INTERNATIONAL UNIVERISTY
SCHOOL OF BIOMEDICAL ENGINEERING

BRAIN-COMPUTER INTERFACE

PROJECT PLAN MANAGEMENT

FALL 2019

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1 INTRODUCTION

1.1 Project overview

This part describes briefly about your project: from problem to purpose, methodology, goals, results.

Background Brain-computer interface (BCI) is an interdisciplinary field which explore the idea of brains controlling devices, such as computer, wheelchair or neural prosthetic. There is a wide range of applications of BCI system in both medical and non-medical fields, including restoring communication with menus, cursors and spellers and monitoring alertness (Rao, 2011). For different purposes and types of clients, invasive, semi – invasive or non – invasive method is applied for the BCI system.

Problem It can be analyzed from recent studies that due to its simple implementation and cost effectiveness, electroencephalogram (EEG) activity recorded from the scalp, which is a non – invasive method, illustrate the priority in recent researches of motor imagery – based BCI (MI – BCI), which is the process of controlling external system by the imagination of motion (Aggarwal & Chugh, 2019). However, the problem occurs since it is difficult to decode the EEG signal to categorize each motor imaginary into specific movement (Wang et al., 2012). Although there is some method about this problem, different measures or different data sets were used so that the results is not easy to compare (Szachewicz, 2013).

Purpose In this project, we would like to do the first four steps in the process of building a BCI system of controlling the cursor in 1D dimension using Graz data set A (Brunner et al., 2008). The main goal is to classify four different motor imagery tasks which include left hand, right hand, both feet, and tongue movement.

Methodology The methodology is including 4 major steps: data acquisition, pre-processing, feature extraction and classification.

Results our classifier has the mean train kappa is 0.5906, while the mean evaluated kappa is 0.4054.

1.2 Abbreviations and Glossary

Abbreviations

Abbreviations	*Full form*
BCI	Brain-computer interface
EEG	Electroencephalogram
MI – BCI	Motor imagery – based brain-computer interface
IIR	Infinite impulse response
EOG	Electrooculogram
MI	Mutual information
LDA	Linear discriminant analysis
CSP	Common spatial pattern
SVM	Support vector machine

Glossary

Technical term	*Definition*
Stimoceiver	An implantable chip that could be used to both stimulate the brain by radio and send electrical signals of brain activity by telemetry, allowing the subject to move around freely.
BioSig toolbox	An open source software library for biomedical signal processing, featuring for example the analysis of biosignals such as the electroencephalogram (EEG), electrocorticogram (ECoG), electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG), respiration, and so on.
Kappa score	Used to measure inter-rater reliability (and also Intra-rater reliability) for qualitative (categorical) items
Mutual information	The measure of the mutual dependence between the two variables.
Linear discriminant analysis	A dimensionality reduction technique
Bayesian optimization	An approach to optimizing objective functions that take a long time (minutes or hours) to evaluate

1.3 References

Project References

#Index	Reference Identifier	Reference Title
(Rao, 2011)	Rao, R. (2011). Brain-computer interfacing: An introduction. *Brain-Computer Interfacing: An Introduction*, 1–335. https://doi.org/10.1017/CBO9781139032803	Brain-Computer Interfacing: An Introduction
(Aggarwal & Chugh, 2019)	Aggarwal, S., & Chugh, N. (2019). Signal processing techniques for motor imagery brain computer interface: A review. *Array*, *1–2*, 100003. https://doi.org/10.1016/j.array.2019.100003	Signal processing techniques for motor imagery brain computer interface: A review
(Wang et al., 2012)	Wang, D., Miao, D., & Blohm, G. (2012). Multi-Class Motor Imagery EEG Decoding for Brain-Computer Interfaces. *Frontiers in Neuroscience*, *6*. https://doi.org/10.3389/fnins.2012.00151	Multi-Class Motor Imagery EEG Decoding for Brain-Computer Interfaces
(Szachewicz, 2013)	Szachewicz, P. (2013). *CLASSIFICATION OF MOTOR IMAGERY FOR BRAIN-COMPUTER INTERFACES*.	Classification of motor imagery for brain-computer interfaces
(Brunner et al., 2008)	Brunner, C., Leeb, R., Müller-Putz, G., Schlögl, A., & Pfurtscheller, G. (2008). BCI Competition 2008–Graz data set A. *Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology*, *16*.	BCI Competition 2008–Graz data set A

1.4 Literature review

Source code

Toolbox BioSig was used for analyzing data.

[BIOSIG] BioSig project http://biosig. sourceforge.net

Existing method

Wei Song et al, the fourth prize of the BCI Competition IV, 2008 (a competition held for the appoarches brain – computer interface) created a model with the mean kappa is 0.31. Their project contains three steps: preprocessing, feature extraction and classification. In the preprocessing step, the data were downsampling to 125 Hz and eye movement was removed by applying linear regression. Then, an 8 – 25Hz bandpass IIR filter was used for the re-referenced signal. In terms of feature extraction and classification, common spatial pattern (CSP) and SVM was used to design 3 two – hierarchy classifier.

2 PROJECT MANAGEMENT

2.1 Team responsibilities

Task managment

Name	*Responsibilities*
Lưu Thanh Ngân	Feature extraction + Classification and Evaluation
Dương Hoàng Lan Anh	Data processing + Classification and Evaluation
Nguyễn Xuân Dung	Data processing + Feature extraction
Đặng Thị Thu Khiết	Classification and Evaluation + Data visualization
Phạm Nữ Ngọc Châu	Data processing + Data visualization

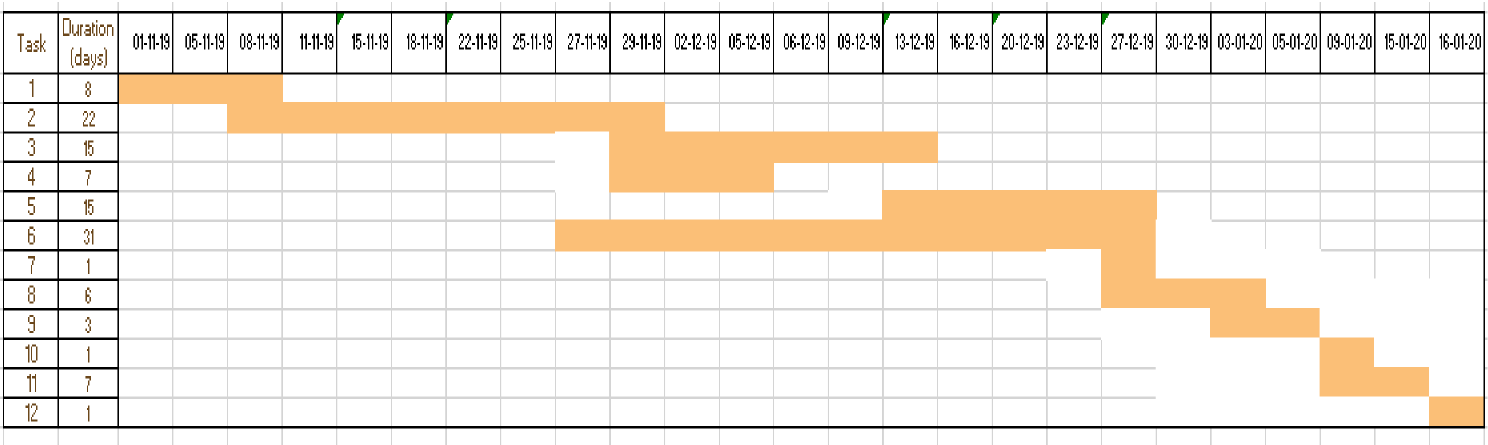
2.2 Project planning

Project timeline

No	*Activities*	*Start Date*	*End date*
1	Read paper and find the information related to the project.	1/11/19	8/11/19
2	Task division + Start Data processing task	8/11/19	29/11/19
3	Feature extraction	29/11/19	13/12/19
4	Update the process + Do homework	29/11/19	5/12/19

5	Classification and Evaluation	13/12/19	27/12/19
6	Data visualization	27/11/19	27/12/19
7	Update the process	27/12/19	27/12/19
8	Debug + run the complete code + get final results	27/12/19	3/01/20
9	Prepare for final presentation	3/01/20	5/01/20
10	Final presentation	9/01/20	9/01/20
11	Write report	9/01/20	15/01/20
12	Submit final report	16/01/20	16/01/20

Gantt chart



2.3 Group communication

During the project, we organized different kinds of meetings that aimed to discuss the project. The most common type is a face-to-face discussion in laboratory classes since it was a good time for us to ask our TA about the project as well as resolve mistakes in our code together. Besides, we created a Github folder as a place to upload the code easily, and all members of group can run code in their own computer. Furthermore, a messenger group was established for online discussion.

3 PURPOSE

3.1 Database description

In this project, we use the BCI Competition IV 2008 dataset IV 2a. This data set is provided by the Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology, (Clemens Brunner, Robert Leeb, Gernot Müller-Putz, Alois Schlögl, Gert Pfurtscheller). It contains four-class motor-imagery data.

Experimental paradigm

The data set 2a recorded EEG data of 9 subjects. For each subject, two sessions were recorded on different days. There are 6 runs for each session and each run consisted of 48 trials for four classes which means a single session during the experiment consisted of 288 trials. For each trial, the cue was related to four different motor imaginary tasks of the left hand (class 1), right hand (class 2), both feet (class 3), and tongue (class 4) which the subject required to perform one of them.

In the beginning, a warning tone is the start sign of a trial, and a fixation cross was displayed on the computer screen at the same time. After two seconds, in the fixation cross position, a cue was shown as a small arrow prompting the subjects to perform the corresponding motor imagery task. And the subjects continue to perform the imaginary movement task until the fixation cross disappeared from the screen at t=6s. After that, there was a short break. The figure below shows the paradigm of a single trial.

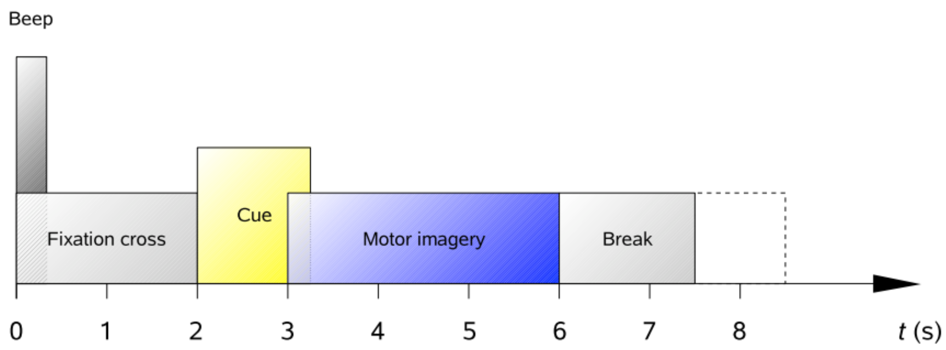


Figure 1. Timing scheme of the paradigm.

Data recording

Twenty-two EEG channels and three monopolar EOG channels. The signals were used to record the data at 250 Hz sample frequency and bandpass-filtered between 0.5 Hz and 100 Hz with 50 Hz notch filtered. The electrodes placement is shown in Figure 2.

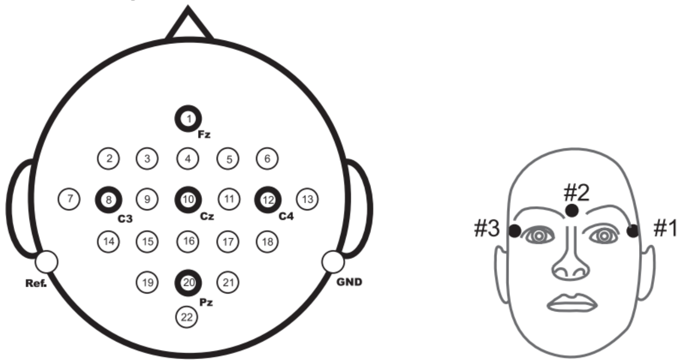


Figure 2. Electrodes placement

Data file description

The data sets are stored in the General Data Format for biomedical signals (GDF), one file is the recording of one subject and session. One session of each subject contained the class labels for all trials and is considered as a training set. The other session does not have the class label which will be used to test the classifier and then to evaluate the performance. The GDF files can be loaded by toolbox BioSig, and we can use SigViewer (part of BioSig) to view the GDF files.

ID	Training	Evaluation
1	A01T.gdf	A01E.gdf
2	A02T.gdf	~~A02E.gdf~~
3	A03T.gdf	~~A03E.gdf~~
4	A04T.gdf	~~A04E.gdf~~
5	A05T.gdf	~~A05E.gdf~~
6	A06T.gdf	~~A06E.gdf~~
7	A07T.gdf	~~A07E.gdf~~
8	A08T.gdf	~~A08E.gdf~~
9	A09T.gdf	~~A09E.gdf~~

Table 1: List of all files contained in the data set

Evaluation

The kappa coefficient is known as the time course of the accuracy which is used to evaluate the performance of the algorithm. This value is from 0 to 1 for the best classifier that always classifies correctly. Besides, the confusion matrices are built from the result after classification for each sample in each trial. From confusion matrices, the kappa value is obtained. The algorithm used for this evaluation will be available in BioSig.

3.2 Step-by-step goals:

Pre-processing

In the EEG, artifacts are caused by the body and eye movements (EOG artifacts), which require us to remove out of the signal. So, in data processing, our aim is to filter the signal and remove all the artifact components from the signal by algorithms, but still, keep intact the EEG signal.

Feature extraction

In this part, we proceed to extract the raw EEG data into more manageable features such as the start of a trial, cue onset left (class 1), cue onset right (class 2), cue onset foot (class 3), cue onset tongue (class 4) and reject trial.

Classification

From the EEG signal, our group tried to separate the data from different classes.

Data visualization

In data visualization, our purpose is to plot all the figures for each event such as before/ after filter signal, or EOG removal, spectrogram...

4 METHODOLOGY

Figure 1. The workflow

4.1 Data acquisition

The Data sets 2a [Graz] were downloaded from BCI Competition IV, which include 18 files of data recordings (9 files for training set and 9 files for evaluation set) and 18 files of true labels for the evaluation step.

In this project, we aim to process all data sets 2a respectively without manual data addition, so the function sload of Biosig toolbox was used to load each file in the data set folder.

```
addpath path\
file='A0%dT.gdf';
for k = 1:9
filename = file(j).name
[s,HDR]=sload(filename);
end
```

The toolbox extracted a matrix which contains electrode potentials of 25 channels with the sampling rate of 250 Hz and the metadata was stored in HDR structure. For visually checking, the sview function of Biosig toolbox was picked to show the channels separately with each other. It can be analyzed from the data description that there are 22 EEG-channels and 3 EOG-channels.

4.2 Preprocessing

There are three steps for preprocessing in order: Bandpass filtering, eye artifacts removal and spatial filtering.

Bandpass filtering

A significant artifact exist in almost every electrical signal is the powerline interference, though its frequency is specific for each country (60 Hz in the United States, 50Hz in European countries). Although the data itself has the notch filter to remove the utility frequency, a lowpass filter of 45Hz should be used to remove the noise.

As the data description, all of the tasks in the data were done in awake state, so there was no theta and delta band in those recordings and the frequency of the EEG signal is in the range of 8 – 30Hz. Thus, to concentrate on the event-related desynchronization information, we applied a 5-th order IIR filter with the passband in range 7 – 30 Hz to avoid utility frequency and other artifacts.

Eye artifacts removal

The eye movement has higher amplitude than the EEG signal and has the frequency about 0 – 4Hz, so by applying the bandpass filter in the previous step, we were removed parts of the EOG signal. Then, we used linear regression method to reduce the EOG artifacts. The function is taken from Biosig toolbox:

```
eogchan=identify_eog_channels(HDR);
eegchan=find(HDR.CHANTYP=='E');
R = regress_eog(s,eegchan,eogchan);
s = s*R.r0;
```

Spatial filtering

Spatial filtering or common spatial pattern (CSP) is a method to uplift the discriminative sectors of classes. This helped the model become easier to distinguish between different classes in the data.

4.3 Feature extraction

Band power features were extracted in this method by applying BioSig library to calculate the target bandwidths by bandpass filtering the signal. Our target frequency bands are 8–14, 19–24 and 24–30 Hz. The signal is fist filtered by 4-th order Butterworth IIR bandpass filter. The bandpass frequencies of this filter are our target frequencies, i.e. 8-14 Hz.

```
[B,A] = butter(4,F(k,:)/HDR.SampleRate*2);
```

Then, filtered signal which contains information about target components, is squared to calculate time course of power:

```
Sig=filter(B,A,tmp).^2
```

In order to prevent leakage effect that reduce the quality of processing signal, we apply smoothing window of 2 seconds by continue implementing filter in which the numerator and denominator coefficients are

```
B1= ones(W*HDR.SampleRate,1)
A1= W*HDR.SampleRate
Output=filter(B1,A1,Sig)
```

Finally, natural logarithms of output signals are calculated to enhance to performance of linear classification.

4.4 Feature Selection

We collected features extracted from 3 bandwidths 8–14, 19–24 and 24–30 Hz in the stage of feature extraction.

To increasing the accuracy and Kappa score of classification model, Mutual Information Best Individual Features is applied to reduce the dimension of features and select only the best meaningful features for classification. Irrelevant features are discarded to prevent negative affect to the whole model performace.

We used function MI.m builded by Okko Rasanen, 2013.

The mutual information (MI) of two random variables is the score of the mutual dependence between the two. It measures the relevance between the two features in random selection, and hence, determine the correlation between individual features and the class.

The function MI estimates the mutual information and use quantity of variables ranking to score the weight of features based on their individual mutual information with four output classes. The more weight feature has, the better performance when applying it to the model.

By experiment many times, we chose the first 15th features in descending orders for the best score of Kappa obtaining.

Result:

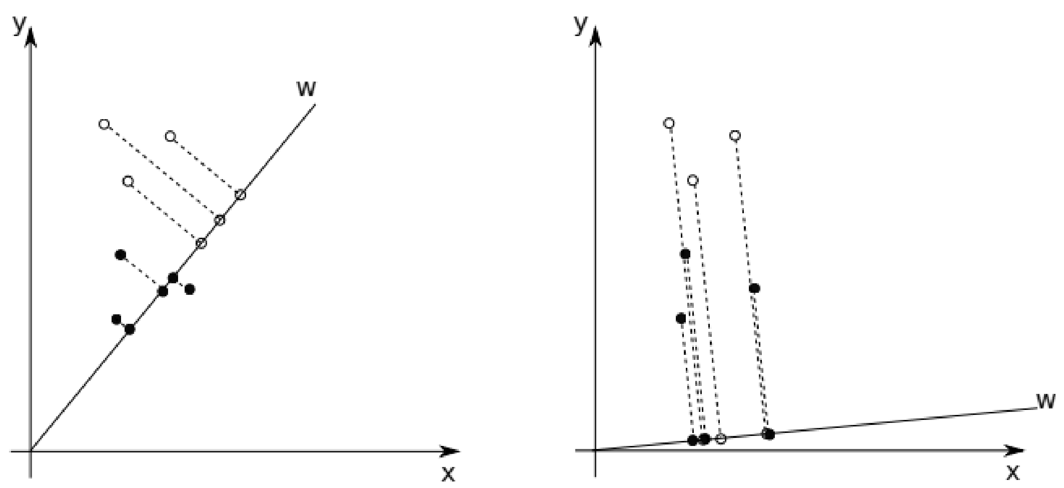
Features	8	3	1	6	16	22	11	14	17	9	24	19
Weight	0.831689	0.783871	0.645213	0.632034	0.516894	0.428443	0.390371	0.389822	0.358828	0.315439	0.304676	0.220538

Feaures	5	13	2	4	7	18	20	15	23	10	21	12
Weight	0.196674	0.059792	0.052682	0.037819	0.036901	0.035938	0.033986	0.030315	0.026756	0.026408	0.023303	0.020658

4.5 Classification

Linear discriminant analysis (LDA) is implemented in our experiment.

A set *A* of data point of two classes, as defined in a two-dimensional feature space. Set *A* is projected onto a direction defined by the vector *w*.



The figures show the projection of dark and white data points representing for 2 types of label in dataset

onto vector *w*. The left one is good model because we can easily draw the threshold line, while projected points of the right one is unseparated.
Based on the hyperparameter of definition of w, a good model will induce a large distance between the two classes when projecting these data points two classes onto vector w, therefore, define the threshold between them and predict for new data points.
We used function fitcdiscr of MatLAB to implement this classification tasks with:

- Bayesian optimization
- Iterations: 30

Through each time of iteration, optimizer algorithm automatically changes the shape of objective function model by changing the hyperparameters to obtaining the best fit to the observed data points. Therefore, the classification accuracy of model is improved.

5 RESULTS AND FUTURE WORKS

5.1 Visualization

Preprocessing

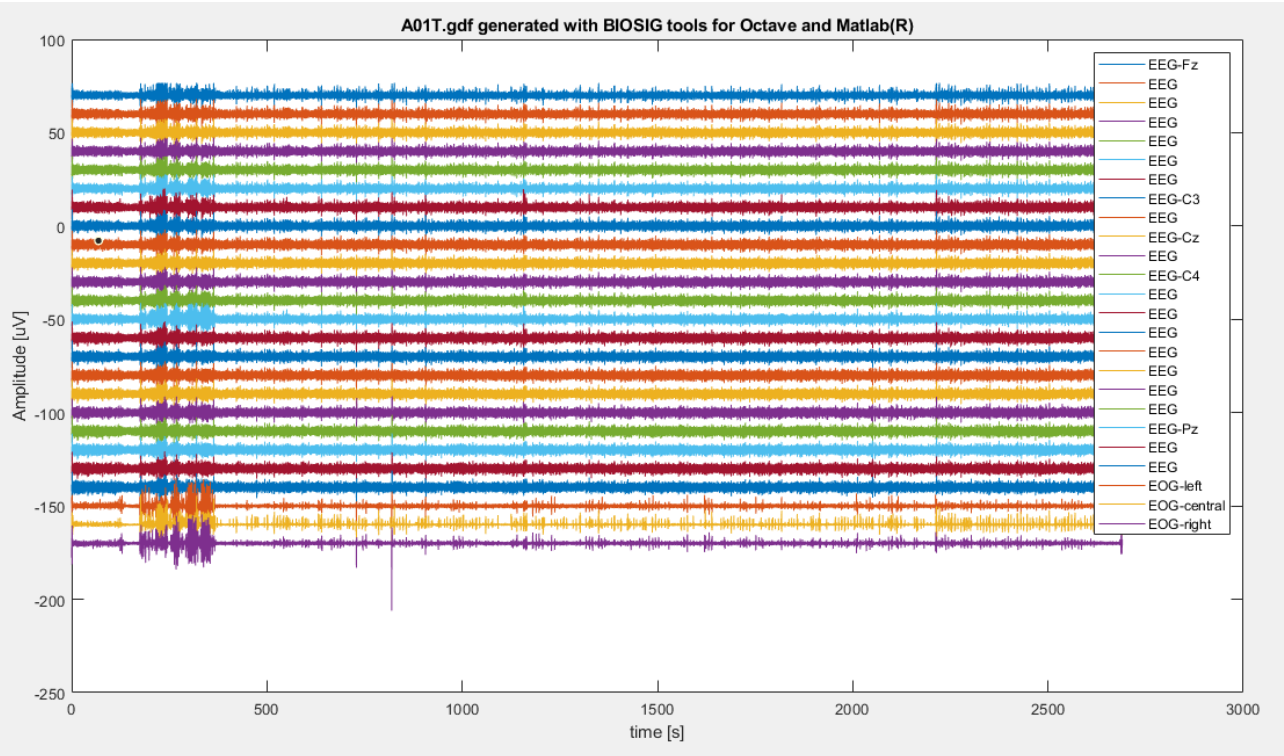


Figure 2. Visualization of 25 channels in A01T.gdf

Remove the EOG after filter the signal with the band-pass 7 – 30 Hz and 5th order Butterworth IIR filter. By this way, we can remove the artifact of the signal.

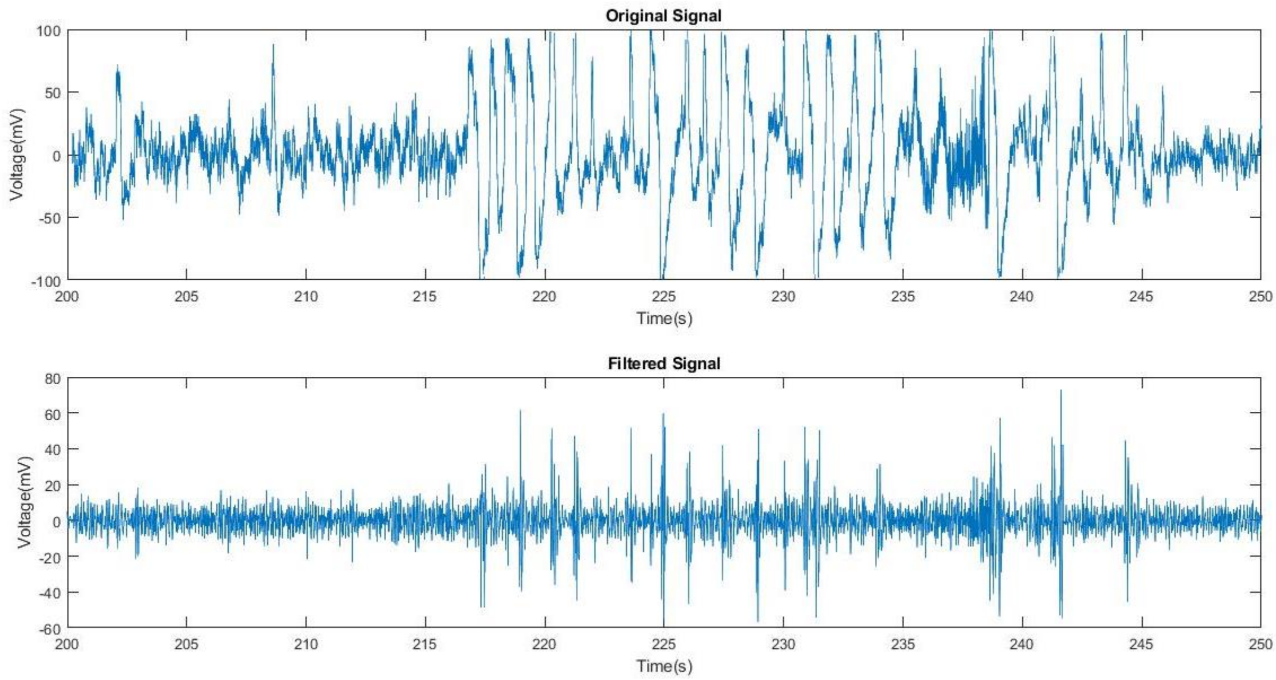


Figure 3. Bandpass filter of chanel 1 in A01T.gdf

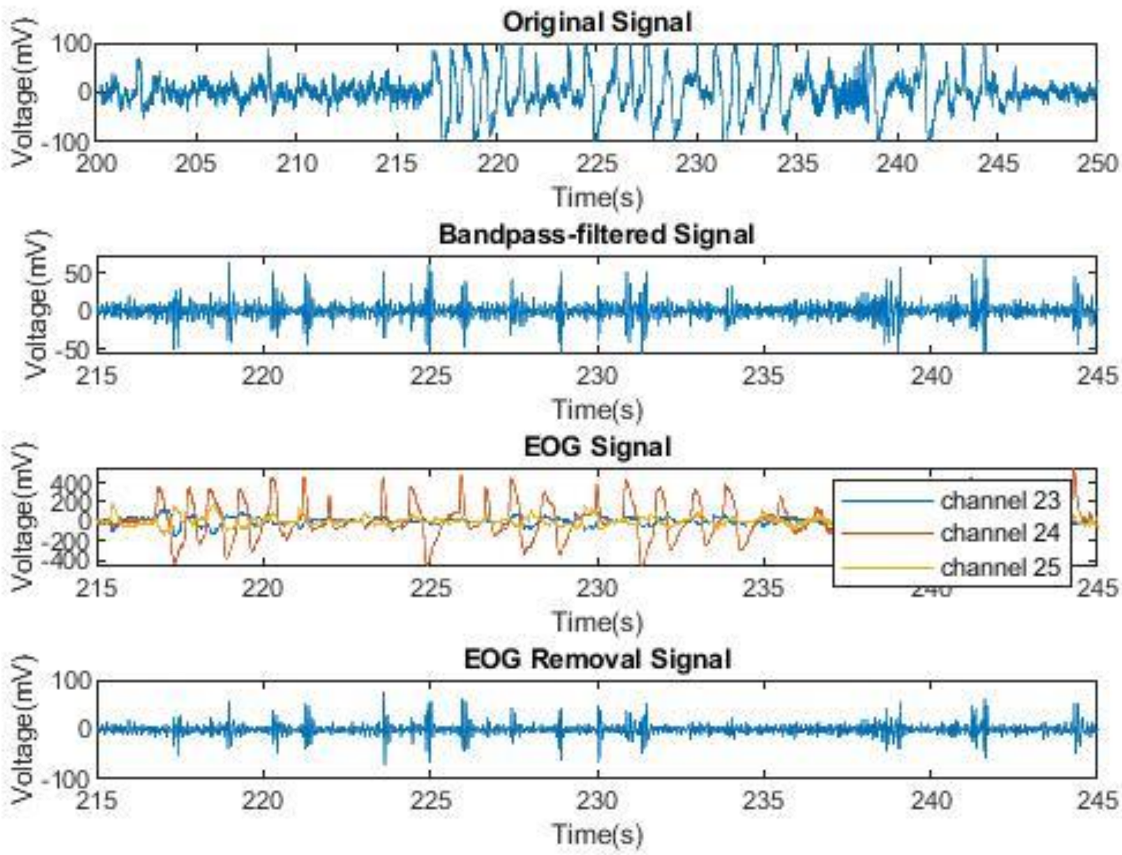
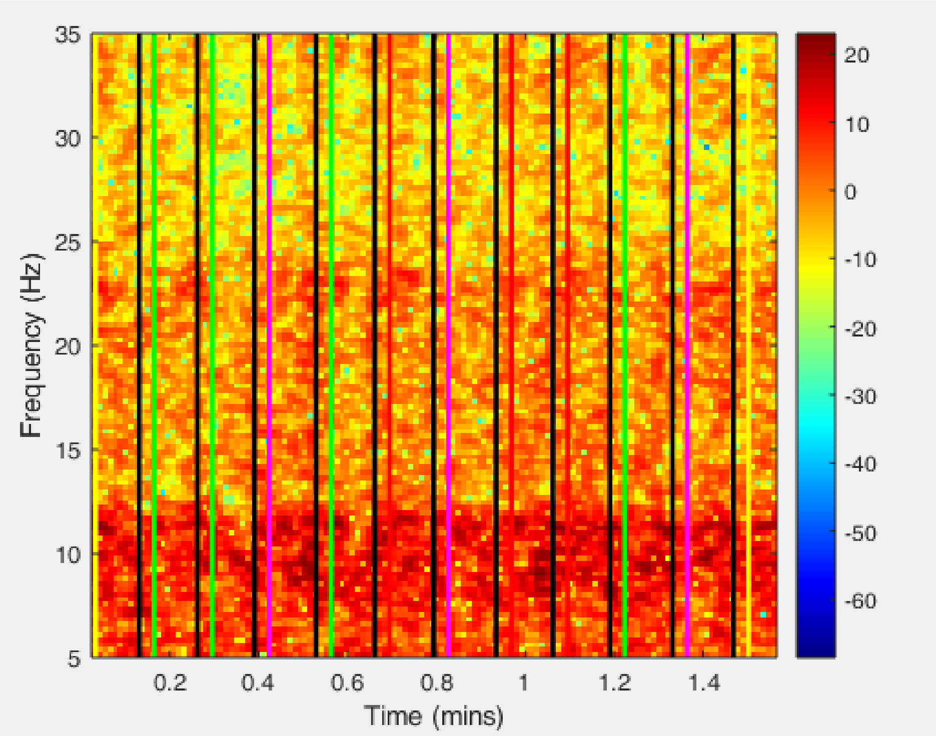


Figure 4. EOG removal of channel 1 in A01T.gdf signal after filtering

Feature extraction

The desynchronization (or decrease in power) of event is marked by the red colors while the blue colors mark the synchronization (increase in power) event. The different desynchronization are fairly similarly in the range 5 to 12.5 Hz. In the other hand, from the 15 to 25 Hz, the event-related desynchronization of the left- and right-hand motor are much weaker than the tongue and foot motor imagery.



The figure shows the time-frequency domain. Black: Start of a trial; Green: Cue onset left (class 1) Magenta: Cue onset right (class 2); Yellow: Cue onset foot (class 3); Red: Cue onset tongue (class 4); Blue: Reject trial

Feature selection

We collected the first 15th features extracted from 3 bandwidths 8–14, 19–24 and 24–30 Hz in descending orders for the best score of Kappa obtaining.

Classification

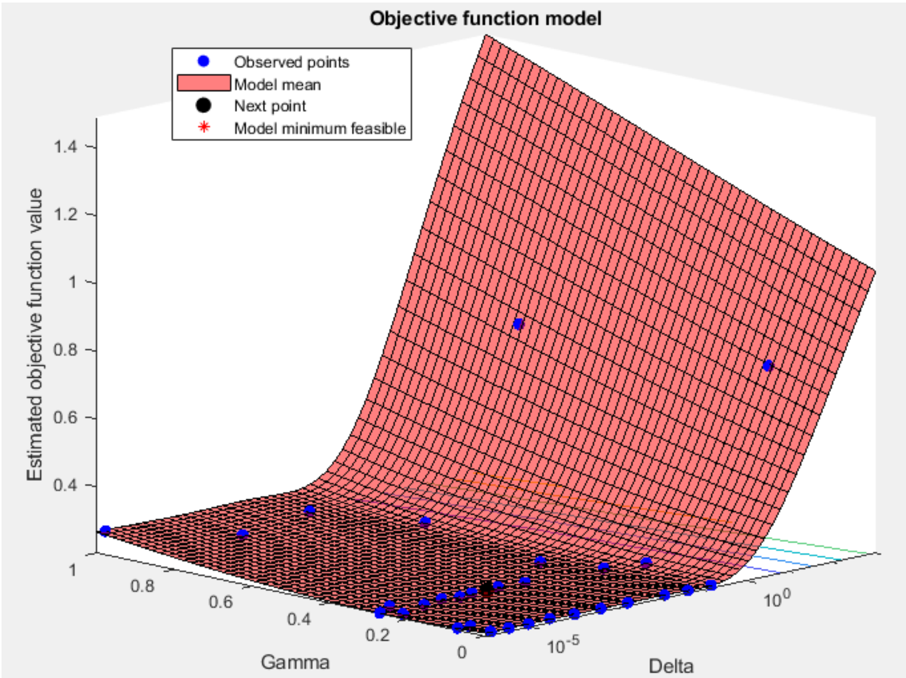


Figure 5. The shape of LDA model of subject 1 at the iteration of 30

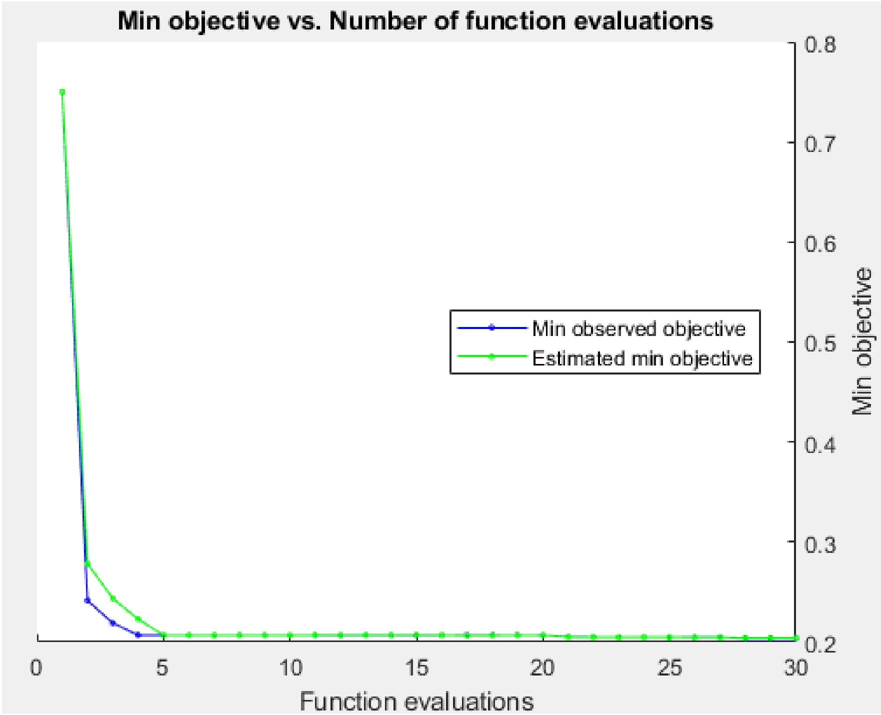


Figure 6. Min objective and number of function evaluation

The figure shows the distance of observed and the estimated data points through each time of iteration. It is clear that, the two set of data points (observed and estimated) are getting closer together over the iteration.

To describe the effective a 4-class classification problem, we use the confusion matrix which illustrate the relationship between the predicted classes (intended labels by user) and the true classes (known labels).

From the figure, we can see that the model works well with all the classes. However, the class 4 is better than other with 87.83% while the class 1 just reach 64.28% in accuracy. Followed the class 4 is class 2, the next is class 3 with 85.09% and 78.82% respectively. Besides, the class 1 and class 2 have quite similarly features, so we can see that they are predicted incorrectly approximate 25%. The same with the class 3 and class 4.

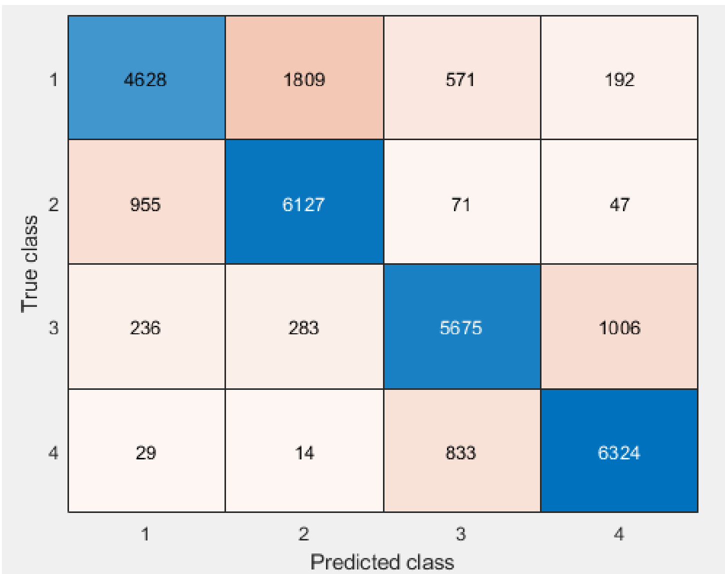


Figure 7. The confusion matrix

The accuracy is often used in the evaluation criteria in BCI research. But in some case, this measure is not recommended because the accuracy of a trivial (random) classifier is the divide of 100% to the number of classes. Then, the maximum of accuracy cannot reach 100% for each class. Due to these reasons, the Kappa values are suggested to address several of accuracy measure problem.

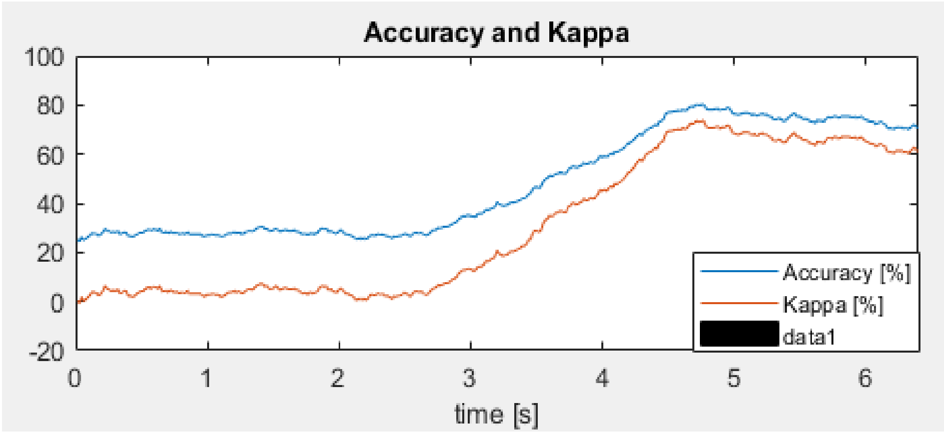


Figure 8. Accuracy and kappa subject 1

5.2 Results

Subject	Mean	1	2	3	4	5	6	7	8	9
Train kappa	0.5906	0.743	0.523	0.805	0.369	0.400	0.424	0.812	0.751	0.483
Evaluate kappa	0.4054	0.722	0.105	0.483	0.134	0.084	0.164	0.713	0.579	0.662

The table show the train and evaluate kappa of 9 subjects.

5.3 Feedback of advisor

In the preprocessing, we did not show the input and output signal in the same figure of visualization, so it is difficult to distinguish the filtered signal and the removal EOG signal with the raw signal.

Moreover, in the EOG removal, we cut a piece of signal (from 0 - 1s) to remove EOG. However, this is not special signal, the special signal is range 215 to 450s.

To handle these problems, we draw the other figure and choose the special signal to process.

The preprocessing starting with EOG removal before applying the bandpass filter cannot show the best signal or we can say that the EOG signal was not almost filtered. Hence, our TA - Mrs. Thuong suggested us to reverse 2 steps: EOG removal after bandpass filter. The results are really better than the previous task

Finally, the spectrogram did not be explained clearly and did not show the parameter, so the audiences and readers cannot understand which colors stand for what. We solve this issue in the section feature extraction in the results part.

5.4 Project problems

During the project process, our group met some issues. The initial methodology was classification many features (about 66 features) as well as preprocessing without spatial filter. Therefore, the result of evaluation kappa was extremely low (just 0.3).

Due to these reasons, we applied the spatial filter combined with feature selection (select 15 features) to enhance the accuracy of evaluation kappa of classes. Thus, the evaluation kappa increases to 0.4054.

5.5 Future works

In the future work, we will apply the 2 feature extraction techniques: linear discriminant analysis (LDA) and support vector machines (SVM) to classify 4 classes. Then compare the results with this project to show the effective of 2 these techniques.