EEG Regression Model for BCI Cursor Control

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Introduction

Background:

Brain-Computer Interface (BCI) systems have become a source of great interest in the recent years. Establishing a link with the brain will lead to many possibilities in the healthcare, robotics, or entertainment fields. Electroencephalography (EEG) is one popular noninvasive technique to establish a BCI. In this method, electrodes are placed along the scalp to record the electric potentials created from the neurons fired in the brain. Through a paradigm known as "imagined body kinematics," a subject can control a computer cursor without making any overt movements. This method of using imagined body kinematics from EEG has shown to decrease training time from days to minutes compared to other methods. This platform could lead to improving neurorehabilitation programs as well as more advanced prosthetic devices that can be controlled by the brain. It can also be beneficial to paralyzed patients or those with other neurodegenerative diseases that inhibits muscle movement since no overt movements are required to control the cursor.

Objective:

The goal of this project was to improve the prediction accuracy for a previously developed BCI model that used linear regression to predict cursor velocity from a subject's thoughts by testing new methods and nonlinear models.

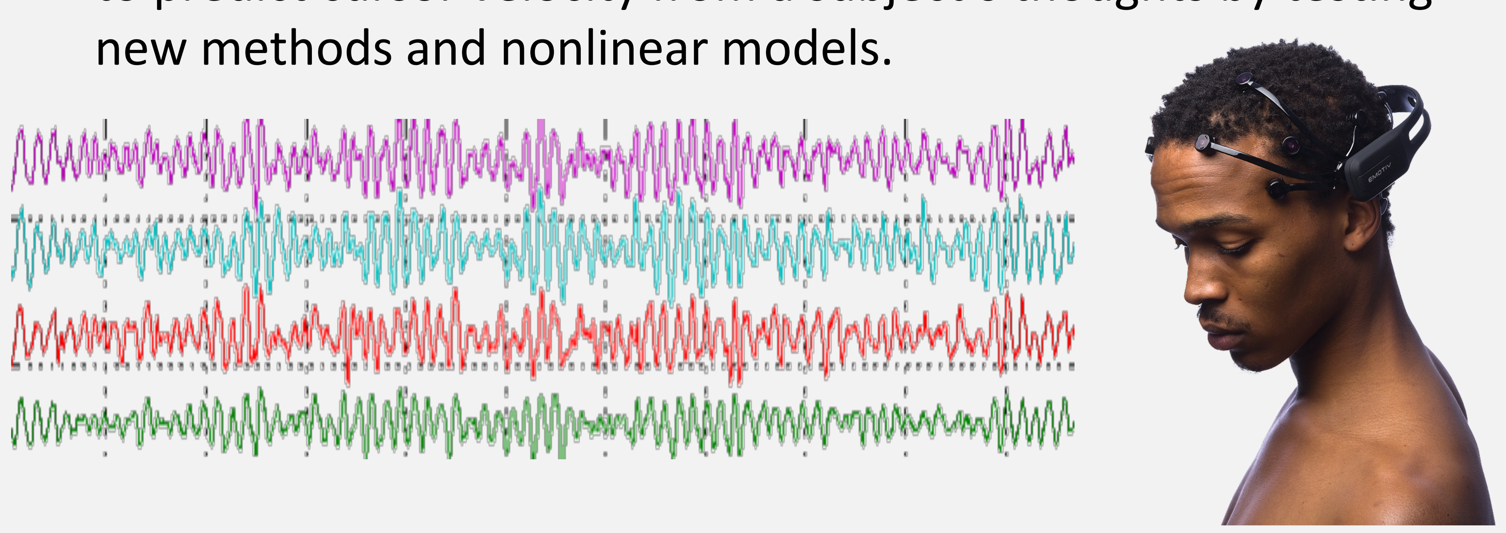

Figure 1: Raw EEG and Emotiv EPOC headset

Training Protocol

The training phase consists of 5 horizontal and 5 vertical trials each lasting 1 minute. The subject was instructed to use the paradigm of imagined body kinematics to track the motion of an automated cursor using their dominant hand as if they were using a computer mouse while making no overt movements (Figure 2).

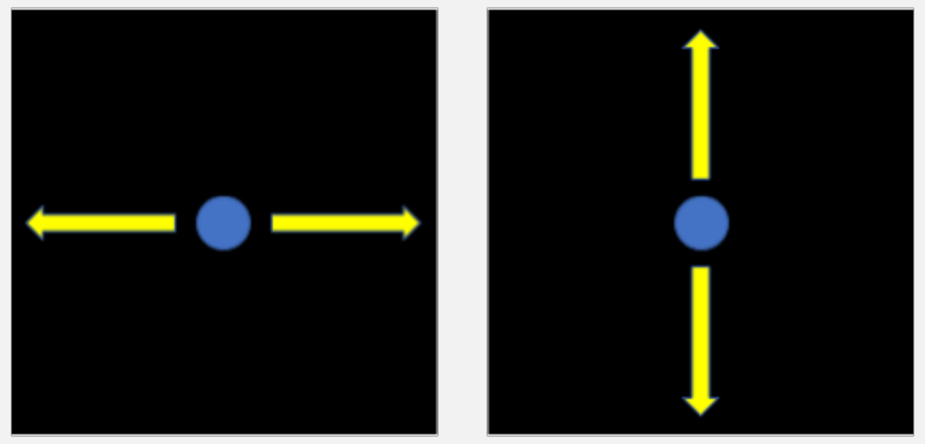

Figure 2: Outline of training task using one dimensional movement

Materials and Methods

An Emotiv EPOC 14-channel wireless EEG headset was used to measure brainwave activity (Figure 3) while BCI2000 program recorded data such as the EEG activity and cursor position. All offline processing was done using Python programming on the Comet supercomputer in San Diego. 13 previous points of EEG data from memory was used as features to train the models.

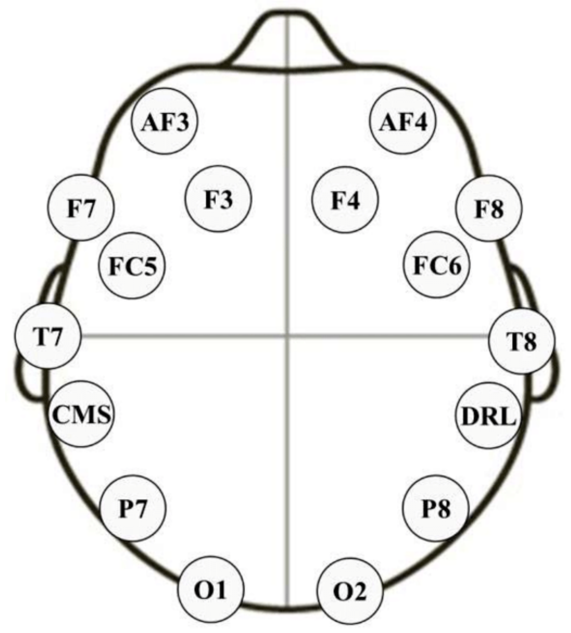

Figure 3: Channel locations

Model Design:

Each channel was tested individually in our linear regression model to determine the most important channels for velocity prediction (Figure 4).

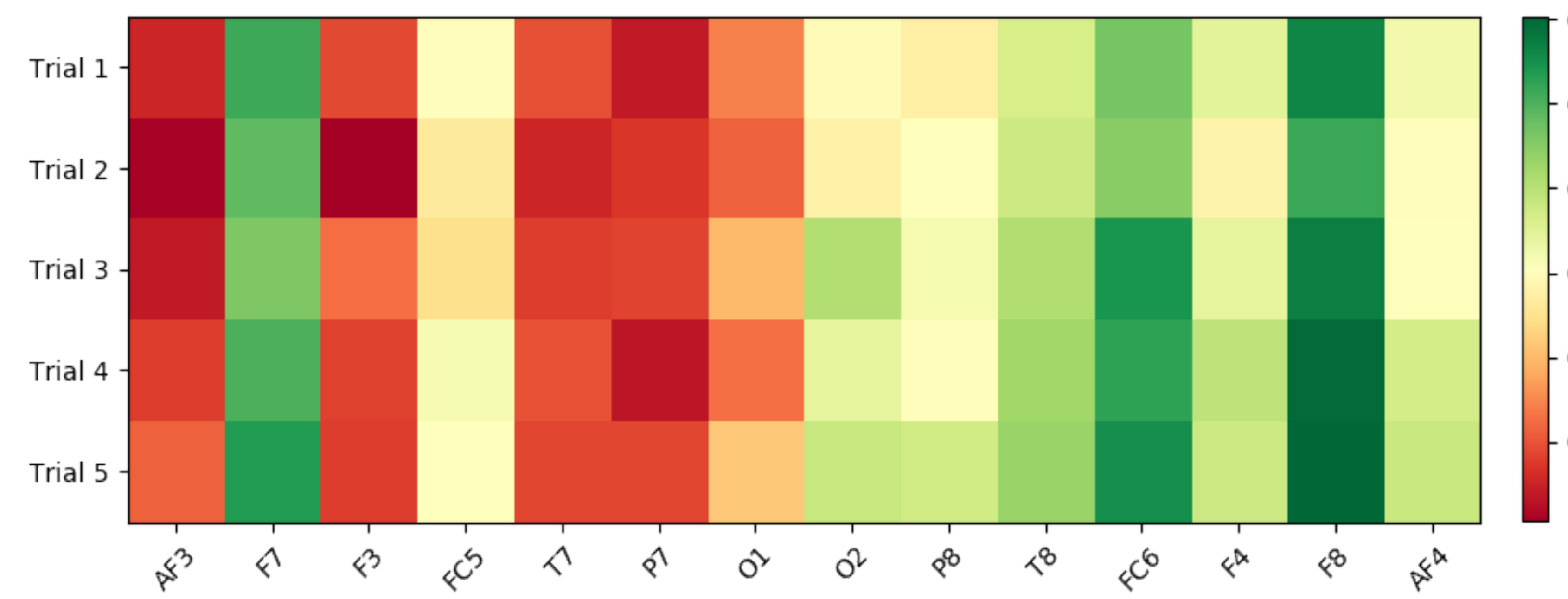

Figure 4: Heat map of prediction accuracy for each channel during 5 horizontal trials

Cross-Validation:

The models were tested with trial wise cross validation where 4 trials were used for training and 1 was used for testing. This was repeated for all 5 combinations of horizontal and vertical trials. This was to ensure the model with the best accuracy of velocity prediction was chosen as the one to be used during the online control.

Serial vs. Parallel:

As we are generating a new model for every individual subject and trial we have many computations that are independent of each other that can be done faster with parallel processing. Doing this also allows us to test different models and hyper-parameters at once returning results faster than running everything in serial. We used Dask Distributed to setup our network with a scheduler and worker nodes. The network was setup on Comet using 4 nodes, 96 workers, 4 cores per worker. Times are shown below.

Serial	AdaBoost	04:30:00
Parallel	AdaBoost	00:04:29

Results

Data from 33 subjects were tested using different combinations of the most important channels found for velocity prediction (Table 1). It was determined that channel combination F7, FC5, T8, FC6, F4, and F8 provided the best accuracy for predicting horizontal velocity, while all the channels were best for vertical velocity. Using only F7 and F8 achieved acceptable accuracy giving the potential for a more covenant real world application with a smaller headset. Future work will include testing these features in new machine learning models to improve the prediction scores from the linear regression model (Figure 5).

Table 1: Prediction accuracy using different channel combinations

Features	Horizontal Accuracy	Vertical Accuracy
All Channels	70.77%	44.67%
F7, 02, P8, T8, FC6, F4, F8, AF4	71.03%	41.68%
F7 and F8	69.93%	25.64
F7, FC5, T8, FC6, F4, F8	72.73%	36.98%

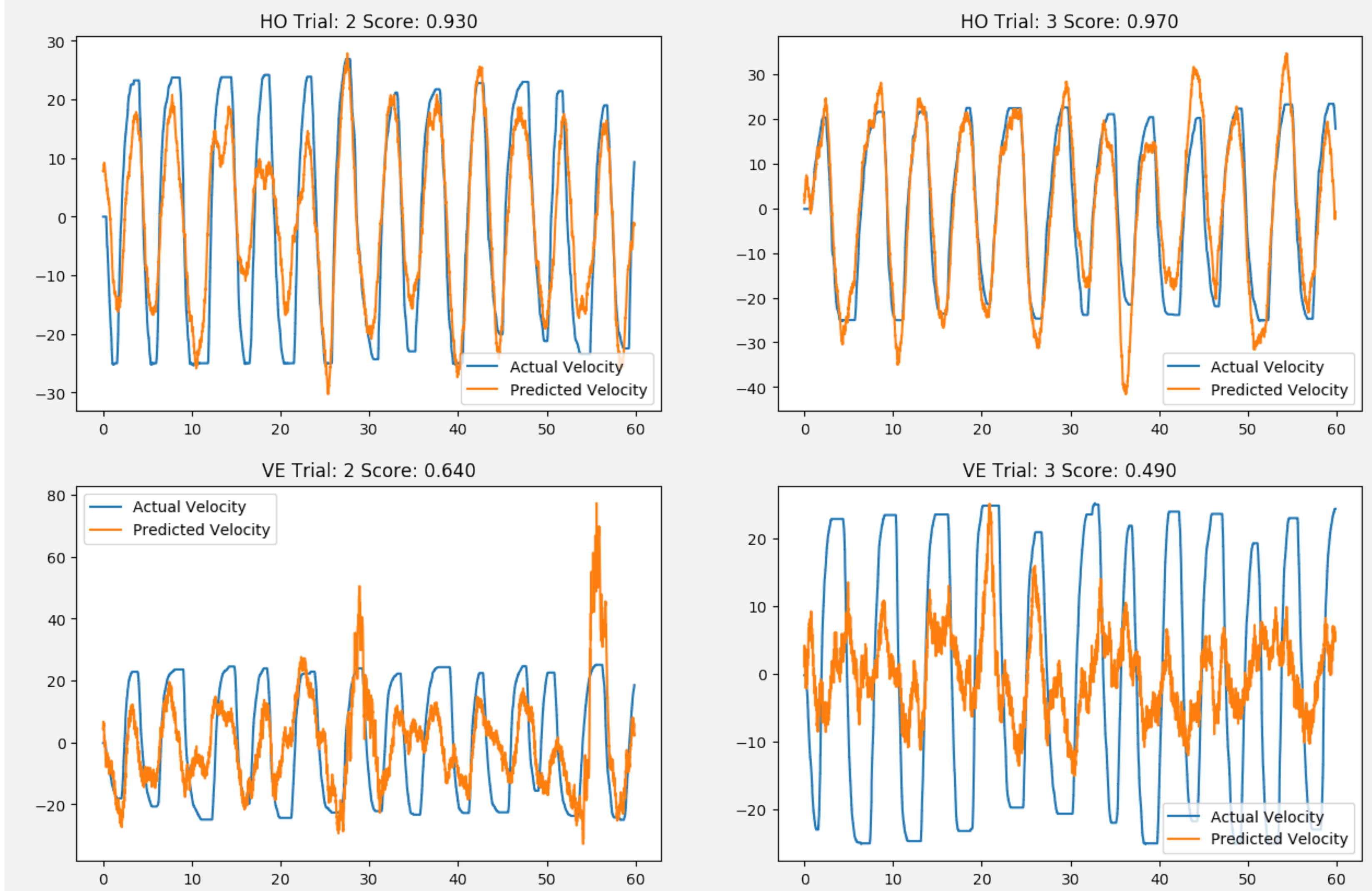

Figure 5: Actual and predicted velocities for two trials horizontal (top) and two trials vertical (bottom)

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