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Noninvasive Brain-Machine Interface to Control Both Mecha TE Robotic Hands Using Emotiv EEG Neuroheadset

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***Abstract*—**Electroencephalogram (EEG) is a noninvasive technique that registers signals originating from the firing of neurons in the brain. The Emotiv EEG Neuroheadset is a consumer product comprised of 14 EEG channels and was used to record the reactions of the neurons within the brain to two forms of stimuli in 10 participants. These stimuli consisted of auditory and visual formats that provided directions of 'right' or 'left.' Participants were instructed to raise their right or left arm in accordance with the instruction given. A scenario in OpenViBE was generated to both stimulate the participants while recording their data. In OpenViBE, the Graz Motor BCI Stimulator algorithm was configured to govern the duration and number of visual stimuli. Utilizing EEGLAB under the cross platform MATLAB®, the electrodes most stimulated during the study were defined. Data outputs from EEGLAB were analyzed using IBM SPSS Statistics® Version 20. This aided in determining the electrodes to use in the development of a brain-machine interface (BMI) using real-time EEG signals from the Emotiv EEG Neuroheadset. Signal processing and feature extraction were accomplished via the Simulink® signal processing toolbox. An Arduino™ Duemilanove microcontroller was used to link the Emotiv EEG Neuroheadset and the right and left Mecha TE™ Hands.

***Keywords*—**Brain-machine interface, EEGLAB, emotiv EEG neuroheadset, openViBE, simulink.

I. Introduction

BRAIN-COMPUTER Interfaces (BCIs) are a relatively new technology in the diagnosis and treatment of conditions in numerous healthcare settings [1].

BCIs have applications for both rehabilitation and gaming. BCIs are capable of allowing an individual to interact with their external world based on specific thoughts recognized by a computer as a recognizable pattern occurring within the brain. Individuals simply think of an action to be fulfilled by an external device, such as a prosthesis, wheelchair or helicopter drone. These thoughts have specific neural patterns that are recorded or enacted in real time using scalp electrodes whose signal(s) are relayed to a computer on which algorithms are generated that are responsible for initiating that action by the external entity. To produce a continuous linkage between thought and action requires extensive iterations in neural training and modification of the software algorithms to the user so that it can properly carry out its facilitating role [6]-[8]. Although some BCI technologies are currently available, research into how to standardize the system across users and stabilize the software is still in its primitive stages [2].

The initial purpose behind this neuroscience study was to determine whether an auditory or visual stimulus is more effective when training a brain-computer interface. In this case simple 'right' and 'left' directions were generated using the freeware program OpenViBE. Also, the study sought to determine which of the 14 electrodes on the Emotiv EEG Neuroheadset were most effective in the creation of a BCI. Based on these findings it should be possible to determine which frequencies and electrode locations should be isolated and filtered and processed in order to use the Emotiv EEG Neuroheadset most effectively as a brain-machine interface (BMI). BMI development will consist of using the Emotiv EEG Headset, Simulink® a MATLAB® toolbox and an Arduino™ Duemilanove microcontroller to establish connection and control to two Mecha TE™ Hands. Controlling the left and right Mecha TE™ Hands in real time via EEG is a proof-of-concept to successfully regulating a prosthesis or wheelchair movement for individuals with compromised motor systems [5].

II. Methods

This BMI project has been separated into four parts; Emotiv EEG Neuroheadset and OpenViBE, Neuroscience Study Procedure, EEGLAB analysis and brain-machine interface setup.

A. Emotiv EEG Neuroheadset and OpenViBE

The 14 active sensors of the Emotiv EEG Headset™ were soaked with 6 drops of saline solution prior to being placed in the headset. The Emotiv Neuroheadset is of the wet sensor type that reduces the amount of artifacts in the data [3], and the sensor locations on the EEG Neuroheadset follow the 10-20 international system [4]. Emotiv EEG Neuroheadset setup software was used to ensure adequate connection during each trial. Recording of the Emotiv EEG signals was attained wirelessly using OpenViBE, a freeware designed to stimulate the subject in both visual and auditory formats, record EEG and display EEG signal output in real time.

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This research was approved by Institutional Review Board at Indiana Institute of Technology, Fort Wayne, IN 46803 USA.

B. Neuroscience Study Procedure

This study was approved by Indiana Tech's Institutional Review Board. Ten (five male and five female) subjects between the ages of 21 and 24 years participated in the study, all of whom read and signed the informed consent form. Participants had the Emotiv EEG Neuroheadset placed on their head and were seated in front of a computer screen in a dimly lit office. It was positioned to ensure that the 'ground' sensors were located over the temporal bone of the skull (directly behind the ear) and that the front-most sensors were located three finger widths above the eyebrow. The Emotiv® software *Headset Setup* ensured the connection between each sensor and the individual's scalp prior to beginning the study, while the OpenViBE acquisition server allowed connection between the headset and the OpenViBE scenario.

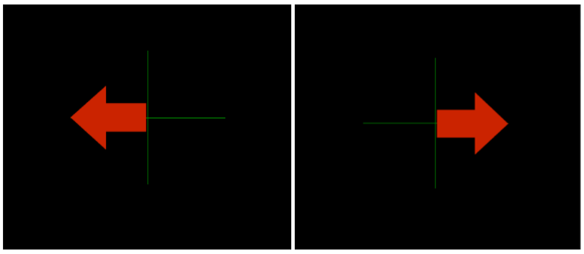

Fig. 1 OpenViBE Graz Motor Visual Stimulations

Participants were asked to remain as still as possible during the experiment to lessen the effect of interference from muscle signals during the EEG recording. The Graz Motor Stimulation in OpenViBE generated 20 right arrows and 20 left arrows presented in a random order on the computer screen as seen in Fig. 1 to act as visual stimuli. They were directed to raise their right arm when a right arrow appeared and to do the same with their left arm when a left arrow appeared. After a short break, participants were asked to respond to auditory (i.e., 20 'right and 20 'left') stimuli presented again in a random order by the computer. The participants were again asked to raise their right arm during a 'right' stimulation and raise their left arm during a 'left' stimulation. Data collection for each of the visual and auditory portions lasted approximately eight minutes with approximately 10-seconds between each stimulus. Each testing session took approximately 35 minutes. All recordings were then saved in the European Data File (.EDF) format.

C. EEGLAB Analysis

Data sets were brought into and analyzed in EEGLAB a toolbox that runs under the cross platform MATLAB®. Each subject's audio and visual .EDF files were processed separately by first reading in the electrode locations, removing the baseline and running an Independent Component Analysis (ICA). The raw data could be viewed by selecting to view EEG scroll data within EEGLAB. When generating the frequency time domain outputs from the channels, a Fast Fourier Transform (FFT) using (1) was performed. X (k) and x (n) are output and input signals respectively, N is the number of points for FFT and k is the index number.

$$X(k) = \sum_{n=0}^{N-1} x(n).e^{-j\left(\frac{2\pi}{N}\right)nk} (k = 0,1, \ldots N-1) \quad (1)$$

Outputs such as the one seen in Figs. 2-7 were generated. The implications of such outputs are noted in the results section.

D. Brain-Machine Interface Setup

The incoming EEG signals from the Emotiv EEG Neuroheadset were relayed to Simulink®, utilizing the EPOC™ Simulink® EEG Importer. Once this connection was established a demultiplexer was used to separate the incoming EEG signals into 14 separate signals. Signal processing was performed on specific channels, determined from the prior neuroscience study, for feature extraction. This consisted of filtering, noise removal, and the control algorithm. Multiple scope boxes were employed to view the EEG output at each stage in the scenario.

An Arduino™ Duemilanove 8-bit microcontroller was used to establish communication between the designed Simulink® model and two Mecha TE™ Hands, a left and right. EEG control algorithms were developed to regulate left and right Mecha TE™ Hands in real-time through Pulse-Width Modulation (PWM) signals.

Two Mecha TE™ Hands are used in the BMI development. Each hand features 5 Futaba® S3114 Micro Servos (one for each of the 5 fingers), and the maximum voltage use is 5 volts direct current (DC).

III. Results

The results were divided into 3 sections; neuroscience study results, neuroscience statistical analysis, and brain-machine interface in real time.

A. Neuroscience Study Results

EEG scroll data for channels F3, FC5, F4 and FC6 according to the 10-20 International System, for all data sets were generated using EEGLAB. Based on the EEG scroll data outputs in EEGLAB, it was clear that the sensors most important during audio and visual stimulation (because they displayed the largest change in amplitude) are F3, F4, FC5, and FC6. All four of which are located over the sensorimotor cortex. There were also peaks in the four most frontal electrodes (F7, AF3, F6, AF4) however these electrodes are the most susceptible to facial muscle signals and were most likely the result of this interference. Figs. 2 and 3 demonstrate this occurrence in both a female and male data set.

Also, as noted prior, a FFT was employed to generate frequency vs. time outputs. These can be seen in Figs. 4 and 5 below. These images demonstrate that as frequency goes above 30 Hz that the power generated starts to taper off. This would be in accordance with the alpha and beta waveforms that range from approximately 8-12 Hz in the case of alpha and 12-28 for beta.

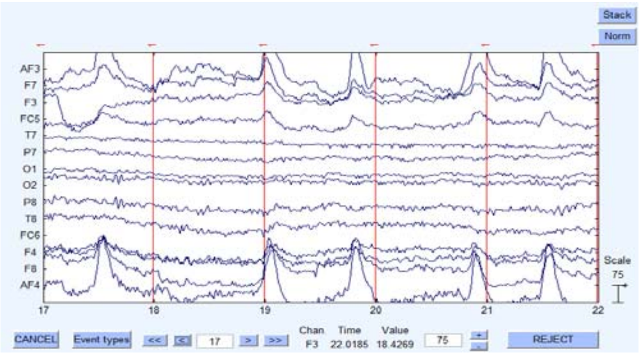

Fig. 2 EEG scroll data from female subject 2

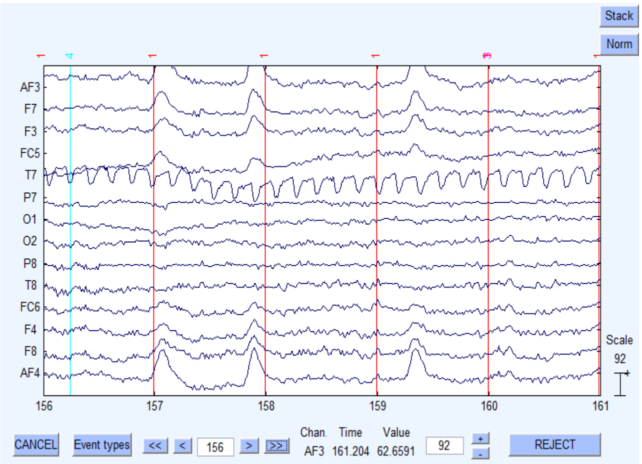

Fig. 3 EEG scroll data from male subject 2

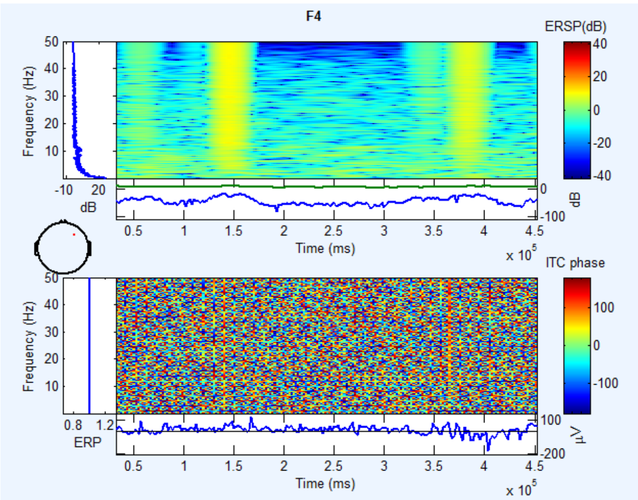

Fig. 4 Frequency vs. time channel F4 for female subject 5

B. Neuroscience Statistical Analysis

The data for the graphed output from the 10 participants were analyzed using IBM SPSS Statistics® Version 20. Four sets of analyses were run using, as the dependent variable, the distribution: 1) means, 2) trimmed means, 3) standard deviations, and 4) trimmed standard deviations two of these outputs used from EEGLAB are shown in Figs. 6 and 7. (Trimmed statistics are based on the removal of the top and bottom 5% of the points on the distribution, a configuration decided on and then implemented by EEGLAB.)

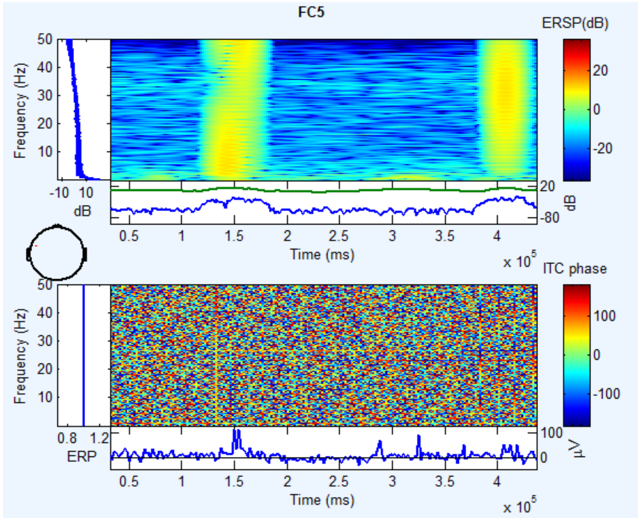

Fig. 5 Frequency vs. time channel FC5 male subject 1

For each of the four analyses a mixed model analysis of variance (ANOVA) was conducted. The variables included gender (2 levels – female and male), channel (4 levels – F3, FC5, FC6, and F4) and sensory modality used (2 levels - auditory and visual).

Analysis of Means - The analysis of means resulted in one significant interaction effect; gender by channel (F (3,24) = 3.300, p = .037). After collapsing across sensory modality independent samples, t-tests showed that the interaction occurred at two channels. Females had a lower mean (-.0026) than males (.0013) on Channel FC5 (t(8) = -2.884, p = .020). Females had a higher mean (.0000) than males (-.0033) on Channel F4 (t(8) = 2.339, p = .047).

Analysis of Trimmed Means - The analysis of trimmed means resulted in no significant effects

Analysis of Standard Deviations - The analysis of standard deviations resulted in a significant main effect of channel (F (3,24) = 10.066, p = .004). After collapsing across gender and sensory modality, Bonferonni-corrected follow-up tests revealed that channel F4 had a more narrow distribution (130.8) than did channel FC5 (147.1) (t (18) = 16.371, p = .006).

Analysis of Trimmed Standard Deviations - The analysis of trimmed standard deviations also resulted in a significant main effect of channel (F (3,24) = 6.868, p = .002). After collapsing across gender and sensory modality, Bonferonni-corrected follow-up tests revealed that channel F4 had a more narrow distribution (20.9) than did channels F3 (27.9) (t(18) = 6.984, p = .015) and FC6 (26.7) (t(18) = 5.799, p = .028).

No other systematic statistical differences based on 1) gender, 2) modality, or 3) channels were observed.

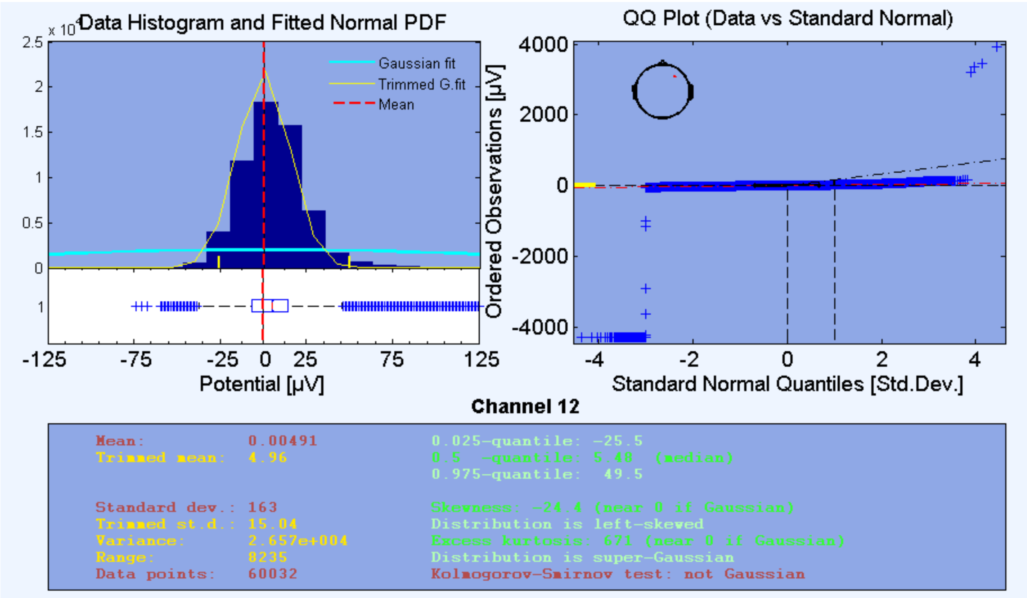

Fig. 6 Statistics output for channel F4 female subject 4

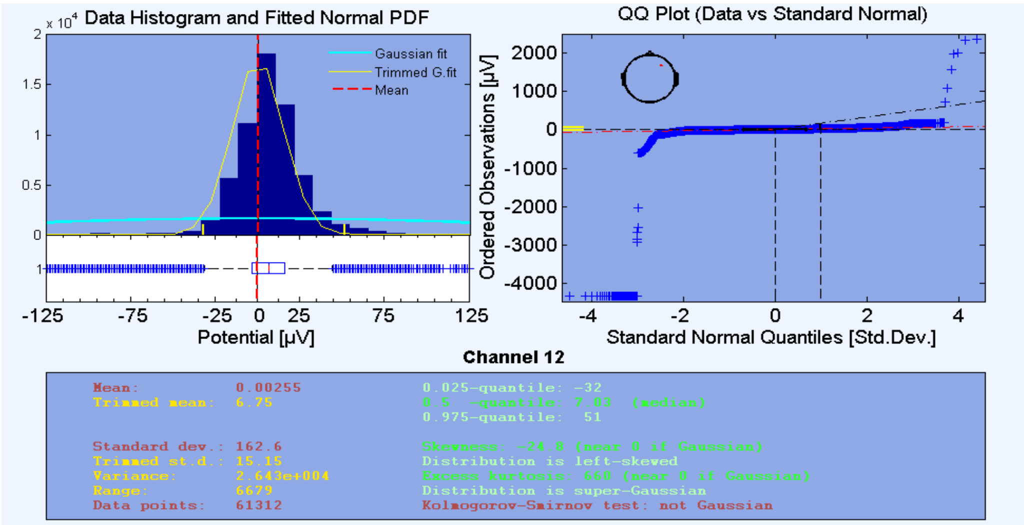

Fig. 7 Statistics output for channel F4 male subject 1

C. Brain-Machine Interface in Real-Time

Fig. 8 highlights the steps involved in the development of a BMI. The electrodes chosen in order to control the Mecha TE™ Hands were determined from the neuroscience study. Using these four signals originating from the Emotiv EEG Neuroheadset were relayed to Simulink® via an EPOC™ Simulink® EEG Importer. Signals were then separated, filtered and amplified. A decision-making algorithm was responsible for designating which hand was controlled.

IV. Discussion

The electrodes most important during audio and visual stimulation were determined to be F3, F4, FC5, and FC6. These sensors are all located along the motor cortex area of the brain. Accuracy can be improved when recording EEG signals by using a headset with additional sensors, and providing resistance to artifacts, thus giving a more comprehensive EEG pattern. The statistical analysis showed no statistical significance between auditory and visual stimulation in initiating a response in the motor cortex. However, it showed a relationship between sex and electrode location. There was found to be a statistical significance between females and F4 (electrode over the right portion of the brain), and between males and FC5 (electrode over the left portion of the brain). This may be the result of a connection between males tending to use more left-brain and females more right-brained [9].

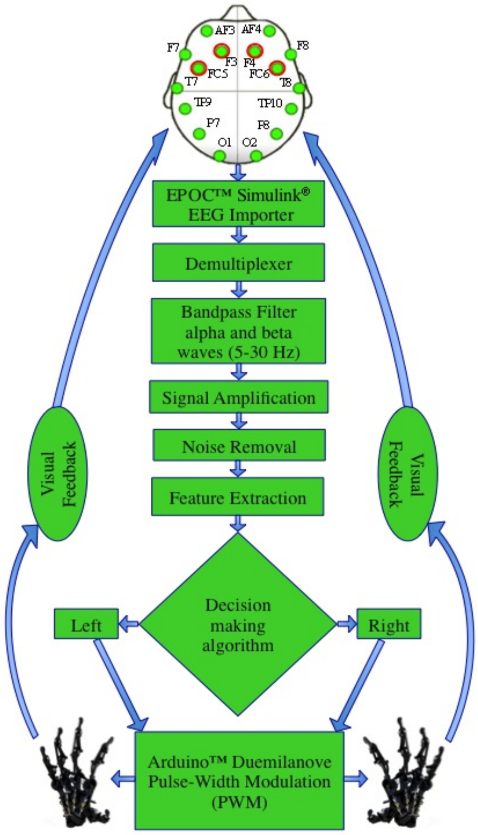

Fig. 8 BMI flowchart

V. Conclusion

Based on the results acquired by completion and analysis of the neuroscience data, it was determined that the main electrodes stimulated when paired with a motor task were F3, FC5, FC6 and F4, as per the 10-20 international system. These results lead to the development of a successful BMI capable of controlling both left and right Mecha TE™ Hands. This BMI can be adjusted to the users' need and preferences. Future work requires more exploration into the effects of sex and channel location, as well as work into making the BMI system more robust and stable.

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