Optimizing Prediction Model for a Noninvasive Brain-Computer Interface Platform using Channel Importance, Classification, and Regression

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Abstract

A Brain-Computer Interface (BCI) platform can be utilized by a patient to control an external device without making any overt movements. This can be beneficial to a variety of patients who suffer from paralysis, loss of limb, or neurodegenerative diseases. In this project, we introduce a noninvasive method to read and decode brain signals using imagined body kinematics to control an onscreen cursor. A linear regression model was designed to predict intended cursor velocity from a subject's thoughts. Using channel identification, clear patterns in relevant horizontal and vertical channels were found. A directional classifier was also investigated to improve the prediction accuracy. By implementing these new techniques, we aim to optimize the training protocol of a BCI platform to control a computer cursor.

1. Introduction

Brain computer interface (BCI) has greatly advanced since the initial establishment in the 1960s [1]. A brain-controlled computer cursor is probably the simplest testbed for BCI. Many systems have been developed for the cursor control problem using invasive brain imaging techniques such as ECoG, single units, and local field potentials on humans and primates [2-6]. Various researchers have also designed and developed cursor control systems using noninvasive brain signals such as electroencephalogram (EEG). Using noninvasive EEG monitoring, several different paradigms have been developed, including mental state, external stimulation, and imagined body kinematics.

As a popular EEG paradigm, the mental states acquired by imaginary movement of large body parts (imaginary movements of hands, legs and tongue) [7] have been employed in many studies to control a computer cursor in one dimension [8], 2D space [9, 10], and 3D space [11]. These mental states cause changes in sensorimotor rhythms which include mu rhythm and beta rhythm, and these changes can be mapped to different command signals in cursor control task.

In addition to using sensorimotor paradigm in controlling a computer cursor, some studies investigated the hybrid EEG paradigm to perform the control task. In hybrid studies, the researchers combined mental states with other paradigms to control a computer cursor. External stimulation as one of the popular paradigms can be detected in recorded EEG signals and was combined with mental states. Trejo et al. [12] in 2006, utilized a target practice BCI system based on mental activity to deal with 1D cursor control problem (right-left) and they also investigated 2D space cursor control problem (right-left, up-down) based on Steady State Visual Evoked Potential (SSVEP) approach. Allison et al. [13] in 2012, combined the mental states and steady state visual evoked potential (SSVEP) for two-dimensional cursor control problem. Li et al. [14] jointed mental states and P300 potential to control a 2D computer cursor. P300 potential is defined as peak reflection of an external stimulation such as flicking on generated EEG signals.

The main drawbacks of mentioned noninvasive BCI systems in 2D or 3D cursor control in those based on sensorimotor rhythms is the lengthy training time required by the subjects to gain satisfactory performance (some weeks to several months). These lengthy training EEG-based systems require subjects to learn how to modulate specific frequency bands of neural activity in order to move the cursor to a specific and corresponding direction and acquire targets. Also, in cases with external stimulations the fatigue phenomenon has been reported by subjects and researchers while it should be noted that this paradigm is not reflecting the natural way of cursor control. Another issue concerning these paradigms is the discrete control of cursor directions due to switching among several imagined large body parts [10] or switching among more than one paradigm [13].

In noninvasive devices, Bradberry et al. [15] investigated the 2D cursor control problem by introducing a new EEG-based BCI paradigm (natural imaginary movement) in time-domain and by minimizing the training time similar to invasive devices. They reported positive performance in cursor control problem just after about 40 minutes of training and practice. This accomplishment substantiated the approach used in invasive devices in which the subjects with implanted electrodes in his/her brain could gain high success rate in target acquisition based on continuous imagined kinematics of just one body part [3, 16]. All these studies proved the employing of natural imagined body kinematics paradigm can dramatically reduce the training time for the subject and even it could be a promise of developing a generic model which can be operated with zero-training.

In previous study, a decoder model of Multiple Linear Regression was used to predict the velocity of the computer cursor from EEG. This model allowed for fast processing times and decent accuracy during online trials. Here in present study, by using the EEG paradigm called "imagined body kinematics" [2-4, 6, 15, 16-18] and nonlinear machine learning techniques, we aim to develop a more accurate cursor control platform in a noninvasive BCI.

2. Methods

2.1 Experimental protocol and tasks

All experimental procedures were approved by the Institutional Review Board at the University of Tennessee. A total of 33 subjects were fully informed about experimental procedures, potential risks and benefits and gave written content. Subjects participated the experiments after signing the informed consent. For the experiments, a PC with dual monitor was provided; one monitor for the experimenter and another one for the subjects. Participants were asked to sit comfortably in a fixed chair and at arm's length in front of their own monitor, with their hands resting in their lap. Data was acquired noninvasively using the 14 channel Emotiv EPOC EEG recording headset with 128 sampling time and filtered using BCI2000 software (0.16 Hz as high pass filter, 30 Hz as low pass filter) [19]. The subjects had to continuously follow the instructions on their own monitors with a 2D workspace dimension of about 33 cm × 33 cm which is placed at one arm's length away from the face of subject. The cursor diameter is chosen to be 1.5cm (0.20% of workspace) and targets are 2.4% of workspace with width 8% and length 30% of screen width.

During the training phase, the healthy subjects with no prior experience in participating in BCI studies, were asked to sit comfortably in a fixed chair with their hands resting in their laps and their faces kept an arm's length from monitor. During the experiments, EEG signals were acquired wirelessly by using an Emotiv EPOC [20] device with 14 channels and through BCI2000 [19] software (with 128 sampling time, high pass filter at 0.16Hz, and low pass filter at 30Hz). In subject's monitor, a computer cursor was shown whose movements started from the center and was controlled by an automated trajectory. The subjects were instructed to track the movement (vertical or horizontal movement) of the cursor (on their own monitor) while they were free to have normal eye movements, as well (Figure 1). During the movements and observation of cursor, the subjects were asked to imagine the same direction and speed-matched movements while imagining that they are moving the cursor with their own right index fingers. Meanwhile, to prevent any further artifacts, they were asked to try not blink or move their own body parts. The training consisted of 10 runs of continuous training (each 60s) for vertical movement (5 runs) and horizontal movement (5 runs) and therefore, the total time of training was around 10 minutes.

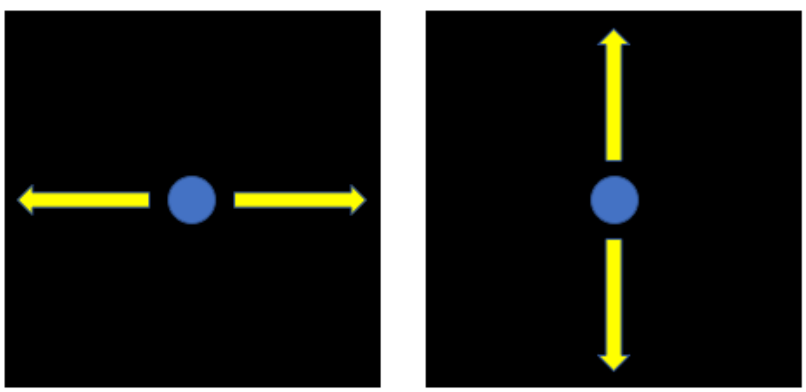

Figure 1: Training protocol for horizontal (left) and vertical (right) trials

The collected EEG data for each subject was decoded and mapped into the observed kinematic movements (directions and speeds). Data was used to correlate the EEG data to subject's observed trajectories parameters and kinematics and obtaining a calibrated decoder for each subject. The EEG data of the assumed subject was decoded into kinematic parameters (cursor velocities) in x (horizontal) and y (vertical) directions by employing some points of memory in recorded EEG data and velocities.

2.2 Data acquisition

A convenient and comfortable EEG headset called Emotiv EPOC with 14 channels was chosen to collect EEG signals wirelessly. The electrodes were hydrated and then the headset was placed on subjects' heads in a way to make correct contact between electrodes and scalp. Emotiv software (TestBench) was used to check the quality of EEG signals during recording EEG signals. Both EEG data and cursor kinematics were collected and stored by BCI2000 software system at 128 Hz during the experiments. Meanwhile, a high pass filter at 0.16 Hz and a low pass filter at 30 Hz was applied in collecting EEG signals. Also, BCI2000 (with MATLAB engine) was employed to deal with the real-time processing in controlling the cursor and acquiring targets by the subjects.

2.3 Regression

Many previous works confirmed that among body kinematics parameters (position, velocity), velocity encoding/decoding showed the most promising and satisfactory performance in theoretical analysis and real-time implementation [15, 21-23].

In order to identify and correlate brain activities and body movements, many decoding algorithms for EEG data have been investigated by researchers in frequency and time domains. Most of sensorimotor-rhythms-based studies were developed in frequency domain for cursor control and external devices control [8-11, 24-29]. Also, in time domain, various linear and nonlinear decoding methods have been developed to directly present a prediction model for the body kinematics parameters based on EEG signals. For example, some nonlinear methods such as Kalman filter [30], particle filter model [31] and kernel ridge [32] were applied in decoding EEG signals for offline analysis and prediction of body velocity parameter. As the most popular method in linear decoding, multiple regression model has been employed for decoding EEG data in offline modes [21-23, 32-34] and in real-time implementation [15] by prediction of body kinematics parameters. This linear analysis can be presented by the following equations. The equations 1 & 2 map the acquired EEG data to the observed cursor velocities in x and y directions in training data. In other words, the aim is to reconstruct the subject's trajectories off-line from EEG data and obtaining a calibrated decoder for real-time implementation. Output velocities at time sample t in x direction is $u[t]$ and in y direction is $v[t]$.

$$u[t] = a_{0x} + \sum_{n=1}^{N}\sum_{k=0}^{K} b_{nkx} e_n[t-k] \tag{1}$$

$$v[t] = a_{0y} + \sum_{n=1}^{N}\sum_{k=0}^{K} b_{nky} e_n[t-k] \tag{2}$$

In these equations $e_n[t-k]$ is the measured voltage for EEG electrode n at time lag k and for the total number of EEG sensors $N = 14$ and total lag number $K = 5$. These numbers were chosen and optimized based on best performance reported in previous published works by authors [35, 36]. The variables a and b are the weights that could be obtained through multiple linear regression.

In training of the multiple linear regression model, the current sample and 12 previous points of EEG data from each channel in memory were used as features to train the model. The model is then cross validated against the other 4 trials of the same dimension. This cross validation is repeated for all 5 combinations of models to ensure the most accurate prediction. The models are evaluated using a goodness of fit correlation score. This scoring technique separates the 60 second trial into 5 windows and averages the Pearson correlation scores. This method provides a better representation of fit by not allowing one improperly fit window to reduce the overall model's score.

2.4 Classification

To improve the prediction accuracy from the linear regression model, it was hypothesized that a classifier for horizontal and vertical motion should be employed. A classification model could be used as a gate in front of regression to generate predictions on a model tailored for horizontal or vertical data. Features for the classifier were collected by taking the Fourier Transform of 1 second of data for each channel. The mean, median, maximum, and minimum power spectral density values across the Theta (4-7 Hz), Alpha (8-15 Hz), Beta (16-32 Hz), and Gamma (32-40 Hz) bands were used to train a Random Forest Classifier. Cross-validation was done by taking the one second samples randomizing their order, and split 70% of samples for training and 30% for testing. Results were quantified using accuracy as the metric.

2.5 Channel Importance/Analysis

Channel importance was identified by running each of the 14 individual channels through the linear regression model. The filtered frequency at each sample along with the 12 previous samples in memory were used as features. Channels with the highest average prediction accuracy for all subjects were determined to be the most important. By identifying what channels are most important for velocity, we can optimize the model using only relevant channels and potentially eliminate channels that are just noise.

Each channel's model for a trial is cross validated using the same trial-wise method presented above in the regression section 2.3. One trial was used as the test set while the other 4 trials in the same dimension were used to train the regression model. The prediction accuracy was then scored using the goodness of fit method.

3. Results

The linear regression model was used as a predictor of cursor velocity from the filtered EEG signals (Figure 2). Ten trials for all 33 subjects analyzed, and their prediction scores were averaged for vertical and horizontal trials. Goodness of fit scoring was also used to calculate the prediction accuracy. Each trial was cross validated by training the linear regression model on the other four trials and testing on the current trials. The results for average horizontal accuracy across all subjects was 70.77%, and the average vertical accuracy was 44.67%.

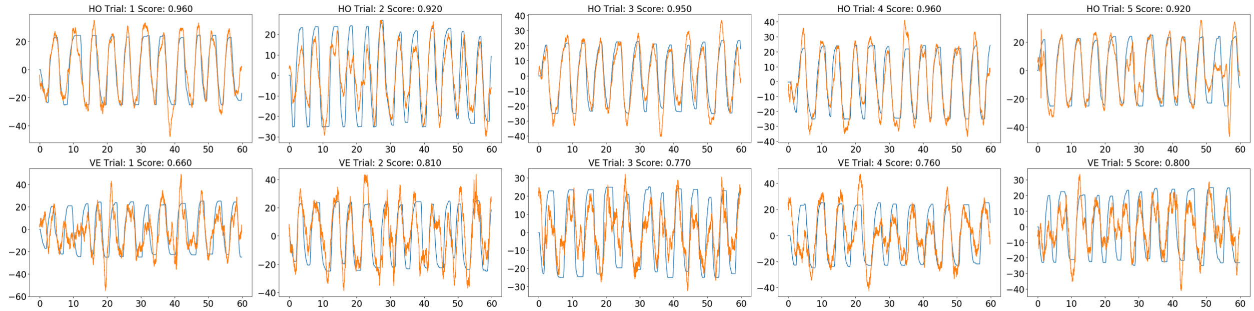

Figure 2: Regression results of one subject across all horizontal (top) and vertical (bottom) trials. Predicted velocity (orange) and target velocity (blue) with goodness of fit score above plot

Aside from linear regression, the model was also trained using several other algorithms such as adaboost regression, ridge regression, kernel ridge regression, support vector regression, and multilayer perceptron. From our cursory analysis of the performance of these models, linear regression demonstrated one of the best results for both horizontal and vertical predictions. Furthermore, many of these models were more computationally expensive than linear regression making them impractical for real time prediction (Figure 3).

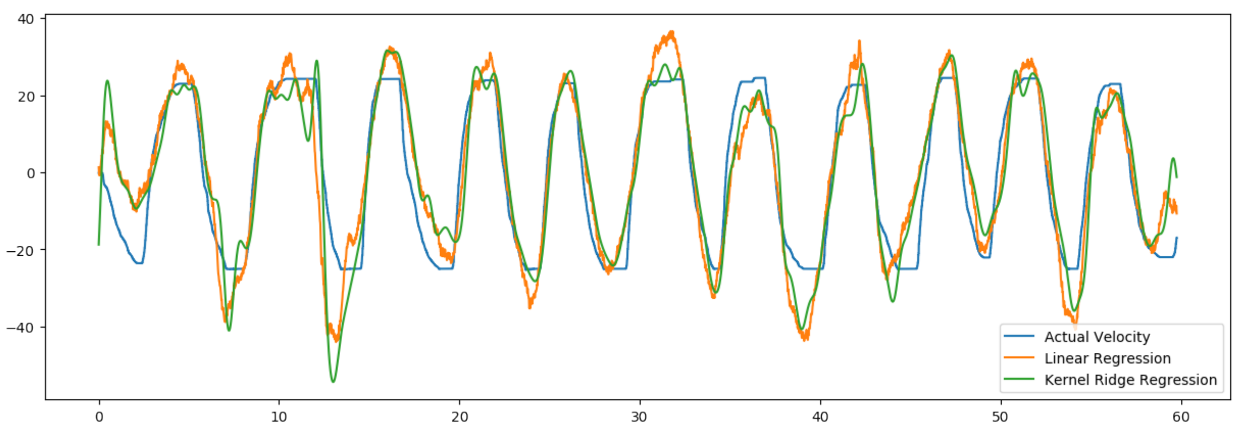

Figure 3: Predicted velocities plotted over the target for linear regression and kernel ridge

Channel-wise identification yielded a significant pattern between the horizontal and vertical data by taking the average prediction accuracy from all 33 subjects (Figure 4). The horizontal data showed that the F7 and F8 channels contributed the most toward velocity prediction. The right hemisphere of the brain also showed higher prediction accuracy over the left hemisphere. The vertical data showed highest prediction in the AF3, F3, F4, and AF4 channels.

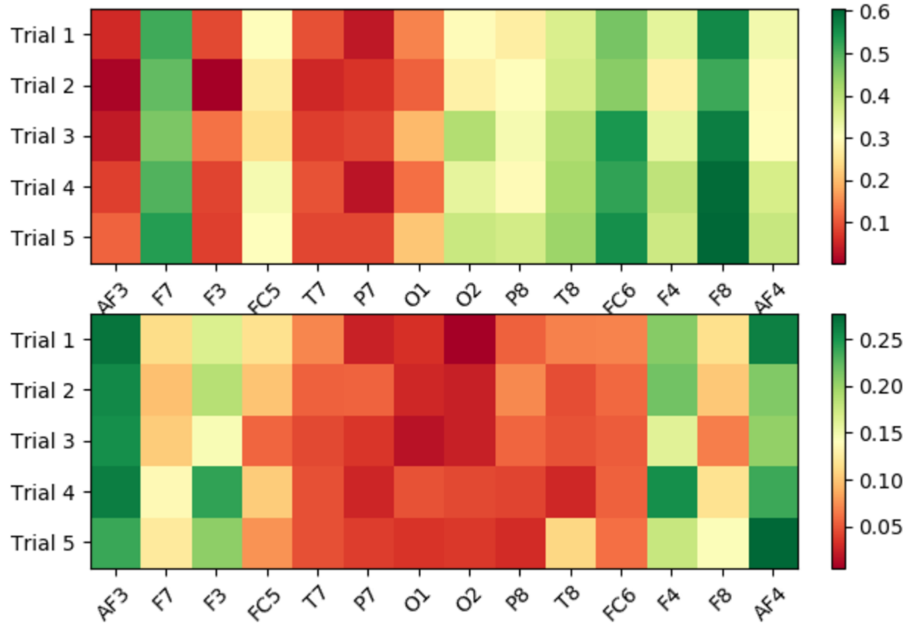

Figure 4: Heat map for channel-wise prediction in horizontal (top) and vertical (bottom) trials

Using this information from the most important channels, different combinations of these relevant channels can be used in our prediction model (Table 1). Horizontal accuracy can be improved most by using the channel combination of F7, FC5, T8, FC6, F4, and F8. For vertical accuracy, it was found that all channels are necessary for the highest prediction accuracy.

Table 1: Prediction accuracy for various channel combinations

Channels	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%
AF3 AND AF4	41.93%	30.29%
AF3, F3, F4, and AF4	49.21%	33.09%
AF3, F3, F7, F8, F4, and AF4	69.97%	41.61%

The Random Forest Classifier was used to determine horizontal or vertical movement. The average classification accuracy was 79% for all channels and all features of mean, median, maximum and minimum of the four frequency bands of Theta, Alpha, Beta, and Gamma. Using only the mean values from the four frequency bands yielded an average classification accuracy of 80%. The same methods of all features and only means were repeated on the 6 frontal EEG channels of AF3, F3, F7, F8, F4, and AF4. These provided an average classification accuracy of 68% and 69% respectively (Figure 5).

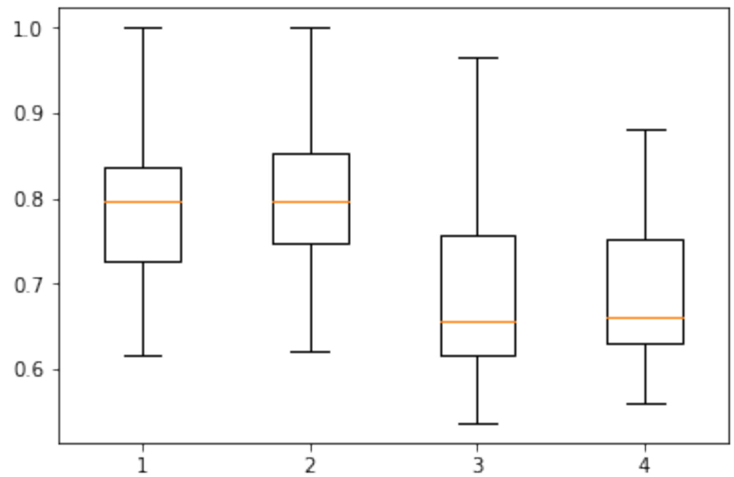

Figure 5: Average classification accuracies. (1) All channels and all features; (2) all channels and means; (3) six channels and all features; (4) six channels and means.

4. Discussion

Several models were used to test the prediction accuracy of the BCI platform. Models such as adaboost regression, ridge regression, kernel ridge regression, support vector regression, and multilayer perceptron often provided comparable accuracy to linear regression, but at a much longer processing time. For this reason, linear regression was chosen as the model to use for the remaining tests.

For channel importance, it is interesting to note that there is a distinct pattern between the most predictive channels for horizontal and vertical trials. The F7 and F8 channels showed the highest standalone prediction for horizontal trials while the AF3, F3, F4, and AF4 channels were the highest for vertical. Using just the F7 and F8 channels as features for the linear regression model provided a prediction accuracy that was less that 1% lower than using all channels for horizontal trials. This implies that a headset with two sensors can be used with great effectiveness in horizontal tasks compared to 14 channels. Vertical channels were unable to be improved by using different channel combinations.

It can be seen in these results that horizontal prediction accuracy is much higher than vertical prediction accuracy. There are many possible reasons why the vertical directions have a significantly lower accuracy, but more research is necessary to draw a definitive conclusion. It is also interesting to note that Figure 4 shows the channels located on the right hemisphere of the brain as more relevant to velocity prediction. This is intriguing because 31 out of 33 subjects were right handed, and right hand movement is usually governed by the left hemisphere of the brain. This shift could be explained by the use of the imagined body kinematics paradigm where the subjects were not making any overt movements.

The results of the classification approach show a very promising method of distinguishing between intended horizontal and vertical movement. By achieving an average accuracy of 80%, this classifier can potentially be used in front of the regression model to improve performance. It is also interesting to note that subjects with high goodness of fit scores did not always achieve high classification accuracies. In some cases, subjects with low velocity prediction scores have much higher classification scores.

5. Conclusion

A decoder model of Multiple Linear Regression was used to predict the velocity of a computer cursor from EEG signals. This model allowed for fast processing times and decent accuracy during online trials. Different channels seem to correspond to different tasks. Both horizontal and vertical trials showed distinct patterns across all subjects. By utilizing different combinations of channels as well as adding a classifier for horizontal and vertical movement, this model can be optimized to provide higher prediction scores. With the combination of these two methods, the real-time prediction model stands a good chance of seeing improvement. By optimizing the training protocol for this BCI platform, we aim to allow a new method of interaction to the environment for those with disability.

6. Future Work

While linear regression has given the best results so far, there remains the question of whether it is optimal. We would like to spend more time tuning other models to see if they can give us better prediction. Furthermore, we aim to implement and tune a long term short term recurrent neural network (LSTM-RNN). We wish to also take steps to implement what we have learned in real-time testing. We would like to implement our classifier along with the regression approach to improve our real-time prediction. It will also be interesting to see if there is a way to implement the different channel combinations in real-time testing. Once the cursor trials receives satisfactory results, we would like to implement our platform on other devices such as controlling a robotic arm or wheelchair.

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