transfer function
- Training
  - Input ~ Feature vector from EMG signals
  - Target Output ~ Vector of CyberGlove data for MCP joints
  - Trained with scaled conjugate descent algorithm



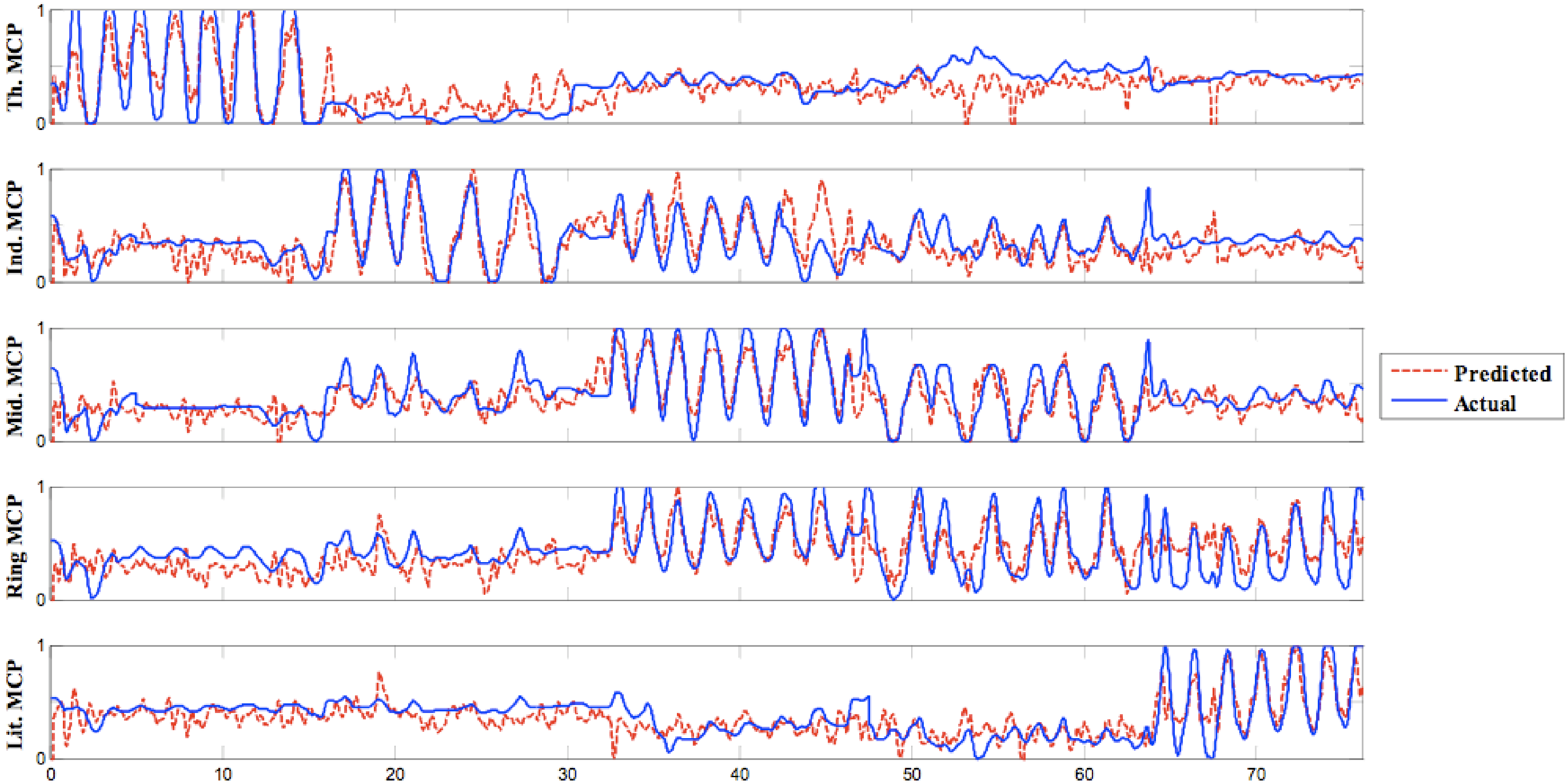
Real-time Finger Tracking to Improve Upper-Limb Prosthetic Control



Huberdeau D, Aggarwal V, Tenore F, Fritz K, Etienne-Cummings R, Thakor NV, “Real-time finger tracking to improve upper-limb prosthetics control”, Proc 34th Ann Northeast Bioeng Conf, Providence, RI, Apr 2008.

Smith R, Tenore F, Huberdeau D, Etienne-Cummings R, Thakor NV, “Continuous decoding of finger position from surface EMG signals for the control of powered prostheses”, 30th Ann Int Conf IEEE Eng in Med and Bio Soc (EMBS 2008) (article submitted)

Predicted Versus Actual MCP Joint Angles

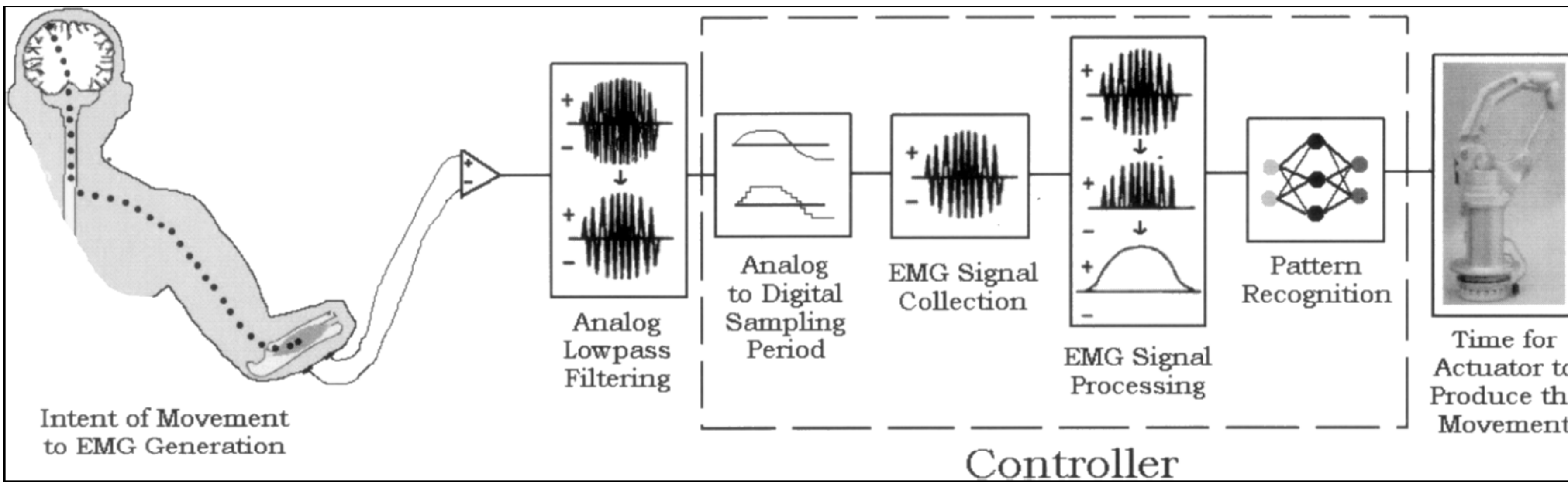


Revolutionary Prosthetics RP2009 Program

Courtsey ; S. Harshbarger and team, APL; T. Kuiken and team: RIRC

An Example Research Problem

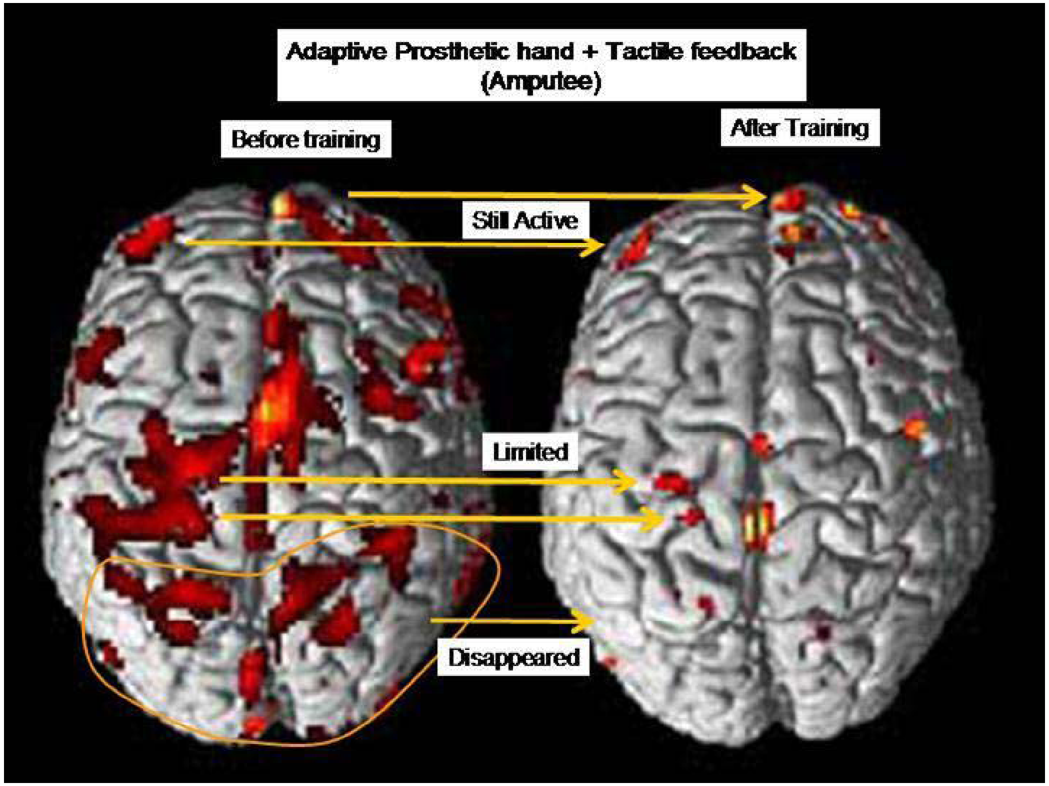
- One constraint in EMG processing is the delay time between activation of the motor units and actuation of the prosthesis
- Trade-off between feature extraction/processing time and responsiveness



Farrell, T.R.; Weir, R.F., "The Optimal Controller Delay for Myoelectric Prostheses," *IEEE Trans.*, *Neural Systems and Rehab. Eng.*, vol.15, no.1, pp.111-118, 2007

Human Adaptation

- Traditional focus exists on machine adapting to the human
- Additional research needed on how performance changes with human adaptation



Arieta, Alejandro Hernandez; et al "A fMRI study of the Cross-Modal Interaction in the Brain with an Adaptable EMG Prosthetic Hand with Biofeedback," *EMBS 2006, IEEE EMBC* 2006

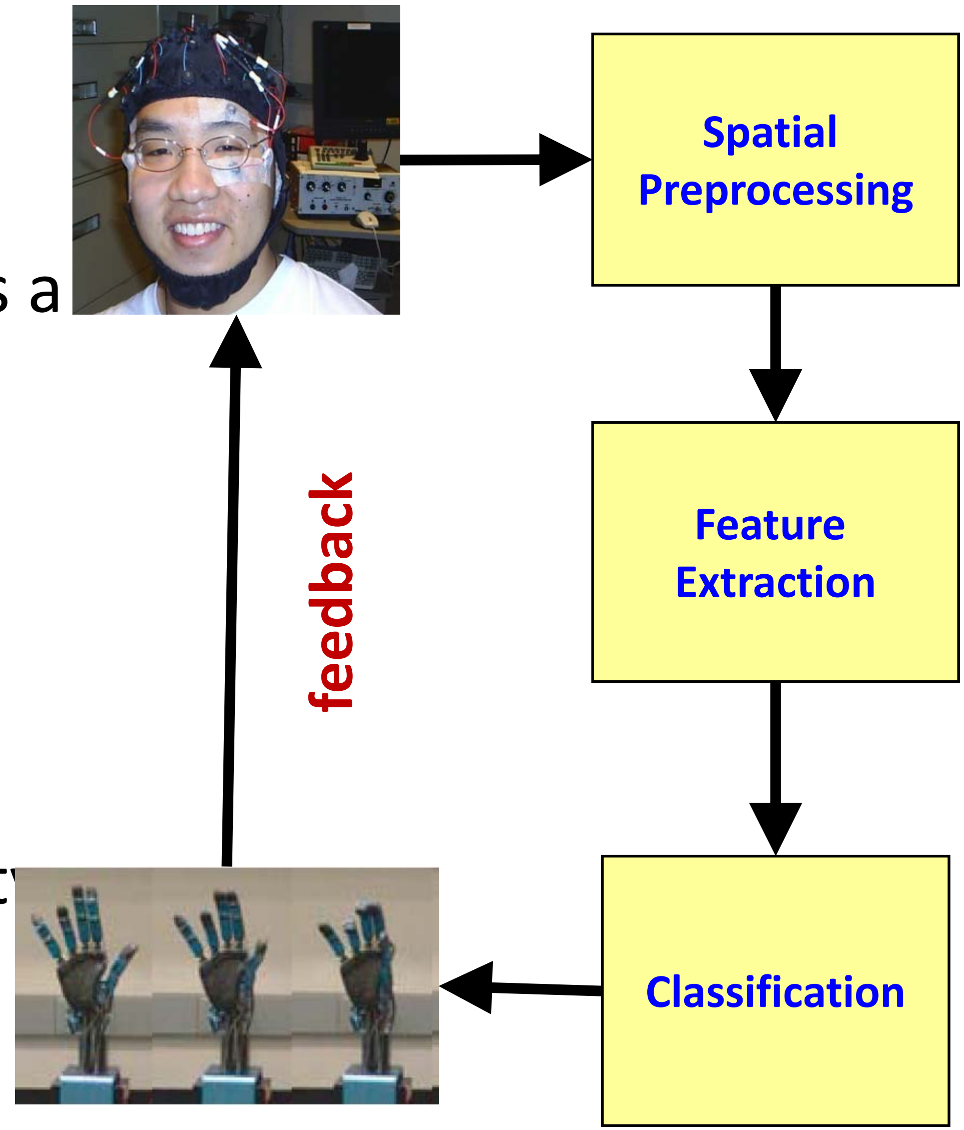
Part II: Nonivasive Cortical Control of Prosthesis

With S. Acharya, V. Aggarwal, et al

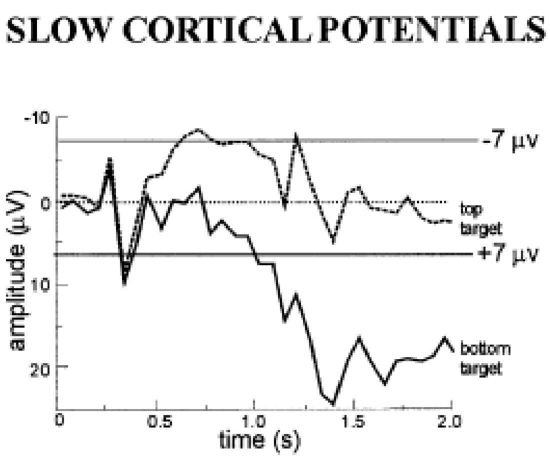
Nonivasive BCI

- Using brain ‘waves’ (signals originating from neurons in the brain), as a direct channel for communication and control.

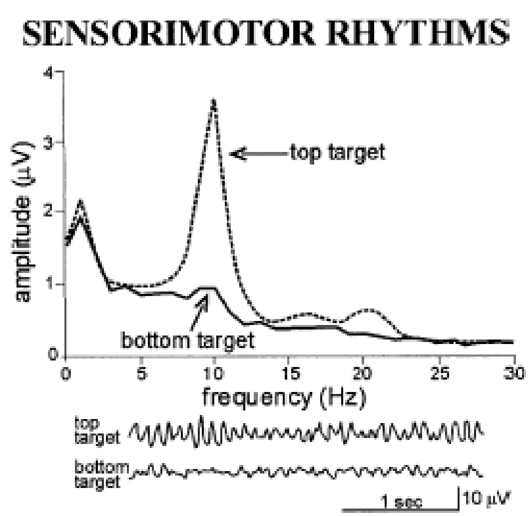
- Multiple scales:
  – Scalp electrical activit (EEG)
  – Neural spikes



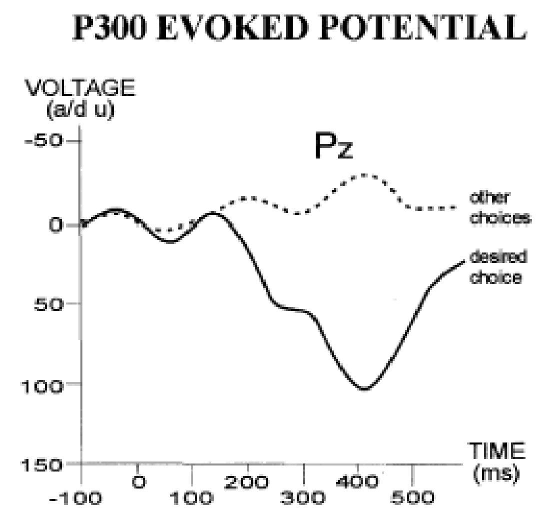
Some common EEG ‘features’ used in BCI



SCP originating from frontal cortex during two separate mental imagery tasks. Subjects employ this repeatable mental strategy to generate the control signal for operating a BCI



‘Mu’ rhythm (8-12 Hz), originating from the motor cortex in two separate motor imagery tasks. With training, subjects learn to control the amplitude of this rhythm for operating a BCI



P300 evoked potentials originating from the occipital cortex in response to seeing two different types of visual cues. The rare, or ‘oddball’ event evokes a P300 potential

Modified from Kubler et. al 2001

Building Blocks of a BCI

Laplacian, ICA, CSP,CSSD…..

FFT, Wavelets, AR-model, Entropy

LDA, SVM, Neural Networks

Spatial Filtering

-to localize the recorded signals to specific brain areas

Feature Extraction

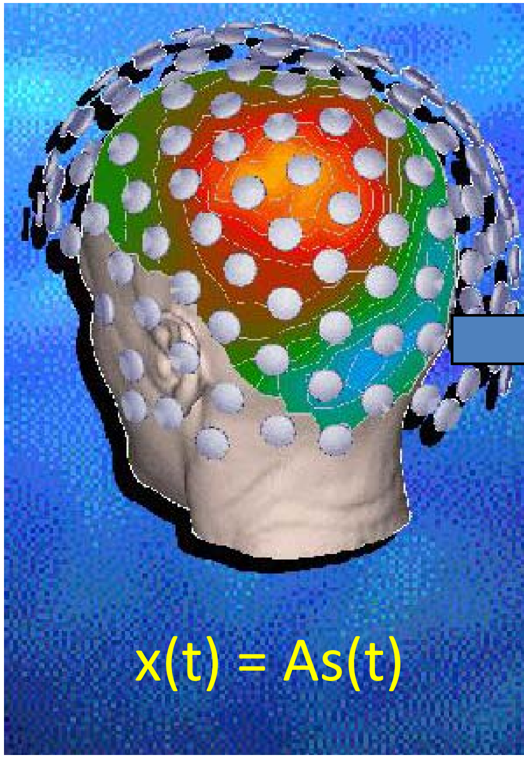
- to enable use of 'controllable' features buried in the signal

Machine Learning

- To map EEG features to desired output states

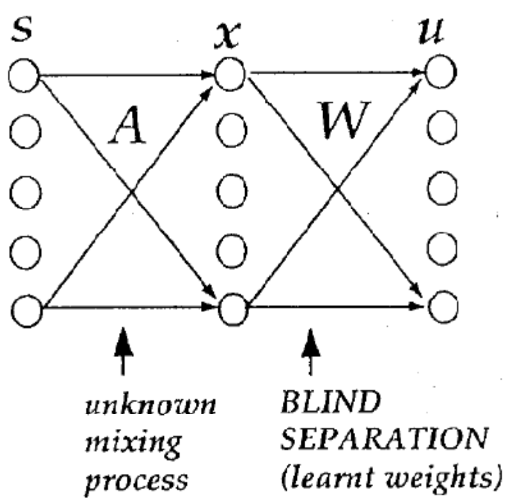
feedback

ICA based Spatial Filtering



1

Deconvolution using
Information Maximization

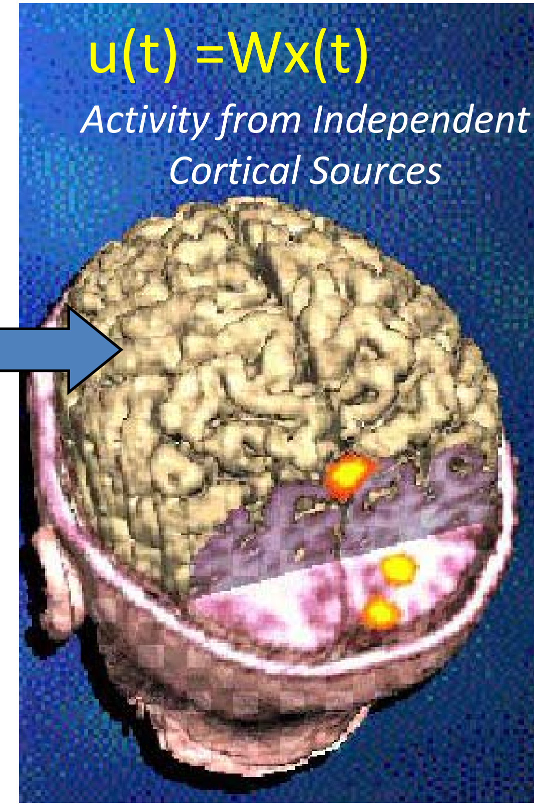


by Maximizing Joint Entropy

$$H(x_1, x_2) = H(x_1) + H(x_2) + I(x_1, x_2)$$

by and minimizing mutual information

2



3 …

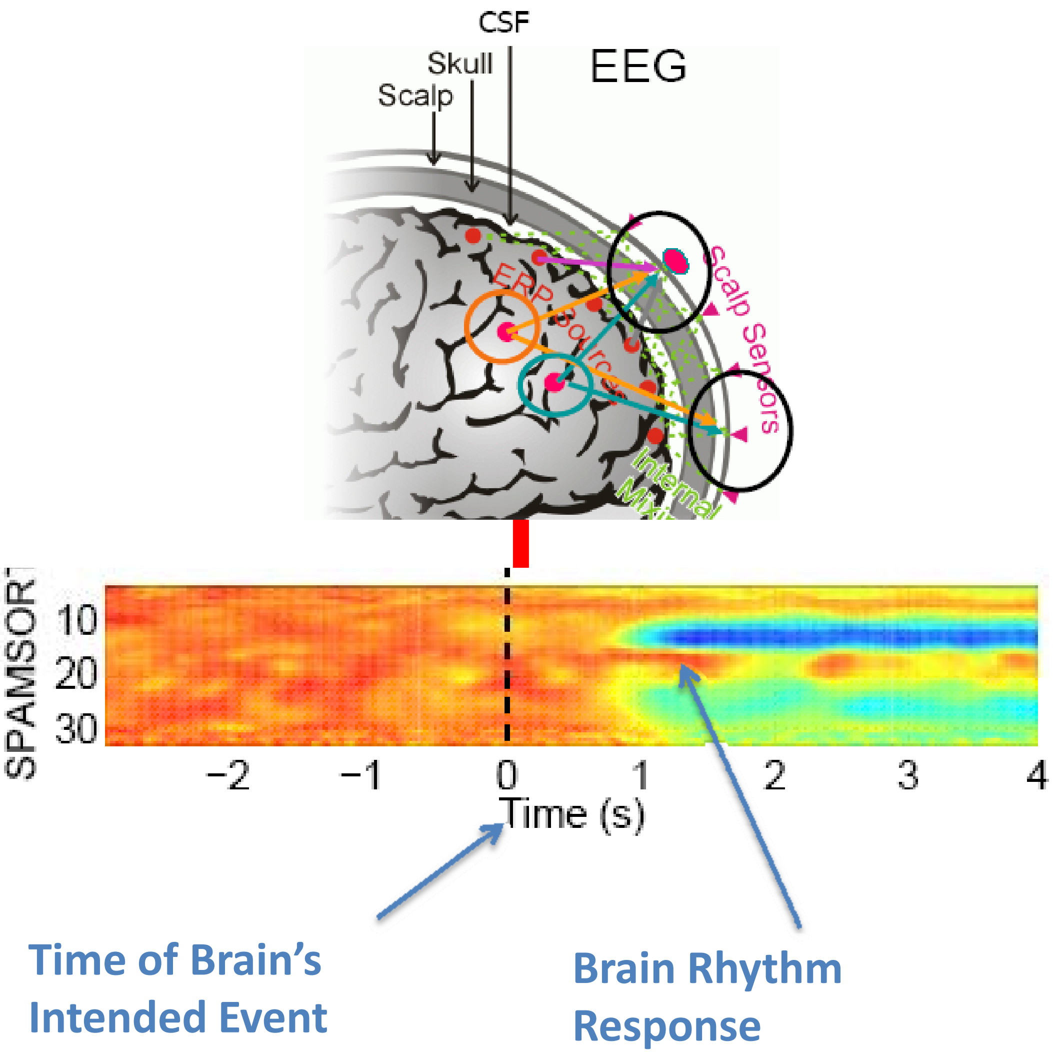
Spatiotemporal Source Tuning Filter Bank for Multiclass EEG based Brain Computer Interfaces

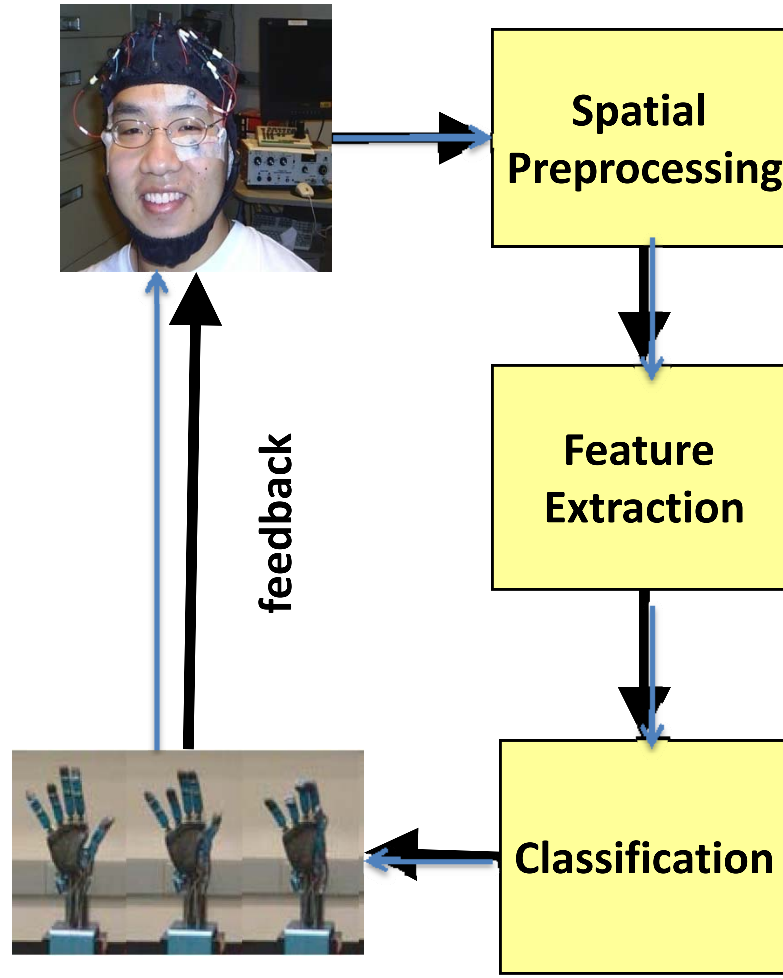
Soumyadipta Acharya, Mohsen Mollazadeh, Kartikeya Murari and Nitish Thakor

Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

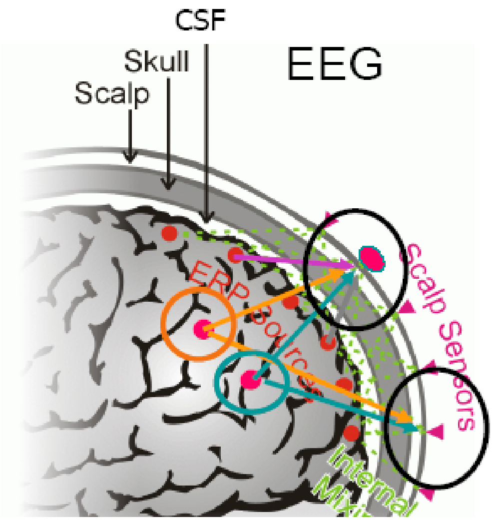
Noninvasive Cortical Control

- **In noninvasive BCIs, users learn to modulate various features of their EEG to convey their intent**

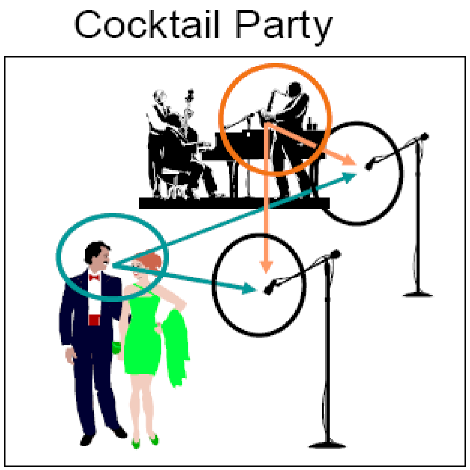


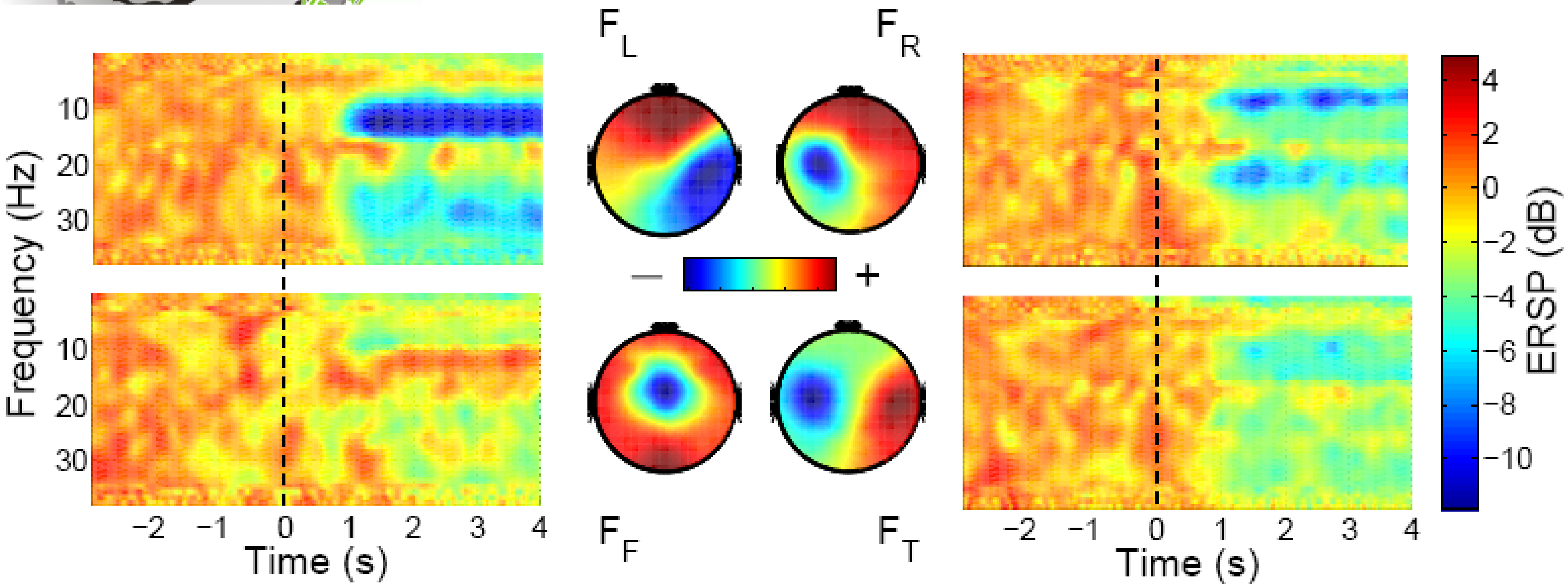


Nonivasive BCI



The method of Independent Component Analysis





Spatial Filtering:
Localizing neural sources

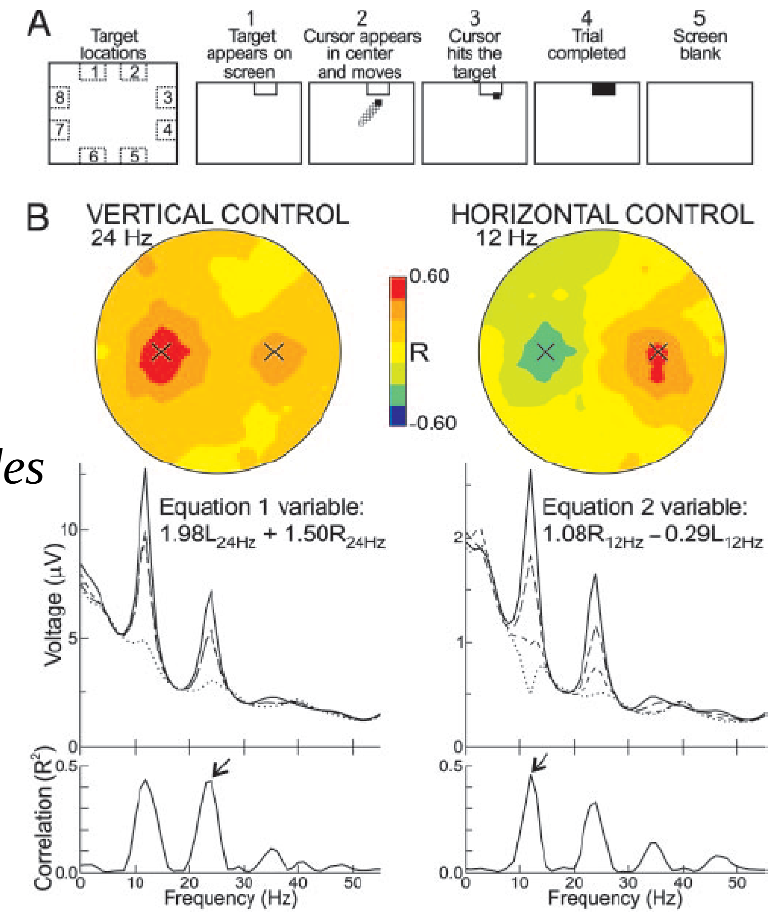
How to ‘focus’ on signals from specific neural source(s) ?

Laplacian:

$$X_j^{Lap} = X_j - \frac{1}{N}\sum_{k \in N} X_k ; where - N \square\ neighbor - electrodes$$

Common Average Reference.

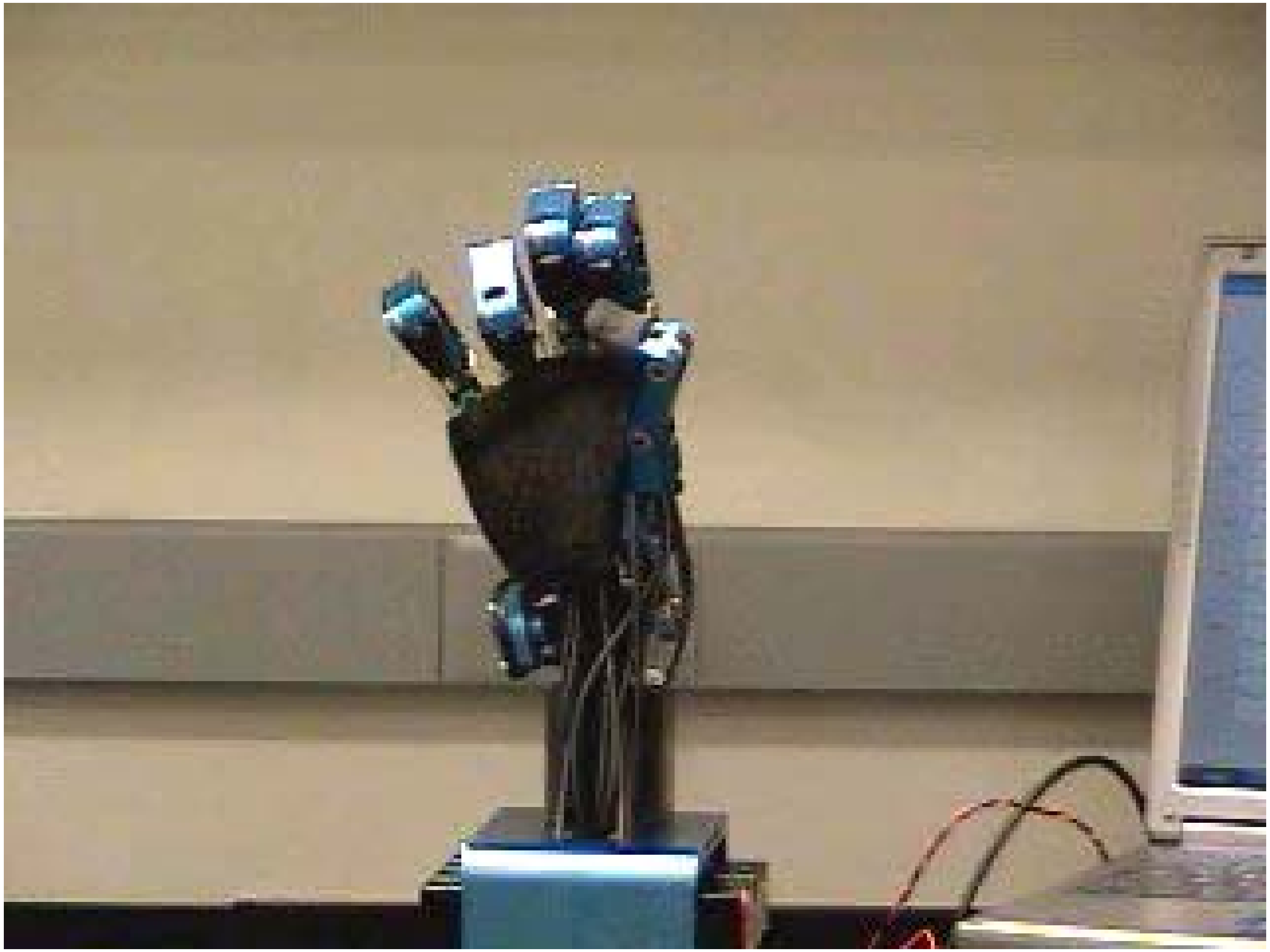
$$X_j^{CAR} = X_j - \sum_{n=1}^{N} X_n ; where : - N \square\ All - electrodes$$



Example of a Large Laplacian Spatial Filter applied to the scalp EEG, to extract spectral features from regions of the motor cortex. **Wolpaw et. al PNAS, 2004**

Brain-Machine Interface (Non Invasive)

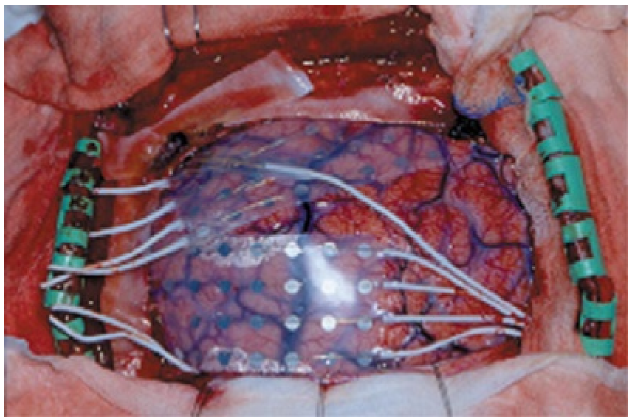
Neuro Prosthesis (Non Invasive)

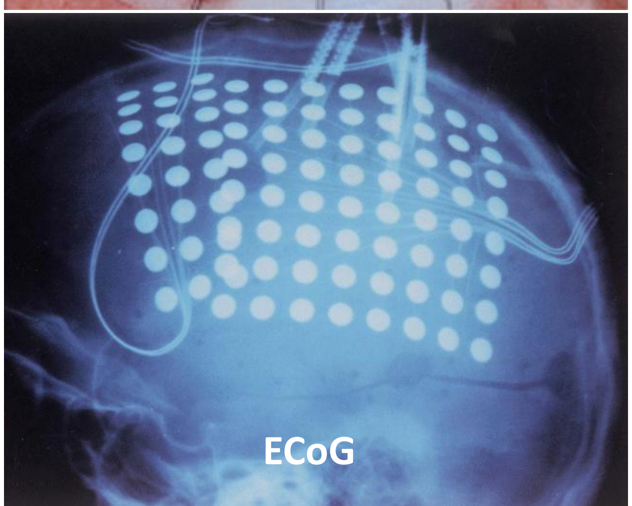


Part III: Less Invasive Cortical Control of Prosthesis

With S. Acharya, M. Mollazadeh, V. Agarwal, N. E. Crone et al

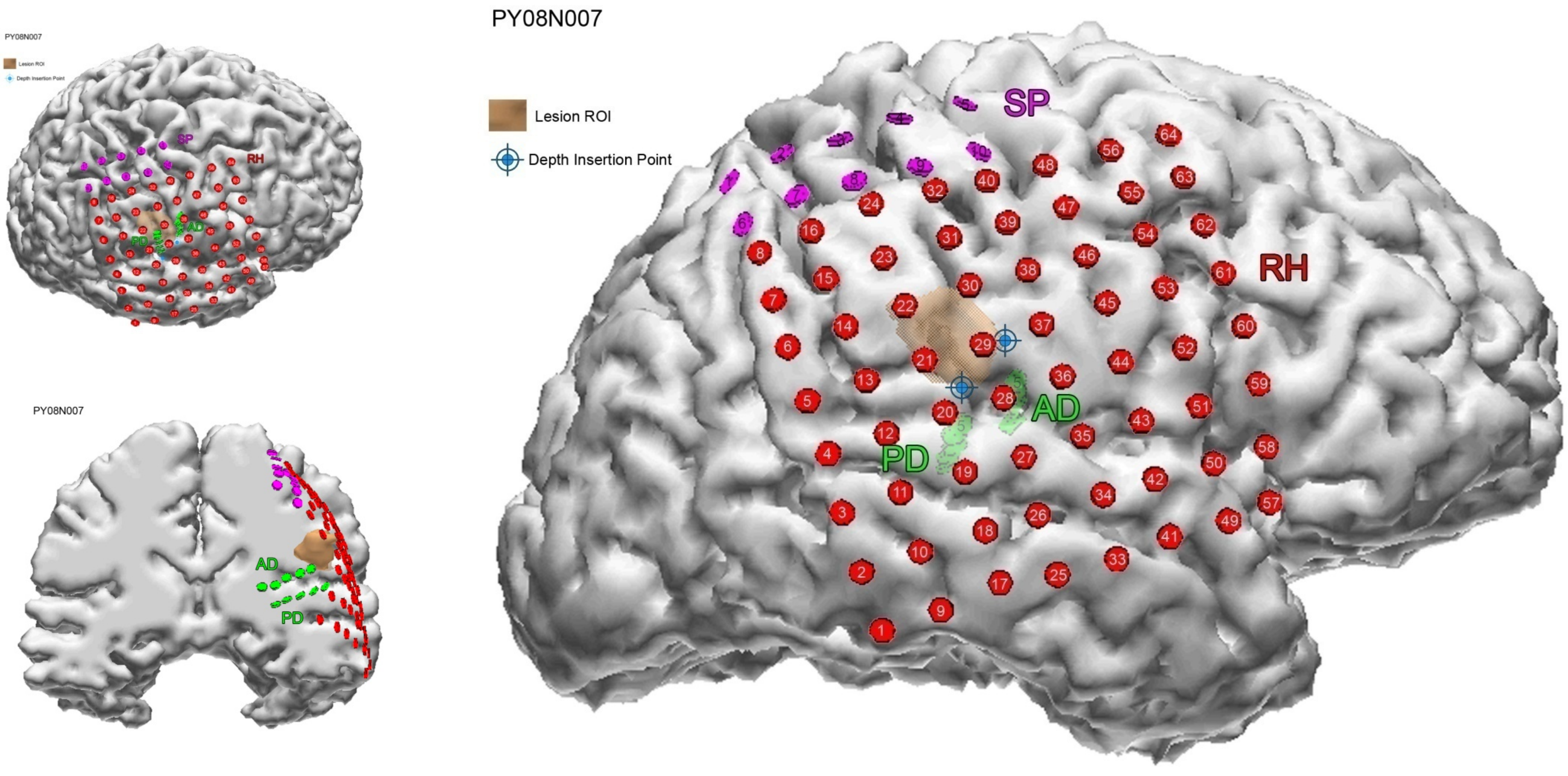
Less Invasive BCI/BMI ElectroCorticogram (ECOG)





- Patients awaiting epileptic surgery with implanted ECoG grids, with coverage over motor and somatosensory cortex.
- 88 channels of ECoG
- Subjects wearing ‘cyberglove’ : 22 sensors recording hand position…co-registered with ECoG
- Subjects perform dexterous hand movements

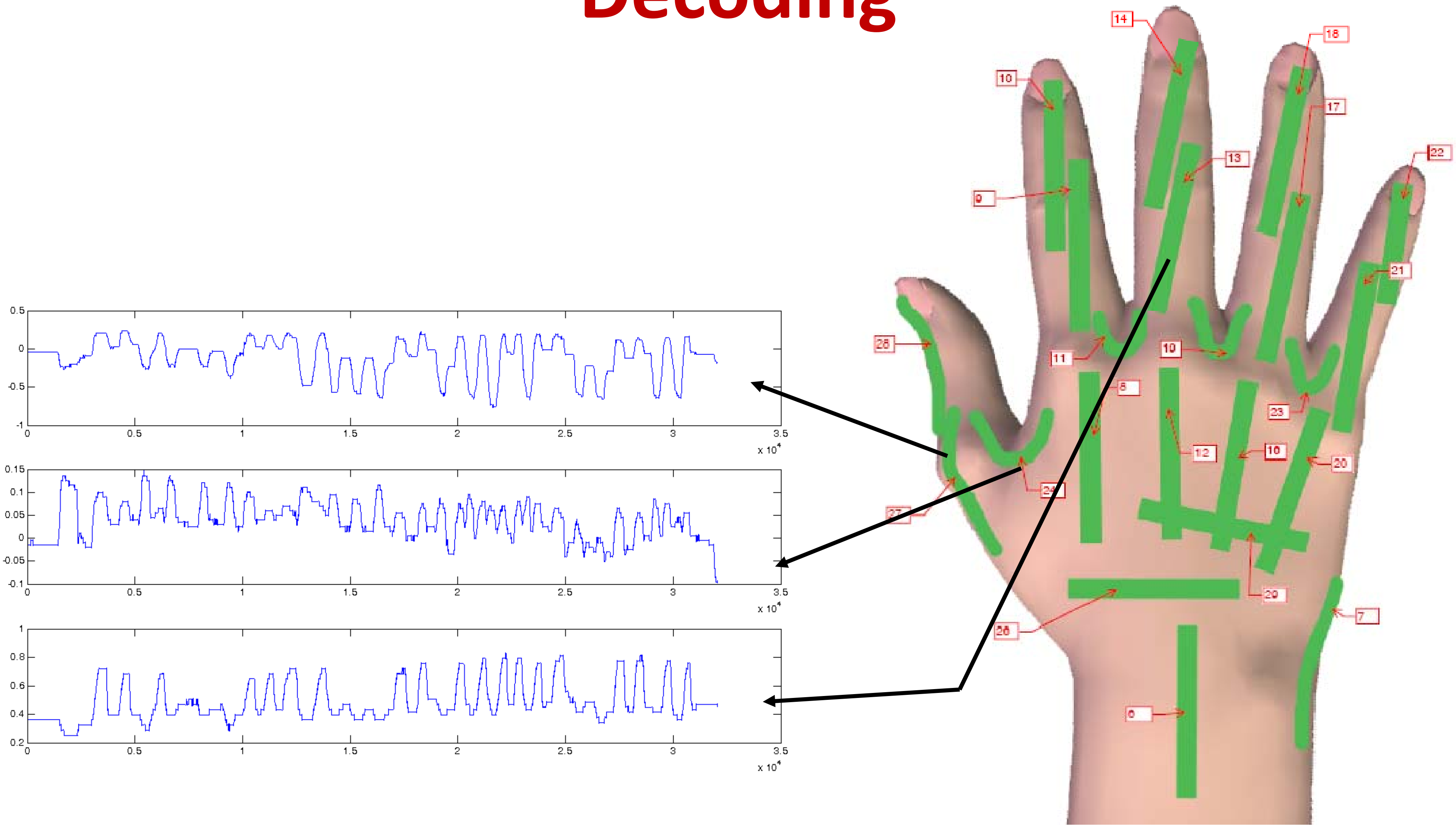
ECoG grid superimposed on MRI image



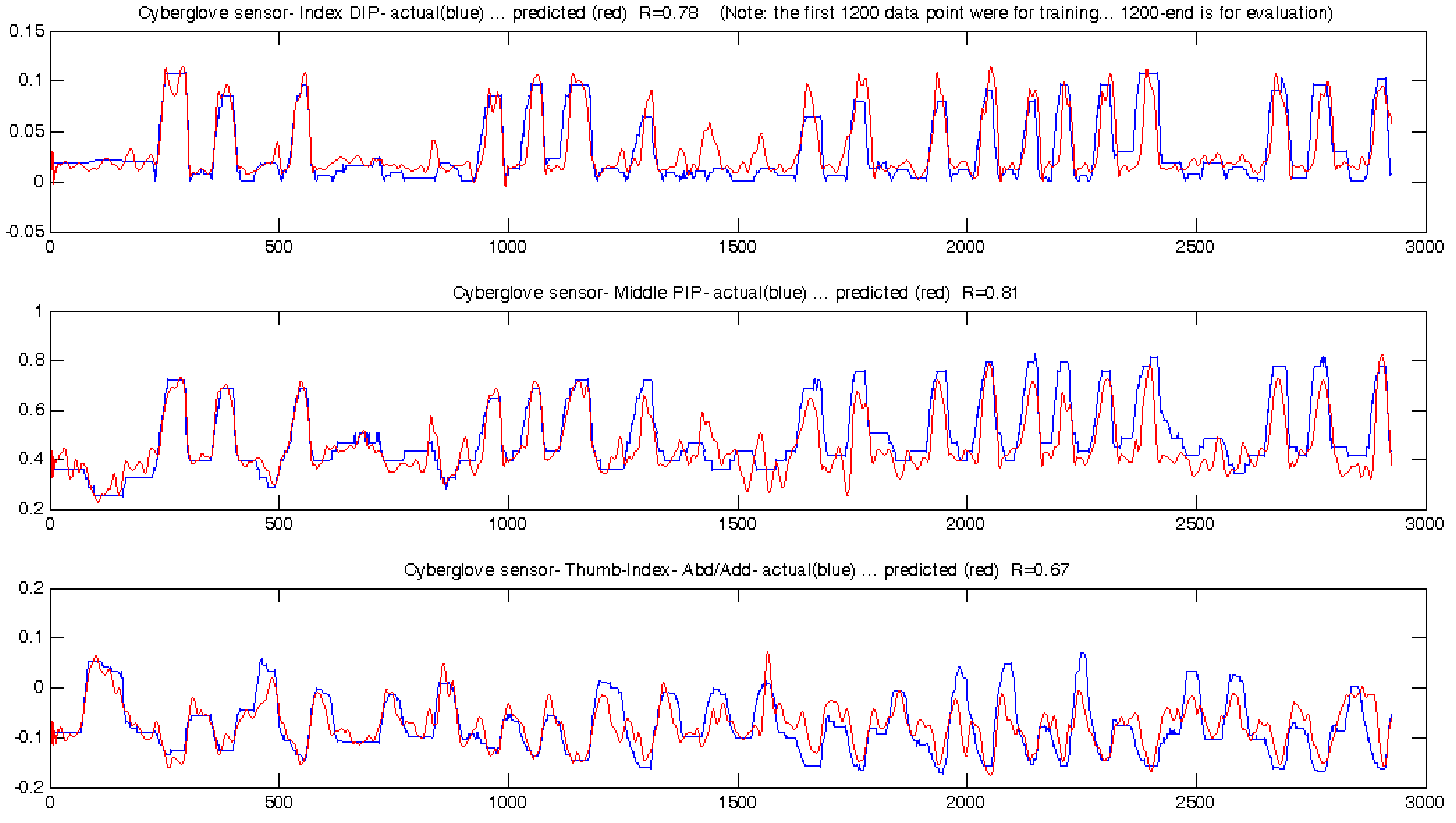
Towards Continuous Position Decoding

- Current focus on classifying limited number of movements e.g. index flexion, wrist abduction
- With aid of tracking systems, e.g. CyberGlove, decoding of continuous range of positions

Real Time Hand/finger Position Decoding



Prediction of joint angles using multiple features in the ECoG



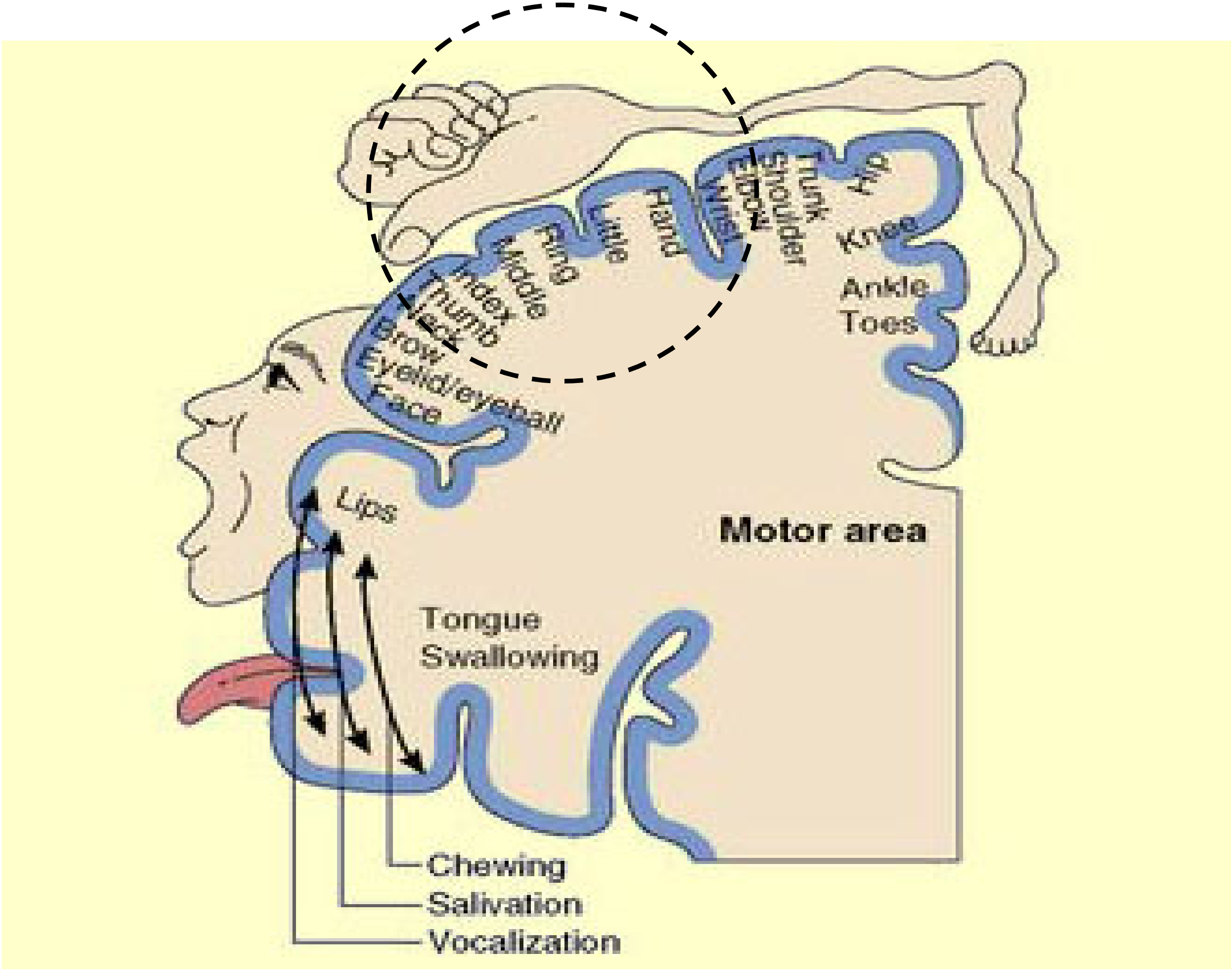
Possible Research Problems

- What is the "error" between cortical signal (command) and the hand motion (response)?
- Is there a phase lag? How to handle delays…or
- Can the limb motion be anticipated/predicted?
- Are the cortical signals "Independent" or "coordinated/synergistic"?

Part IV: Invasive Cortical Control of Prosthesis

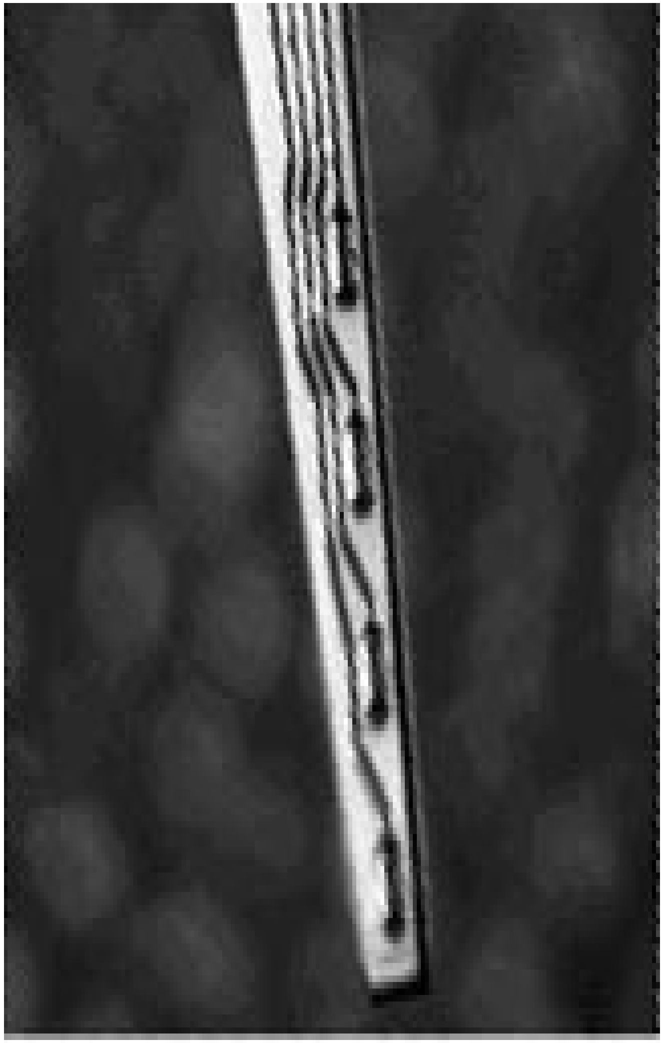
With V. Agarwal, S. Acharya, H. Shin, G. Singhal, M. Mollazadeh, F. Tenore, M. Schieber, et al

Background



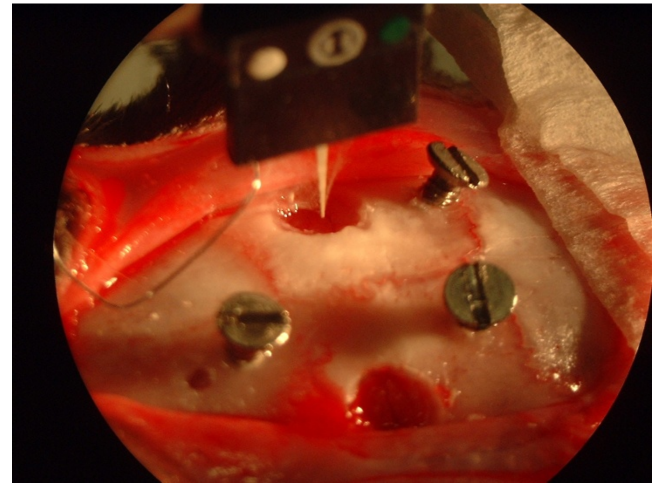
Hip
Trunk
Shoulder
Elbow
Wrist
Hand
Little
Ring
Middle
Index
Thumb
Neck
Brow
Eyelid/eyeball
Face
Knee
Ankle
Toes
Lips
Motor area
Tongue
Swallowing
Chewing
Salivation
Vocalization

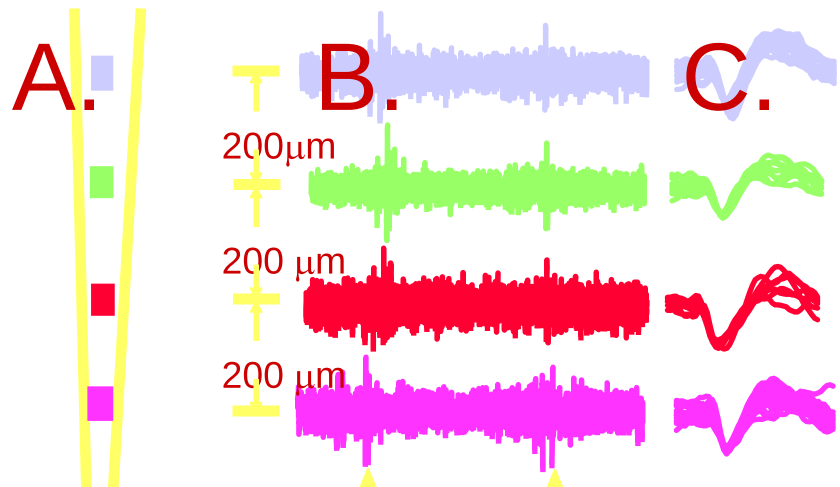
Ceramic - based Multisite Electrode



Courtesy K. Moxon

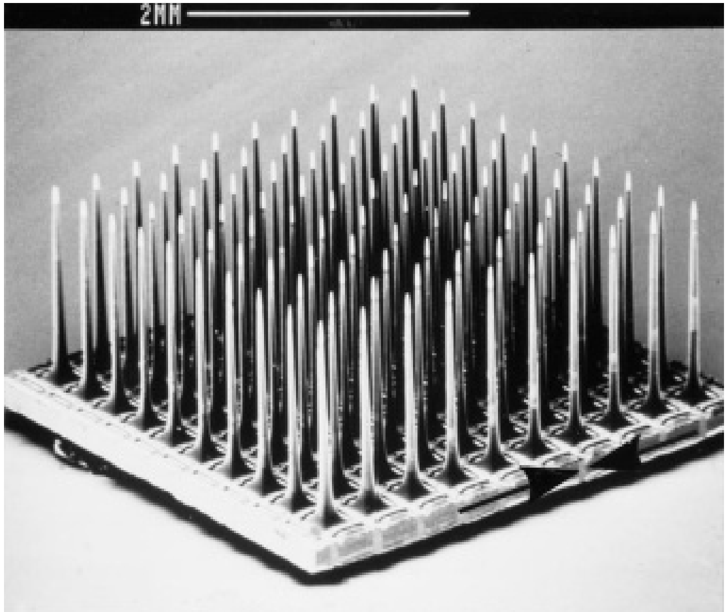
In Vivo Implantation and Recording





Multisite recording from barrel cortex

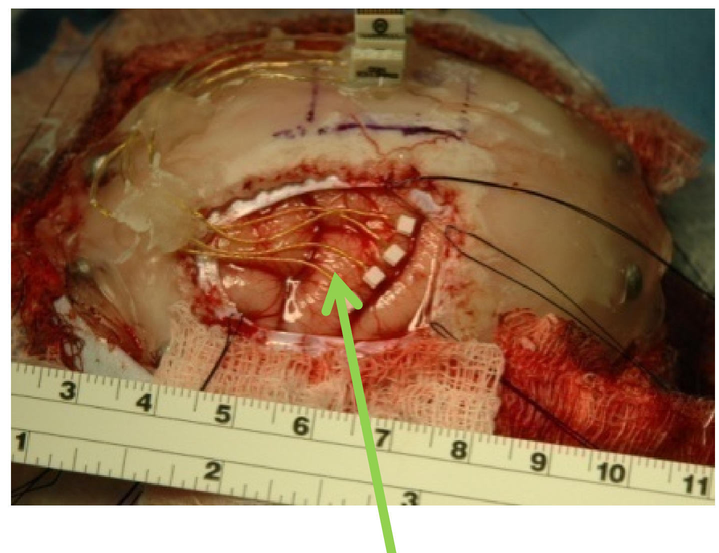
Cortical Microelectrodes



Implantable Silicon micromachined electrodes to stimulate the cortex.

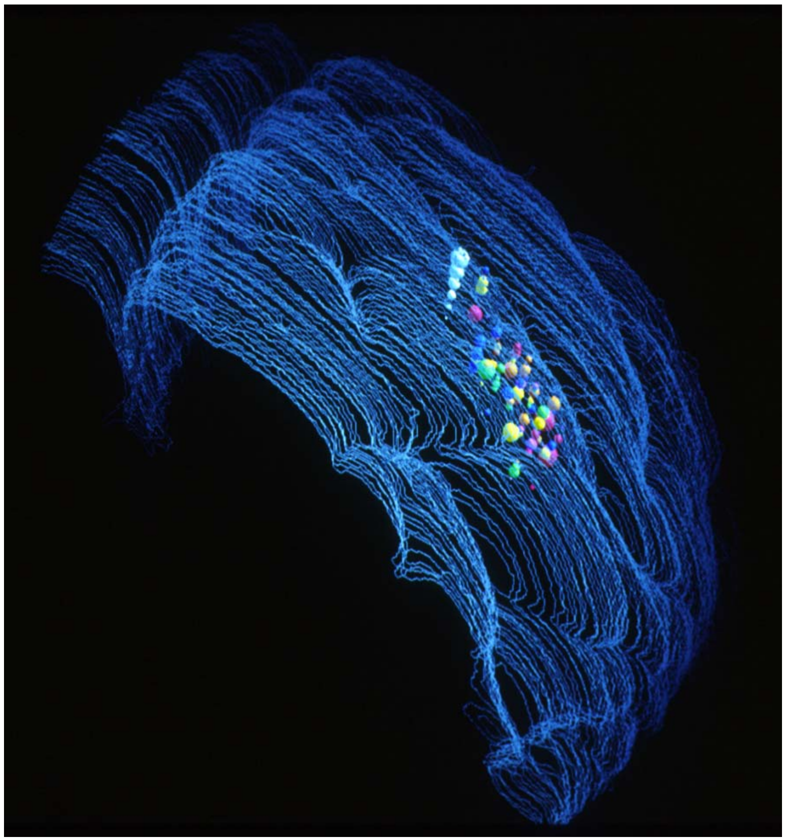
PJ Rousche , RA Norman, “Chronic intracortical microstimulation (ICMS) of cat sensory cortex using Uthan intracortical electrode array”, Rehabilitation Engineering, IEEE Transactions, vol 7, pp. 56-68

Implantation in
Primate Brain
M. Schieber and team

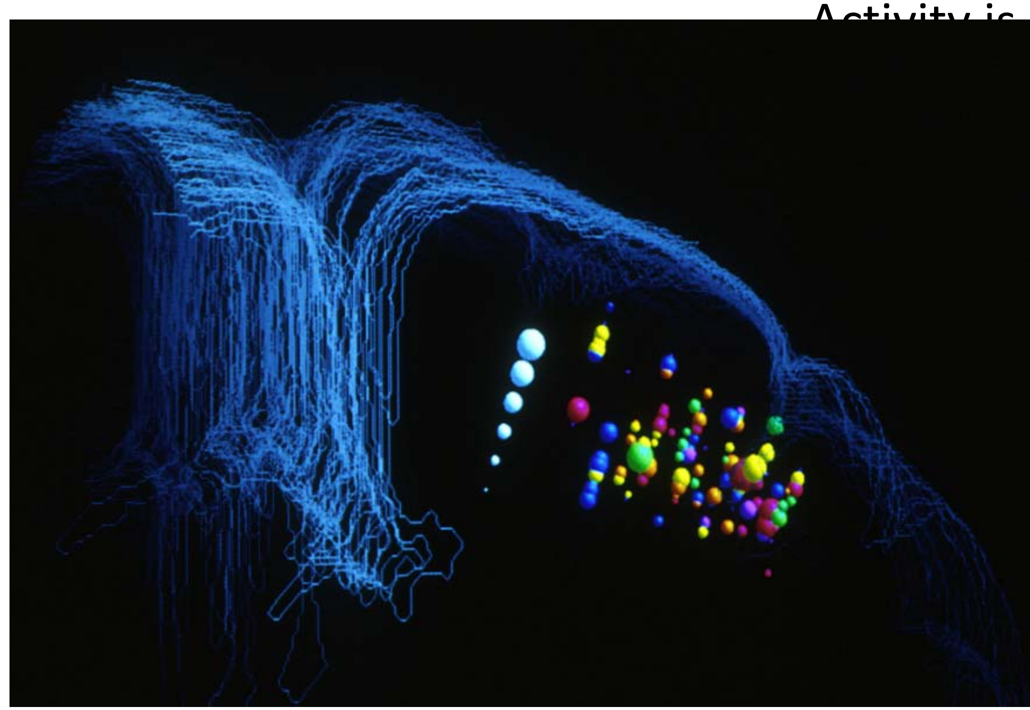


central sulcus

Electrical Recording for Prosthetic Control



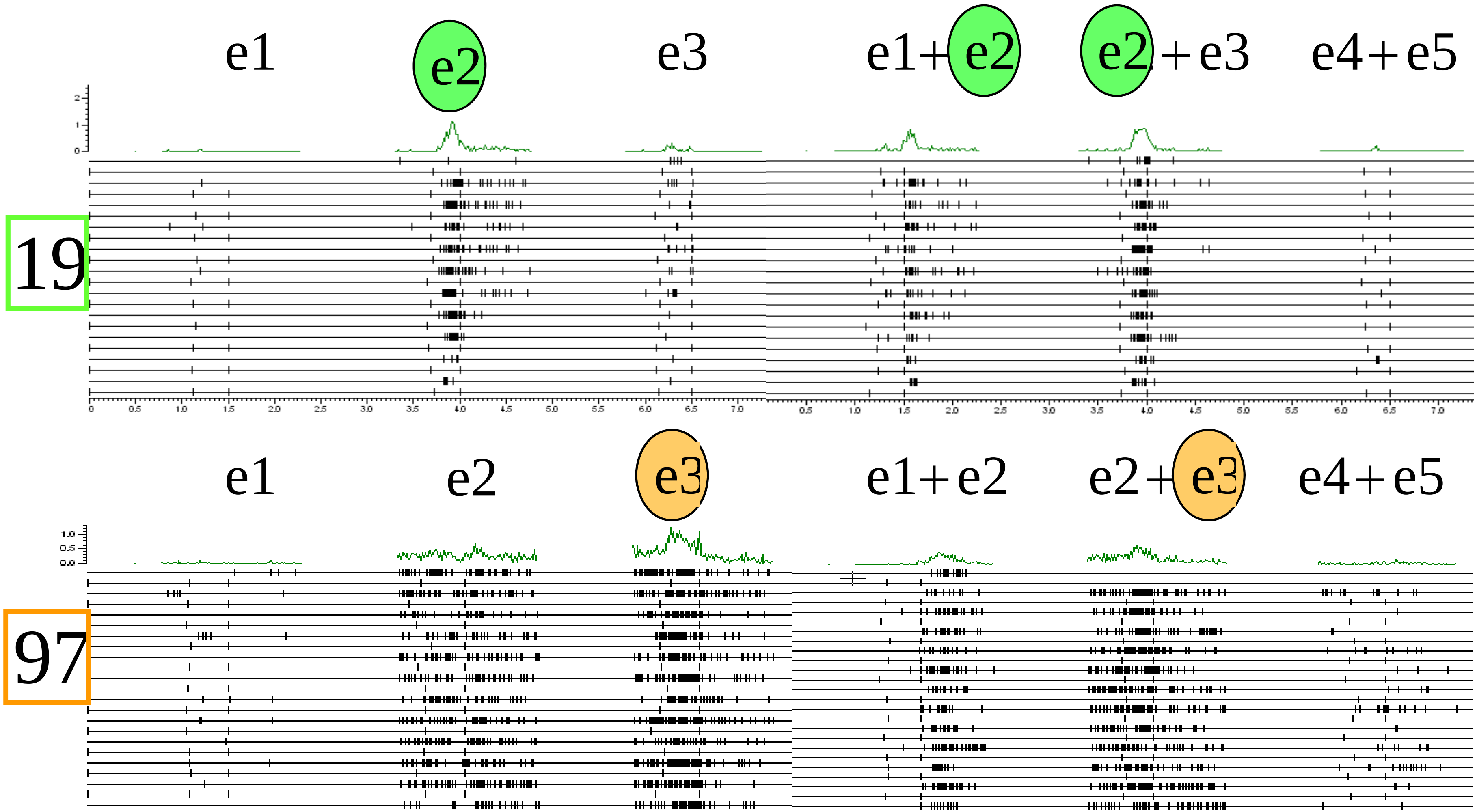
Neuron
Activity is

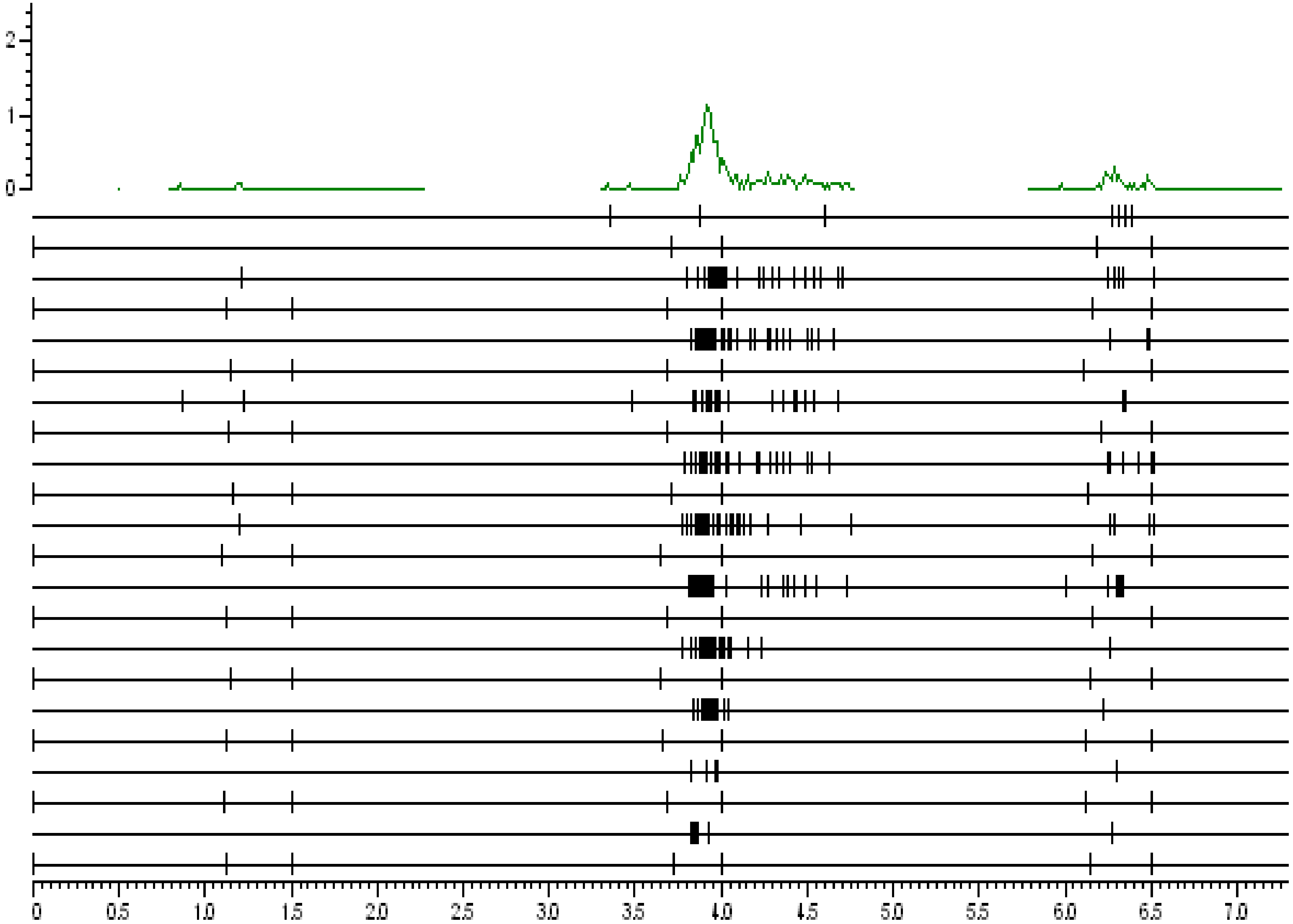


(Schieber & Hibbard, 1993)

With M. Schieber, URMC

Neural Recording – Single and Multiple Finger Movements





0
1
2
0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
6.0
6.5
7.0

Building Blocks of an 'invasive' BMI:

Decoding neural spikes

Matched Filter, …..

Leaky Integrator, Time-frequency decomposition….

Population Vector, Wiener Filter, MLE, Kalman Filter, Neural Networks

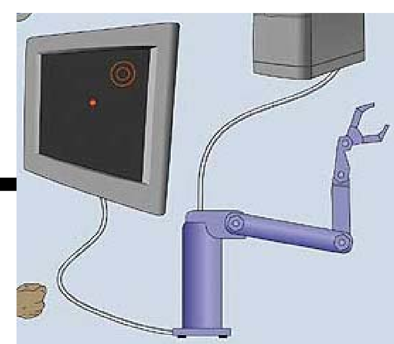
Real Time Spike Sorting
-to isolate firing patterns of individual neurons

Feature Extraction
- To convert the binary signals to continuous variables

Machine Learning
- To map multi neuronal features to desired output states

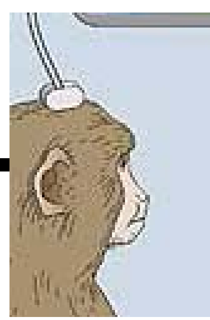
Cursor Position,

Robotic Arm/ Hand Kinematic



Feedback

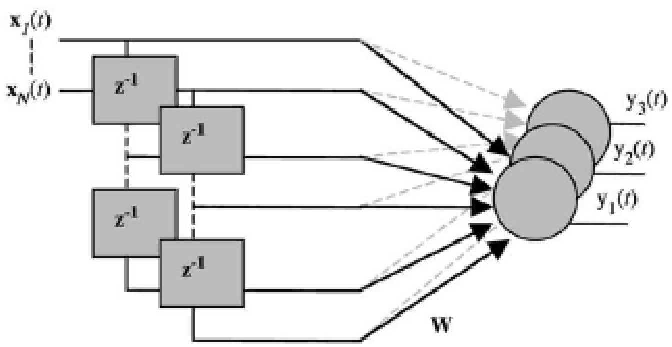
Learning, Plasticity



Simultaneous Activity of multiple neurons

A Brain Machine Interface for Predicting Hand Position: Wiener Filter

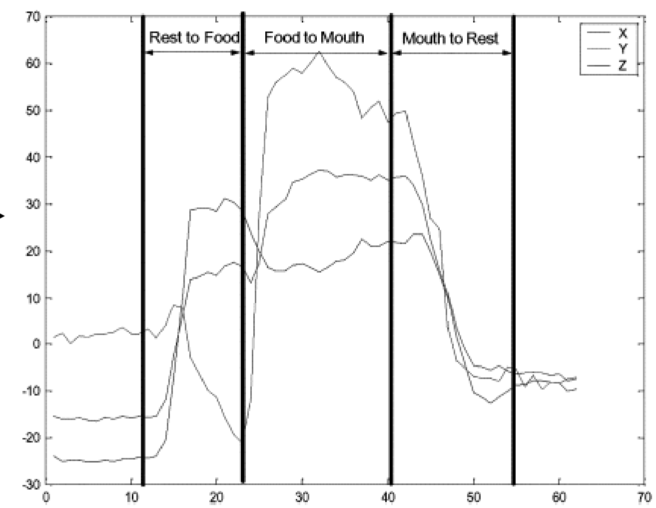
Neuronal firing rates *$x_i[nT]$* for N neurons recorded from motor cortex



Wiener filter Topology for BMI (*Sanchez et al 2004)*

$$y[nT] = \sum_{i=1}^{N} W_i x_i[nT - i]$$

Spatial Co-ordinates Hand position ***<x,y,z>***



Typical trajectory of the monkey's hand (x,y,z co-ordinates) during a reaching movement

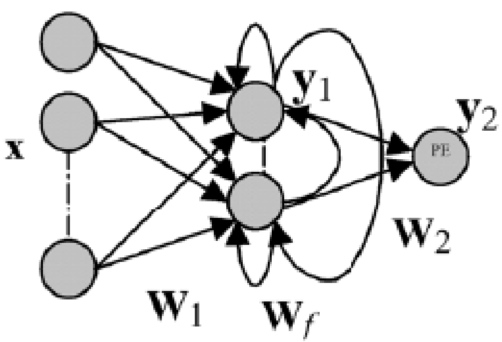
Where the outputs y, track the spatial x, y, z co-ordinates of the hand.

Sanchez, Nicolelis, Principe et.al, 2004

The training process consists of finding the optimal weights that minimize the prediction error

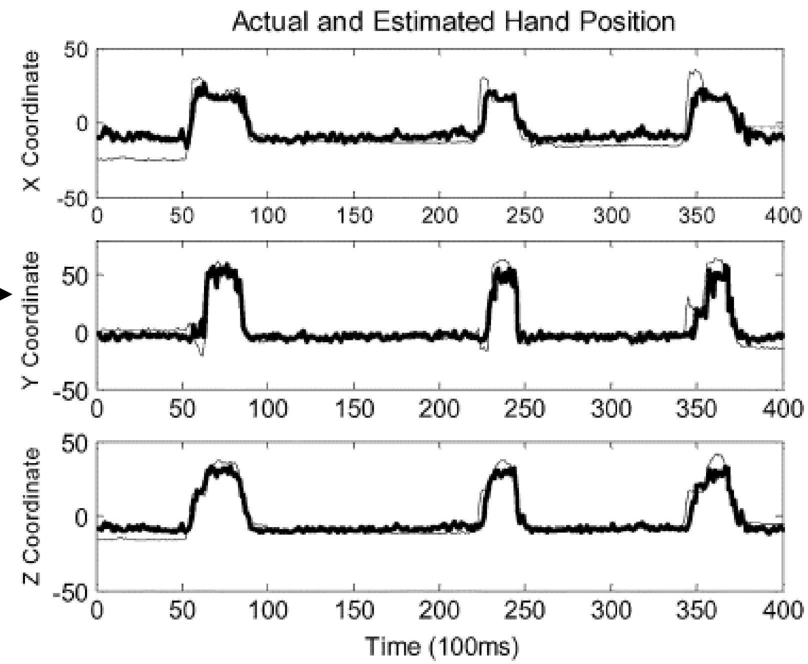
A Recurrent Neural Network based BMI

Neuronal firing rates *$x_i[nT]$*
for N neurons recorded from
motor cortex



Fully Connected Recurrent Neural Network Topology
(*Sanchez et. al 2005)*

$$\mathbf{y}_1(t) = f(\mathbf{W}_1\mathbf{x}(t) + \mathbf{W}_f\mathbf{y}_1(t-1) + \mathbf{b}_1)$$
$$\mathbf{y}_2(t) = \mathbf{W}_2\mathbf{y}_1(t) + \mathbf{b}_2.$$



Actual (thin) and Predicted (bold) hand co-ordinates during a series of reaching movements (*Sanchez et. al 2005)*

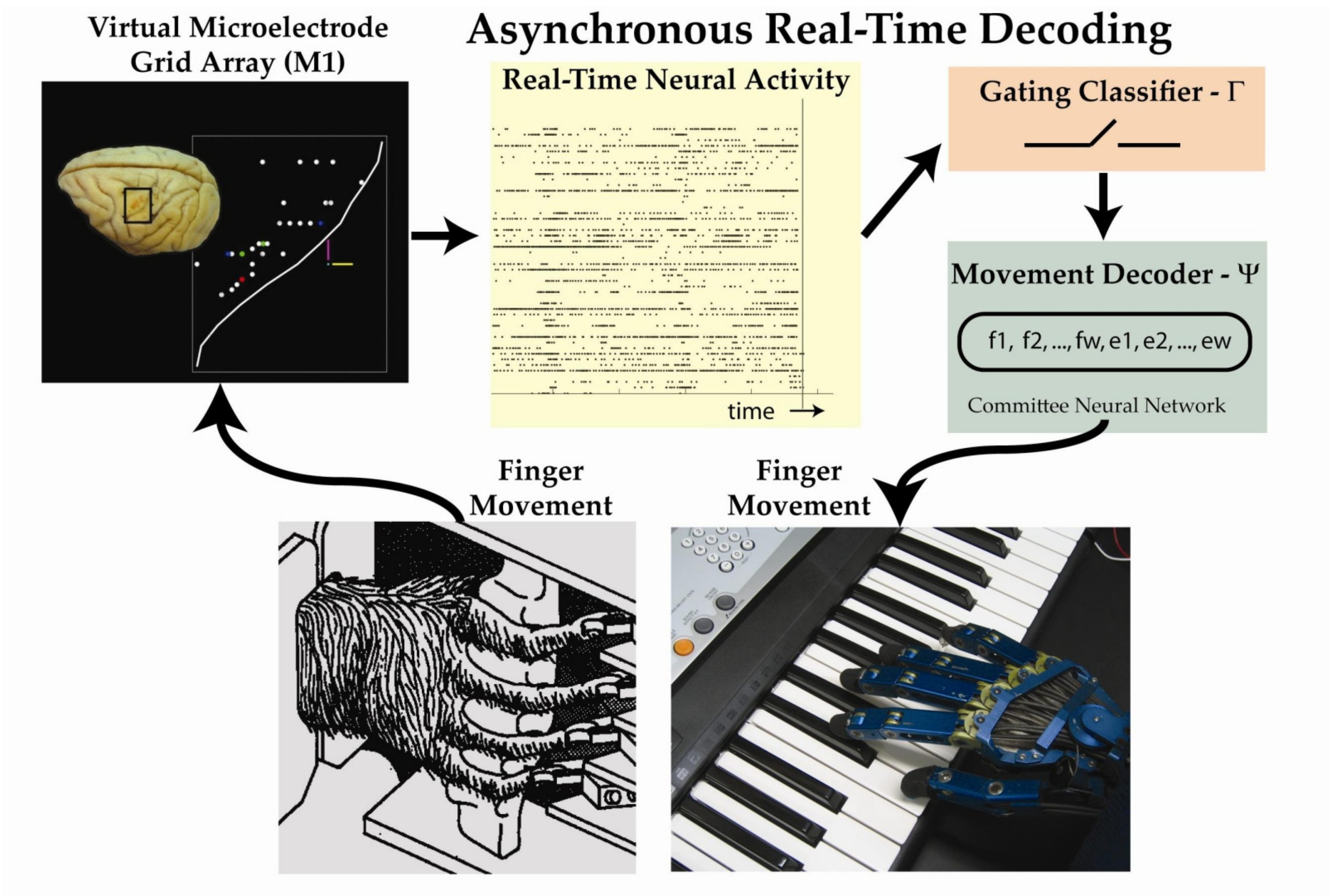
Where 'f' denotes a non-linear basis function

The 'neural to motor' transfer function is approximated by optimizing the Weight and Bias vectors (W, b), acting on these basis functions

Sanchez, Principe et.al, 2005

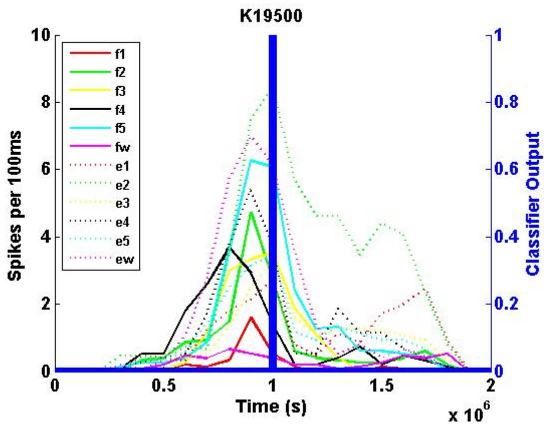
Towards a Brain-Computer Interface for Dexterous Control of a Multi-Fingered Prosthetic Hand

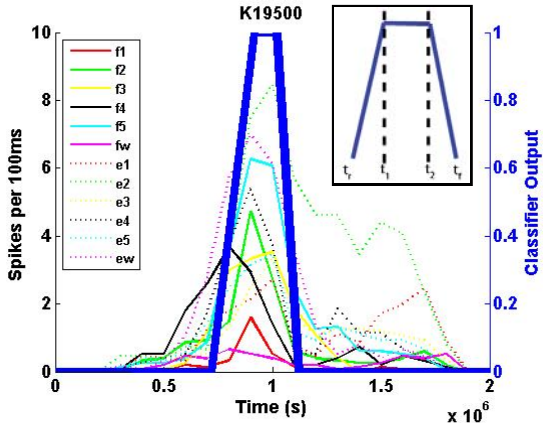
Soumyadipta Acharya, Vikram Aggarwal, Francesco Tenore, Hyun-Chool Shin,
Ralph Etienne-Cummings, Marc H. Schieber, Nitish V. Thakor



Dexterous BMI: The first step: Detecting movement intent/ onset from neural activity

- train ANN to distinguish between baseline activity and movement periods





- threshold to produce binary variable

$$g_n(t_k) = \begin{cases} 1 & if \;\; P_n\{I(t_k)\} > T_1 \\ 0 & else \end{cases}$$

- majority voting rule chooses committee output of gating classifier

$$G(t_k) = \begin{cases} 1 & if \;\; \sum_{t=t_k-t_j}^{t_k} \left(\sum_{n=1}^{N} (g_n(t_k)) > \frac{N}{2} \right) > T_2 \\ 0 & else \end{cases}$$

Dexterous BMI:

Decoding movement type (which finger/ what movement??)

- train ANN to distinguish amongst each movement type

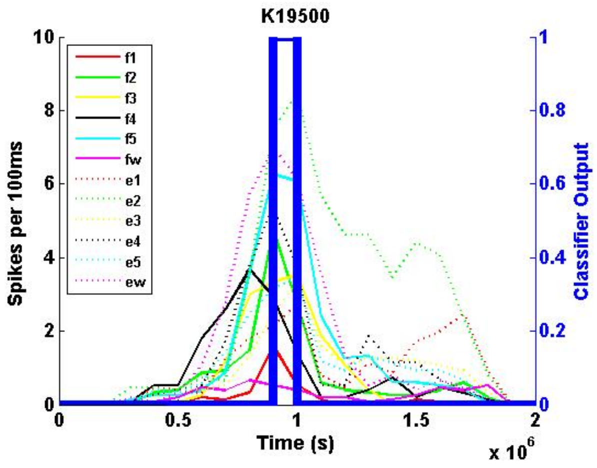
- networks were trained with binary membership function and assigned an output label for each movement type

- select movement type with greatest output activity

$$s_n(t_k) = \arg\max P_n\{M_i\}$$

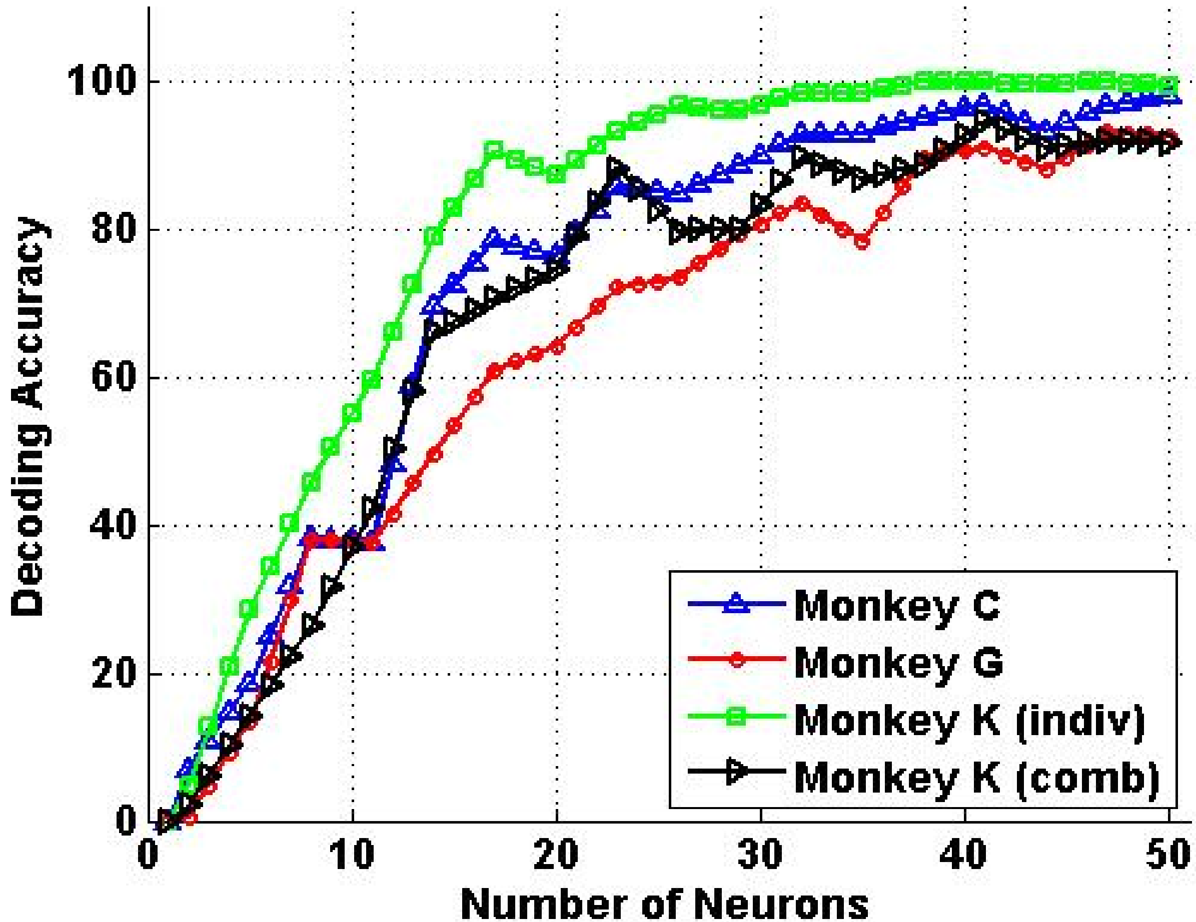
- majority voting rule chooses committee output of movement classifier

$$S(t_k) = \mathrm{mode}\{s_n(t_k)\}$$



Playing the Cortical Piano

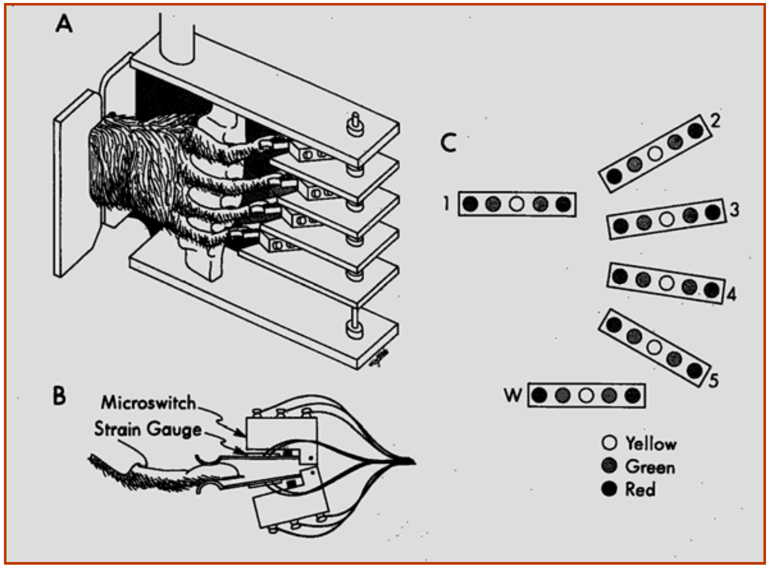
Asynchronous Decoding of Dexterous Finger Movements Using M1 Neurons

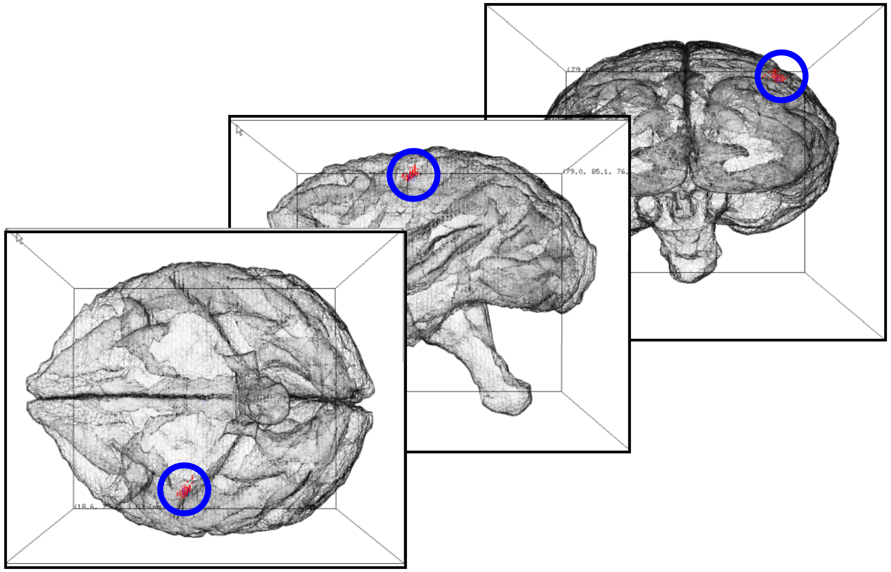


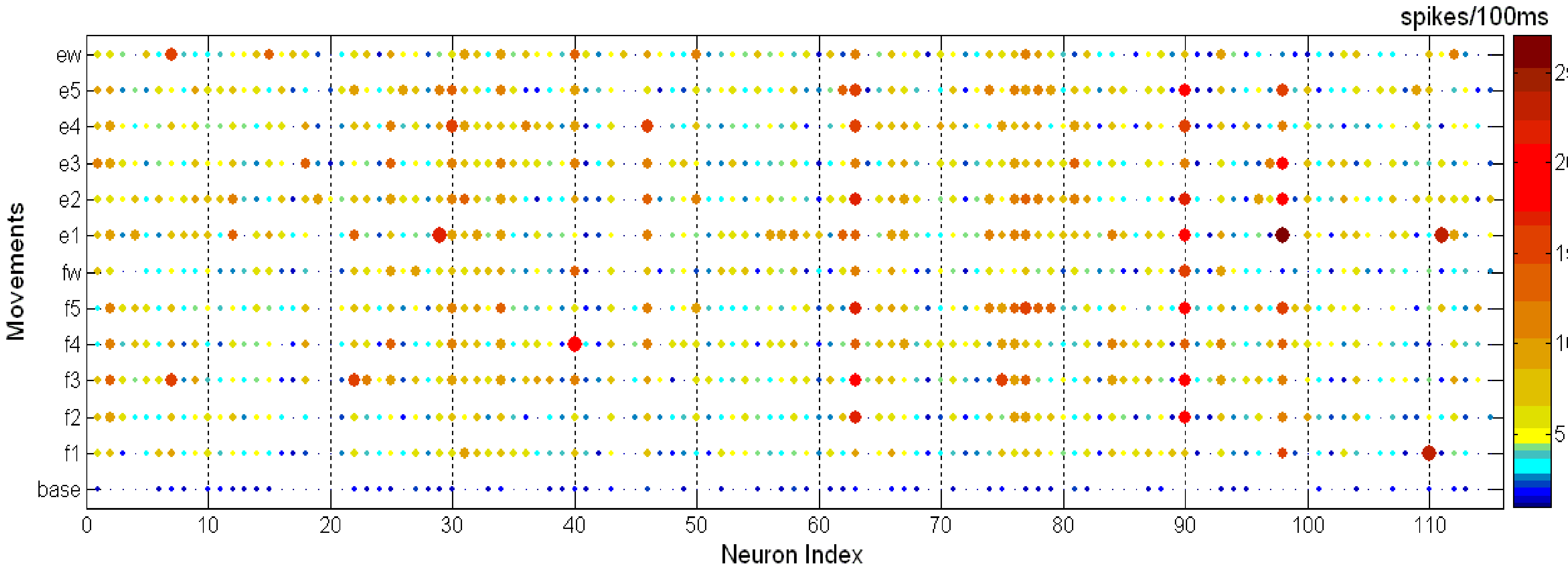
V. Aggarwal, S. Acharya, N.V. Thakor et al

IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING, VOL. 16, NO. 1, FEBRUARY 2008

M1 Neural Response During Finger Movements





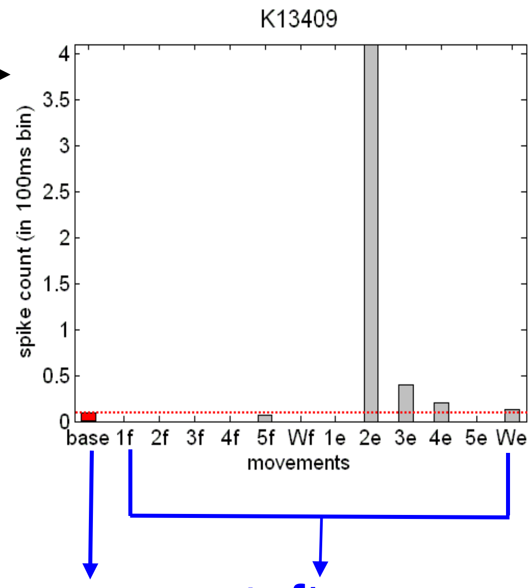


•Shin H-C, Aggarwal V., Acharya S., Scieiber M. H., and Thakor N. V., "Neural decoding of finger movements using Skellam based maximum

Maximum Likelihood (ML) Decoding

We define the neural activation:

Firing rate



before movement **after movement**

$x_n(m)$: **Neural activation = firing rate after movement - firing rate before movement**

m: **Finger movements**

n: **Neuron index, 1 … N**

ML decoding: $\hat{m} = \arg_m \max Pr(x_1, x_2, \ldots, x_N | m)$

Shin H-C, Aggarwal V., Acharya S., Scieiber M. H., and Thakor N. V., "Neural decoding of finger movements using Skellam based maximum likelihood decoding," IEEE Trans. Biomed. Eng., In Press.

Maximum Likelihood (ML) Decoding

Probability model of $x_n(m)$ given finger movement, m:

- Firing rate: Poisson

$$f_n(k|m) = e^{-\mu_n(m)\Delta t} \cdot \frac{(\mu_n(m)\Delta t))^k}{k!}$$

$\mu_n(m)$: mean firing rate

- Neural activation, $x_n(m)$ (difference of two firing rates)
: Skellam distribution (difference of two Poisson distribution)

$$h_n(x_n|m) = \alpha_n(m)\left(\frac{\mu_n(m)}{\mu_n(0)}\right)^{x_n/2} I_x\left(2\sqrt{\mu_n(m)\mu_n(0)\Delta t^2}\right)$$

$\mu_n(0)$: mean firing rate before movement

$\mu_n(m)$: mean firing rate after movement

$\alpha_n(m) = e^{-(\mu_n(m)+\mu_n(0))\Delta t}$

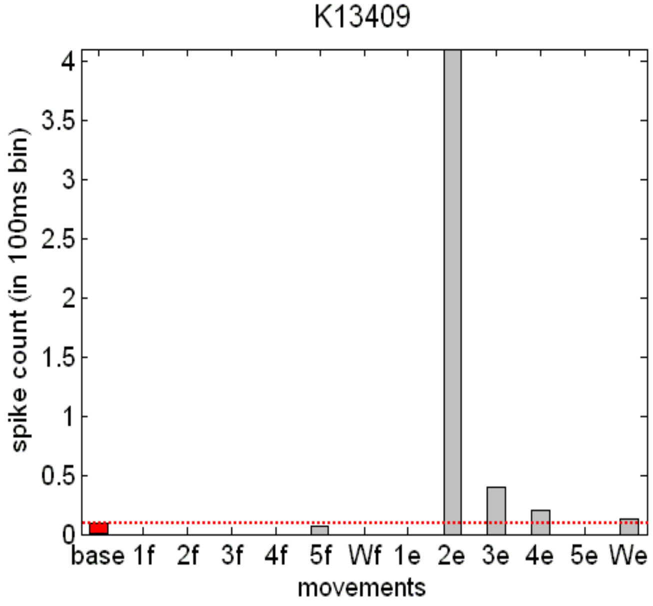
$I_x(z)$: modified vessel function of the first kind

Shin H-C, Aggarwal V., Acharya S., Scieiber M. H., and Thakor N. V., “Neural decoding of finger movements using Skellam based maximum likelihood decoding,” IEEE Trans. Biomed. Eng., In Press.

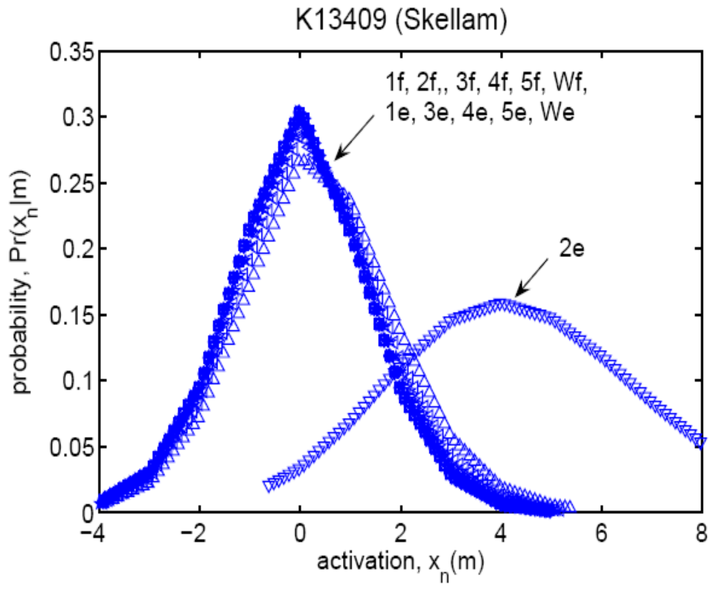
Maximum Likelihood (ML) Decoding

Skellam modeling of neural activation (neuron K13409):

Firing rate



$$h_n(x_n|m)$$



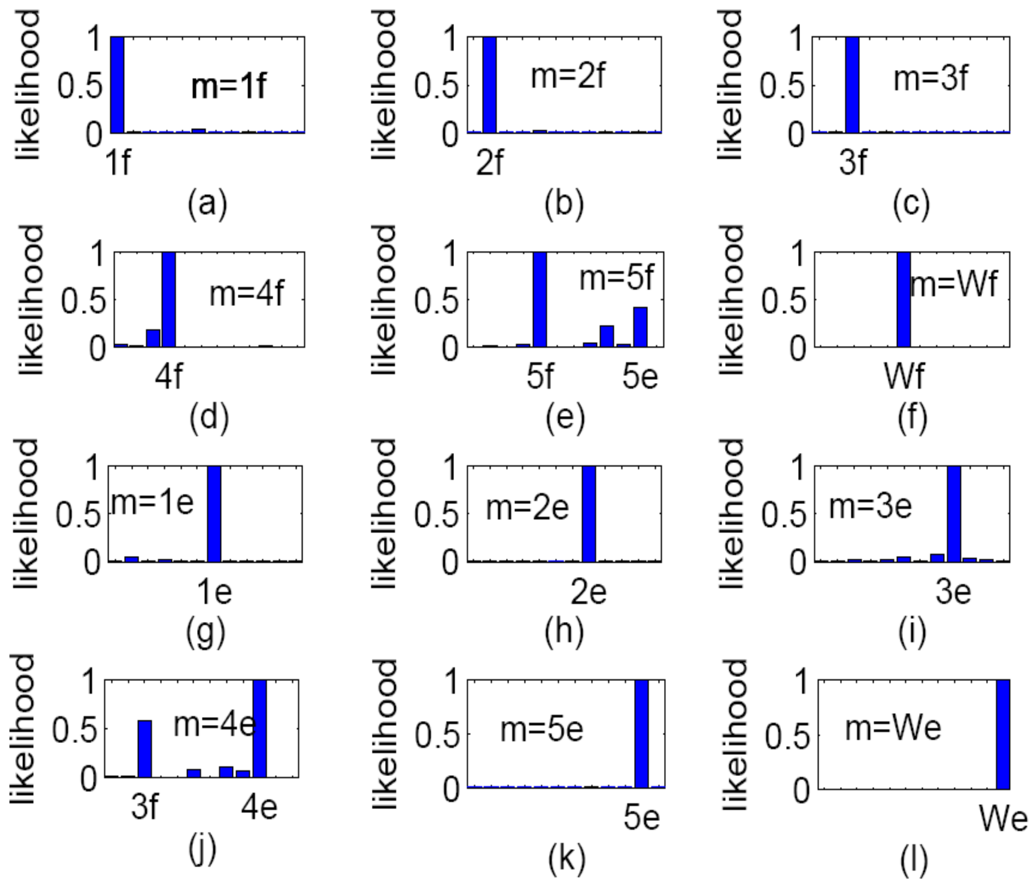
Skellam ML decoding: $$\boxed{\hat{m} = \arg_m \max \prod_{n=1}^{N} h_n(x_n|m)}$$

Maximum Likelihood (ML) Decoding

Skellam ML decoding:

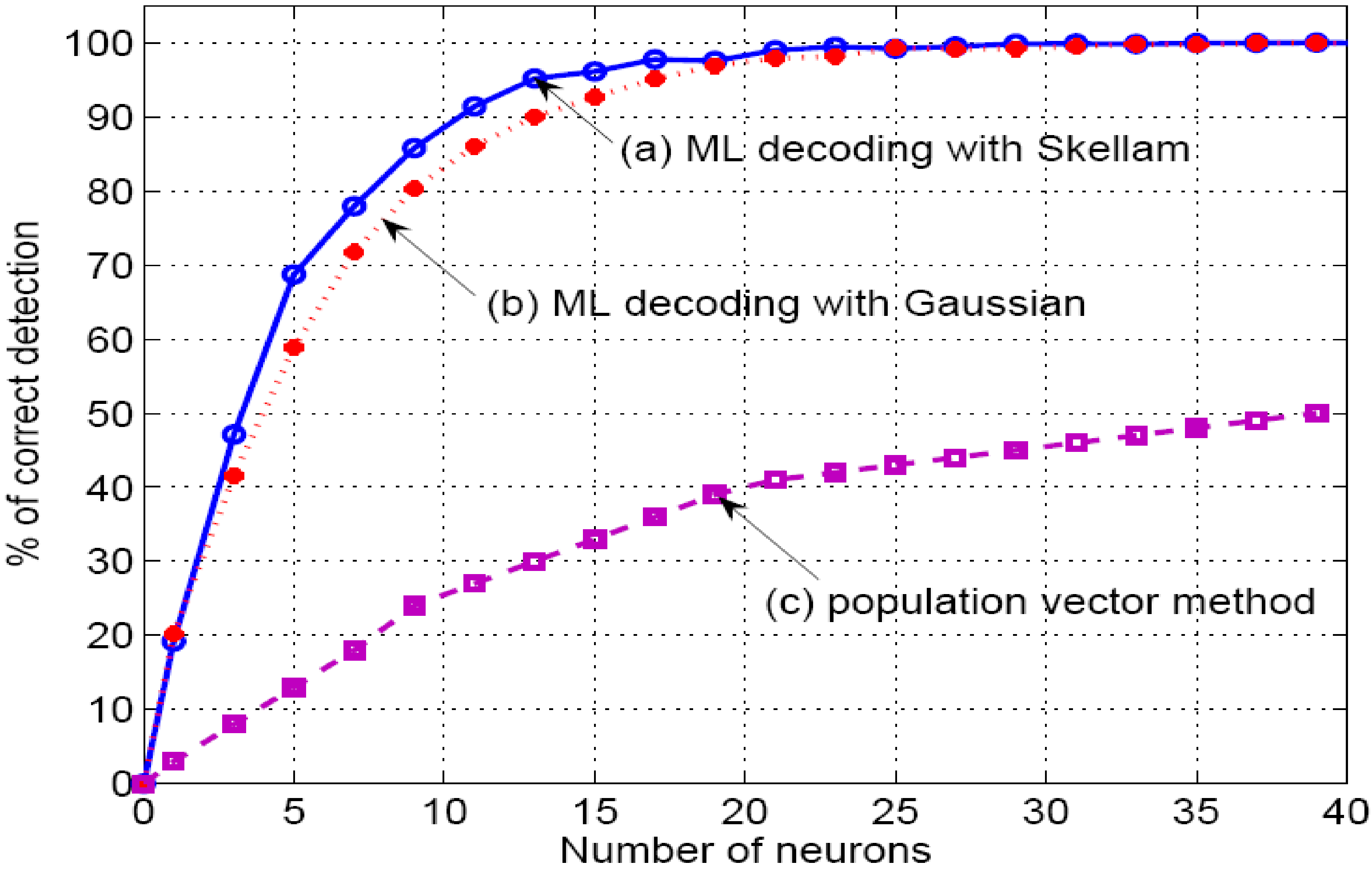
$$\hat{m} = \arg_m \max \prod_{n=1}^{N} h_n(x_n|m)$$

$$\prod_{n=1}^{N} h_n(x_n|m)$$



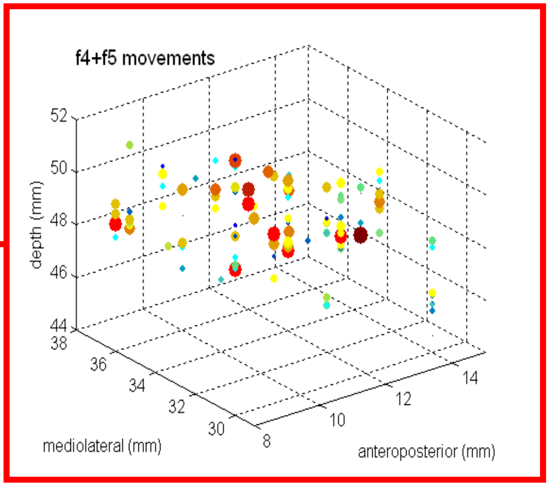
Decoding Accuracy

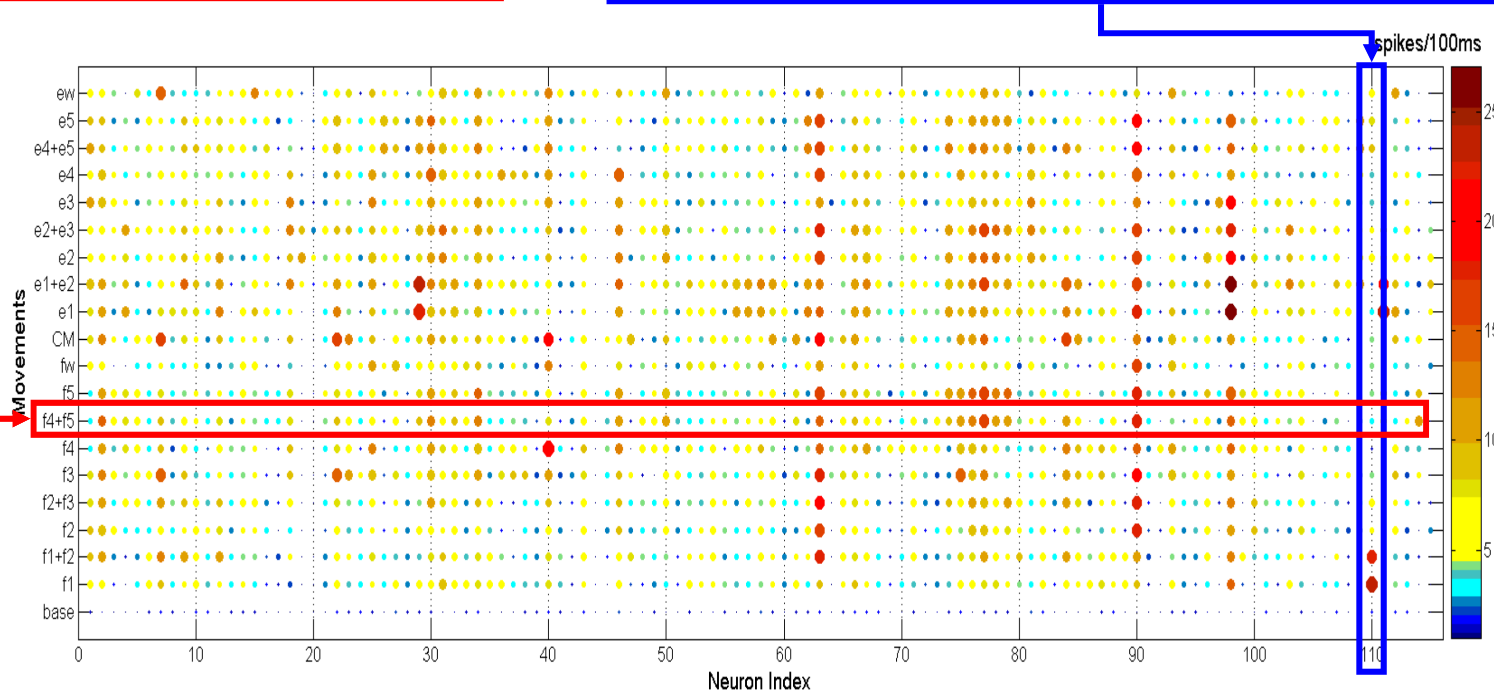
: How many neurons are needed for desired performance?



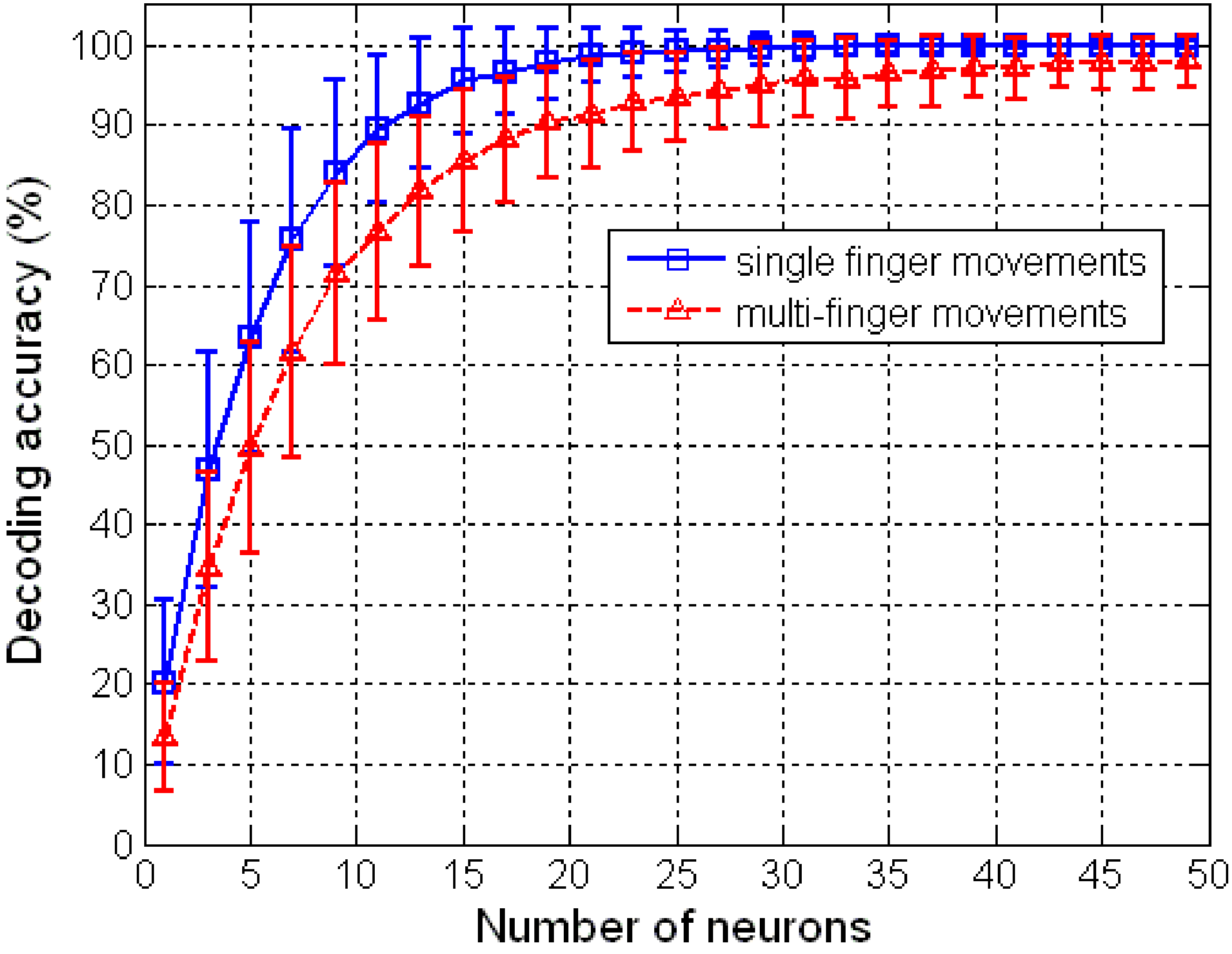
Decoding Multi-finger Movements

Movements: 12 single finger + 6 two-finger movements

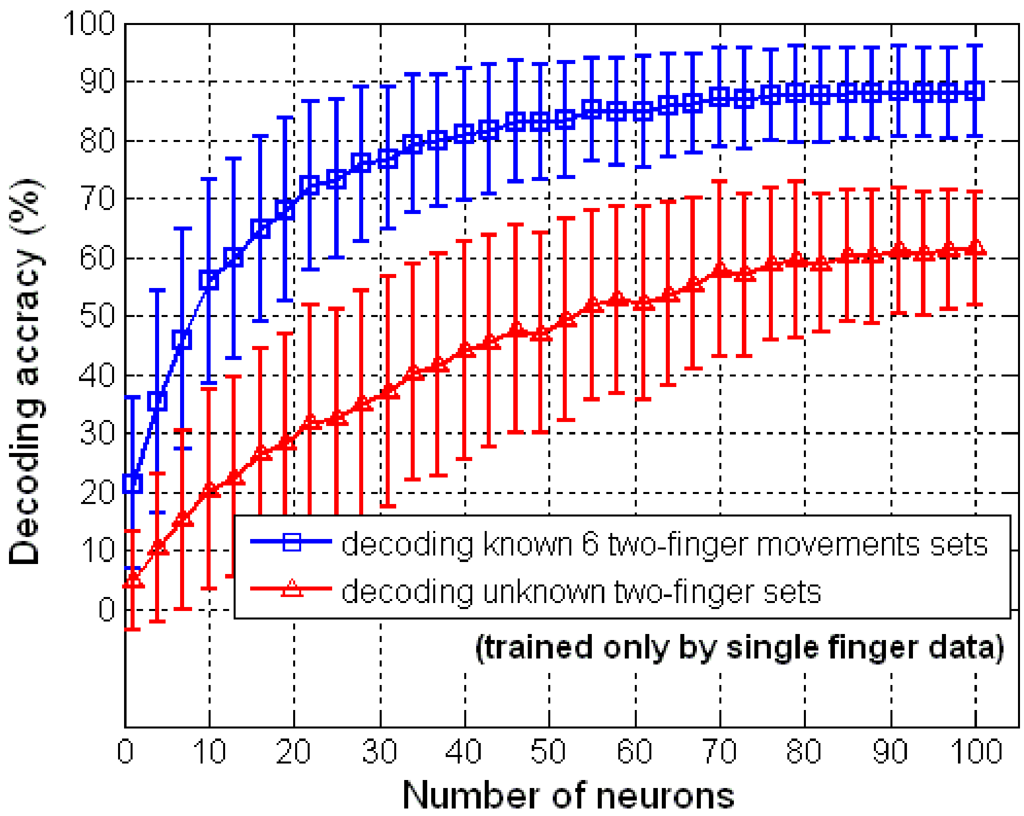


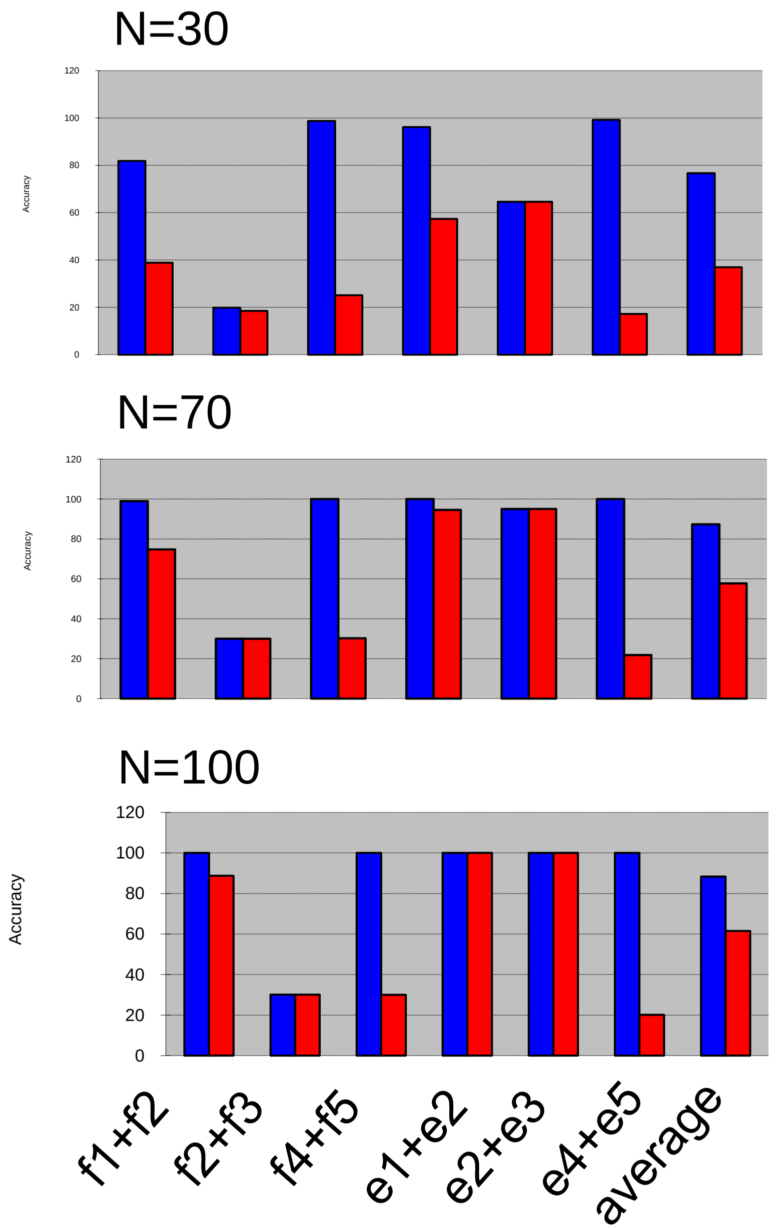


Decoding Accuracy of Multi-finger Movements



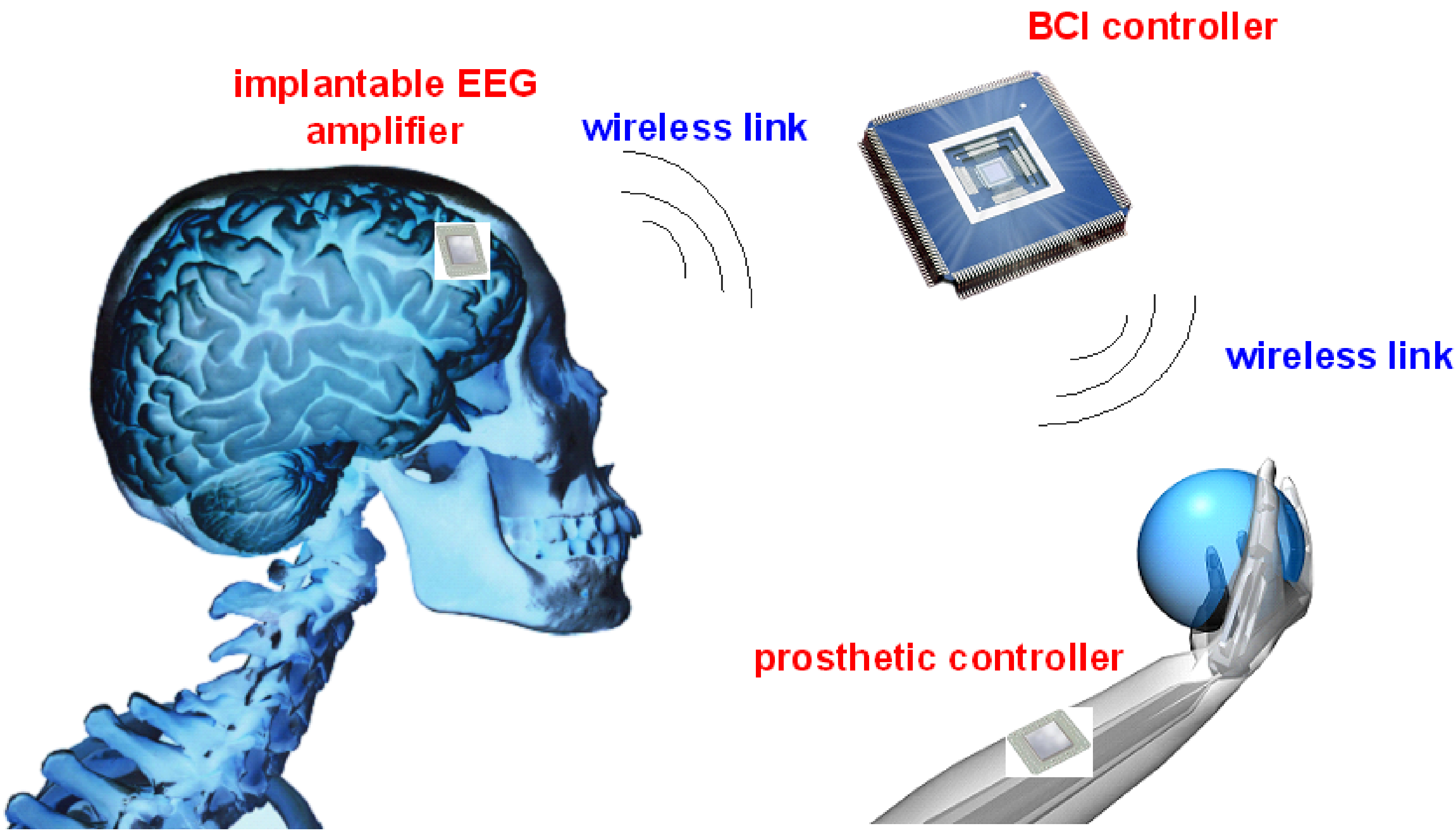
Blind Decoding Accuracy of Two-finger Movements



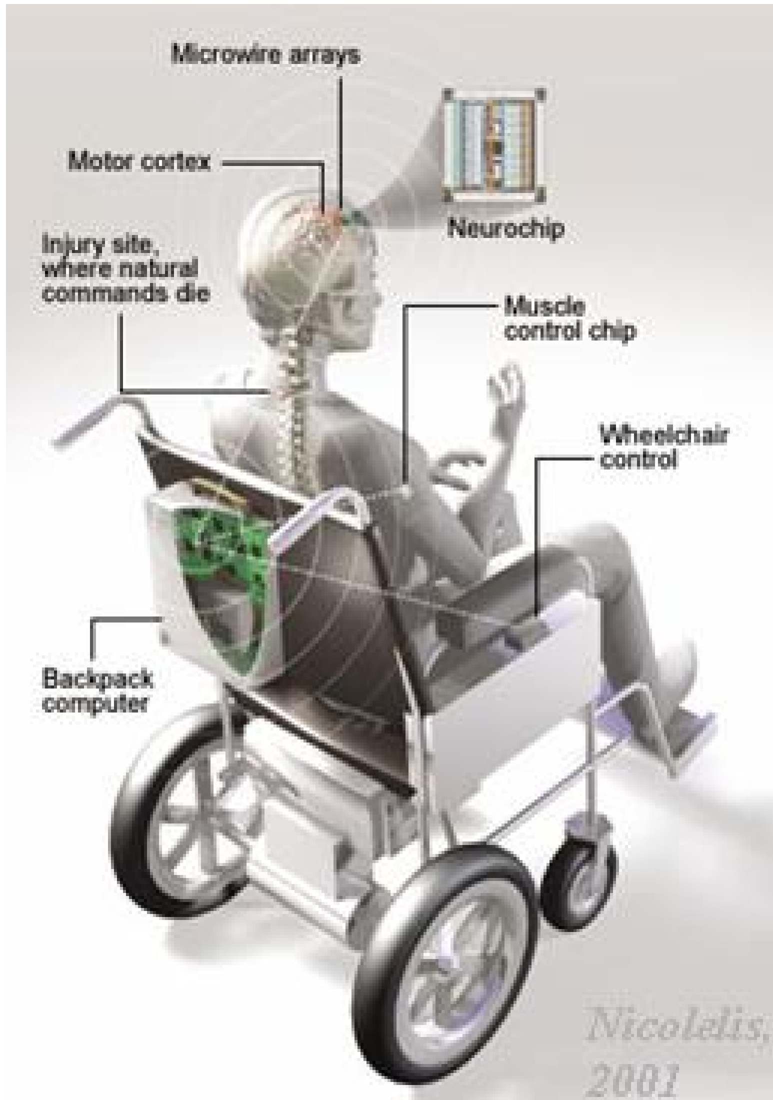


In the Near Future…

Fully Implanted BMI for Prosthetic Control



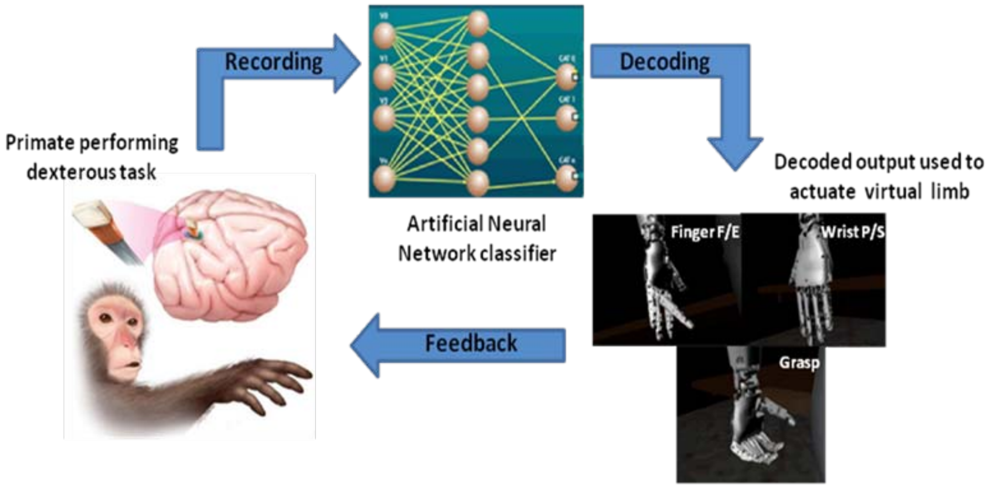
BCI control of Wheelchair

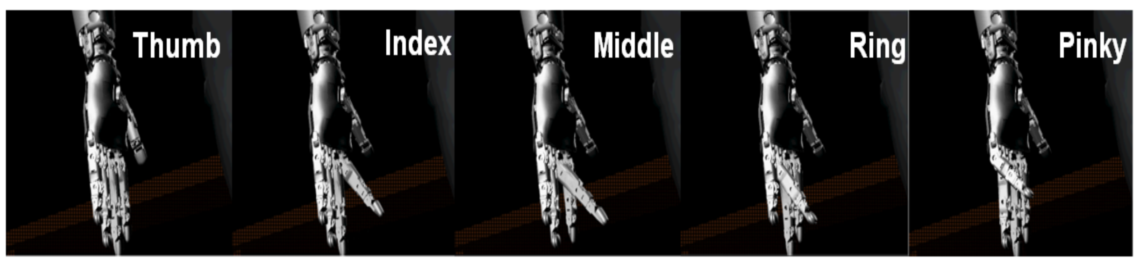


Brain Computer Interface (Invasive)

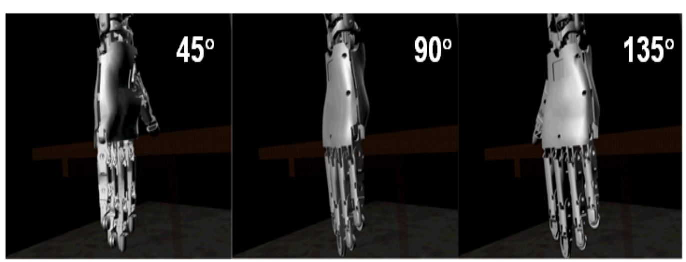
J. Donoghue, Brown Univ & Cyberkinetics

Towards Closed-Loop Decoding of Dexterous Hand Movements using a Virtual Integration Environment

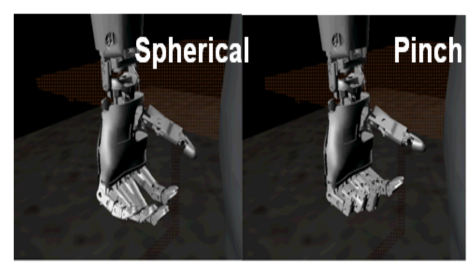




A) Individual Finger Flexion/Extension



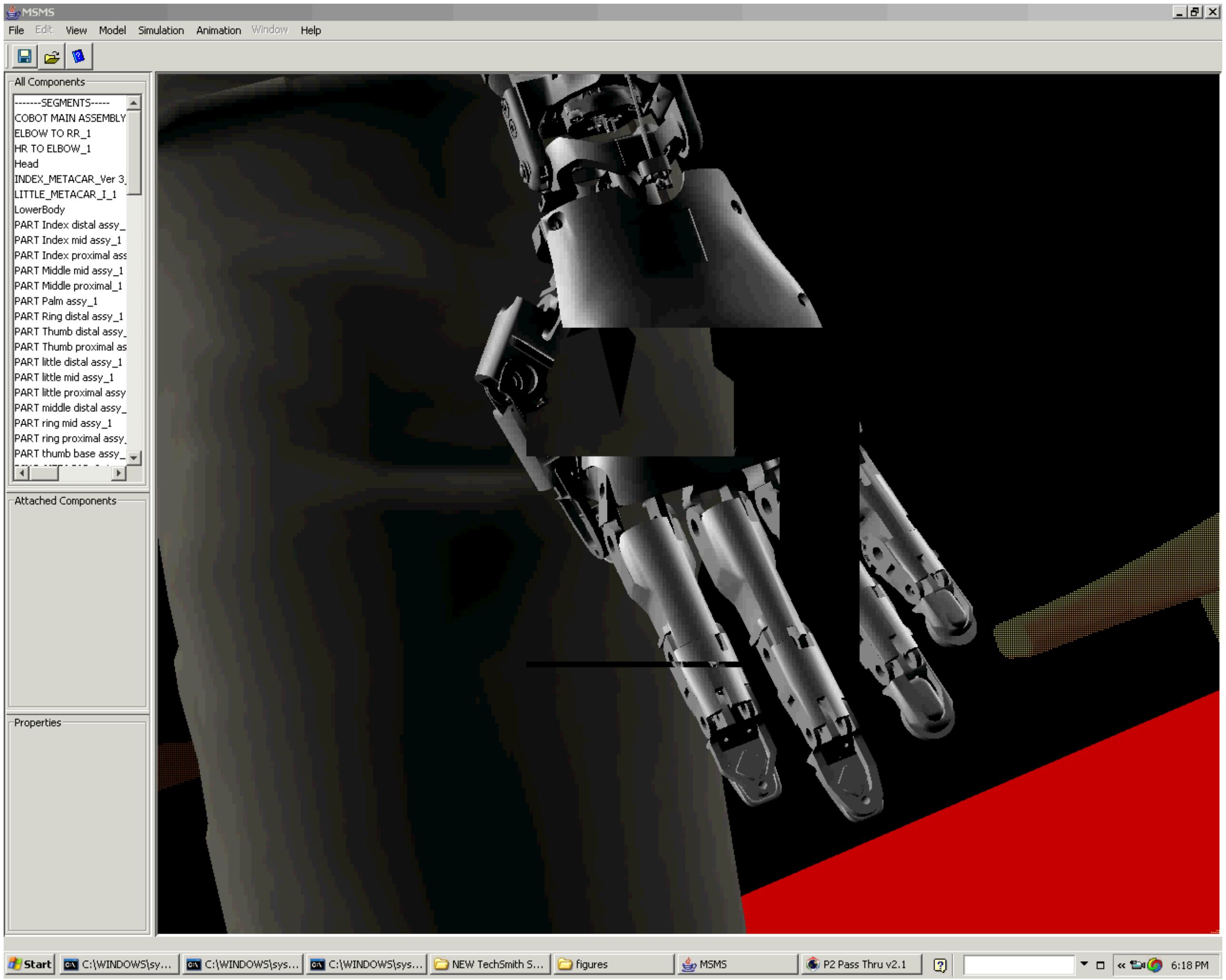
B) Wrist Rotation



C) Grasp

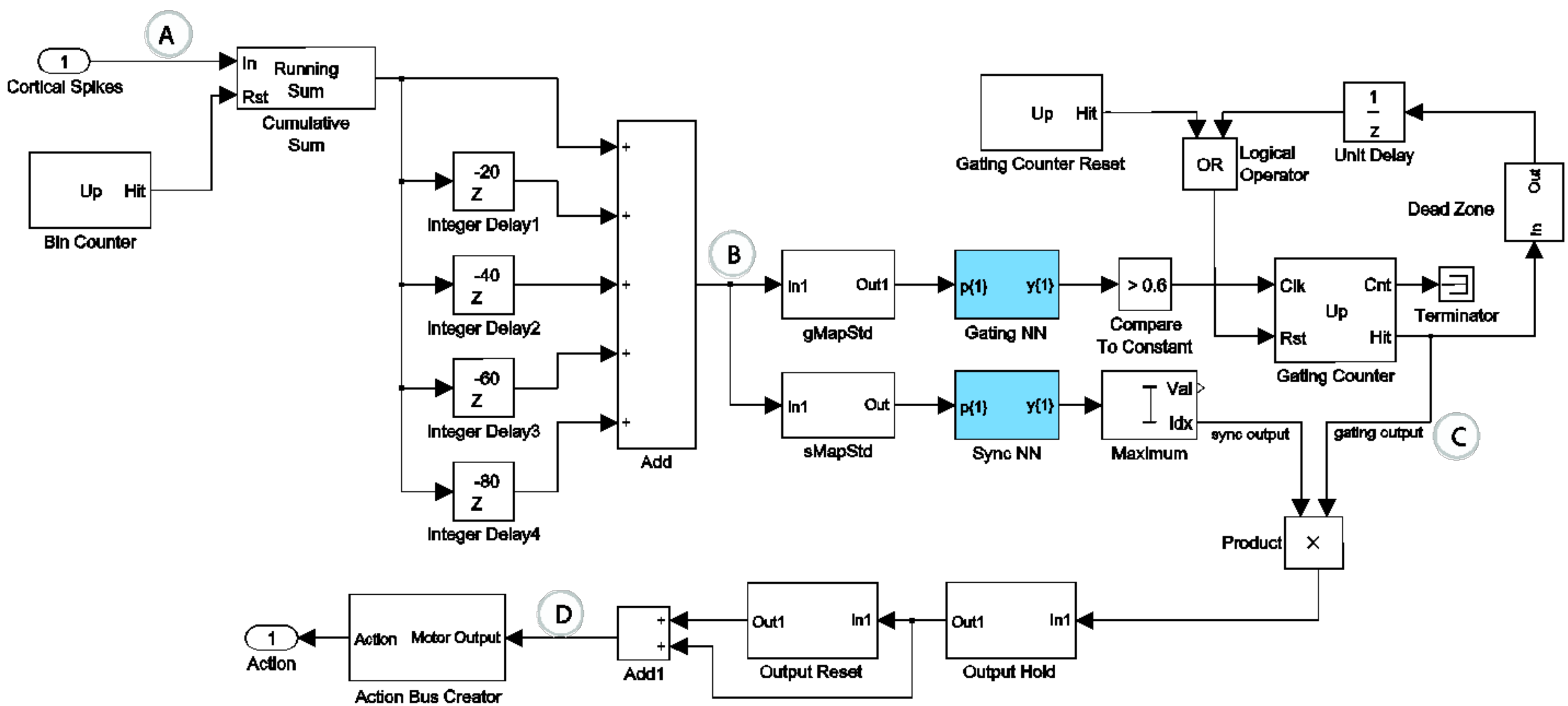
Aggarwal V, Singhal G, MH Schieber, NV Thakor, “Towards closed-loop decoding of dexterous hand movements using a Virtual Integration Environment”, 30th Ann Int Conf IEEE Eng in Med and Bio Soc (EMBS 2008) (article submitted)

Prosthetics
Virtual Integration Environment

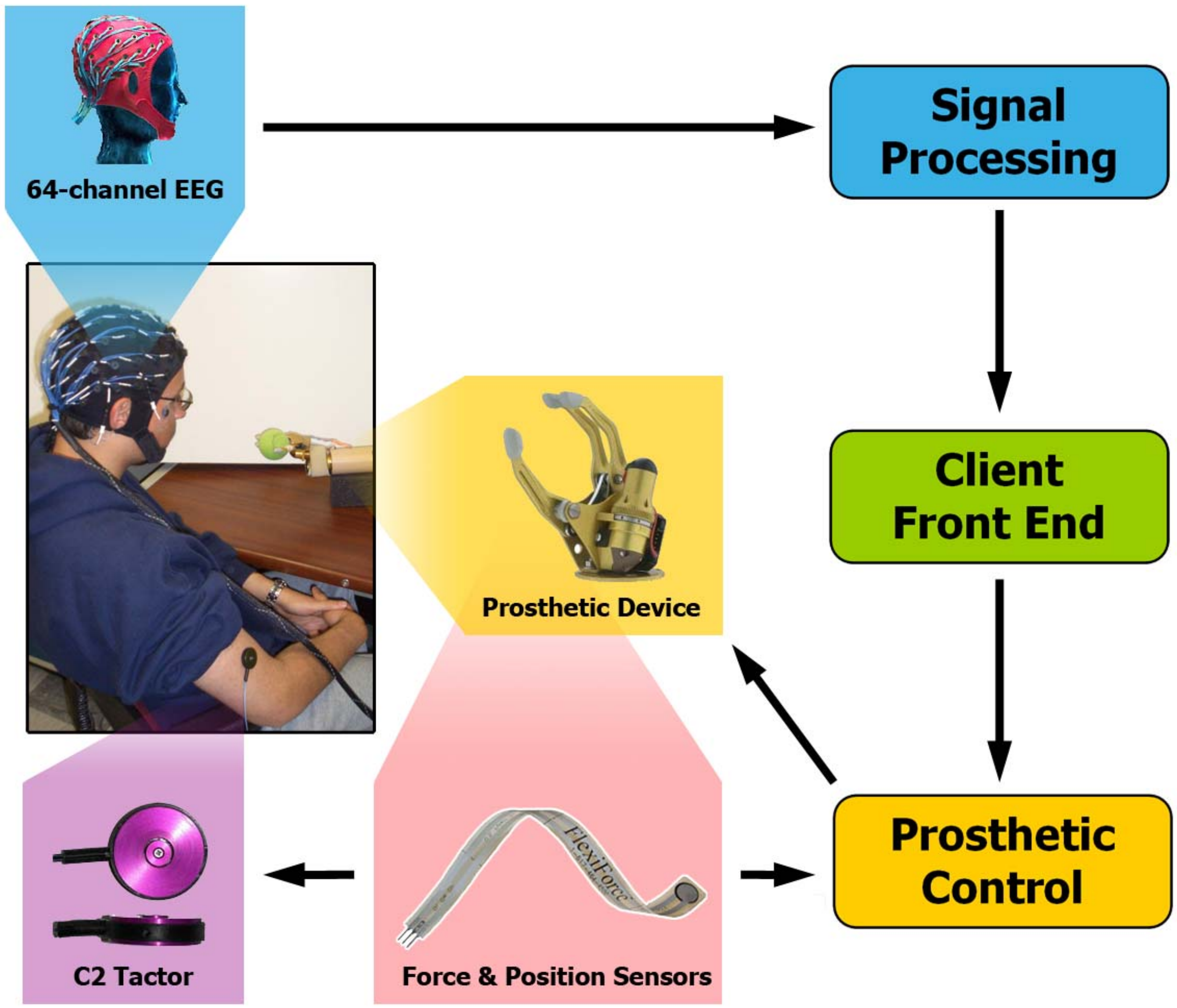


Courtsey:
Johns
Hopkins
Applied
Physics
Lab

Virtual Integration Environment in Simulink

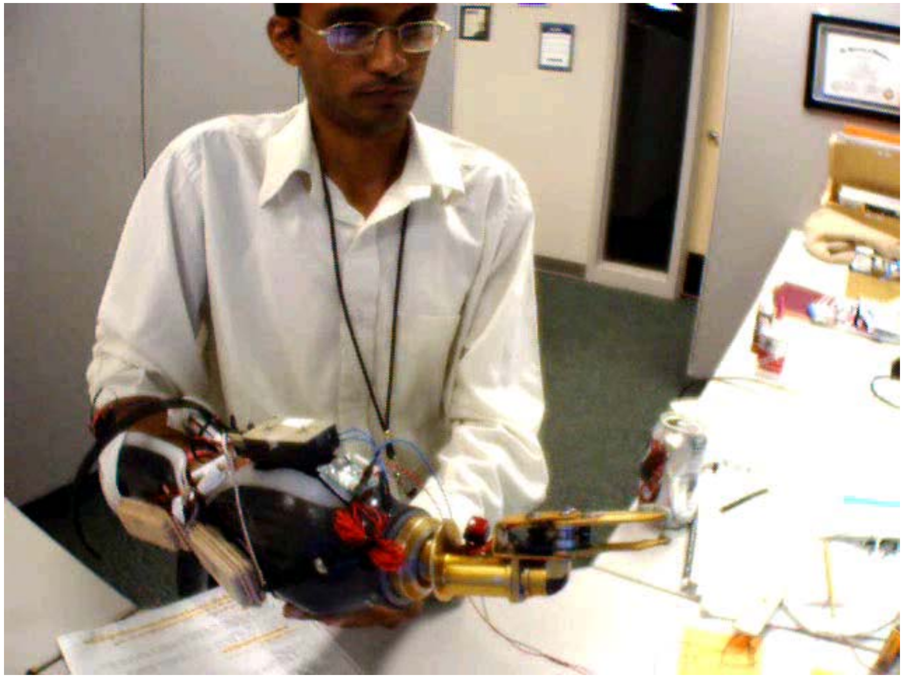


FUTURE: EEG-Based BCI with Local Machine Control and Haptic Feedback



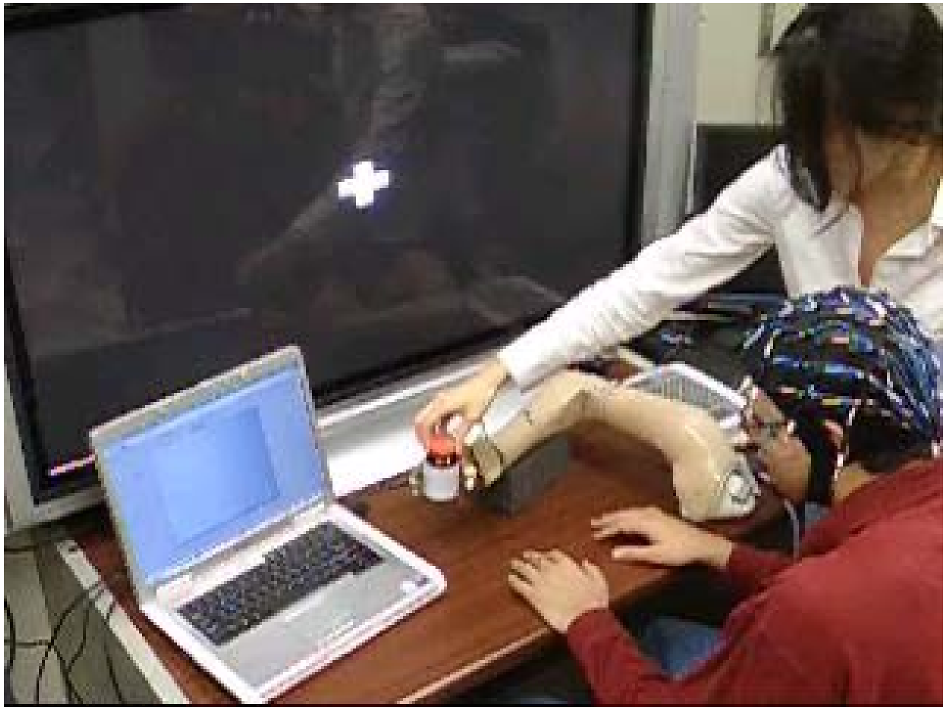
New Directions

Sensory (Haptic) Feedback



With Martin Bionics

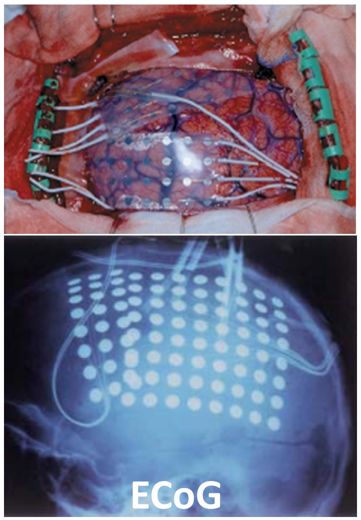
BCI with Haptic Feedback

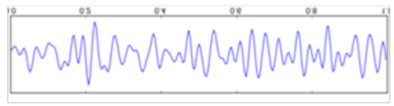


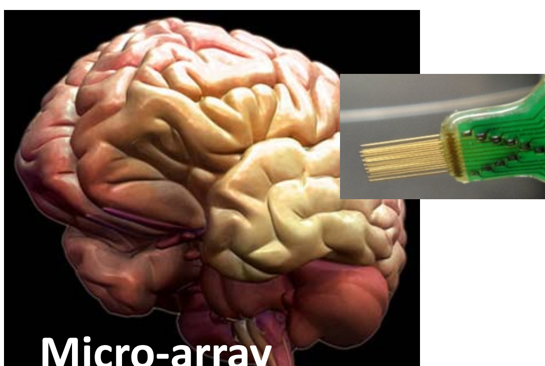
Chatterjee, 2007

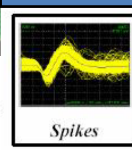
A Speech Prosthesis:

Talking directly with the Brain









Neural Signals from Speech Areas of the Brain

Decoding Algorithms

Spoken Words

Preliminary work illustrating the potential of this approach: with 1 ‘locked in’ subject, with microwire array implanted in Broca’s area. J. Brumberg et.al, SFN 2007

Peer-Reviewed Journal Articles

- Singhal G, Acharya S, **Aggarwal V**, He J, Thakor NV, “Optimal selection of neurons using ensembles of trained models for decoding motor tasks”, Journ of Neural Engineering (manuscript submitted)
- **Aggarwal V**, Acharya S, Tenore F, Shin HC, Etienne-Cummings R, Schieber MH, Thakor NV, “Asynchronous decoding of dexterous finger movements using M1 neurons”, IEEE Trans on Neural Sys and Rehab Eng, Vol. 16, No. 1, pp. 3-14, Feb 2008.
- Acharya S, Tenore F, **Aggarwal V**, Etienne-Cummings R, Schieber MH, Thakor NV, “Decoding finger movements using volume-constrained neuronal ensembles in M1”, IEEE Trans on Neural Sys and Rehab Eng, Vol. 16, No. 1, pp 15-23, Feb 2008.

Peer-Reviewed Articles

- Mollazadeh M, **Aggarwal V**, Singhal G, Law A, Davidson A, Schieber MH, Thakor NV, “Spectral modulation of LFP activity in M1 during dexterous finger movements”, 30th Ann Int Conf IEEE Eng in Med and Bio Soc (EMBS 2008) (article submitted)
- **Aggarwal V**, Singhal G, MH Schieber, NV Thakor, “Towards closed-loop decoding of dexterous hand movements using a Virtual Integration Environment”, 30th Ann Int Conf IEEE Eng in Med and Bio Soc (EMBS 2008) (article submitted)

Other Articles

- Huberdeau D, **Aggarwal V**, Tenore F, Fritz K, Etienne-Cummings R, Thakor NV, “Real-time finger tracking to improve upper-limb prosthetics control”, Proc 34th Ann Northeast Bioeng Conf, Providence, RI, Apr 2008.
- **Aggarwal V**, Singhal G, Davidson AG, Acharya S, Schieber MH, Thakor NV, “Decoding unconstrained grasp movements for a BMI”, Proc 34th Ann Northeast Bioeng Conf, Providence, RI, Apr 2008.
- Acharya S, Singhal G, **Aggarwal V**, He J, Thakor NV, “Decoding wrist angle using recurrent neural network ensembles for BMIs”, Proc 34th Ann Northeast Bioeng Conf, Providence, RI, Apr 2008.

Abstracts

- **Aggarwal V**, Acharya S, Schieber MH, Thakor NV, “Cortical decoding of individual finger and wrist kinematics for an upper-limb neuroprosthesis,” Soc for Neurosci (SfN 08), Washington, DC, USA, Nov 2008. (abstract submitted)
- **Aggarwal V**, Singhal G, Mollazadeh M, Acharya S, Tenore F, Etienne-Cummings R, He J, Schieber MH, Thakor NV, “Decoding Neural Activity for Dexterous Control of an Upper-Limb Neuroprosthesis,” Neural Interfaces Conf, Cleveland, USA, June 2008.
- Singhal G, **Aggarwal V**, Acharya S, He J, Thakor NV, “An ensemble approach to neuron selection for a Brain-Machine Interface,” 11th Intl Conf on Cogn and Neural Systems (ICCNS 08), Boston, USA, May 2008.
- **Aggarwal V**, Acharya S, Tenore F, Etienne-Cummings R, Schieber MH, Thakor NV, “Real-time neuronal decoding for individuated and combined finger movements of a robotic hand,” Ann Meeting of Biomedical Engineering Soc (BMES 2007), Los Angeles, USA, Sep 2007.

Thank you to the students and post-docs

Funded by NIH, NSF, DARPA…