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IPSIHAND BRAVO: An Improved EEG-based Brain-Computer Interface for Hand Motor Control Rehabilitation

Charles Damian Holmes, Mark Wronkiewicz, *Member, EMBS,* Thane Somers, *Member, IEEE*, Jenny Liu, Elizabeth Russell, DoHyun Kim, Colleen Rhoades, Jason Dunkley, David Bundy, Elad Galboa, Eric Leuthardt

Abstract— **Stroke and other nervous system injuries can damage or destroy hand motor control and greatly upset daily activities. Brain computer interfaces (BCIs) represent an emerging technology that can bypass damaged nerves to restore basic motor function and provide more effective rehabilitation. A wireless BCI system was implemented to realize these goals using electroencephalographic brain signals, machine learning techniques, and a custom designed orthosis. The IpsiHand Bravo BCI system is designed to reach a large demographic by using non-traditional brain signals and improving on past BCI system pitfalls.**

I. Introduction

Every year in the United States, nearly three quarters of a million people suffer a stroke [1]. Along with other forms of damage to the central nervous system, e.g. traumatic brain injury, spinal cord injuries, and neurodegenerative diseases, strokes can cause devastating loss to functional motor control. Hand impairment is often a lasting result of these conditions, and there are approximately 900,000 people suffering from severe grasping impairment in the U.S [2]. Individuals affected by hand impairment face considerable difficulty performing everyday tasks.

After a stroke or other form of nerve damage, there is a 3 month window in which rehabilitation efforts are most effective [3]. However, the average stroke rehabilitation patient spends fewer than five hours at the clinic each week [4] despite research that shows rehabilitation outcomes are time dose-dependent [5]. Furthermore, conventional therapeutic techniques require that the patient exhibits some residual movement post-injury as a starting point for rehabilitation and entails frequent visits to the therapist's office.

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C.D. Holmes is with the Electrical and Systems Engineering Department and the Computer Science Department, Washington University in St. Louis, MO 63130 USA (phone: 518-469-2835; e-mail: holmes@ wustl.edu).

M. Wronkiewicz is with the Biomedical Engineering Department, Washington University in St. Louis, MO 63130 USA. (e-mail: mdw4@cec.wustl.edu).

T. Somers, J. Liu, E. Russell, D. Kim, C. Rhodes, and J. Dunkley are with the School of Engineering, Washington University in St. Louis, MO 63130 USA.

David Bundy is with the Biomedical Engineering Department, Washington University in St. Louis, MO 63130 USA (email: dtbundy@wustl.edu).

E. Gilboa is with the Electrical and Systems Engineering Department, Washington University in St. Louis, MO 63130 USA.

Eric Leuthardt is with the Department of Neurosurgery, Washington University in St. Louis, MO 63130 (email: leuthardt@wustl.edu).

A technology called brain computer interfaces (BCIs) offers hope of motor rehabilitation for patients with virtually all forms of brain or central or peripheral nerve damage, without the limitations of conventional therapy. BCIs work by processing brain activity into a control signal, which can be used to control a computer or any device interfacing with that computer. There are three major methods of obtaining voltage signals from the brain: electroencephalography (EEG) (scalp surface recordings), electrocorticography (ECoG) (brain surface recording), and single unit recordings (intra-brain recordings). The last two methods give higher signal resolution, but the often prohibitively high risk of infection and cost associated with implanting electrodes under the skull make EEG more desirable for most BCI systems today [6].

BCI systems make an excellent platform for nervous system rehabilitation because they can bypass damaged or destroyed nerve pathways. Basic neurophysiology states that each side of the human body is controlled by the opposite, or contralateral, side of the brain. However, the signals of interest for the IpsiHand system are acquired from the movement *ipsilateral motor planning* areas of the brain, anterior to the sensory-motor strip typically used for other BCIs. These ipsilateral signals come from the same side of the brain as this injury, which is advantageous because IpsiHand is still applicable even after a severe hemiparetic stroke that completely destroys the motor area in the brain [7]. Sensorimotor based BCIs would fail in this case without a useful signal to read, and conventional rehabilitation techniques also have no starting point if a patient lost all voluntary hand control.

The purpose of this paper is to present the IpsiHand Bravo BCI system aimed at immediately restoring hand function and providing a long-term rehabilitation solution. This device uses commercially available components, machine learning algorithms, and a custom designed hand orthosis to provide a cost-effective solution that can be worn and used independently (outside healthcare facilities) in a patient's daily life. The goal of this project is to provide a better overall rehabilitation outcome following a stroke or other nerve damage by overcoming rehabilitation barriers and providing more effective hand motor control therapy.

II. Technical Description

A graphical representation of the system overview can be seen in Fig. 1. In summary, an EEG headset is used to acquire signals from the subject's brain. That signal, transmitted wirelessly to a personal computer, is used to train a machine learning system. This machine learning system can then be used to process future brain signals, to estimate the subject's intention to open or close his or her hand. This intention is used to control the position of a motorized exoskeletal orthosis via a Bluetooth Arduino unit.

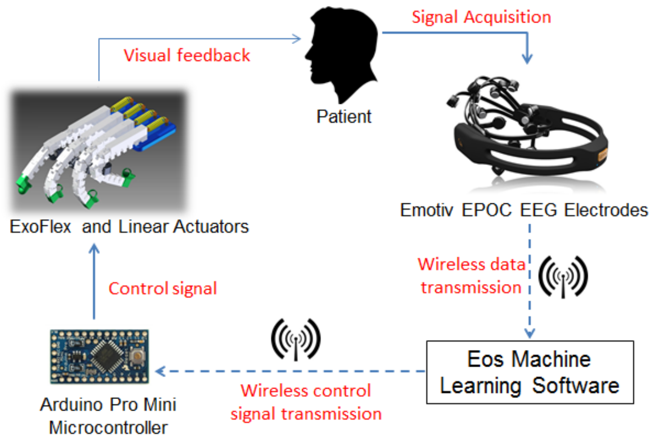

Figure 1 - IpsiHand Bravo System Overview

A. Signal Acquisition Hardware

EEG voltage signals were acquired from the subject's scalp using a commercial, dry-electrode Emotiv EPOC (Emotiv; Australia) headset. The EPOC has 14 electrodes located over 10-20 international system positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. The EPOC also has 2 reference electrodes positioned behind the ear. The headset aligns, band-pass filters, and digitizes the signal at 128 Hz. This signal is transmitted wirelessly to a laptop for processing.

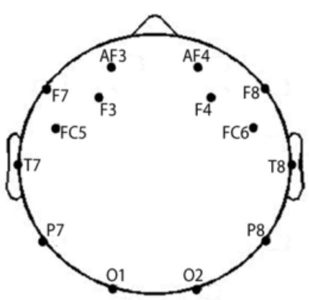

Figure 2 - Spatial Location of Electrodes for the Emotiv EPOC Headset

B. Machine Learning Software

IpsiHand Bravo makes use of the *Eos Machine Learning Software Suite*, developed specifically for IpsiHand. This software suite contains three distinct subunits: 1) A signal recording subunit, 2) a training subunit, and 3) a real-time subunit. The system overview of the Eos software is visually represented in Fig. 3 and fully explained in the following subsections.

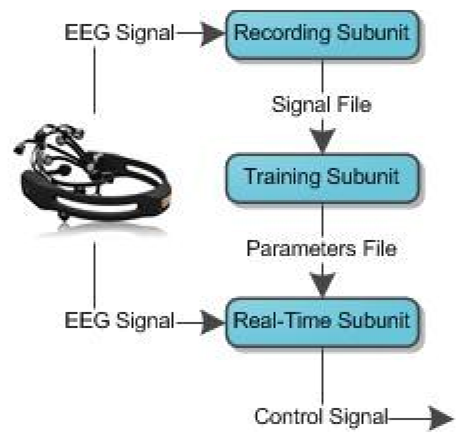

Figure 3 - System Overview of Eos Machine Learning Software

1) Signal Recording

The signal recording subunit is used to produce a data file which contains the raw data collected during a single recording session. A session is divided into 3 runs, and each run is divided into 30 trials. During a trial, the user is presented with one of two prompts to solicit a response. The prompt is chosen by a randomizing algorithm that guarantees each prompt occurs 15 times per run. Following the prompt, there is a 5-second recording period, during which the user is to act based on the prompt presented. While the user is acting, the signals from the EPOC electrodes are recorded and associated with the prompt. After the recording period, there is a 5-second rest period before the next prompt.

For the IpsiHand Bravo design, the two prompts are "move" and "pause". During the "move" prompt, the user moves, or imagines moving, their hand in a significant and/or specific way. During the "pause" prompt, the user remains perfectly motionless and is asked to not imagine hand motion.

2) Training

The training subunit reads in the signal file. Frequency analysis is carried out on each trial's 5-second recording period to produce 90 examples of 910 features each. Each example represents one of the recording periods and each feature represents a channel-frequency combination (for example: electrode F3 at 12 Hz). 65 frequency bins per channel with 14 channels results in 910 features.

Using each trial's feature set, feature extraction is carried out using Kernel Principle Component Analysis (KPCA) [8] to produce 90 instances of 90 features each. These features contain more variance per feature than the original feature set, giving these features additional discriminative potential.

The extracted feature set is used to produce a Support Vector Machine model with the software library LibSVM [9]. This model produces a function of extracted feature sets, which outputs an estimate of the user's action.

Using an optimizing iteration algorithm, an ideal set of parameters for KPCA and SVM are produced and written to a TXT file called the parameters file for each user.

3) Real-Time

The real time subunit acquires data similarly to the signal recording subunit. However, the real-time subunit differs by maintaining a one-second signal buffer for all electrodes. Using the parameters from the parameters file, the real-time subunit processes the 14 one-second signal buffers with spectral analysis, KPCA, and SVM. This signal processing is used to estimate whether or not the user was attempting to mover their hand. This estimation is called the *control state*.

These calculations are carried out about once every 150 milliseconds using the previous second of signal buffer. At the end of each of these iterations, a new control state is produced.

For each iteration, a position value between 0 and 999 (corresponding to hand completely open or closed respectively) is determined based on the hand position from the previous iteration and the desired position corresponding to the control state. This position value is also called the *control signal*. Depending on the user, the delay between attempting to activate the device and physical linear actuation is 300-500 milliseconds.

C. Arduino Bluetooth Controller

The control signal from the Eos software is sent wirelessly via Bluetooth to an Arduino Pro Mini (SparkFun Electronics; Boulder, CO) worn by the user. The desired hand position is then mechanically realized by forwarding his signal to linear actuators on the exoskeleton hand orthosis.

D. Exoskeletal Hand Orthosis

The low profile hand orthosis system, known as ExoFlex, is a custom-designed hand exoskeleton for mechanical manipulation of the wearer's fingers. It was designed and completed with wearability, ease of attachment, and customizability in mind. See Fig. 4 and Fig. 5 for a Computer Aided Design model of the exoskeleton. From the distal finger-tip toward the hand, the mechanical component consists of four finger end caps that connect to finger chains. These chains run along the back of each digit and all connect to a central hub that sits on the dorsal side (or back) of the hand. At each of the most proximal links in the chain, there are two holes where two thin wires are inserted into each finger chain. These holes continue through all links down the length of each chain with one wire is positioned over the axis of rotation for each link, and one under. By applying tension to either the top or bottom cable, the individual exoskeletal chains flex or extend in order to manipulate the wearer's fingers. The wires are tensioned via a set of linear actuators (Firgelli miniature Linear Motion Series L16) worn on the arm or waist. The linear actuators are controlled by the Arduino system. Tensional force is transmitted from the linear actuators to the chains with a Bowden cable (compressionless outer sheath with force transmitting wire contained inside), just like a bicycle brake system. Because the ExoFlex is powered by a lithium polymer battery, the ExoFlex and Arduino can be worn and operated without a power cord or other restraining cables for at least two hours.

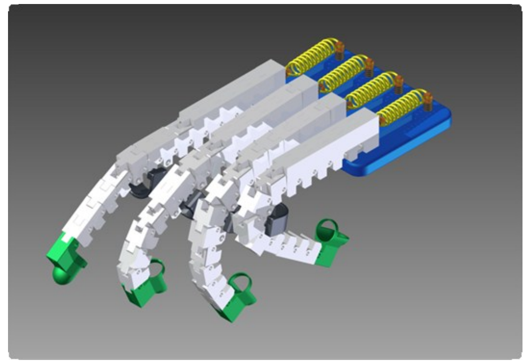

Figure 4 - Front View of ExoFlex

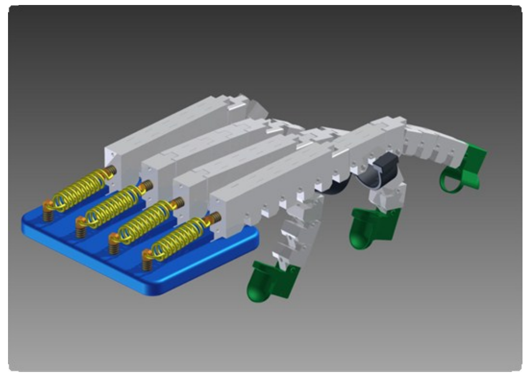

Figure 5 - Rear View of *ExoFlex*

III. RESULTS

A. Eos Machine Learning Software

The performance of Eos was analyzed through *10-fold-cross-validation*. This method involves training the system with 90% of the data from the *signal file*. Then, accuracy is determined by testing the trained system with the remaining 10% of the data. This training and testing is carried out on the whole data set ten times, using a different 10% of the data as a training set each time. A mean accuracy is calculated and used as the calculated system accuracy.

Six subjects volunteered to use test Eos. All the subjects were young adult males in good health. Average accuracies for each subject can be seen in Table I.

TABLE I. ACCURACY OF THE *EOS MACHINE LEARNING SOFTWARE*

Accuracy of *Eos Machine Learning Software*	
Subject ID	***Accuracy***
T001	95%
T002	98%
D001	91%
U001	93%
E001	87%
E002	86%

B. ExoFlex

The ExoFlex component of IpsiHand was physically converted from a CAD model to the physical device by having the model 3D-printed out of a light Nylon 12 plastic polymer by a company called Shapeways (New York City, New York). 3D-printing every component that contacts the wearer's hand enables rapid customization of the orthosis's key dimensions to the intended user.

The chain link design of this orthosis is able to prevent hyperextension because each link rotates from level to 45 degrees of flexion. As each link adds 1 cm of length to the chain, they are also short enough to closely hug the finger even in full finger flexion. By removing the "station" aspect rehabilitation, this system encourages a wider range of environmental interaction both in the therapist's office and the patient's home.

The possibility of in-home use, size (and color) customization, low-profile, and wearability of the orthosis makes it a very attractive orthosis system. Together with the headset, electronics, 3D printing, and cables, the materials cost of the IpsiHand Bravo system is under $1200.

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C. Long-term Therapy

At the time of this paper's submission, a case study involving an individual stroke patient using the IpsiHand system had commenced. While the patient seemed to acquire reasonable control using our system, the results of this long term study will give insight into the rehabilitation potential associated with extended use of the IpsiHand system.

IV. Discussion

The IpsiHand Bravo design offers hope for rehabilitation for those who suffer brain injury. Through preliminary analyses, it is possible to achieve greater than 90 percent accuracy in most cases with this system. In addition, the sleek and effective design of the orthosis allows for a natural range of motion during use.

This should prove to be effective in therapy, such as stroke rehabilitation therapy, in the coming months. As mentioned in Section III Part C, IpsiHand Bravo is currently undergoing a medical case study at Washington University in St. Louis. The hope is that this single case study will not only lead to more study participants, but also to using IpsiHand as a common stroke and brain trauma therapy method in the near future.

Aside from its performance, IpsiHand also proves to be an attractive therapy option because of its low cost. Together with the headset, electronics, and cables, the materials cost of the system is under $1200. As a comparison, most medical EEG systems can cost upwards of $10,000 and take 30 to 60 minutes to set up. While these systems have significantly higher sampling rates and greater coverage, the motor planning signals of interest for IpsiHand are well obtained by the Emotiv headset. The IpsiHand system is designed to be set up in 5 to 15 minutes, allowing for more therapy time in place of set up time.

Future development of IpsiHand will be aimed at moving the signal processing and Eos Machine Learning Software to an on-board micro-computer, to increase portability and ease-of-use. Improving system accuracy and training speed will also maximize the time available for patient therapy.

Acknowledgment

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