Extracting Motor Imagery Features to Control Two Robotic Hands

Adam Reust
Department of Biomedical Engineering
Wichita State University
Wichita, KS, USA
axreust@shockers.wichita.edu

Jaydip Desai
Department of Biomedical Engineering
Wichita State University
Wichita, KS, USA
jaydip.desai@wichita.edu

Louis Gomez
Department of Elec. Engg.
Wichita State University
Wichita, KS, USA
lagomez@shockers.wichita.edu

***Abstract*—Brain-Machine Interface (BMI) technology has the potential to restore physical movement of the arm or leg by acquiring electroencephalogram (EEG) signals from the human brain, detecting changes associated with a human arm or leg movements, and generate control signals for the assistive devices in real-time. This project was designed to understand motor imagery tasks associated with human hand movement during visual stimulation, record EEG signals for actual and imagery tasks, and train artificial n eural n etwork a lgorithms u sing three different methods: Scaled Conjugate Gradient, Levenberg-Marquardt, and Bayesian Regularization. Hjorth parameters were calculated prior to train neural network algorithm in order to extract four features: rest, right hand, left hand and both hands. The experiment includes 16-channel wired EEG system from g.tec to acquire real-time signals from the human scalp in Simulink at a sampling rate of 512 samples/second. Eight human subjects between ages of 18 to 52 were recruited to perform both studies associated with human hand movements. Motor imagery signals from C3, FCz, and C4 were used for feedforward pattern recognition neural network algorithm. Sixteen features were calculated during EEG signals recording to achieve overall 95 percent accuracy to successfully detect four different classes. A successful BMI model was developed to control two robotic hands using Arduino-Simulink library in real time with trained artificial n eural networks.**

***Keywords*—Neural Networks, Brain-Machine Interface, Electroencephalography, Motor Imagery, Simulink**

I. Introduction

There are 5.4 million Americans living with some form of paralysis caused by spinal cord injury, multiple sclerosis, strokes, and post-polio syndrome [1]. Brain-Machine Interface (BMI) technology can be used in the rehabilitation and prosthetic industries to improve the quality of life of individuals with neuromuscular disorders causing paralysis. BMI devices rely on the continuous real-time interaction between living neuronal tissue and artificial e ffectors [2]. N on-invasive EEG-based BMI systems measure specific features of EEG activity and translate these features into device commands [3]. The most commonly used features are sensorimotor rhythms, slow cortical potentials, and P300. Systems, which are based on P300, are in the time domain and it uses timed responses for stimuli to activate a reaction, while sensorimotor rhythms and slow cortical potentials can function in either the time or frequency domains [4]. Sensorimotor rhythms can be seen corresponding to imagine hands, legs, and tongue movements at frequencies of 8-28 Hz. These frequency bands subdivided into alpha (8-12 Hz), low-range beta (12.5-16 Hz), mid-range beta (16.5-20 Hz), and high-range beta (20.5-28 Hz) bands. Motor imagery, a type of sensorimotor rhythm, uses the decrease in EEG activity during initiation and imagination of movements to extract features related to hand and leg movement and use those as device commands [5]. Researchers have tried time and frequency domain analysis for feature extraction on offline and online studies [6-8]. Both short-time fourier transform and fast fourier transform have shown to be successful for converting amplitude versus samples/time into the magnitude versus frequency in order to observe the response in the frequency domain [9]. Once EEG signals have been converted to the frequency domain, changes in signal frequency related to movements can be identified. It has been shown that Hjorth parameters can be used to extract features from both time and frequency domains related to motor imagery tasks [10]. By using Hjorth parameters as features of the EEG signal, it decreases the computation time compared to power spectrum analysis [11]. Both regression and classification networks have been used to identify output commands. The regression approach focuses on fitting to input data, while the classification approach separates signals into classes and the network is trained to identify the classes. There's no specific answer on what type of neural network algorithm works best with motor imagery data utilizing Hjorth parameters for real-time BMI system. This study investigates the use of 16 EEG electrodes for neuroscience study to identify changes into alpha and beta bands during actual and motor

imagery movements in eight participants followed by integrating Hjorth parameters to extract features for left, right, both and resting hand states using three electrodes (C3, C4 and FCz), and classify them using three different neural networks. An institutional Review Board (IRB) was approved this study to perform both neuroscience and real-time BMI control experiments on human subjects. The network recognizes patterns in the EEG signal associated with the hand states. Real-time control of external devices can then be accomplished by combining the Hjorth parameters for feature extraction and the proposed classification method to successfully control two robotic hands.

II. METHODS

A. Neuroscience Study

This study includes neuroscience experiments related to actual and motor imagery tasks using Graz scenario from OpenViBE software. Two trials were conducted on eight participants between ages of 18 to 52 years. EEG signals were acquired using a 16-channel gel-based g.USB amplifier at a sampling rate of 512 Hz. EEG electrodes were C3, Cz, C4, FCz, Pz, CPz, O1, O2, C5, FC3 CP3, C1, C2, FC4 CP4, and C6 based on 10-20 International Standards as shown in Fig 1.

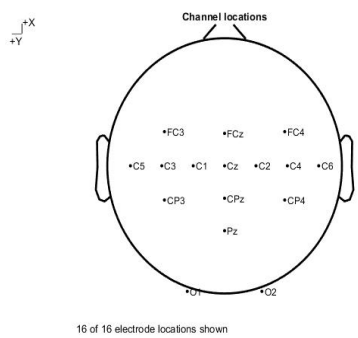

Fig. 1. EEG electrodes placed on motor and sensory cortex regions of the human brain for neuroscience experiments

Participants were asked to close their right/left hand when the right/left arrow appears on the screen in the first trial whereas the second trial includes imagination of the associated hand movement during visual stimuli. Institutional Review Board approval for the study was acquired prior to conducting the experiment. Graz-BCI scenario for actual and motor imagery tasks was used to generate 20 random arrows on screen during visual stimulations. EEG datasets were recorded in .OV, .EDF, .GDF, .VHDR file formats for time-frequency analysis using EEGLAB.

B. Signal Processing Technique

Using the Guger Technologies' g.USBamp, EEG signals were recorded at a sampling rate of 512 Hz from the C3, C4, and FCz locations. C3 and C4 signals were subtracted over FCz using a bipolar montage. These signals were then converted to a double data type and broken into alpha (8-12 Hz) and mid-range beta (16.5-20 Hz) frequencies using tenth order bandpass filtering. Each of those four signals were then averaged before estimating Hjorth parameters. The Hjorth parameters were used as a method of feature extraction to train neural networks. The parameters use time-domain calculations of an input signal rather than the method of frequency analysis by conversion to the power spectrum. The first Hjorth parameter is activity, which is the signals variance over time. Activity is calculated by squaring the standard deviation of the EEG signal as seen in (1, 2).

$$A^2 = \frac{1}{T}\int_{\tau-T}^{T} x^2(t)dt \quad [V^2] \tag{1}$$

$$Activity = var(x(t)) \tag{2}$$

The second parameter is mobility, which is the mean frequency or standard deviation of the slope of D2 as seen in (3, 4).

$$D^2 = \frac{1}{T}\int_{\tau-T}^{T} (\frac{dx(t)}{dt})^2 dt \quad [V^2 s^{-2}] \tag{3}$$

$$Mobility = \sqrt{\frac{D^2}{Activity}} = \sqrt{\frac{D^2}{A^2}} \quad [s^{-1}] \tag{4}$$

The third parameter is complexity, which finds the changes in frequency by estimating with a sine wave and finding the deviation from that sine wave as seen in (5).

$$Complexity = \frac{Mobility(\frac{dx(t)}{dt})}{Mobility(x(t))} \tag{5}$$

The above Hjorth parameters were sampled with a window length of 750 (4 seconds), along with the original filtered signals. Table I shows sixteen features calculated for this study.

TABLE I
FEATURES CALCULATED PRIOR TO TRAIN ARTIFICIAL NEURAL NETWORKS

#	Features	#	Features
1	C3-FCz Alpha Mean	2	C3-FCz Alpha Activity
3	C3-FCz Alpha Activity	4	C3-FCz Alpha Complexity
5	C3-FCz Beta Mean	6	C3-FCz Beta Activity
7	C3-FCz Beta Activity	8	C3-FCz Beta Complexity
9	C4-FCz Alpha Mean	10	C4-FCz Alpha Activity
11	C4-FCz Alpha Activity	12	C4-FCz Alpha Complexity
13	C4-FCz Beta Mean	14	C4-FCz Beta Activity
15	C4-FCz Beta Activity	16	C4-FCz Beta Complexity

C. Artificial Neural Network Training

Using Simulink, data was recorded of four states of actual and imagined hand movements: both, left, resting, and right for 20 seconds at 512 Hz sampling frequency. Due to the time, it takes to stabilize the model, only samples from 10-20 seconds were used to train neural networks. Two datasets for each of the eight test subjects were then used to train three different neural networks using Matlab. Fig. 2 shows a neural network architecture generated using Simulink for this project. Pattern recognition neural networks are

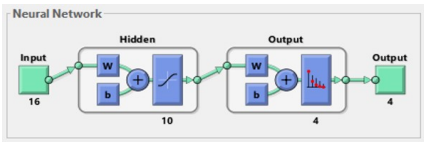

Fig. 2. Artificial neural network structure with hidden layers

feedforward networks that take input data and train it to classify according to target classes. For this experiment, input and target files were created in excel for both cases and imported into Matlab workspace for neural network training. Three neural network training methods Bayesian Regularization, Levenberg-Marquardt, and Scaled Conjugate Gradient were applied on the datasets to evaluate the classification percentage.

D. Control Assembly for Two Robotic Hands

This project utilized two Youbionic robotic hands (left and right) using DRV 8835 motor driver circuit for linear actuators. Each robotic hand contains six linear actuators (one for each finger and two for thumb). An Arduino Mega 2560 microcontroller board used to generate control signals for the motor driver circuit for finger flexion and extension. Fig. 3 shows a BMI-based control process flowchart used in this project for two robotic hands. Each hand received a +5 V DC power

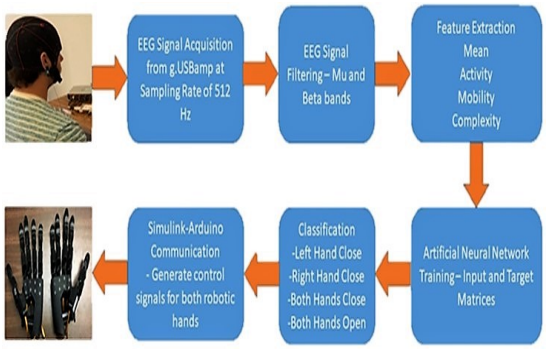

Fig. 3. BMI-based control process flowchart for two robotic hands

for the linear actuator. An Arduino-Simulink library has been used in our previous studies to control robotic hand using EEG [6,8] and EMG [12,13] signals. The library was also used to successfully create a real-time Simulink based robotic system to study force feedback mechanism during instrument-object interaction [14]. A real-time communication between designed Simulink model and two robotic hands was achieved using the same library.

III. Results and Discussion

A. EEGLAB Analysis

The recorded datasets from OpenViBE scenario were imported into an EEGLAB using Matlab for analysis. Independent Component Analysis was performed on the dataset to generate component spectral images and maps. Fig. 4 and 5 display a comparison between actual and motor imagery tasks during visual stimulation on C4 electrode in subject 4.

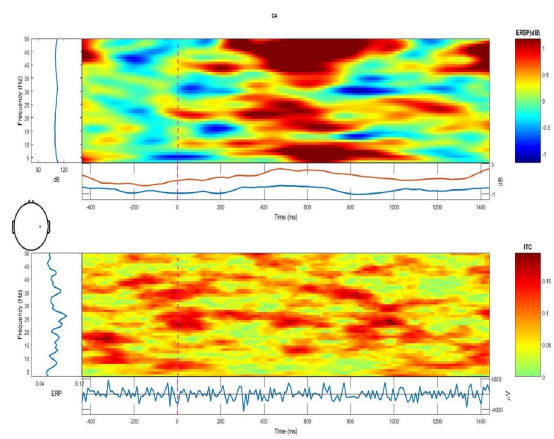

Fig. 4. EEGLAB time-frequency analysis on C4 electrode during actual left hand movement

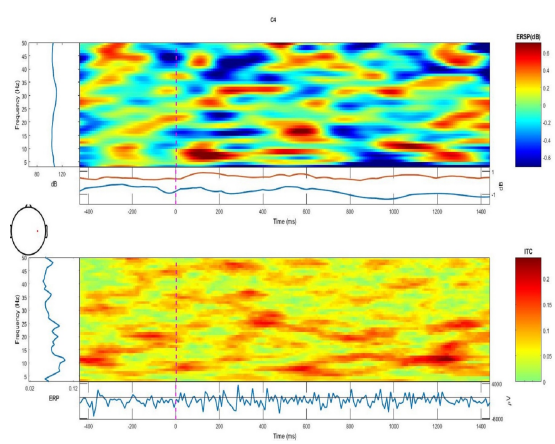

Fig. 5. EEGLAB time-frequency analysis on C4 electrode during imagery left hand movement

Motor imagery signal displays higher activity in alpha band compared with beta band. Upon successful

completion of analyzing the data, bipolar signals C3-FCz and C4-FCz were selected to process with Hjorth parameters in order to extract 16 features for 20 seconds of time frame.

B. Neural Network Data Analysis

In total, 49 neural networks were trained and re-trained for confirmation of consistent results. Comparisons were made between the Bayesian Regularization, Levenberg-Marquardt, and Scaled Conjugate Gradient training methods. Table II shows a detailed breakdown of the accuracy of the training algorithms and how they perform for the eight subjects on the actual and imagined movements of the hands. The mean square error (MSE) shows how well the networks perform in classifying data with respect to actual outputs while the epoch values show the number of times the entire dataset was passed through the neural network. Both Bayesian Regularization and Levenberg-Marquardt produced similar accuracies compared to the Scaled Conjugate Gradient training algorithm. Major differences in the performance can be seen with respect to the mean square error values. The Scaled Conjugate Gradient algorithm had much lower error values as opposed to the other two algorithms. The epoch values also show better results for the Scaled Conjugate Gradient compared to the other two algorithms. Because optimum mean square error values are reached for lower epoch values for Scaled Conjugate Gradient, it trains the networks more efficiently and accurately than the Bayesian Regularization and Levenberg-Marquardt. Table II shows the artificial neural network training and validation on actual and imagery datasets for each participant.

IV. Conclusion

The proposed method of using Hjorth parameters to generate sixteen features from three EEG signals proved to be successful in detecting four hand states. Pattern recognition neural networks are good for classifying patterns within data and this study showed that when given input EEG signals, trained pattern recognition networks approximately achieved 95 % accuracy, with the exception of the Bayesian method for subject 5, incorrectly identifying changes in EEG signal pattern associated with actual and imagined hand movement states. The results also showed that Bayesian Regularization and Levenberg-Marquardt training algorithms offer accurate classification but increased training time. At a higher sampling frequency, correct classification percentages would increase with better inputs for classification. The designed Real-time Simulink-based BMI model was successfully able to extract motor imagery features to generate control signals for two robotic hands using trained artificial neural networks.

TABLE II
Summary of classification accuracy, MSE, epoch value and training algorithm

Subject #	MT	TA	ACM	MSE	Epoch value
1	AM	SCG	99.90%	2.79E-03	187
		BR	98.30%	0.202	1000
		LM	99.90%	0.191	1000
1	IM	SCG	99.50%	4.17E-03	236
		BR	97.70%	0.199	1000
		LM	98.30%	0.194	1000
2	AM	SCG	100.00%	1.31E-06	297
		BR	100.00%	0.190	1000
		LM	100.00%	0.190	1000
2	IM	SCG	99.70%	3.31E-03	116
		BR	99.40%	0.190	1000
		LM	99.40%	0.189	1000
3	AM	SCG	94.60%	4.32E-02	88
		BR	96.60%	0.200	1000
		LM	98.10%	0.194	573
3	IM	SCG	97.30%	1.98E-02	140
		BR	99.60%	0.189	1000
		LM	99.20%	0.190	980
4	AM	SCG	99.50%	2.83E-03	166
		BR	99.40%	0.190	1000
		LM	97.80%	0.195	1000
4	IM	SCG	100.00%	4.59E-05	459
		BR	97.70%	0.199	1000
		LM	99.40%	0.200	1000
5	AM	SCG	100.00%	3.41E-07	153
		BR	74.90%	0.240	1000
		LM	100.00%	0.187	997
5	IM	SCG	99.70%	4.25E-03	105
		BR	100.00%	0.188	1000
		LM	99.80%	0.189	1000
6	AM	SCG	100.00%	1.06E-07	109
		BR	100.00%	0.188	1000
		LM	100.00%	0.188	1000
6	IM	SCG	100.00%	1.94E-05	191
		BR	100.00%	0.188	1000
		LM	99.50%	0.190	1000
7	AM	SCG	100.00%	3.18E-05	335
		BR	99.70%	0.189	1000
		LM	99.20%	0.192	999
7	IM	SCG	98.80%	9.57E-03	257
		BR	97.50%	0.196	1000
		LM	98.40%	0.194	1000
8	AM	SCG	93.90%	4.32E-02	128
		BR	99.10%	0.192	1000
		LM	99.40%	0.191	988
8	IM	SCG	99.10%	7.27E-03	124
		BR	96.80%	0.197	1000
		LM	99.50%	0.189	1000

MT: Movement Type, AM:Actual Movement, IM:Imagery Movement, SCG: Scaled Conjugate Gradient, BR:Bayesian Regularization, LM:Levenberg-Marquardt, TA: Training Algorithm, ACM:All Confusion Matrix, MSE: Mean Square Error

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