NON-INVASIVE CORTICAL CONTROL OF REVOLUTIONARY PROSTHESES

N.V. Thakor, S. Acharya, A. Chatterjee, V. Aggarwal, H. Shin, Y. Cho, R. Rasmussen, R. Yang, W. Spier, K. Yeh
Department of Biomedical Engineering, Johns Hopkins University

Introduction

Control of a robotic hand using neuronal signals directly recorded from motor cortex. 2004 www.cyberkineticsinc.com

It has been widely assumed that only invasive neural interfaces, using electrodes directly implanted in the brain can provide multidimensional movement control of a robotic arm or neuroprosthetic. However, recent advances in non-invasive brain-computer interfaces have opened the possibility of generating control signals for multi-dimensional prosthetic control. In a pilot study we have demonstrated the feasibility of using non-invasive EEG signals for controlling a robotic arm.

Using a combination of innovative signal processing, advanced machine learning algorithms, and intelligent controllers, we propose to establish non-invasive and semi-invasive BCIs as a paradigm for reliable control of prosthetic arms with multiple degrees of freedom. Due to their low clinical threshold for use, extensive human experimentation could augment the remarkable advances being made with direct neurally controlled prostheses.

Brain Computer Interfaces

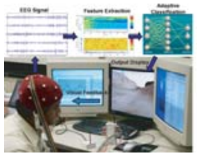
A direct channel of communication between the brain and the external world, bypassing normal neuromuscular pathways.

Current BCI approaches can be broken down into:

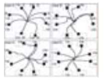
1) Invasive: Cortical Neuronal Recording

2) Semi-Invasive: ECoG

3) Non-Invasive: EEG
  - Mu and Beta rhythm
  - Slow Cortical Potentials (SCP)
  - P300 potentials
  - Steady state visual evoked potentials



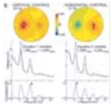
Successful operation of a brain-computer interface involves two way adaptation. Adaptive algorithms learn the user's EEG patterns in response to different mental states, and the user learns to encode the desired control signal in his/her EEG based on adaptive feedback. A reliable BCI should not have high demands in terms of learning requirements and cognitive load. Mental strategies employed should produce reliable and repeatable changes in EEG.



2D cursor control in human subjects. (Wolpaw et. al, PNAS, Dec 2004)

Two dimensional cursor control using EEG has recently been demonstrated with precision, accuracy and speed comparable to those reported with invasive methods in monkeys.

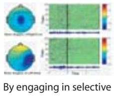
Users learn to control the amplitude of the Mu and Beta band in their EEG over multiple scalp locations by employing different mental strategies. A linear adaptive algorithm finds an optimally weighted combination of these amplitudes to generate two independent control signals, corresponding to the two movement axes.



Scalp maps and corresponding control signal equations for 2D cursor control. Wolpaw et.al, PNAS, Dec 2004

Non-Invasive BCI Control

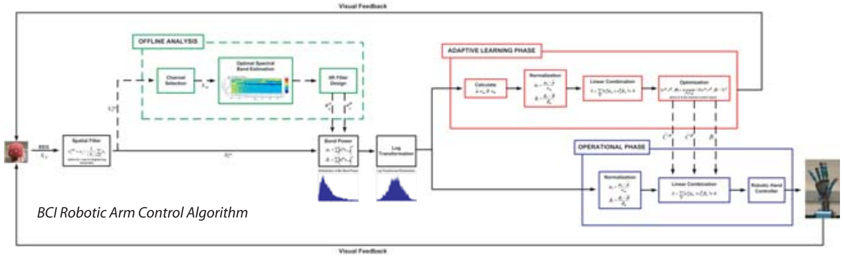
Using motor imagery and adaptive learning algorithms, we have demonstrated control of a robotic arm for simple grasping tasks.



Motor imagery provides a simple and repeatable mental strategy, which is well mapped to changes in spatiotemporal features of the EEG.

By engaging in selective (imagined) motor tasks, a subject can generate a signal to move a cursor on a screen or control a prosthetic arm. Since this technique does not require any external stimuli, and is directly mapped to specific mental tasks, it serves as a reliable underlying basis for BCIs.

Two state motor imagery, combined with adaptive controllers, used to open and close a robotic hand. (Johns Hopkins University)

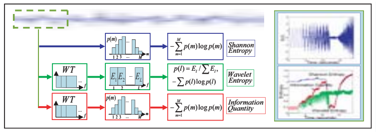


BCI Robotic Arm Control Algorithm

Algorithms Under Development

The pace of advancement in BCI control schemes in recent years shows that sophisticated algorithms can produce control signals with larger bandwidth and greater reliability. Some promising avenues of research include:
  - sub-band entropy, mutual information
  - source localization based algorithms
  - phase synchrony and coherence

1) Entropy-Based Feature Extraction



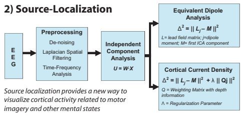
$-\sum_{m=1}^{M} p(m)\log p(m)$ Shannon Entropy

$p(l) = E_l / \sum E_l$, $-\sum p(l)\log p(l)$ Wavelet Entropy

$-\sum_{m=1}^{M} p(m)\log p(m)$ Information Quantity

Sub-band entropy and mutual information can further enhance the accuracy of a BCI control signal

2) Source-Localization



EEG

Preprocessing
De-noising
Laplacian Spatial Filtering
Time-Frequency Analysis

Independent Component Analysis
$U = W \cdot X$

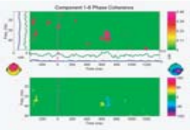
Equivalent Dipole Analysis
$\Delta^2 = \| L_j - M \|^2$
L= lead field matrix; j=dipole moment; M= first ICA component

Cortical Current Density
$\Delta^2 = \| L_j - M \|^2 + \lambda \| Qj \|^2$
Q = Weighting Matrix with depth information
Λ = Regularization Parameter

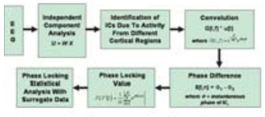
Source localization provides a new way to visualize cortical activity related to motor imagery and other mental states

Dipole source localization during a working memory experiment at JHU. Using this approach could allow for the classification of a greater number of mental states.

3) Phase Synchrony and Coherence for BCI



Transient phase synchrony between different cortical regions during a working memory experiment.



EEG

Independent Component Analysis
$U = W \cdot X$

Identification of ICs Due To Activity From Different Cortical Regions

Convolution

Phase Difference

Phase Locking Value

Phase Locking Statistical Analysis With Surrogate Data

Phase synchrony provides an exciting possibility for generating a multidimensional BCI control signal by unravelling changes associated with self-initiated mental tasks.

Towards Integration With Higher DoF Prostheses

Virtual Reality Environments

Virtual arm with multiple degrees of freedom. Using a combination of context sensitive controllers, a low bandwidth BCI signal can achieve simple tasks like reach-grab-fetch. (Johns Hopkins University)

Virtual reality environments (VRE) provide an intermediate step between theory and clinical application. With this platform, users can interact with virtual objects using neural control strategies. We are currently developing a virtual prosthetic arm with multiple degrees of freedom that will be used to test non-invasive, multidimensional control using a combination of BCI algorithms and context-sensitive controllers.

Intelligent Local Control Strategy

An intelligent controller can accept low bandwidth commands from a non-invasive BCI and output a higher bandwidth control signal to a prosthetic hand. The controller would have built-in functionality that would allow it to grip objects intelligently. This can be done by processing kinesthetic sensory feedback from the prosthesis to dynamically adjust the force distribution across the fingers. Further enhancements would include allowing the user to choose between multiple precision and power grips.

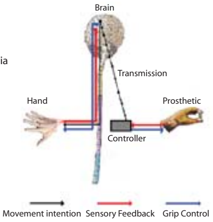
Neuromuscular Pathway

1) Brain sends movement intention command to hand via spinal cord

2) Hand moves and returns haptic feedback

3) Brain subconsciously processes feedback and dynamically adjusts grip

4) Loops continuously until movement intent change



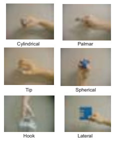
Neuroprosthetic Pathway

1) Non-invasive control scheme sends movement intention to prosthetic controller

2) Prosthetic returns force sensory information to controller

3) Controller processes feedback and adjusts grip

4) Loops until BCI input to controller changes



http://ww.bsu.edu/web/jkshim/handfinger/overvieww/overview.htm

Non-invasive BCI can pass a low-bandwidth signal to the controller to represent movement intention. Afterwards, the intelligent controller would be capable of grasping objects with adaptable prehension through a sophisticated local control loop

Conclusions

Non-invasive BCI is an exciting, viable alternative that can supplement current prosthetic control paradigms.

While rapid advances in direct neural interfaces may ultimately offer high-precision, multidimensional control of revolutionary prosthetics, non-invasive BCI is a readily accessible platform for human testing. This includes evaluating cognitive loading impact of the prosthetic limb on the patient, understanding human learning strategies, refining local control algorithms, and assessing human factors. Non-invasive BCI is a potentially high-impact technology that could greatly accelerate the development of a revolutionary prosthetic limb.

References

N. Birbaumer, A. Kubler, N. Ghanayim, T. Hinterberger, J. Perelmouter, J. Kaiser, I. Iversen, B. Kotchoubey, N. Neumann, and H. Flor, "The thought translation device (TTD) for completely paralyzed patients," *IEEE Trans. Rehab. Eng.*, vol. 8, pp. 190-193, June 2000.

J. Donoghue, "Connecting cortex to machines: recent advances in brain interfaces" *Nat. Neurosci.* vol. 5, pp. 1085-1088.

L. Qin, L. Ding, and B. He. "Motor imagery classification by means of source analysis for brain-computer interface applications," *Journal of Neural Engineering*, vol. 1, issue 3, pp. 135-141, 2004.
G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proc. IEEE,* vol. 89, pp. 1123-1134, July 2001.

J. Sarnthein, H. Petsche, P. Rappelsberger, G. Shaw, and A. von Stein, "Synchronization between prefrontal and posterior association cortex during human working memory," *Proc. Natl. Acad. Sci.*, vol. 95, pp. 7092-7096, 1998.

J. Wolpaw and D. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proc. Natl. Acad. Sci,* vol. 101, no. 51, pp. 17849-17854, 2004