EEG-Based Control of a Computer Cursor with Machine Learning

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Abstract

Brain computer interface (BCI) has greatly advanced since the initial establishment in the 1960s [Nicolas-Alonso, L.F. and J. Gomez-Gil, 2012]. 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 [Hauschild, M., et al., 2012] [Hochberg, L.R., et al., 2006] [Kim, S.-P., et al., 2008] [Mulliken, G.H., et al., 2008] [Hauschild, M., et al., 2012] [Gilja, V., et al.., 2012]. Various researchers have also designed and developed cursor control systems using noninvasive brain signals such as electroencephalogram (EEG). In the project, we have analysed the EEG data that captured during imagining controlling a computer cursor by using signal processing technique, such as filter bank, and machine learning methods, neural network, recurrent neural network and gradient boosting. With the aid of supercomputers, we achieve impressive result that we built a model that can predict the direction of horizontal movement with 0.90 of AUC and that of vertical movement with 0.71 AUC.

I. Introduction

In this report, we are going to present the detail of the purposes and objective of our project, the data collecting processes, the methods that we used to build our models and the results of the models.

i. Objective

The goal of our project is to provide a usable interface that users can use to control a computer cursor. Accuracy and responding time from the system are critical to users' experience. Besides that, the EEG-based method can avoid the risk of invasive methods and, more importantly, EEG-signal can be captured readily and with low cost, Hence, our objectives are as follow:

- To classify users intending cursor movement direction by using EEG-signal with high accuracy, and
- To accelerate the classify processes to acceptable speed

ii. Background Knowledge: EEG

Electroencephalography (EEG) is an electrophysiological monitoring method that records electrical activity on the surface of brains by placing electrodes on the scalp. Some significant advantages of EEG are that it is non-invasive and has low operating cost. Comparing to other brain state monitoring techniques, such as fMRI, which has high operation cost, and PET, which injects radioactive material to patients body, EEG can capture signals with a tiny headwear device, and thus it is a promising technique for BCI.

iii. Data Description

The training data were collected in Nonlinear Biodynamics Lab of University of Tennessee. During the experiments, subjects was instructed to imagine that they were controlled the cursor moving on the monitor by their master hand. Meanwhile, a headwear EEG device on the subjects' scalp was collecting data in 128Hz. For each subject, there were 5 trials and each of them lasted for 1 minutes. [Abiri, R., Zhao, 2017]

iv. Formulated Problem

In the sense of machine learning, our work is to solve a supervised multiclass classification. In this type of problems, a training and a testing dataset are given. In the training dataset, each input datapoint is corresponding to a label, the classifiers will make use of them to predict the label of the datapoint in the testing dataset, in which only datapoints are given. For our application, the specification is as follow:

- Input Data: The past EEG signal, a time series with 128 Hz and 14 channels, of a given time point.
- Labels: The direction of the velocity of a cursor that experimental subjects instructed to imagine. Each axis has 3 labels.

Table 1: *The details of the labels*

Axis	Direction		
Horizontal	Left	Right	No Movement
Vertical	Up	Down	No Movement

v. Related Study

As a popular EEG paradigm, the mental states acquired by imaginary movement of large body parts (imaginary movements of hands, legs and tongue) [Morash, V., et al., 2008] have been employed in many studies to control a computer cursor in one dimension [Wolpaw, J.R., et al., 1991], 2D space [Wolpaw, J.R. and D.J. McFarland, 2004] [Xia, B., et al., 2015], and 3D space [McFarland, D.J., et al., 2010]. These mental states cause changes in sensorimotor rhythms which include mu rhythm (8-12Hz) and beta rhythm (18-26Hz), 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. [Trejo, L.J., R. Rosipal, and B. Matthews, 2006] in 2006, utilized a target practice BCI system based on mental activity to deal with 1D cursor control problem (right-left) and also they investigated 2D space cursor control problem (right-left, up-down) based on Steady State Visual Evoked Potential (SSVEP) approach. Allison et al. [Trejo, L.J., R. Rosipal, and B. Matthews, 2006] in 2012, combined the mental states and steady state visual evoked potential (SSVEP) for two dimensional cursor control problem. Li et al. [Li, Y., et al., 2010] 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 or switching among more than one paradigm.

In noninvasive devices, [Bradberry, T.J., et al., 2011] 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 [Kim, S.-P., et al., 2008]. 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" [Mulliken, G.H., et al., 2008] [Bradberry, T.J., et al., 2011] [Velliste, M., et al., 2008] [Dangi, S., et al., 2014] and nonlinear machine learning techniques, we aim to develop a more accurate cursor control platform in a noninvasive BCI.

vi. Our Contribution

We have applied various machine learning techniques, such as neural network and logistic regression, combining with domain related techniques, such as filter bank, to achieve high AUC and accuracy in classification.

II. Methods

This section presents the feature extraction and machine learing techniques that involved in our project.

i. Overview of the models

In this project, there were two level of models. The first level consisted of numerous logistic classifiers and neural network. The second level consisted of ensemble models, which took the models in that first level as meta-features to construct a more accurate model.

Our models did point-to-point prediction. For any given timepoint, the models took the past 128 timepoints as input data to predict the label. If the timepoint is in the first 128 timepoints, we padded 0 as EEG signal.

i.1 Feature Extraction: Filter Banks

Filter banks is a signal processing technique that separates a segment of time series into multiple components which are some of the frequency bands of the input signal. In our implementation, 5th-order butter filter from SciPy was used.

Table 2: *The used frequency on low-pass filters*

0.5, 1, 2, 3, 4, 5, 6, 7, 9, 15, 30	Hz
1, 5, 10, 30	Hz

The main purposes of applying filter banks are to denoise the EEG-signal and extract the information that related to psychological states. EEG is very sensitive. For example, the muscle contraction that closes to the scalp would generates noise with high-frequency component. On the other hand, the existence of the relationship between EEG rhythm and behavioral states has been revealed [Wnek, G. E., 2008]. Hence, filter banks are promising features for the classification.

i.2 Classification: Multiplelayer Perceptron

Multiplelayer perceptron, as known as Neural Network, is a widely used neural network architecture. The network consists of layers, which have input and output units, a weighting matrix and a non-linear activation function. The principle of this neural network is providing a simplified version of biological neural network and using it to intimate some simple decision-making processes that human does. In the recent years, This architecture has applied to various aspects and some of them obtained impressive results. Hence, we included it in our models.

i.3 Classification: Recurrent Neural Network

Recurrent Neural Network (RNN) is another type of Neural Network. Comparing with Multiplelayer Perceptron, which assumes that the order of input data is not important, It has the capability to handle sequential data input. The units in this network would remember some input sequence of previous and forget some of them so that it can be stateful but would not request excessive memory space.

In some applications which input data have temporal structure, such as speech recognition, RNN performed very well. Hence, we applied this technique on our application since the EEG-signal is time series.

i.4 Ensembling: Gradient boosting

Gradient boosting is a machine learning technique that aggregates many weak models to produce a more predictive models. In practice, machine learning models are not perfect, but, base on the randomness of the models, they perform well at different areas. Hence, The idea of ensembling is to give different weighting for different areas in the input data space.

In the ensemble models training process, gradient boosting computes the error between the ground truth and the models prediction, and takes the derivative this point. By using gradient descent method, the ensemble models can give the optimal weighting of basic models at a given input data.

In our implementation, we took all the basic models that adopted neural network, recurrent neural network and logistic regression as input models, and used XGBoost to compute the ensemble models on GPU.

ii. Multithreading

Since we need to generate massive models for 12 subjects and to perform cross-validation for each of them, the amount of computation was huge. Fortunately, the model generation and each validation could run idependently. To shorten the time we take, we had changed the code so that the training processes could run in multithreads.

In our implementation, we used 32 threads for the data preprocessing and the logistic regression training, resulting in a huge decrease in total training time.

III. Experimental Setup

During the models training, 12 subjects' data were used, each of them has 5 trials of horizontal and vertical movement.

i. Cross-validation

To ensure the models that we built has the capability to classify the EEG signal instead of fitting its parameters to the noise in EEG signal, we conducted cross-validation to prevent overfitting problems. In the basic models training process, we took the 3 out of 5 trials as training data, and validate the models on the others 2 trials. Hence, there are $C_3^5 = 10$ combinations of training-validation sets.

ii. Envirnment

The modeling processes ran on an XSEDE-bridges GPU node, which had 32 CPU-cores and Nvidia P100 GPU.

IV. Results

In this section, we are going to present the average AUC and accuracy of each model.

As shown in 1, in the best model we built for horizontal movement, the prediction and the ground truth were matched at most of the time.

The best model for the horizontal movement is the ensemble model using gradient boosting for the neural network, which achieved 0.905 AUC and 79.95% accuracy. The details of each model are listed in 3 and 4.

However, the model's performance on vertical movement were worse than that of the horizontal movement. As shown in 5 and 6, the best model has accuracy of 56.7% and 0.701 AUC.

It is worth noting that the accuracy and AUC of the models vary from subjects to subjects. The models can perform poorly on some subject, However, as shown in 2 and 3, they perform well in most of the cases.

The total training time of the models for horizontal and vertical movement are 9.96 and 8.92 hours respectively.

V. Discussion

The models that we built have achieved impressive AUC, but the models training time was massive. To make the model building process usable for Brain-Computer Interface, the thing we need to do is as follow:

- To simplify the models building processing.
- To accelerate the neural network model by building it on MAGMA-DNN, which is a fast deep learning framework that possible to increase the model speed by a factor of 10.

VI. Conculsion

In the project, we have analysised the EEG data that captured during imagining controlling a computer cursor by using signal processing technique, such as filter bank, and machine learning methods, neural network, recurrent neural network and gradient boosting. With the aid of supercomputers, we achieve impressive result that we built a model that can predict the direction of horizontal movement with 0.90 of AUC and that of vertical movement with 0.71 AUC.

VII. Acknowledge

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Table 3: *The accuracy, ACC and computational time of the basic models on horizontal movement, sorted by AUC. PCA stands for Principle Component Analysis*

The Basic Models For Horizontal Movement	Accuracy	AUC	Time (second)
Neural Network with 32 units	0.725771	0.806242	1066.207867
Neural Network with 64 units	0.727846	0.805542	1059.964792
Neural Network with 128 units	0.724649	0.803369	1051.489179
Neural Network with 16 units	0.723575	0.803126	1058.706210
Logistic Regression with Filter Bank	0.729182	0.797780	406.529090
Neural Network with Filter Bank and 16 units	0.727568	0.797431	1514.881835
Neural Network with Filter Bank and 32 units	0.726114	0.797262	1512.066839
Neural Network with Filter Bank, PCA and 32 units	0.722109	0.794807	1518.229784
Neural Network with Filter Bank, PCA and 16 units	0.722529	0.794776	1508.930046
Neural Network with Filter Bank and 64 units	0.721976	0.793812	1513.289220
Neural Network with 8 units	0.716212	0.792267	1097.740819
Neural Network with Filter Bank, PCA and 64 units	0.720077	0.790742	1519.925173
Neural Network with Filter Bank and 128 units	0.715865	0.788756	1509.581109
Neural Network with Filter Bank, PCA and 128 units	0.712094	0.782328	1502.705873
Neural Network with Filter Bank and 8 units	0.716167	0.780918	1508.611929
Neural Network with Filter Bank, PCA and 8 units	0.710887	0.774018	1517.232316
Neural Network with 4 units	0.704784	0.763604	1064.123257
Neural Network with Filter Bank and 4 units	0.704303	0.753136	1507.605297
Neural Network with Filter Bank, PCA and 4 units	0.693063	0.746401	1519.505052
Recurrent Neural Network with Filter Bank and 64 units	0.624445	0.718184	2189.044291
Recurrent Neural Network with Filter Bank and 32 units	0.615834	0.706730	2168.059829
Recurrent Neural Network with Filter Bank and 16 units	0.603917	0.691557	2186.597372
Recurrent Neural Network with Filter Bank and 4 units	0.628402	0.683206	2190.748247
Recurrent Neural Network with Filter Bank and 8 units	0.589090	0.666758	2178.431342

Table 4: *The accuracy, ACC and computational time of the ensemble models on horizontal movement, sorted by AUC. PCA stands for Principle Component Analysis NN stands for Neural Network*

The Basic Models For Horizontal Movement	Accuracy	AUC	Time (second)
Gradient Boosting with the NN Models	0.799546	0.905200	144.865309
Gradient Boosting with the NN, Filter Bank and PCA Models	0.797972	0.904438	224.737503
Gradient Boosting with the NN and Filter Bank Models	0.797678	0.905202	187.536030

Table 5: *The accuracy, ACC and computational time of the basic models for vertical movement, sorted by AUC*

The Basic Models For Vertical Movement	Accuracy	AUC	Time (second)
Recurrent Neural Network with Filter Bank and 64 units	0.528191	0.623572	2188.234048
Recurrent Neural Network with Filter Bank and 128 units	0.530132	0.623200	2131.600924
Neural Network and 32 units	0.528703	0.621362	989.125282
Neural Network and 64 units	0.527434	0.620336	982.597968
Logistic Regression with Filter Bank	0.536444	0.620087	1129.119794
Neural Network with Filter Bank and 64 units	0.537087	0.619620	1410.017158
Neural Network and 128 units	0.530119	0.619255	978.031274
Neural Network with Filter Bank and 32 units	0.536616	0.618402	1400.734973
Neural Network and 16 units	0.524865	0.618376	987.327580
Neural Network with Filter Bank and 16 units	0.537359	0.618097	1393.121692
Neural Network and 8 units	0.521785	0.614292	990.296301
Neural Network with Filter Bank and 8 units	0.536701	0.613716	1401.227266
Recurrent Neural Network with Filter Bank and 32 units	0.518252	0.611834	2142.493766
Neural Network with Filter Bank and 128 units	0.526426	0.611520	1409.297503
Neural Network and 4 units	0.514401	0.609085	993.969200
Neural Network with Filter Bank and 4 units	0.526606	0.602391	1397.103773
Recurrent Neural Network with Filter Bank and 16 units	0.506556	0.595184	2125.818702
Recurrent Neural Network with Filter Bank and 8 units	0.496167	0.579068	2137.976398
Recurrent Neural Network with Filter Bank and 4 units	0.487520	0.553930	2192.026060

Table 6: *The accuracy, ACC and computational time of the ensemble models for vertical movement, sorted by AUC*

The Ensemble Models For Vertical Movement	Accuracy	AUC	Time (second)
Gradient Boosting for Neural Network with Filter Bank	0.567199	0.700547	191.888139
Gradient Boosting for Neural Network	0.564843	0.697473	142.679986

Figure 1: *The Prediction v.s. the Ground Truth on Horizontal Movement.*
Red: GroundTurth, Blue: Our Prediction

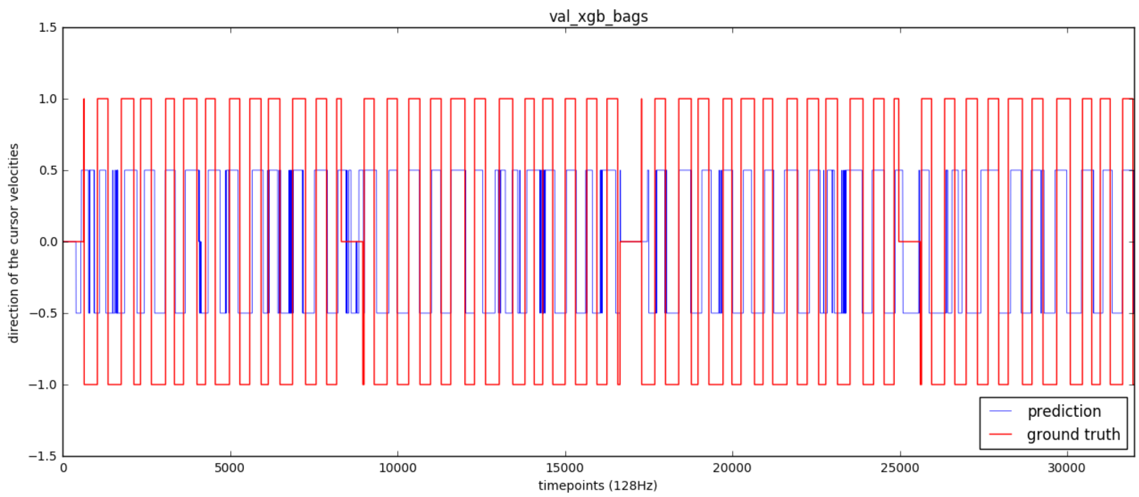


Figure 2: *The accuracy of each subject on the best model*

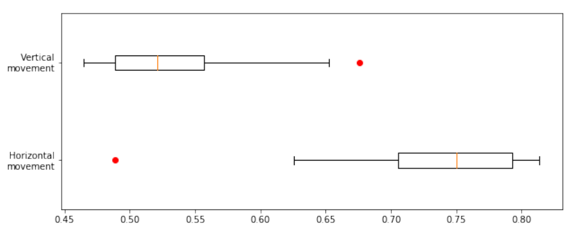
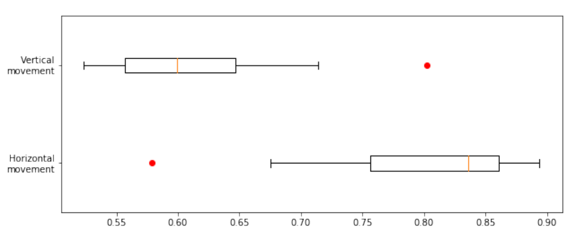


Figure 3: *The AUC of each subject on the best model*



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