BCI/BMI research for Neural Prosthesis
(or Brain to Hand
Or Decoding Dexterity)

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Revolutionizing Prosthesis
DARPA RP 2009 Grand Challenge

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
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

Coarse (mm)

Non-invasive

Invasive

fMRI

~ 10^3 neurons

EEG

10^4

MEG

10^3

LFP

10^2

Optical imaging

10^1

Spikes

10^0

Fine (microns)

Course (mm)

SPACE
(# indep. signals)
Noninvasive: EEG based BCI

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

Mussa-Ivaldi & Miller, 2003
Neuron Spike based BMI

- high speed real time control
- precise control of movement
- invasive
- high risk for clinical application
Part I: Muscle Control 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

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:
  – Variance:
  – Waveform length:
  – Willison Amplitude:
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


Predicted Versus Actual
MCP Joint Angles
Revolutionary Prosthetics RP2009 Program

Courtesy; 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.

Human Adaptation

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

Part II: Noninvasive Cortical Control of Prosthesis

With S. Acharya, V. Aggarwal, et al
Noninvasive BCI

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

• Multiple scales:
  – Scalp electrical activity (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

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

Laplacian, ICA, CSP, CSSD.....

FFT, Wavelets, AR-model, Entropy

LDA, SVM, Neural Networks
ICA based Spatial Filtering

1. \( x(t) = As(t) \)

2. Deconvolution using Information Maximization

3. \( u(t) = Wx(t) \)

Activity from Independent Cortical Sources

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

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

Soumyadipta Acharya, Mohsen Mollazadeh, Kartikeya Murari and Nitish Thakor
Noninvasive Cortical Control

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

The method of Independent Component Analysis
Spatial Filtering: Localizing neural sources

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

Laplacian:

\[ X_{j}^{Lap} = X_j - \frac{1}{N} \sum_{k \in N} X_k; \text{where} \quad N \ni \text{neighbor}\text{–electrodes} \]

Common Average Reference.

\[ X_{j}^{CAR} = X_j - \sum_{n=1}^{N} X_n; \text{where} \quad -N \ni \text{All}\text{–electrodes} \]

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

Cyberglove sensor - Index DIP - actual (blue) ... predicted (red) \( R = 0.78 \) (Note: the first 1200 data points were for training ... 1200 and is for evaluation)

Cyberglove sensor - Middle PIP - actual (blue) ... predicted (red) \( R = 0.81 \)

Cyberglove sensor - Thumb - Index - Abd/Add - actual (blue) ... predicted (red) \( R = 0.67 \)
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

Background
Ceramic - based Multisite Electrode

In Vivo Implantation and Recording

Multisite recording from barrel cortex

Courtesy K. Moxon
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
Neuron Activity is Widely Distributed in M1 During Each Finger Movement (Schieber & Hibbard, 1993)

Electrical Recording for Prosthetic Control

With M. Schieber, URMC

(Schieber & Hibbard, 1993)
Neural Recording – Single and Multiple Finger Movements
Building Blocks of an ‘invasive’ BMI: Decoding neural spikes

- **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

**Feedback**
- Learning, Plasticity

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

- **Matched Filter, Leaky Integrator, Time-frequency decomposition**

- **Simultaneous Activity of multiple neurons**

- **Cursor Position, Robotic Arm/Hand Kinematic**
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)

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

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

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

Sanchez, Nicolelis, Principe et al., 2004
A Recurrent Neural Network based BMI

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

$$y_1(t) = f(W_1x(t) + W_fy_1(t - 1) + b_1)$$
$$y_2(t) = W_2y_1(t) + b_2.$$ 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

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

*Sanchez, Principe et.al, 2005*
Towards a Brain-Computer Interface for Dexterous Control of a Multi-Fingered Prosthetic Hand

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

Asynchronous Real-Time Decoding

Virtual Microelectrode Grid Array (M1) -> Real-Time Neural Activity

Gating Classifier - $\Gamma$

Movement Decoder - $\Psi$

Committee Neural Network

Finger Movement

Finger Movement

Finger Movement
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

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

- majority voting rule chooses committee output of gating classifier

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

\[ S(t_k) = \text{mode}\{s_n(t_k)\} \]
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
Maximum Likelihood (ML) Decoding

We define the neural activation:

\[ x_n(m) : \text{Neural activation} = \text{firing rate after movement} - \text{firing rate before movement} \]

\( m \): Finger movements

\( n \): Neuron index, 1 \ldots N

ML decoding:

\[ \hat{m} = \arg_m \max Pr(x_1, x_2, \ldots, x_N | m) \]

Maximum Likelihood (ML) Decoding

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

- Firing rate: Poisson

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

$\mu_n(m)$: mean firing rate

- Neural activation $r_n(m)$ (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 Bessel function of the first kind

Maximum Likelihood (ML) Decoding

Skellam modeling of neural activation (neuron K13409):

Firing rate

\[ h_n(x_n|m) \]

K13409 (Skellam)

1f, 2f, 3f, 4f, 5f, Wf, 1e, 3e, 4e, 5e, We

Skellam ML decoding:

\[ \hat{m} = \arg_m \max \prod_{n=1}^{N} h_n(x_n|m) \]
Maximum Likelihood (ML) Decoding

Skellam ML decoding:

\[
\hat{m} = \arg_m \max_n \prod_{n=1}^{N} h_n(x_n|m)
\]
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

The graph shows the decoding accuracy (%) of single finger movements (blue squares) and multi-finger movements (red triangles) as the number of neurons increases. The accuracy improves as the number of neurons increases, reaching near-perfect accuracy with a sufficient number of neurons.
Blind Decoding Accuracy of Two-finger Movements

Decoding accuracy (%) vs. Number of neurons

- Blue line: decoding known 6 two-finger movements sets
- Red line: decoding unknown two-finger sets

(trained only by single finger data)

Accuracy

N=30
N=70
N=100

Bar charts for different N values:
- Left: f1+f2
- Middle: f2+f3
- Right: f4+f5, e1+e2, e2+e3, e4+e5
- Bottom: average
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

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  BCI with Haptic Feedback

With Martin Bionics  Chatterjee, 2007
A Speech Prosthesis:
Talking directly with the Brain

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
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Abstracts


Thank you to the students and post-docs

Funded by NIH, NSF, DARPA...