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

Soheil Borhani, Justin Kilmarx, David Saffo, Lucien Ng, Reza Abiri, and Xiaopeng Zhao

***Abstract*— A Brain-Computer Interface (BCI) platform can be utilized by a user to control an external device without making any overt movements. An EEG-based computer cursor control task is commonly used as a testbed for BCI applications. While traditional computer cursor control schemes are based on sensorimotor rhythm, a new scheme has recently been developed using imagined body kinematics (IBK) to achieve natural cursor movement in a shorter time of training. This article attempts to explore optimal decoding algorithms for an IBK paradigm using EEG signals with application to neural cursor control. The study is based on an offline analysis of 32 healthy subjects' training data. Various machine learning techniques were implemented to predict the kinematics of the computer cursor using EEG signals during the training tasks. Our results showed that a linear regression least squares model yielded the highest goodness-of-fit scores in the cursor kinematics model (70% in horizontal prediction and 40% in vertical prediction using a Theil-Sen regressor). Additionally, the contribution of each EEG channel on the predictability of cursor kinematics was examined for horizontal and vertical directions, separately. A directional classifier was also proposed to classify horizontal versus vertical cursor kinematics using EEG signals. By incorporating features extracted from specific frequency bands, we achieved 80% classification accuracy in differentiating horizontal and vertical cursor movements. The findings of the current study could facilitate a pathway to designing an optimized online neural cursor control.**

***Index Terms*—BCI, Classification, Cursor control, EEG, Imagined body kinematics, Multivariate regression**

I. Introduction

THE interest in Brain Computer Interface (BCI) applications has grown and advanced since its initial establishment in the 1960s [1]. A brain-controlled computer cursor is commonly investigated as one of the primary testbeds for BCI applications. The cursor control platform can be used to control external devices, which may be used to help individuals who are suffering from the most severe motor disabilities, including people with amyotrophic lateral sclerosis (ALS), spinal cord injury, stroke, and other serious neuromuscular diseases or injuries. The activities of the brain during control of the computer cursor are recorded by either invasive or noninvasive means [1]. In the invasive domain, many systems have been developed using electrocorticography (ECoG), single units, and local field potentials on humans and primates [2-4]. While these systems have achieved impressive results, there are potential risks from surgeries and implantations associated with invasive BCIs. To combat some of these issues, noninvasive methods such as electroencephalography (EEG) has been investigated as a more attractive option due to its low-cost, portability, and less associated risks [1]. Using these techniques, several paradigms have been developed for EEG [5], including sensorimotor rhythms (SMR) [6-9], external stimulation [10], and imagined body kinematics (IBK) [11-13].

SMR has been one of the most prevalent paradigms in BCI applications that involves extracting the mental states from imagined movements of large body parts such as the hands, legs, or tongue [12]. This approach is based on the variations in the mu and beta rhythms from the sensorimotor cortex [14, 15]. Using SMR, various researchers have mapped these signals to the kinematic parameters of a computer cursor in one dimension (1D) [6], two dimensions (2D) [7, 16, 17], and three dimensions (3D) [8]. Other studies have explored using a hybrid EEG

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J. Kilmarx is with the Department of Mechanical, Aerospace, and Biomedical Engineering, The University of Tennessee, Knoxville, TN 37996 USA (e-mail: jkilmarx@vols.utk.edu).

D. Saffo is with the Department of Computer Science, Loyola University, Chicago, IL 60660 USA (e-mail: dsaffo@luc.edu).

L. Ng is with the Department of Information Engineering, The Chinese University of Hong Kong, Sha Tin, Hong Kong (e-mail: nkl015@ie.cuhk.edu.hk).

R. Abiri was with the Department of Mechanical, Aerospace, and Biomedical Engineering, The University of Tennessee, Knoxville, TN 37996 USA. He is now with the Department of Neurology, University of California, San Francisco/Berkeley, CA 94158 USA (e-mail: reza.abiri@ucsf.edu).

S. Borhani is with the Department of Mechanical, Aerospace, and Biomedical Engineering, The University of Tennessee, Knoxville, TN 37996 USA (e-mail: sborhani@vols.utk.edu).

X. Zhao is with the Department of Mechanical, Aerospace, and Biomedical Engineering, The University of Tennessee, Knoxville, TN 37996 USA (e-mail: xzhao9@utk.edu).

paradigm between SMR and other methods [18]. For example, SMR has been merged with Steady State Visual Evoked Potential (SSVEP) [10] and P300 potential [19] to attempt 1D and 2D cursor control. The issue with SMR-based approaches is a lengthy training time (often several days or weeks) for subjects to learn how to modulate the specific frequency bands necessary to manipulate the cursor in the desired manner [6-8, 17].

Recently, IBK has been proposed as a novel approach for noninvasive computer cursor control [11, 13] and real-time robotic manipulation [20]. In IBK, the subject is asked to imagine the continuous movement of one body part in multi-dimensional space. The recorded signals are then decoded in the time domain. Bradberry et al. [11] investigated the 2D cursor control problem with this EEG-based BCI paradigm. They instructed their subjects to use the natural imaginary movement of the right-hand index finger to track a computer-controlled cursor. The approach has been previously investigated in the invasive BCI domain, where subjects with implanted electrodes could achieve target acquisition using imagined kinematics of one body part [3, 21]. Also, Ofner et al. [22] studied the underlying neural patterns in continuous and natural imaginary movements of the right hand in a 2D plane. They used continuous EEG signals to estimate the imagined velocities. Andres et al. [23] investigated the influence of eye movements on both linear and nonlinear EEG decoding models on a two-dimensional trajectory of imagined right-hand movements. Kim et al. [24] conducted a similar study in 3D space using linear models. Gu et al. [25] decoded the imaginary movements of the right wrist at two different speeds and in another study [26] utilized the imagined speed of wrist movements in paralyzed ALS patients. There are other studies on the imaginary movements of the shoulder, elbow, wrist, and finger [27-29]. It is believed that the IBK paradigm is a more natural cursor control method compared to SMR and SSVEP since the IBK decoder directly maps the user's intention to the cursor kinematics [30, 31]. In contrast, the SMR paradigm requires the user to imagine activating a body part, which is associated with a predefined cursor movement [16]. On the other hand, the SSVEP paradigm utilizes shifting gaze between lights flickering at different frequencies [32]. IBK also provides the benefit of a significantly reduced training time compared to these other approaches [30]. Using IBK, Bradberry et al. controlled a cursor in a 2D space with just 40 minutes of training and calibration [11]. This suggests that using the more natural paradigm of imagined body kinematics can significantly reduce training time. The paradigm of IBK utilizes the low-frequency components of EEG (less than 1 Hz) to extract the kinematic information necessary for control of external devices [11, 33]. In the previous study, a decoder model of multiple linear regression was used to predict the velocity of a computer cursor from EEG [13]. This model allowed for fast processing times and decent accuracy during online trials. In this work, we aim to explore optimal channels and algorithms to decode cursor kinematics from IBK data.

II. Methods

A. Data

Data used in this work was collected in [13]. A total of 32 healthy subjects with no prior experience in participating in any BCI studies were fully informed about experimental procedures, potential risks, and benefits. All experimental procedures were approved by the Institutional Review Board at the University of Tennessee. The subjects were recruited from the University of Tennessee. The study included 32 healthy subjects (7 females and 25 males; with age of 22.7 ± 3.5) with no prior experience of using BCI. No subjects reported any neurophysiological problems. Twenty-nine participants were right-handed, two were left-handed, and one was ambidextrous. Subjects participated in the tests after signing informed consent. For the experiments, a dual-monitor PC 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 monitor, with their hands resting in their lap. An Emotiv EPOC headset with 14 channels was chosen to collect EEG signals wirelessly [34]. The electrodes were hydrated and placed on the subjects' heads in a way to make correct contact with the scalp (scalp-electrode resistance < 10KΩ). The quality of electrodes' contact with the scalp skin was monitored via the TestBench software from Emotiv during recordings. Both EEG data and cursor kinematics were collected and stored by the BCI2000 software system at 128 Hz during the experiments. Meanwhile, a band-pass filter with cutoff frequencies at 0.2 Hz and 30 Hz was applied to the collected EEG signals [35].

B. Training Protocols

During the training phase, the participants were shown a computer cursor whose movements started from the center of the workspace and advanced with an automated trajectory in one dimension; refer to Fig. 1. The subjects were instructed to track the cursor while imagining moving a computer mouse with their dominant hand at the same speed and direction. They were asked to maintain normal eye movement while keeping their focus on the cursor. Meanwhile, they were asked to avoid blinking or moving their own body parts to prevent any further artifacts while the test was active. The dimension of the workspace was a 33 cm × 33 cm square on the monitor. The diameter of the cursor was selected to be 1.5cm (0.20% of the workspace) and targets were 2.4% of workspace with width 8% and length 30% of screen width. The training phase consisted of 5 runs of cursor horizontal movement and 5 runs of cursor vertical movement. The duration of each run was 60 seconds. The cursor movement in each run was a replay from a record, where the cursor was manually moved. The 5 horizontal runs and 5 vertical runs were recorded beforehand, and the sequence of the runs was kept the same for all participants. Fig. 2 shows the cursor trajectory in runs 1 and 2 in horizontal and vertical directions, respectively.

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C. Multivariate Regression of Cursor Velocity

It has been identified in multiple studies that among various kinematic parameters (position, velocity, and acceleration), decoding velocity of body parts has shown higher predictive capabilities in both offline analysis and real-time implementation [11, 36-38]. To correlate the brain's activities and the movement of body parts, many decoding algorithms for EEG data have been investigated by researchers in both frequency and time domains. Most of the studies based on the sensorimotor-rhythms paradigm were developed in the frequency domain for cursor control and external devices control [6-8, 16, 39-44]. 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, Kalman filter [45], particle filter model [46], and kernel ridge [24] were applied in decoding EEG signals for offline analysis and prediction of body velocity parameters.

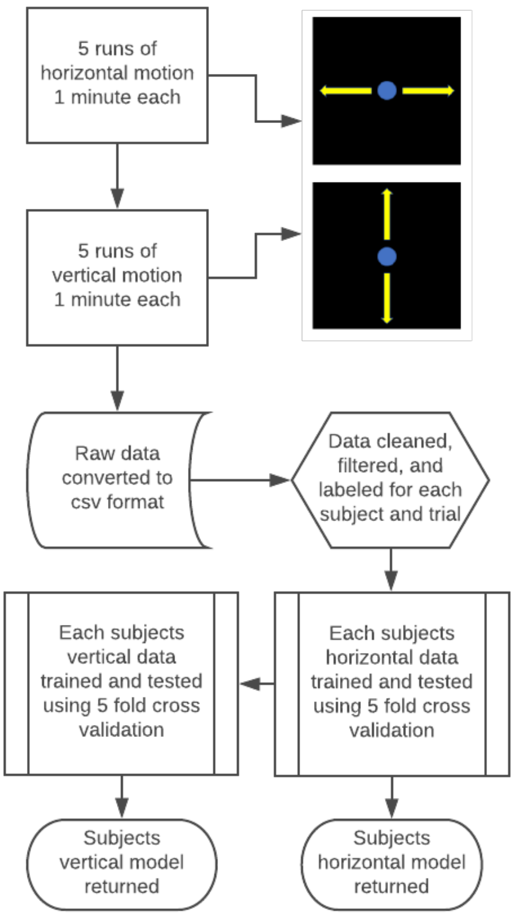

Fig. 1. Training protocol and model generation for horizontal and vertical trials

Ordinary least square (OLS) as a multiple linear regression has been the most common method for decoding EEG data in offline modes [24, 36-38, 47, 48] and in real-time implementation [11]. It is a generalized multiple linear regression model to estimate a single response variable by multiple explanatory variables (features). It uses the least square error as an objective function. The OLS minimizes the sum of the squared error (L2 norm); see Equation (1)

$$\beta_{OLS} = argmin \sum_{i=1}^{n} (y_i - X\beta)^2 \qquad (1)$$

where y_i represents the response (dependent variable), X represents the independent variables, and β is the model coefficient. The technique is unbiased since the expected values of the model coefficients (β) over multiple sets of data samples is very close to each other. This analysis can be represented by the following equations. Equations 2 and 3 map the acquired EEG data to the observed cursor velocities in the horizontal (x) and vertical (y) directions from the training data. In other words, the aim is to reconstruct the cursor trajectories off-line from EEG data and obtain a calibrated decoder for real-time implementation for each subject, individually. Output velocities at time sample t in the x (horizontal) direction is $u[t]$ and in the y (vertical) direction is $v[t]$.

$$u[t] = a_{0x} + \sum_{n=1}^{N} \sum_{k=0}^{K} b_{nkx} e_n[t-k] \qquad (2)$$

$$v[t] = a_{0y} + \sum_{n=1}^{N} \sum_{k=0}^{K} b_{nky} e_n[t-k] \qquad (3)$$

In these equations, $e_n[t-k]$ is the measured voltage of EEG electrode n at time lag k where the total number of EEG sensors is $N = 14$ and the total lag number is $K = 12$. These numbers were determined during previously published works by the authors [13]. The variables a and b are the weights that could be obtained through multiple linear regression. To assess whether this method is the optimal model for velocity prediction, a standard least squares model was tested against several other regression techniques. The OLS allows more than one explanatory feature to be employed in the model, which may raise concern when there is correlation (multicollinearity) between the explanatory variables. Two other models selected for comparison were ridge regression and Theil-Sen regression [49]. Ridge regression is a multiple regression method, which tries to address the multicollinearity problem in the data feature. OLS regression although unbiased, can suffer a high variance if data features are highly correlated. This causes dramatically large regressor coefficients. Ridge regression minimize the squared residuals in addition to a regularization term to reduce unregularized errors; see Equation (4)

$$\beta_{Ridge} = argmin \sum_{i=1}^{n} (y_i - X\beta)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \qquad (4)$$

where λ is a regularization term to avoid large regressor coefficient. We also used a nonlinear estimator named Theil-Sen regressor. It is less sensitive to outliers and potentially can achieve more robust and accurate results compared to OLS linear regression. The regressor looks at all possible pairs of the data points and computes a list of slopes. Then, the regressor considers median for the estimation. Since the median does not care about a single value but it cares about the data rank, the Theil-Sen regression can be robust to the outliers. These models were chosen to assess the inclusion of L2 regularization on velocity prediction as well as to better deal with outlier data.

For training of the multiple linear regression model, 12 previous points of EEG data from each channel in memory

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along with the current sample were used as features. The model was then cross-validated against the other four trials of the same dimension (leave-one-trial-out cross-validation). This cross-validation was repeated for all five combinations of models to ensure the most accurate prediction. The models were evaluated using a developed correlation score called Goodness-of-Fit (GoF). This scoring technique separated the trial into segments of 5 seconds and averaged the Pearson correlation scores between the predicted and actual cursor velocities. Then, the averaged value of the Pearson correlation scores over each trial was defined as the GoF. Pearson correlation coefficient indicates how far away the predicted velocity is to the scaled cursor velocity [49]. Although we asked participants to minimize their body movement, noise caused by eye blinks is non-separable part of EEG response. Despite the very short period of spikes caused by the eye blinks, it usually affects the Pearson correlation to a great extent. Instead, our proposed definition of Goodness-of-fit takes the average Pearson correlation among segments of the 5-second period into the account. The 5-second period is roughly the period of pre-recorded cursor movement. The new definition of Goodness-of-fit is more robust to abrupt changes and occurring artifacts in one segment may not exceedingly affect the GoF of the whole trial. Thus, the method provided a better representation of fit by not allowing one improperly fit window to reduce the overall model's score. Equation 3 represents the custom Goodness-of-Fit metric:

$$\mathrm{GoF} = \frac{1}{M}\sum_{i=1}^{M} Corr\left(\mathrm{V}_{decoded}^{i}, \mathrm{V}_{observed}^{i}\right) * 100\% \qquad (3)$$

Where $\mathrm{V}_{\mathrm{decoded}}^{i}$ and $\mathrm{V}_{\mathrm{observed}}^{i}$ represents the decoded velocity and the observed velocity for the ith segment, respectively. The number of segments for each 60 second trial is defined as $M = \frac{60}{5} = 12$.

Channel-wise prediction accuracy was investigated to identify patterns in predictive capability for both horizontal and vertical trials. The channels with the higher prediction accuracy could then be weighted more heavily during online testing while the channels with lower prediction can be eliminated. To perform the channel-wise identification, only the data from one channel was analyzed using the optimal regression model. The filtered data from each sample along with the 12 previous samples in memory were used as features. The model was then validated using leave-one-trial-out cross-validation. The prediction accuracy for the channel was scored using the Goodness-of-Fit metric.

D. Classification of Cursor Movement Direction

It was hypothesized that a classifier for horizontal and vertical motion could be employed as a method to improve the accuracy of the prediction model. This classifier could be used as a gate to generate predictions on a model tailored for horizontal or vertical data. The foundation of the hypothesis is based on the assumption that imagined hand movements in the horizontal and vertical directions correspond to different brainwave patterns in EEG. Our assumption is indirectly motivated and supported by previous studies that successfully decode individual finger movement using EEG [50]. To classify cursor movement direction, EEG data in each trial were divided into 60 non-overlapping segments, each of which is 1-second duration. Features for each segment were collected by taking the Fourier Transform of the EEG data from each channel. Specifically, the mean, median, maximum, and minimum values of the power spectral density 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 Classifier to discriminate between horizontal and vertical movements.

We chose to use the random forest for classification. The method uses a multitude of decision trees trained at training time to model the data [49]. Decision tree tends to overfit the data. However, by using an ensemble model like a random forest that utilizes underlying decision trees, we can reduce the variance. The method aims to reduce the correlation between decision trees using the pruning technique. It is robust to scaling and inclusion of sometimes irrelevant features. The classifier was cross-validated by splitting 70% of the randomized samples for training data and 30% for testing. Results were quantified using accuracy as the metric.

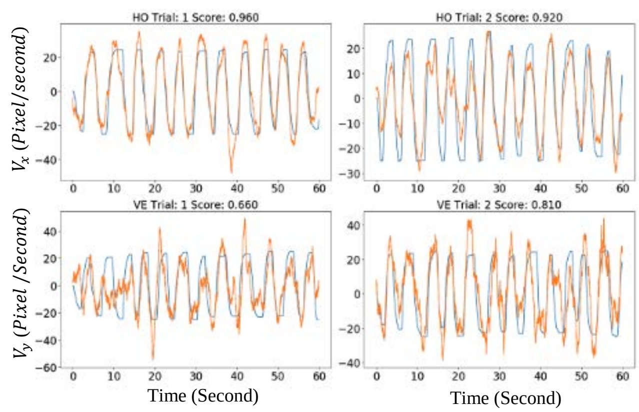

Fig. 2. Regression results of one subject across two horizontal (top) and vertical (bottom) trials. Predicted velocity (orange) and target velocity (blue) with goodness of fit score above plot.

III. Results

A. Multiple Linear Regression

The multiple linear regression model was used as a predictor for cursor velocity from the filtered EEG signals. Goodness-of-Fit scoring was 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. For comparison, we evaluated the decoding algorithm using randomly generated signals and ran the simulations for 1000 times, which indicates the outcome at chance level [51]. The mean [standard deviation] from the chance level simulations is 12.9% [5.5]. Fig. 2 shows a sample of two horizontal and vertical trials for illustration. Ten trials for all 32 subjects were analyzed, and their prediction scores were averaged for vertical and horizontal trials. The mean [standard deviation] of GoF for horizontal accuracy using least squares regression across all subjects was 70.79% [29.14] and the mean [standard deviation] of GoF for vertical accuracy was 38.33% [30.14], both of which are significantly higher than the chance level.

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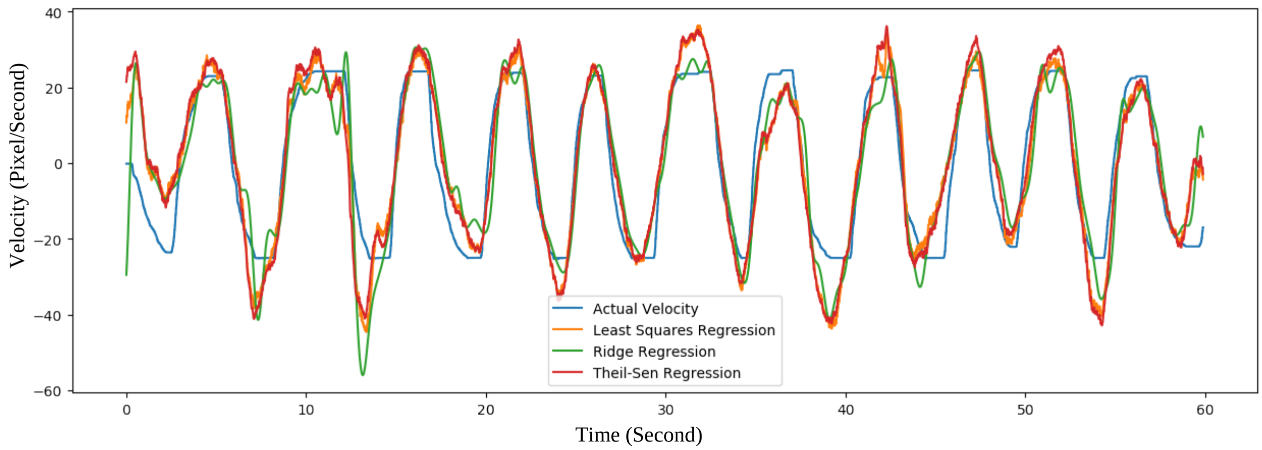

Fig. 3. Predicted velocities plotted over the target for least squares, Ridge, and Theil-Sen regression for one sample subject and one sample horizontal trial.

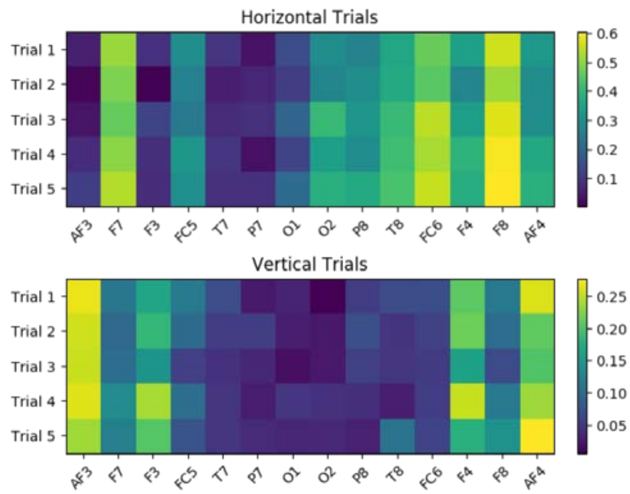

Fig. 4. Heat map for channel-wise prediction in horizontal and vertical trials.

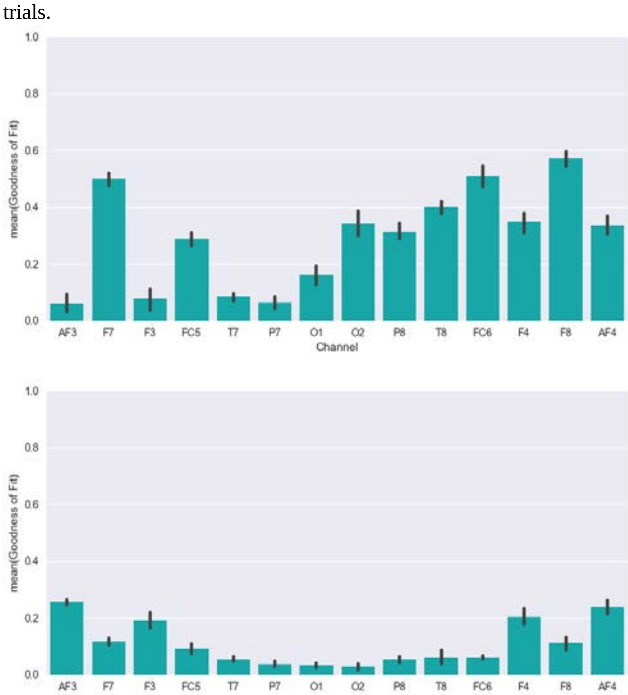

Fig. 5. Average goodness of fit of each channel for horizontal trials (top) and vertical trials (bottom).

TABLE I
MODEL COMPARISON FOR HORIZONTAL AND VERTICAL TRIALS

Model	Avg. Horizontal GoF	Horizontal STD	Avg. Vertical GoF	Vertical STD
Multiple Linear Regression	70.79	29.14	38.33	30.14
Ridge Regression	68.18	28.30	35.40	28.23
Theil-Sen Regression	71.04	29.69	40.28	30.21

Aside from least squares, the model was trained using several other variations of the least-square algorithm such as ridge regression and Theil-Sen regression. Ridge regression was trained using a regularization alpha of 1.0. The higher regularization of the data leads to less accurate results across all subjects. Theil-Sen regression was trained with a subpopulation of 10,000 and showed slight improvements in most subjects. Table I and Fig. 3 shows a comparison between the three models to illustrate the similarities in prediction capabilities. From our analysis of the performance of these models, linear regression demonstrated one of the best results for both horizontal and vertical predictions across all subjects. Theil-Sen regression preformed close to and in some places better than linear regression; however, this was often at the cost of a higher time complexity leading to longer training times. For this reason, the least squares model was identified as the optimal model out of the three evaluated techniques when taking into account time and GoF performance. Fig. 5 shows the average GoF of individual EEG channels for horizontal and vertical trials.

B. Channel-Wise Regression

Fig. 4 shows a heat map of the average GoF scores across all subjects using each individual channel. Here, the channel-wise analysis was based on the optimal regression model to determine which channels contributed the most to the overall prediction. The results are based on leave-one-trial-out cross-validation. For reference, the 14-channel layout for the Emotiv Epoc headset used in this study is presented in Fig 5. The

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horizontal data showed that the F7 and F8 channels contributed the most toward velocity prediction. It is also noteworthy to mention that the right hemisphere demonstrates much higher prediction accuracy than the left hemisphere for horizontal trials. The vertical data indicates that the AF3, F3, F4, and AF4 channels contribute the most.

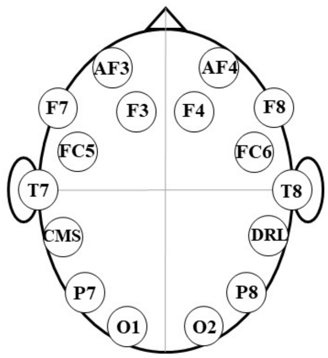

Fig. 6. Emotiv EPOC channel locations; figure copied from [20].

TABLE II
PREDICTION ACCURACY FOR VARIOUS CHANNEL COMBINATIONS

Channels	Horizontal Accuracy	Vertical Accuracy
F7, F8	69.96%	15.27%
F7, F8 + FC5, FC6, F4, T8	72.41%	31.78%
F7, F8 + O2, P8, T8, FC6, F4, AF4	71.03%	33.67%
AF3, AF4	41.89%	27.55%
AF3, AF4 + F3, F4	49.21%	28.35%
AF3, AF4 + F3, F4, F7, F8	70.02%	34.32%
All Channels	70.79%	38.33%

Using this information, different combinations of these relevant channels can be used in our prediction model in an attempt to improve the overall accuracy. The combinations were selected based on the prediction capability represented by the heat map in Fig. 4. Table II shows the results of channel analysis for horizontal and vertical accuracy. Our results showed that horizontal accuracy could 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. However, it is interesting to note that the six frontal channels (AF3, AF4, F3, F4, F7, and F8) demonstrated accuracy comparable to all 14 channels (see Fig. 6).

C. Classification

We also conducted numerical experiments to determine the movement direction from a segment of EEG signals. A Random Forest Classifier was used to discriminate between horizontal or vertical movement (refer to section II.D for a full description of features and cross-validation methods). Fig. 7 presents the classification accuracies for four different features sets. 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 six frontal EEG channels of AF3, AF4, F3, F4, F7, and F8. These provided an average classification accuracy of 68% and 69% respectively.

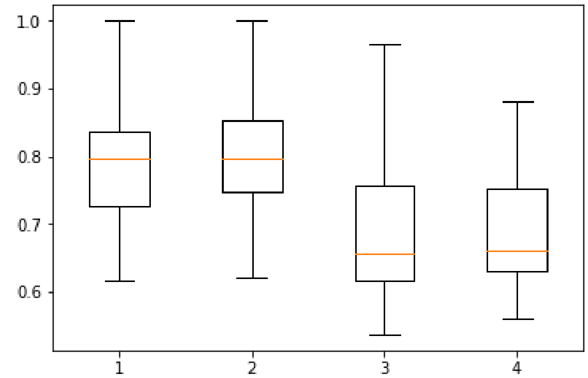

Fig. 7. Boxplots of the classification accuracies using four different feature sets. (1) All channels and all features; (2) all channels and mean of the 4 frequency bands independently; (3) six channels (AF3, AF4, F3, F4, F7, and F8) and all features; (4) six channels (AF3, AF4, F3, F4, F7, and F8) and mean of the 4 frequency bands independently.

IV. DISCUSSION

Several models were used to test the prediction accuracy of the BCI platform. From a cursory analysis of various models and previous literature [24, 36-38, 47, 48], we choose to focus on variations of the least squares algorithm as they have typically shown the best performance. Ridge regression was chosen to test how the inclusion of L2 regularization affected the predicted velocity. Ridge regression saw the lowest GoF scores even when the regularization parameter was set to near zero (zero regularization simply being least squares). Theil-Sen regression was chosen for its advantages in dealing with outlier data and general robustness to corrupted data [52]. Theil-Sen reported slightly better GoF for most subjects which suggests that some noise, artifacts, or outliers are still present even after filtering. This shows the potential usefulness of robust least square estimators for BCI implementations. Models such as Theil-Sen regression and ridge regression often provided comparable accuracy to our multiple linear regression model based on least squares regression but at a much longer processing time. For this reason, the least squares model was chosen for the remaining tests. As demonstrated in the literature [12, 39, 41], the contribution of (electrooculogram) EOG to the decoding accuracy is insignificant. Bradberry et al. [12] also showed that the influence of muscle activity on the cursor movement is low. Since the EEG signal is subjected to a band-pass filter [0.2, 1] Hz, artifacts out of this range are removed from the regression.

During the evaluation of individual channels, 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, AF4, F3, and F4 channels were

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the highest for vertical. Using just the F7 and F8 channels as features for the linear regression model provided a GoF score that was less than 1% lower than using all channels for horizontal trials. This suggests 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. The combination of AF3 and AF4 channels gives the worst score among the tested combinations in Table II. Since AF3 and AF4 are influenced the most by eye movement, this indicates that eye movement may play an insignificant role in velocity prediction. It is worthy of pointing out that using EEG headsets with 32 or 62 electrodes may improve the decoding accuracies.

It can be seen from the results that horizontal prediction accuracy is much higher than vertical prediction accuracy. Further research is needed to determine the cause of this difference. It is also interesting to note that Fig. 4 shows the channels located on the right hemisphere of the brain as more relevant to velocity prediction. The results of the classification approach show a very promising method of distinguishing between the 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 noteworthy to mention 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. Unlike previous work in the literature [11, 23], this research separated the training for two-dimensional cursor control into two simple one-dimensional training in horizontal and vertical directions, respectively. The results here suggest a novel approach to expand the cursor control experiment from one direction to higher dimensions. Since the horizontal and vertical training are conducted separately, it allows us to distinguish between horizontal and vertical trials. The classification results suggest that patterns of the brain activities are different during horizontal and vertical cursor movements. The classification models developed here may be used to inform better decoding mechanisms.

V. Conclusion

In this article, an EEG-based Brain-Computer Interface platform was optimized through the evaluation of machine learning techniques, channel selection, and classification of cursor movement direction. Offline analysis of 32 healthy subjects' training data from a two-dimensional cursor control task was analyzed. A multiple linear regression decoder model derived from least squares was compared to models of ridge regression and Theil-Sen regression. While our results showed that the Theil-Sen model demonstrated the highest accuracy, the model generated from least squares regression provided comparable accuracy at a lower processing time which is necessary for online trials. Therefore, it was determined that the least squares method is the optimal model of the three regression techniques.

The platform can also see minor improvement through channel selection during dimensional tasks. For instance, tasks involving primarily horizontal movement can place a higher weight on channels F7 and F8 along with channels located on the right hemisphere of the brain. However, for vertical trials, there was no combination of channels that provided improved results found in this study. A classifier for horizontal and vertical direction can also be implemented as a gate to generate predictions on a model tailored for the intended dimension. The approach can be used to improve the accuracy of the model beyond regression alone. Our results showed a classification accuracy of 80% for mean values of power spectral density across the Theta, Alpha, Beta, and Gamma frequency bands for all channels.

It is interesting to note that prefrontal electrodes produce the best decoding results. This probably indicates that the IBK paradigm relies on higher cognitive functions compared to sensorimotor and externally triggered sensory paradigms. As pointed out in Min et al. [53], paradigms based on prefrontal cognitive functions are natural candidates for efficient and intuitive applications in goal-directed BCIs, which have great potential for applications in improving the quality of life of individuals with sensorimotor or cognitive impairments [54, 55]. While linear regression has given the best results so far, there remains the question of whether it is optimal. Further research needs to be done to explore other models and parameters (such as a Long Short-Term Memory network and variations of support vector machines) as well as methods to transfer knowledge from other subjects' data [56]. Future work will also include implementing what we have learned from channel selection and classification in real-time testing.

References

[1] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," *Sensors,* vol. 12, pp. 1211-1279, 2012.

[2] L. R. Hochberg, M. D. Serruya, G. M. Friehs, J. A. Mukand, M. Saleh, A. H. Caplan, *et al.*, "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," *Nature,* vol. 442, pp. 164-171, 2006.

[3] S.-P. Kim, J. D. Simeral, L. R. Hochberg, J. P. Donoghue, and M. J. Black, "Neural control of computer cursor velocity by decoding motor cortical spiking activity in humans with tetraplegia," *Journal of neural engineering,* vol. 5, p. 455, 2008.

[4] G. H. Mulliken, S. Musallam, and R. A. Andersen, "Decoding trajectories from posterior parietal cortex ensembles," *the Journal of Neuroscience,* vol. 28, pp. 12913-12926, 2008.

[5] R. Abiri, S. Borhani, E. W. Sellers, Y. Jiang, and X. Zhao, "A comprehensive review of EEG-based brain-computer interface paradigms," *Journal of Neural Engineering*, 2018.

[6] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An EEG-based brain-computer interface for cursor control," *Electroencephalography and Clinical Neurophysiology,* vol. 78, pp. 252-259, 3// 1991.

[7] J. R. Wolpaw and D. J. McFarland, "Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans," *Proceedings of the National Academy of Sciences of the United States of America,* vol. 101, pp. 17849-17854, 2004.

[8] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, "Electroencephalographic (EEG) control of three-dimensional movement," *J Neural Eng,* vol. 7, p. 036007, Jun 2010.

[9] E. Abdalsalam, M. Z. Yusoff, A. Malik, N. S. Kamel, and D. Mahmoud, "Modulation of sensorimotor rhythms for brain-computer interface using motor imagery with online feedback," *Signal, Image and Video Processing,* vol. 12, pp. 557-564, 2018.

[10] L. J. Trejo, R. Rosipal, and B. Matthews, "Brain-computer interfaces for 1-D and 2-D cursor control: designs using volitional control of the EEG spectrum or steady-state visual evoked potentials," *Neural Systems and Rehabilitation Engineering, IEEE Transactions on,* vol. 14, pp. 225-229, 2006.

[11] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Fast attainment of computer cursor control with noninvasively acquired brain signals," *Journal of neural engineering,* vol. 8, p. 036010, 2011.

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[12] V. Morash, O. Bai, S. Furlani, P. Lin, and M. Hallett, "Classifying EEG signals preceding right hand, left hand, tongue, and right foot movements and motor imageries," *Clinical neurophysiology,* vol. 119, pp. 2570-2578, 2008.

[13] R. Abiri, S. Borhani, J. Kilmarx, C. Esterwood, Y. Jiang, and X. Zhao, "A Novel User-Centered Approach for EEG-Based Computer Cursor Control via Imagined Body Kinematics," *Manuscript submitted for publication,* 2018.

[14] H. Yuan and B. He, "Brain-Computer Interfaces Using Sensorimotor Rhythms: Current State and Future Perspectives," 2014.

[15] B. He, B. Baxter, B. J. Edelman, C. C. Cline, and W. Y. Wenjing, "Noninvasive brain-computer interfaces based on sensorimotor rhythms," *Proceedings of the IEEE,* vol. 103, pp. 907-925, 2015.

[16] B. Xia, O. Maysam, S. Veser, L. Cao, J. Li, J. Jia, *et al.*, "A combination strategy based brain–computer interface for two-dimensional movement control," *Journal of neural engineering,* vol. 12, p. 046021, 2015.

[17] J. R. Wolpaw and D. J. McFarland, "Multichannel EEG-based brain-computer communication," *Electroencephalography and Clinical Neurophysiology,* vol. 90, pp. 444-449, 6// 1994.

[18] G. Pfurtscheller, B. Z. Allison, G. Bauernfeind, C. Brunner, T. Solis Escalante, R. Scherer, *et al.*, "The hybrid BCI," *Frontiers in neuroscience,* vol. 4, p. 3, 2010.

[19] Y. Li, J. Long, T. Yu, Z. Yu, C. Wang, H. Zhang, *et al.*, "An EEG-based BCI system for 2-D cursor control by combining Mu/Beta rhythm and P300 potential," *Biomedical Engineering, IEEE Transactions on,* vol. 57, pp. 2495-2505, 2010.

[20] J. Kilmarx, R. Abiri, S. Borhani, Y. Jiang, and X. Zhao, "Sequence-Based Manipulation of Robotic Arm Control in Brain Machine Interface," *International Journal of Intelligent Robotics and Applications*, 2018.

[21] D. M. Taylor, S. I. H. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," *Science,* vol. 296, pp. 1829-1832, 2002.

[22] P. Ofner and G. R. Müller-Putz, "EEG-Based Classification of Imagined Arm Trajectories," in *Replace, Repair, Restore, Relieve–Bridging Clinical and Engineering Solutions in Neurorehabilitation*, ed: Springer, 2014, pp. 611-620.

[23] A. Úbeda, J. M. Azorín, R. Chavarriaga, and J. d. R. Millán, "Evaluating decoding performance of upper limb imagined trajectories during center-out reaching tasks," in *Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on*, 2016, pp. 000252-000257.

[24] J.-H. Kim, F. Biessmann, and S.-W. Lee, "Decoding Three-Dimensional Trajectory of Executed and Imagined Arm Movements from Electroencephalogram Signals," 2014.

[25] Y. Gu, K. Dremstrup, and D. Farina, "Single-trial discrimination of type and speed of wrist movements from EEG recordings," *Clinical Neurophysiology,* vol. 120, pp. 1596-1600, 8// 2009.

[26] Y. Gu, D. Farina, A. R. Murguialday, K. Dremstrup, P. Montoya, and N. Birbaumer, "Offline identification of imagined speed of wrist movements in paralyzed ALS patients from single-trial EEG," *Frontiers in Neuroscience,* vol. 3, 2009-August-10 2009.

[27] A. Vuckovic and F. Sepulveda, "Delta band contribution in cue based single trial classification of real and imaginary wrist movements," *Med Biol Eng Comput,* vol. 46, pp. 529-39, Jun 2008.

[28] T. Chakraborti, A. Sengupta, D. Banerjee, A. Konar, S. Bhattacharyya, A. Khasnobish, *et al.*, "Implementation of EEG based control of remote robotic systems," in *Recent Trends in Information Systems (ReTIS), 2011 International Conference on*, 2011, pp. 203-208.

[29] A. K. Mohamed, T. Marwala, and L. R. John, "Single-trial EEG discrimination between wrist and finger movement imagery and execution in a sensorimotor BCI," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2011, pp. 6289-93, 2011.

[30] P. Ofner and G. R. Müller-Putz, "Using a noninvasive decoding method to classify rhythmic movement imaginations of the arm in two planes," *IEEE transactions on biomedical engineering,* vol. 62, pp. 972-981, 2015.

[31] J.-H. Kim, F. Bießmann, and S.-W. Lee, "Decoding three-dimensional trajectory of executed and imagined arm movements from electroencephalogram signals," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 23, pp. 867-876, 2015.

[32] B. Z. Allison, C. Brunner, C. Altstätter, I. C. Wagner, S. Grissmann, and C. Neuper, "A hybrid ERD/SSVEP BCI for continuous simultaneous two dimensional cursor control," *Journal of neuroscience methods,* vol. 209, pp. 299-307, 2012.

[33] R. Abiri, G. Heise, F. Schwartz, and X. Zhao, "EEG-based control of a unidimensional computer cursor using imagined body kinematics," in *Biomedical Engineering Society Annual Meeting (BMES 2015)*, 2015.

[34] Emotiv. Available: http://emotiv.com/

[35] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: a general-purpose brain-computer interface (BCI) system," *Biomedical Engineering, IEEE Transactions on,* vol. 51, pp. 1034-1043, 2004.

[36] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Reconstructing Three-Dimensional Hand Movements from Noninvasive Electroencephalographic Signals," *The Journal of Neuroscience,* vol. 30, pp. 3432-3437, March 3, 2010 2010.

[37] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Decoding three-dimensional hand kinematics from electroencephalographic signals," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2009, pp. 5010-3, 2009.

[38] P. Ofner and G. R. Muller-Putz, "Decoding of velocities and positions of 3D arm movement from EEG," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2012, pp. 6406-9, 2012.

[39] K. LaFleur, K. Cassady, A. Doud, K. Shades, E. Rogin, and B. He, "Quadcopter control in three-dimensional space using a noninvasive motor imagery-based brain–computer interface," *Journal of neural engineering,* vol. 10, p. 046003, 2013.

[40] T. Li, J. Hong, J. Zhang, and F. Guo, "Brain–machine interface control of a manipulator using small-world neural network and shared control strategy," *Journal of neuroscience methods,* vol. 224, pp. 26-38, 2014.

[41] M. K. Hazrati and U. G. Hofmann, "Avatar navigation in Second Life using brain signals," in *Intelligent Signal Processing (WISP), 2013 IEEE 8th International Symposium on*, 2013, pp. 1-7.

[42] B. J. Edelman, J. Meng, N. Gulachek, C. C. Cline, and B. He, "Exploring cognitive flexibility with a noninvasive BCI using simultaneous steady-state visual evoked potentials and sensorimotor rhythms," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 26, pp. 936-947, 2018.

[43] J. Meng, S. Zhang, A. Bekyo, J. Olsoe, B. Baxter, and B. He, "Noninvasive electroencephalogram based control of a robotic arm for reach and grasp tasks," *Scientific Reports,* vol. 6, p. 38565, 2016.

[44] B. S. Baxter, B. J. Edelman, N. Nesbitt, and B. He, "Sensorimotor rhythm BCI with simultaneous high definition-transcranial direct current stimulation alters task performance," *Brain stimulation,* vol. 9, pp. 834-841, 2016.

[45] J. Lv, Y. Li, and Z. Gu, "Decoding hand movement velocity from electroencephalogram signals during a drawing task," *Biomedical engineering online,* vol. 9, p. 64, 2010.

[46] J. Zhang, J. Wei, B. Wang, J. Hong, and J. Wang, "Nonlinear EEG Decoding Based on a Particle Filter Model," *BioMed Research International,* vol. 2014, 2014.

[47] J. M. Antelis, L. Montesano, A. Ramos-Murguialday, N. Birbaumer, and J. Minguez, "On the usage of linear regression models to reconstruct limb kinematics from low frequency EEG signals," *PloS one,* vol. 8, p. e61976, 2013.

[48] A. Ubeda, E. Ianez, E. Hortal, and J. M. Azorin, "Linear decoding of 2D hand movements for target selection tasks using a non-invasive BCI system," in *Systems Conference (SysCon), 2013 IEEE International*, 2013, pp. 778-782.

[49] A. J. Izenman, "Modern multivariate statistical techniques," *Regression, classification and manifold learning,* 2008.

[50] K. Liao, R. Xiao, J. Gonzalez, and L. J. P. o. Ding, "Decoding individual finger movements from one hand using human EEG signals," vol. 9, p. e85192, 2014.

[51] G. Müller-Putz, R. Scherer, C. Brunner, R. Leeb, and G. Pfurtscheller, "Better than random: a closer look on BCI results," *International Journal of Bioelectromagnetism,* vol. 10, pp. 52-55, 2008.

[52] X. Dang, H. Peng, X. Wang, and H. Zhang, "Theil-Sen Estimators in a Multiple Linear Regression Model," *Olemiss. edu,* 2008.

[53] B.-K. Min, R. Chavarriaga, and J. del R. Millán, "Harnessing Prefrontal Cognitive Signals for Brain–Machine Interfaces," *Trends in Biotechnology,* vol. 35, p. 13, 2017.

[54] S. Borhani, R. Abiri, S. Esfahani, J. Kilmarx, Y. Jiang, and X. Zhao, "Decoding Visual Attentional State using EEG-based BCI," in *2018 Annual Meeting Society for Neuroscience (SfN2018)*, 2018.

[55] S. Borhani, J. Yu, J. Cate, J. Kilmarx, R. Abiri, and X. Zhao, "Clash of Minds: A BCI Car Racing Game in Simulated Virtual Reality Environment," in *2018 Biomedical Engineering Society (BMES) Annual Meeting*, 2018.

[56] S. Borhani, R. Abiri, X. Zhao, and Y. Jiang, "A Transfer Learning Approach towards Zero-training BCI for EEG-Based Two Dimensional Cursor Control," in *Society for Neuroscience (SfN 2017)*, 2017.