NATIONAL INSTITUTE OF TECHNOLOGY DELHI

Project Report

on

Classification of EEG signals associated with Left-Hand Right-Hand using ERP, ERS & ERD

(For utility in Brain Computer Interfaces)

submitted

in partial fulfilment of the course

Data Mining (CSB-352)

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Abstract 1

In this report, we propose a machine learning algorithm based on Event-Related Synchronization & Event-Related Desynchronization (ERS/ERD) for the purpose of classifying Electroencephalography (EEG) signals associated with left-hand and right-hand movements to facilitate utility for Brain Computer Interfaces (BCI).

Brain-Computer Interface (BCI) is a device that leverages technologies like AI, signal processing and computational neuroscience to enables the use of the brain's neural activity to communicate with others or to control machines, artificial limbs, or robots without direct physical movements.

The EEG dataset used in this research was created and contributed to PhysioNet by the developers of the BCI2000 instrumentation system. Data is preprocessed and visualized using Python's MNE Package. The data is then epoched to identify event timings using Event related potentials, ERS & ERD analysis. These extracted waveform features can then be used to train neural network or SVMs to classify the left- and right-hand movement.

2.1 Brain Activity & EEG

Weighing about only three pounds, the human brain is one of the most intricate, complex and fascinating elements of the universe. It allows you to remember past events, process sensory perceptions, projection and creation of thoughts and essentially all the physical or mental activity a human can perform.

Every cognitive and motor activity that you perform is a result of billions of neurons firing inside your brain. These electro-chemical reactions directly translate to voltage fluctuations along the scalp and convolutions (cortical surface) of brain. These electrical voltage fluctuations associated with the neural activity are known as Electroencephalography (EEG) signals.

The term "***Electroencephalography***" ***(EEG) is the process of measuring the brain's neural activity as electrical voltage fluctuations along the scalp that results from the current flows in brain's neurons.***

There are several reasons why EEG is an exceptional tool for studying the neurocognitive process underlying human behaviour-

- EEG has very high time resolution and captures cognitive processes in the time frame in which cognition occurs.
- EEG directly measures neural activity.
- EEG monitors cognitive-affective processing in absence of behavioral responses.
- EEG is inexpensive, lightweight, and portable

2.2 Brain Computer Interfacing

The importance of understanding brain waves is increasing with the ongoing growth in the Brain-Computer Interface (BCI) field, and as computerized systems are becoming one of the main tools for making people's lives easier, BCI or Brain-Machine-Interface (BMI) has become an attractive field of research and applications, BCI is a device that enables the use of the brain's neural activity to communicate with others or to control machines, artificial limbs, or robots without direct physical movements.

In a typical EEG test, electrodes are fixed on the scalp to monitor and record the brain's electrical activity. BCI measures EEG signals associated with the user's activity then applies different signal processing algorithms for the purpose of translating the recorded signals into control commands for different applications.

The strength of BCI applications lies in the way we translate the neural patterns extracted from EEG into machine commands. The improvement of the interpretation of these EEG signals has become the goal of many researchers; hence, our work intends to explore the possibility of multi-trial EEG classification between left and right hand movements in an offline manner, which will enormously smooth the path leading to online classification and reading of executed movements, leading us to what we can technically call "Reading Minds".

2.3 BCI – components and architecture

The primary motivation for building BCIs today is their potential for restoring lost sensory and motor function. Examples include sensory prosthetic devices such as the cochlear implant for the deaf and retinal implant for the blind. Other implants have been developed for deep brain stimulation (DBS) to treat the symptoms of debilitating diseases such as Parkinson's. A parallel line of research has explored how signals from the brain could be used to control prosthetic devices such as prosthetic arms or legs for amputees and patients with spinal- cord injuries, cursors and word spellers for communication by locked- in patients suffering from diseases such as ALS (amyotrophic lateral sclerosis) or stroke, and wheelchairs for paralyzed individuals.

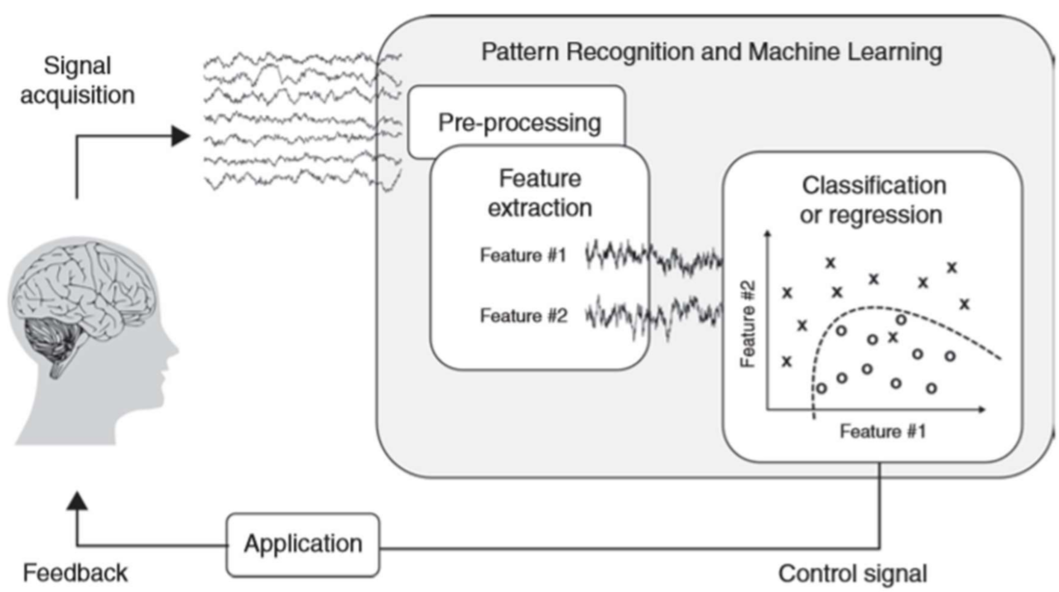
Following figure demonstrates a generic BCI system. The aim is to translate brain activity into control commands for devices and/or stimulate the brain to provide sensory feedback or restore neurological function. One or more of the following processing stages are typically involved:

1. Brain recording: Signals from the brain are recorded using either invasive or noninvasive recording techniques.

2. Signal processing: Raw signals are preprocessed after acquisition (e.g., by bandpass filtering) and techniques for artifact reduction and feature extraction are used.

3. Pattern recognition and machine learning: This stage generates a control signal based on patterns in the input, typically using machine- learning techniques.

4. Sensory feedback: The control signal from the BCI causes a change in the environment (e.g., movement of a prosthetic arm or a wheelchair, change in the grip of a prosthetic hand).



Related Work | 3

- The idea of BCI was originally proposed by Jaques Vidal in [1] where he proved that signals recorded from brain activity could be used to effectively represent a user's intent.
- In [2], the authors recorded EEG signals for three subjects while imagining either right- or left-hand movement based on a visual cue stimulus. They were able to classify EEG signals into right- and left-hand movements using a neural network classifier with an accuracy of 80% and concluded that this accuracy did not improve with increasing number of sessions.
- The author of [3] used features produced by Motor Imagery (MI) to control a robot arm. Features such as the band power in specific frequency bands (alpha: 8-12Hz and beta: 1330Hz) were mapped into right and left limb movements. In addition, they used similar features with MI, which are the Event Related Desynchronization and Synchronization (ERD/ERS) comparing the signal's energy in specific frequency bands with respect to the mentally relaxed state.
- It is shown in [4] that the combination of ERD/ERS and Movement-Related Cortical Potentials (MRCP) improves EEG classification as this offers an independent and complimentary information.
- In [5], a hybrid BCI control strategy is presented. The authors expanded the control functions of a P300 potential based BCI for virtual devices and MI related sensorimotor rhythms to navigate in a virtual environment. Imagined left/right hand movements were translated into movement commands in a virtual apartment and an extremely high testing accuracy results were reached
- A three-class BCI system was presented in [6] for the translation of imagined left/right hands and foot movements into commands that operates a wheelchair. This work uses many spatial patterns of ERD on mu rhythms along the sensory-motor cortex and the resulting classification accuracy for online and offline tests was 79.48% and 85.00%, respectively.
- The authors of [7] proposed an EEG-based BCI system that controls hand prosthesis of paralyzed people by movement thoughts of left and right hands. They reported an accuracy of about 90%.
- A single trial right/left hand movement classification is reported in [8]. The authors analyzed both executed and imagined hand movement EEG signals and created a feature vector consisting of the ERD/ERS patterns of the mu and beta rhythms and the coefficients of the autoregressive model. Artificial Neural Networks (ANNs) is applied to two kinds of testing datasets and an average recognition rate of 93% is achieved.

Overview of Dataset and Methodology 4

4.1 The PhysioNet Dataset [11]

This data set consists of over 1500 one- and two-minute EEG recordings, obtained from 109 volunteers. Subjects performed different motor/imagery tasks while 64-channel EEG were recorded using the BCI2000 system (http://www.bci2000.org). Each subject performed 14 experimental runs: two one-minute baseline runs (one with eyes open, one with eyes closed), and three two-minute runs of each of the four following tasks:

1. A target appears on either the left or the right side of the screen. The subject opens and closes the corresponding fist until the target disappears. Then the subject relaxes.
2. A target appears on either the left or the right side of the screen. The subject imagines opening and closing the corresponding fist until the target disappears. Then the subject relaxes.
3. A target appears on either the top or the bottom of the screen. The subject opens and closes either both fists (if the target is on top) or both feet (if the target is on the bottom) until the target disappears. Then the subject relaxes.
4. A target appears on either the top or the bottom of the screen. The subject imagines opening and closing either both fists (if the target is on top) or both feet (if the target is on the bottom) until the target disappears. Then the subject relaxes.

The data are provided here in EDF+ format (containing 64 EEG signals, each sampled at 160 samples per second, and an annotation channel). In summary, the experimental runs were:

1. Baseline, eyes open
2. Baseline, eyes closed
3. Task 1 (open and close left or right fist)
4. Task 2 (imagine opening and closing left or right fist)
5. Task 3 (open and close both fists or both feet)
6. Task 4 (imagine opening and closing both fists or both feet)
7. Task 1
8. Task 2
9. Task 3
10. Task 4
11. Task 1
12. Task 2
13. Task 3
14. Task 4

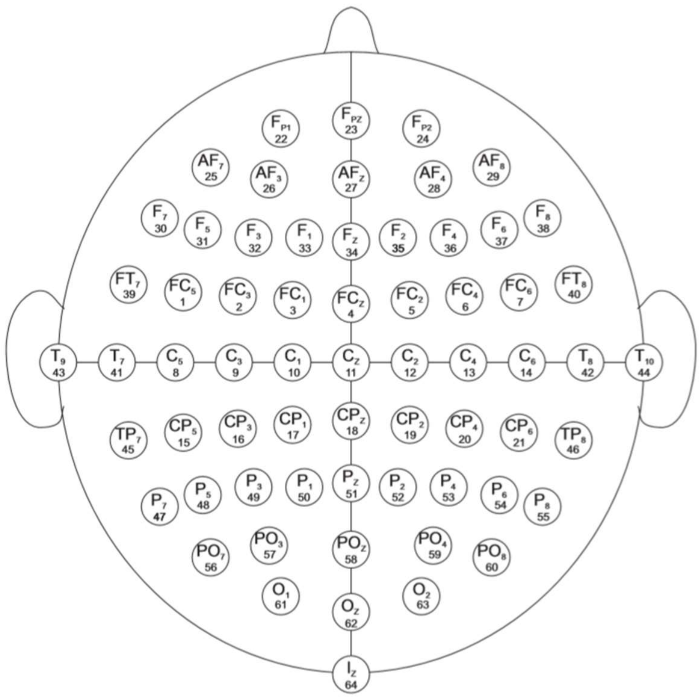
Each annotation includes one of three codes (T0, T1, or T2):

- **T0** corresponds to rest
- **T1** corresponds to onset of motion (real or imagined) of
  - the left fist (in runs 3, 4, 7, 8, 11, and 12)
  - both fists (in runs 5, 6, 9, 10, 13, and 14)
- **T2** corresponds to onset of motion (real or imagined) of
  - the right fist (in runs 3, 4, 7, 8, 11, and 12)
  - both feet (in runs 5, 6, 9, 10, 13, and 14)

We created an EEG data subset corresponding to the first ten subjects (S001 to S010) including three runs of executed movement for ***Task 1 Run 3,7,11 annotation T2 (for right hand) and T1 (for left hand)*** specifically per subject for a total of 30 two-minute records.

4.2 Montage Setup

The EEGs were recorded from 64 electrodes as per the international 10-10 system ***(excluding electrodes Nz, F9, F10, FT9, FT10, A1, A2, TP9, TP10, P9, and P10)***, as shown in this figure. The numbers below each electrode name indicate the order in which they appear in the records; note that signals in the records are numbered from 0 to 63, while the numbers in the figure range from 1 to 64.



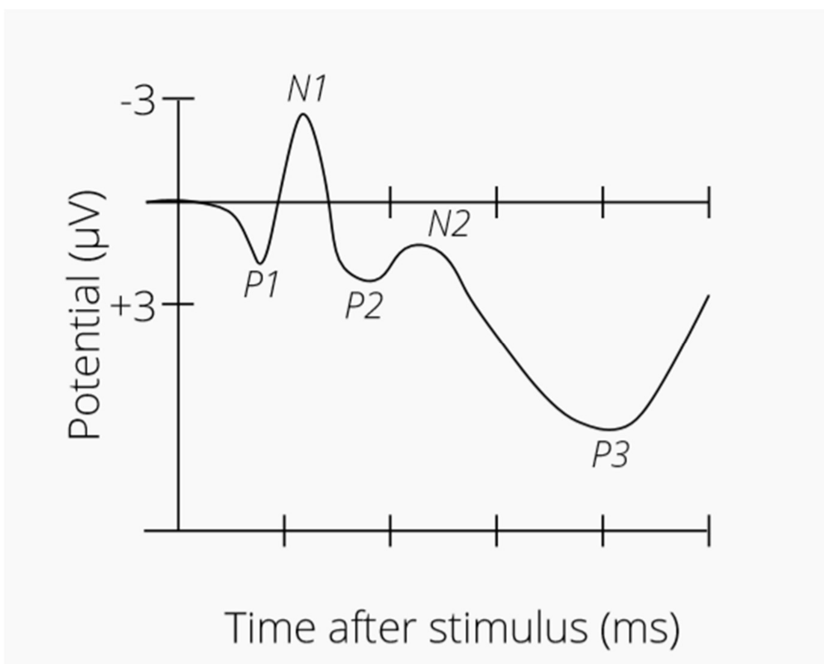
4.3 Understanding Event-Related-Potentials

There is continuous and ongoing brain (EEG) activity along with random noise completely unrelated to the onset of a stimulus continually occurring. Hence there are two activities – default activity and stimulus-related activity.

In order to uncover the stimulus-related activity the stimulus is shown a number of times. At the end we will have a number of trials which are time-locked to stimulus (meaning the relative timing of stimulus is same for all trials).

From all these EEG recording certain data portions are selected typically 0.2 second prior to stimulus to 1 second after the stimulus. This is called epoching or segmentation.

Then artifact removal is performed on these epochs (to remove signals from blinking, breathing etc.). The remaining data is averaged for all trials. Now the random noise will cancel out on averaging. The remaining average EEG waveform is the event related potential which reflects the average stimulus-related activity. ERPs can be described by several characteristics: Appearance and shape, number, latency, amplitudes of the "wiggles", ERP components (positive and negative peaks) and topography (which is the voltage distribution at peak times across all electrodes).



4.4 ERS and ERD

When no sensory inputs or motor outputs are being processed, the mu (8–12 Hz) and beta (13–30 Hz) rhythms are said to be synchronized. These rhythms are electrophysiological features that are associated with the brain's normal motor output channels.

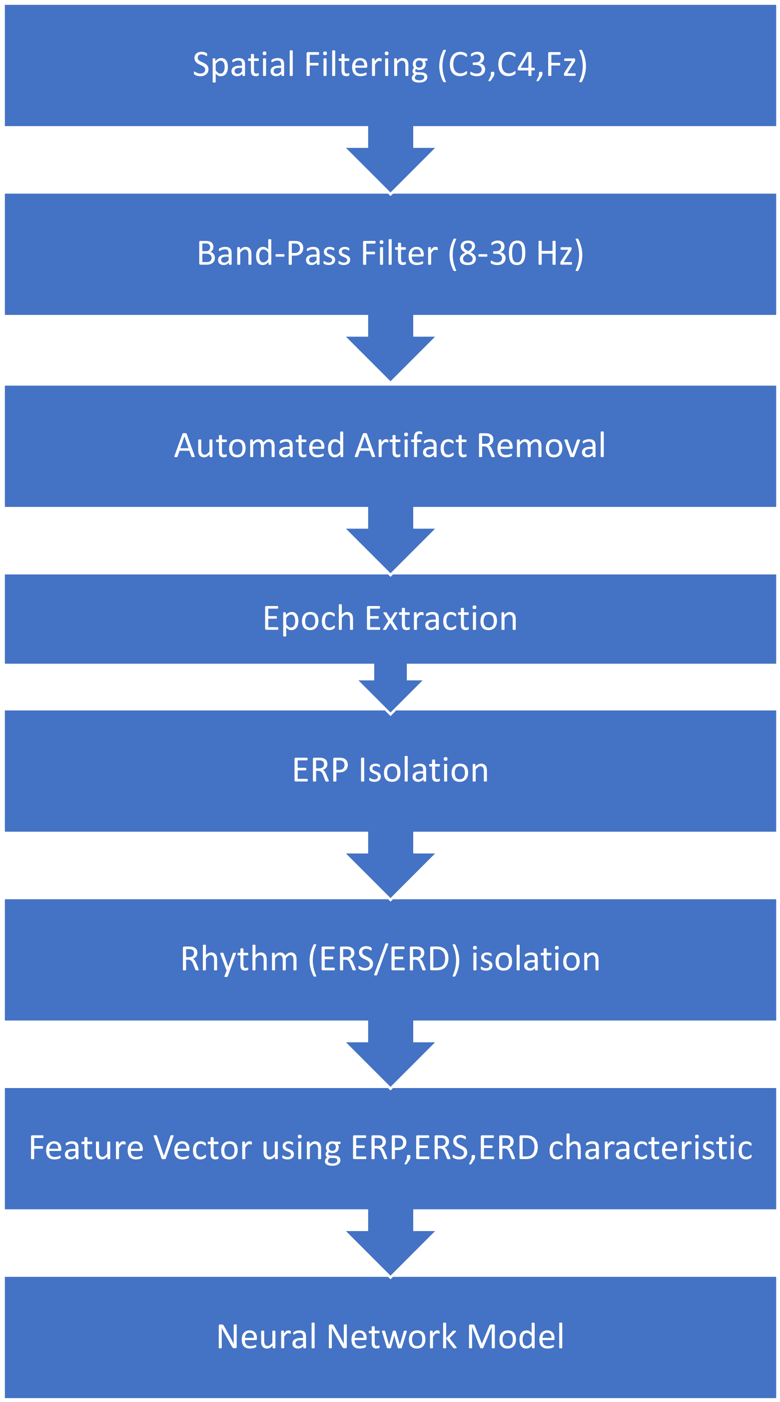
While preparing for a movement or executing a movement, a desynchronization of the mu (8-12 Hz) and beta (13-30 Hz) rhythms occurs which is referred to as ***Event Related Desynchronization*** and it can be extracted 1-2 seconds before onset of movement.

Later, these rhythms synchronize again within 1-2 seconds after movement, and this is referred to as ***Event Related Synchronization***.

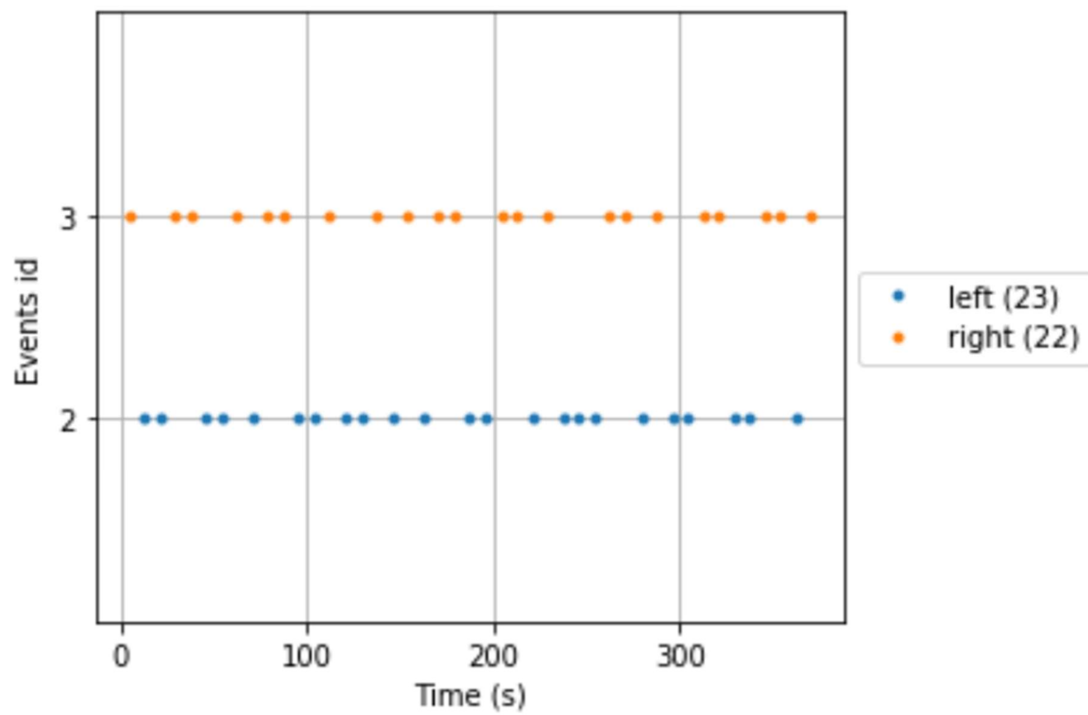
Hence the events can be identified by identifying corresponding ERD, ERS and ERP EEG waveform. Using following procedure

4.5 Our Approach

Data is preprocessed and visualized using Python's MNE Package. The data is then epoched to identify event timings using Event related potentials, ERS & ERD analysis. These extracted waveform features can then be used to train neural network or SVMs to classify the left- and right-hand movement.



Using the above pipeline we can detect the event timing which can then be used to train a Neural network. The following plot shows the timings of event of left and right hand movement for subject 1.



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