EEG Motor Imagery Classification

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Chapter 1

Project Purpose

Introduction

This project aims to achieve a dream that it seems to get close as days pass by because of the many researchers that are making great efforts to find solutions for this problem every day. As it is very well known there are people that have certain dysfunctions or impairments from different reasons and so they are not able to perform a particular set o activities because of those conditions. Those people are still hoping that one day a brilliant solution might appear and get the freedom they so eagerly seek. **Even if someone is unable to perform a certain task it does not mean that they cannot imagine it**, so the objective of this project is to take steps in motor imaginary classification based on EEG(*Electroencephalogram*) signals and reduce the gap between dream and reality.

1.1 Objectives

1. To achieve a subpart of a BCI(*Brain Computer Interface*) system
2. Find a better way of classification EEG signals other than classic machine learning
3. Selecting only motor imagery related information from the EEG recordings
4. Training a CNN(*Convolutional Neural Network*) to classify motor imagery tasks
5. Verify the subject independence

1.2 Specifications

The project aims to achieve great accuracy performances using CNN's while limiting the computational load that is needed when training a model that could integrate in a AI driven system.

There are many channels with EEG neuronal activity information but not all of them are related to motor imagery classification so this paper aims to keep only relevant components.

For performance and accuracy improvements a CNN will be the choice but how to adapt signals so they can be inputs for the model?

Lastly it is to be verified how much decrease in accuracy results when a model trained for a certain person is used to classify EEG signal from anoter person.

Chapter 2

Bibliography Study

Introduction

This chapter will present just the relevant scientific background needed that was gathered to understand the concepts used throughout this paper. Because the main objective of this project is to classify motor functions using EEG signals the next sections will provide the needed details about those signals and how they can be integrated in a BCI (*Brain Computer Interface*) system.

2.1 EEG (*Electroencephalogram*) signals

The EEG signal is a recording of the electrical activity of the brain which measures field potential in the space around neurons. The more synchronized is a given population of neurons, the easier it is to measure the EEG signal. This signal does not have constant amplitude and frequency, the waveform is never a simple harmonic signal. The EEG signal is characteristic of a high time activity of about 1 ms.

EEG signals are prone to artifacts originating from different parts of the body like the eye, head, neck, or any other muscle. Moreover, the power cable of the recording device and electrode displacement might both cause some artifacts. This form of recording EEG produces weak, non-stationary, and low signal-to-noise ratio signals. Consequently, it complicates the classification and interpretation of signals belonging to a particular case of consideration.

In this signal we can separate a few types of activities which are characteristic of specific signal frequencies and amplitudes such as: Alpha, Beta, Delta, Gamma, Theta, Mu. Research showed that both the frequency of brain waves and their amplitude are not strictly constant and strictly depends on the activity the brain performs.

Another great asset that those types of brain activity signals provide is that the process of data acquisition is a non-invasive one this lets us gather considerable amounts of data without putting the patient in danger, this makes this domain more approachable for researchers.

2.2 BCI (*Brain Computer Interface*)

Brain Computer Interfaces (BCI) based on *electroencephalogram* (EEG) have received a huge interest as a direct communication pathway between a human brain and an external device. The non-invasive recording procedure is safe and easy to apply, and it is potentially applicable to almost all people including those seriously amputated and paralyzed patients.

This paradigm dates back to the 1990s but it's importance and attention has grown significantly in recent years because of the computational power that has increased over the years. In figure 2.1 a general BCI system structure is shown, with other words a BCI system architecture can take the form of a closed loop control system.

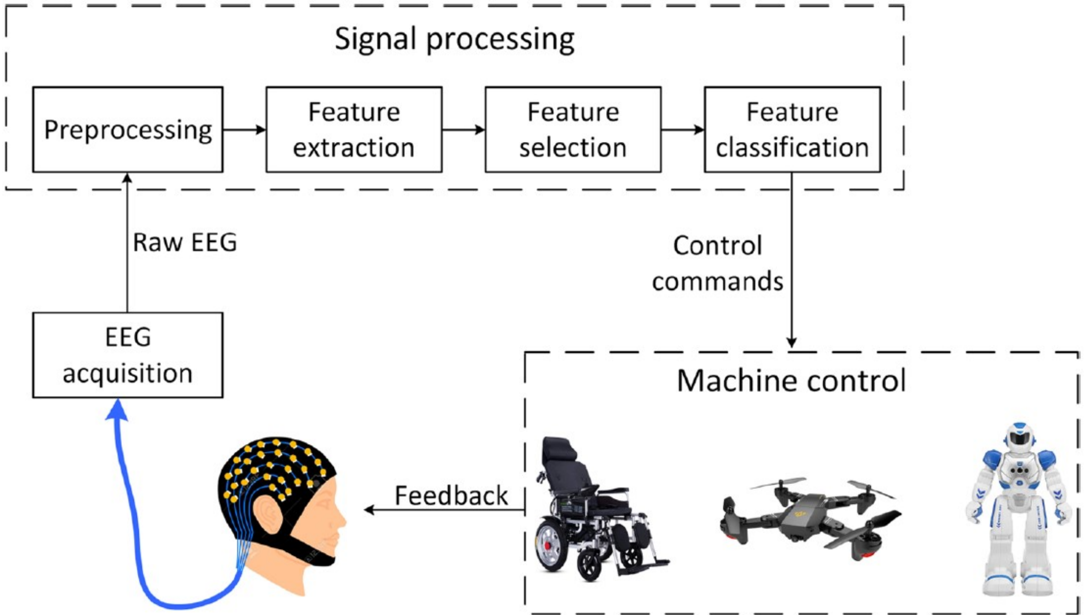

Figure 2.1: EEG based BCI control system

Given the fact that quite a series of tasks must be complete before the thought action of a person to take place a significant delay is expected. This delay represents a great challenge having the objective to minimize it so that the BCI can be a quick response system for real-time applications such as driving a car through a EEG based BCI and other application as such.

2.3 EEG Classification using Deep Learning

EEG signals by their non-linear and irregular nature without specific patterns that can be observed with the naked eye are a short list of problems that appear while trying to classify EEG signals to specific tasks and so there is no straight forward solution for this problem, and this is where Deep Learning comes into play. Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain by learning and achieving a model that solves a certain problem. There are many approaches when it comes to training, one of them is using labeled data witch means that every input has a known output this is known as Supervised Learning the same approach is used further in this paper.

There are 4 key components when talking about applying Deep Learning

1. **Data**
   The more data the batter, when huge amounts of data are available we can train more powerful models and rely less on pre-conceived assumptions, but it is not enough to have lots of data. We need the right data. If the data are full of mistakes, inconsistencies or if the chosen features are not relevant the training is going to fail and result in poor predictive performance.

2. **Models**
   The most AI driven systems involves transforming data in some sense using a model, and model means a computational machinery for ingesting data and then giving a output or a prediction in our case.

3. **Objective Functions**
   By learning it is safe to assume that it means improving as a specific task over time, but who is to measure this improving? Objective functions are a formal mathematical way of measuring that improvement when training a model, generally when we think about objective functions we think that lower is better.

4. **Optimization Algorithm**
   Once we have data, a model and well defined objective functions, there needs to be a algorithm that is capable

to search for the best possible parameters for minimizing the loss function.

The conventional classification methods based on machine learning requires great effort to extract features because the EEG recordings have artifacts that came from noise in the data acquisition process or other factors such as eye blinks and other neuronal activity that has no value for a good classification. Given those conditions certain pre-processing techniques needs to be applied such as ICA (*Independent Component Analysis*) a technique that strips the EEG recording of certain artifacts that originates from the body but by doing so relevant features can be removed as well, these techniques are computationally demanding and they may decrease the classification accuracy .

In recent research studies better results were found using Deep Learning, by training a model based on a deep neural network such as a CNN(*Convolutional Neural Networks*). Using CNN's other than improved accuracy no special pre-process is needed because inside a CNN architecture there could be several convolutional layers that are performing feature extraction in our place and then a fully connected layer is processing the information and gives an output.

2.4 Convolutional Neural Networks(*CNN*)

Convolutional Neural Networks are a powerful family of neural networks that shows great interest in computer vision applications. CNN's tend to be computationally efficient, both because they require fewer parameters than fully-connected architectures and because convolutions are easy to parallelize across GPU cores.

A CNN architecture has two main parts

1. **Feature extraction**
   The input of a CNN is a image, a two dimensional vector and to maintain the spatial domain information a great solution is to take patches from the image and look for features, this process is done using convolution. A convolutional layer can have multiple filters or kernels that can find specific features in the input image. By applying those filters feature maps are generated, a graphical representation can be observed in figure 2.2.

   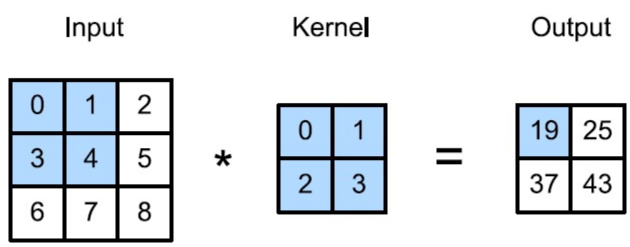

   Figure 2.2: Convolution operation

   From there a activation function is used to introduce non-linearity and complexity in our model and by doing so it can reproduce reality more precisely. In most case ReLU activation function is used to process the feature maps witch turns the negative values into zero and keeps the positive values.

   So that a model becomes spacial size invariant a pooling operation is done witch down samples the input. Maxpooling is commonly used and the basic idea is that it takes the greatest value from a patch.

2. **Classification**
   After the features were extracted we need to feed them to a dense neural network, witch has fully connected layers and can process those provided features to perform classification by giving as output a probability categorical distribution.

2.5 Wavelet Transform

The wavelet transform (WT) is a mapping with superior time-frequency localization as compared with the STFT(*Short Time Fourier Transform*). In recent studies researchers have found that using CNN's motor imagery classification is done with a pretty high accuracy but in order to use a CNN we need a image as input. Wavelet transform is used to perform a frequency analysis and transformation witch can be mapped in a image.

Chapter 3

Implementation

3.1 EEG data acquisition

For the purpose of this project an open database that has various sets of data available for researchers was used, the database is available on physionet.org. From this database a motor imagery specific data set was used. The EEG recordings were gathered from 109 volunteers that performed different motor imagery tasks while 64 channels of EEG were recorded, the channels ware organized in a standard format as shown in figure 3.1.

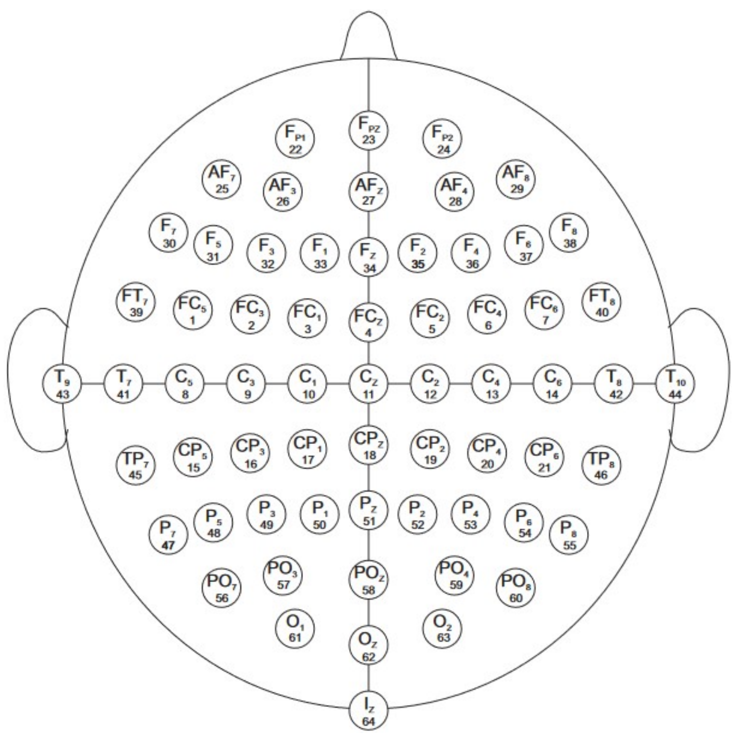

Figure 3.1: International 10-10 system

Each subject performed 14 experimental runs. The first and the second run do not include motor activity, then the rest of the runs provide motor functions activity.

Those experimental runs used a screen that was used to notify the subject at specific moments in time to invoke or to perform a motor activity, those moments ware captured as events in a .event file to help us in the analysis of the recordings.

The data was provided in EDF+ format and the sample rate is 160 samples per second.

3.2 EEG recordings in EEGLAB

After the data was collected we need a way to visualize and analyze it, to accomplish that Matlab software development environment along with EEGLAB was used. EEGLAB is pen source application that can operate with EEG recordings and perform any processing needed such as filtering, epoching, ICA and many others so that is more approachable to work with those types of neural activity recordings.

In figure 3.2 EEG recordings are graphically represented using EEGLAB.

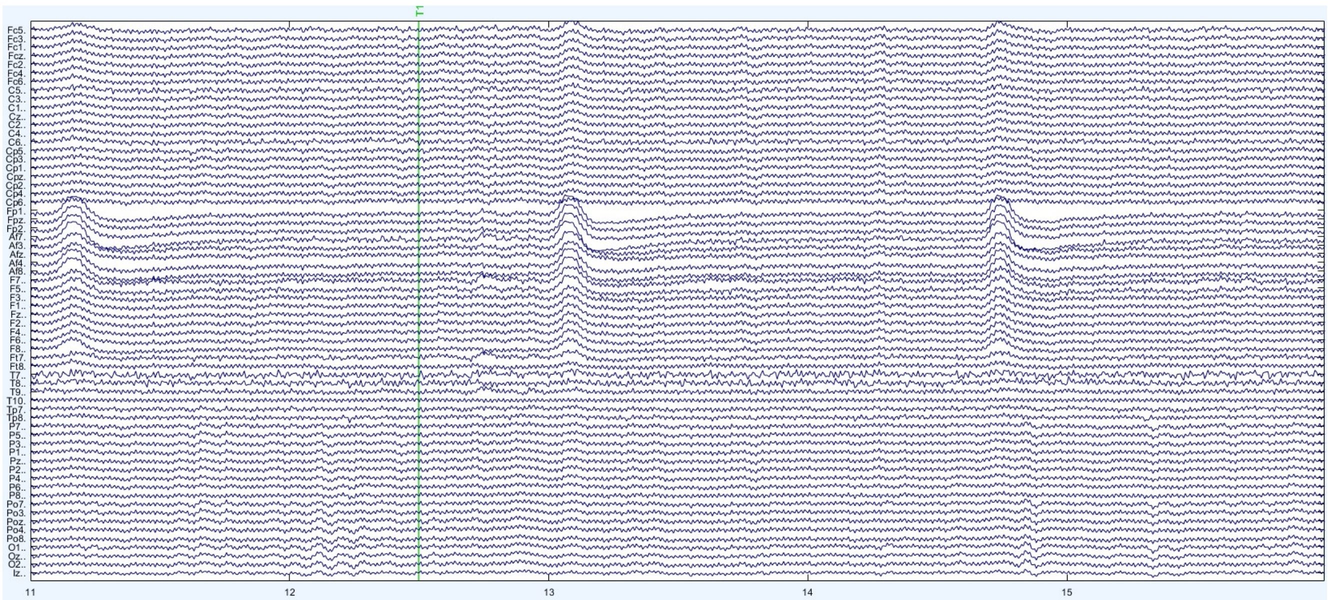

Figure 3.2: EEG recording plot

As we already know for a good classification enough data won't suffice, only good quality data will train a model that has high accuracy.

To pre-process the data we need to take into account that after certain operations we might lose relevant features so this operation needs to be done thoughtfully while keeping in mind the fact that features are going to be extracted by the CNN.

Since motor imagery is our main objective we need to keep just the relevant aspects concerning this matter, in the figure 3.3 the frequency band relevant for motor imagery functions are shown.

Band name	Frequency band (Hz)	MI related frequency bands (Hz)
Delta	1–3	–
Theta	4–7	–
Alpha	8–13	8–12
Beta	13–30	16–24
Gamma	above 30	30–35

Figure 3.3: Frequency bands of EEG and MI related tasks

Knowing that, a band pass filter with the lower edge frequency of 8 Hz and the higher edge frequency of 30 Hz is applied using EEGLAB to keep just the frequencies of interest for this application.

Having all this 2-3 minutes long recording won't help much regarding the classification task, we need to be more specific and more precise. In our case of motor imagery classification the interest should be around the moment of the evoked action, so we need to partition the data and get just the moments of interest. Using EEGLAB this process is called data epoching and for this project we took in consideration one second before the stimuli and 2 seconds after to comprehend as much relevant information as possible since accuracy is our main objective.

In figure 3.4 the EEG recording after epoching and filtering is shown.

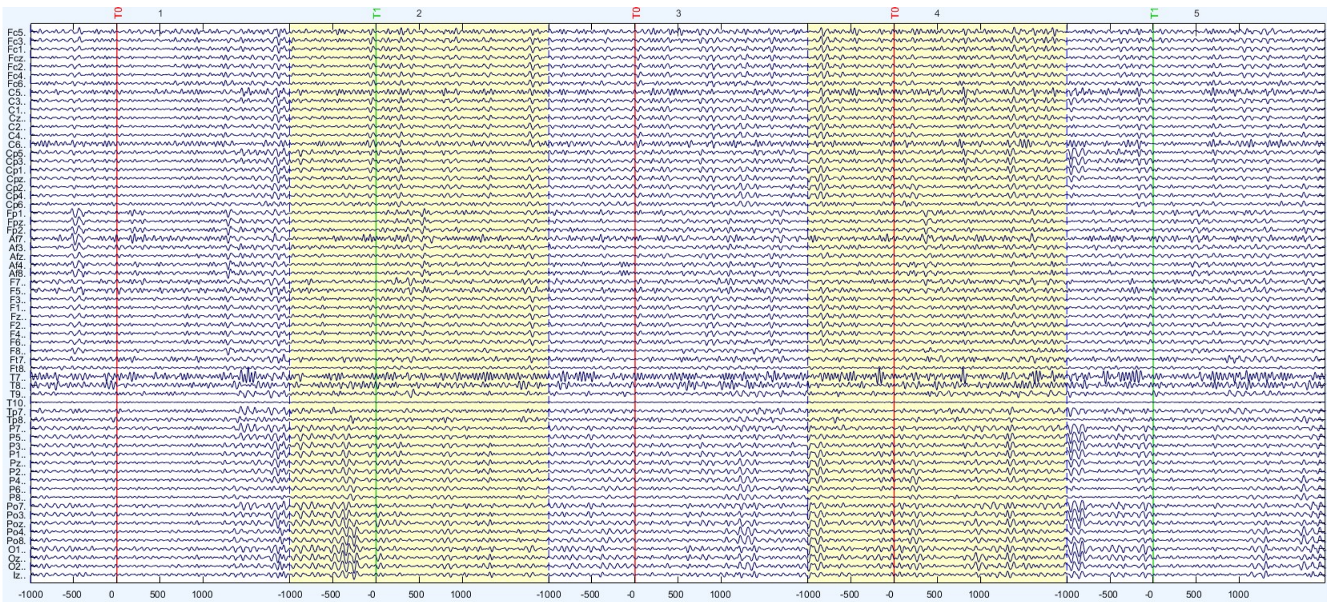

Figure 3.4: Filtered and epoched EEG recording

In a EEG recording are present 64 channels worth of neural activity data and it is known that neighbor electrodes share same the effects but with different proportionality. No all of the 64 channels are needed for classification. In figure 3.5 relevant channels for motor imagery related tasks are presented based on the brain region that activates the most during those actions.

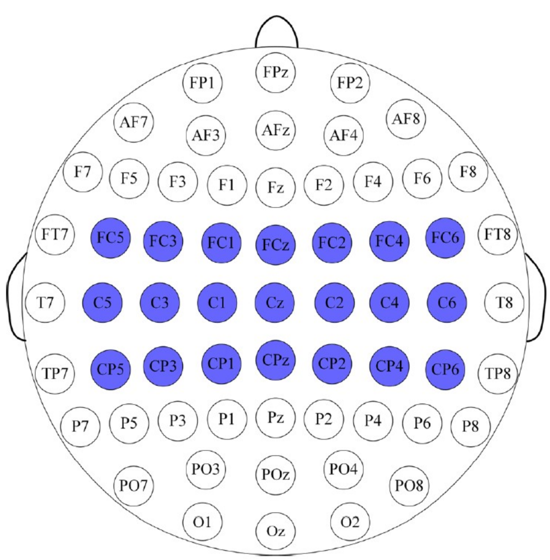

Figure 3.5: The related motor imagery electrodes are identified in blue color

Because of the heavy computational load required when training a network only 3 channels were chosen: Cz, C3 and C4.

3.3 Getting data ready for training

Now that we have the signals of interest we need to interface those signals with the input requirements of the CNN. To do that Wavelet Transform was used to obtain a *Scalogram* that maps the time-frequency analysis and transformation into a image witch numerically is represented into a two dimensional vector, and since the obtained image can be a gray-scale image only one matrix will represent the image numerically.

In figure 3.6 a EEG channel event related epoch is represented then in figure 3.7 the image obtained after applying the Wavelet Transform on the signal.

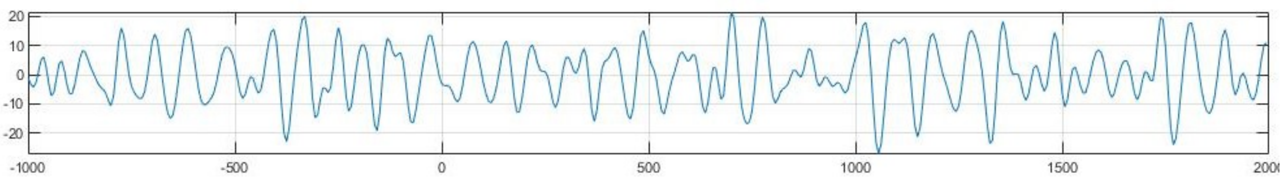

Figure 3.6: EEG epoch

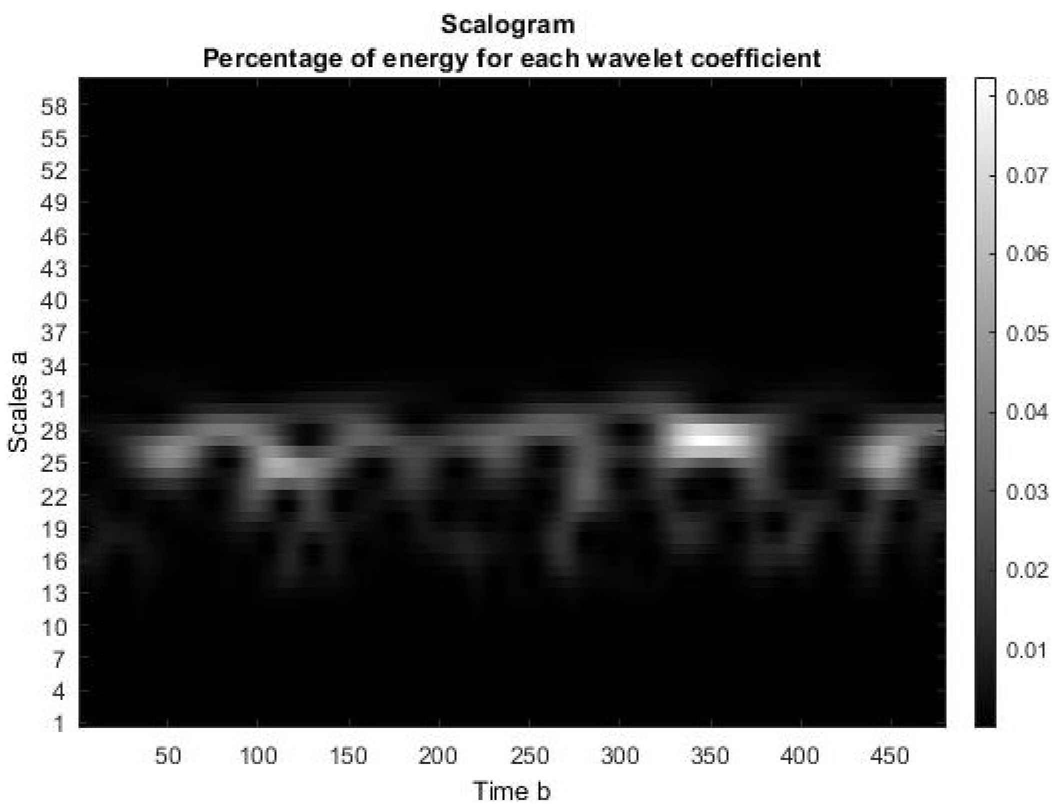

Figure 3.7: Scalogram

Since three relevant EEG channels were selected each channel after the Wavelet Transformation will represent a matrix, in total there will be three matrices staked one over the other resulting in the input for the convolutional neuronal network. The image might need to be resized to fit as input in the CNN. Finally the data consists in a matrix of size [224 x 224 x 3 x numberOfEpochs] and the labels are represented by a vector with categorical values [T0 and T1] where T0 - resting state and T1 - motor imagery task

3.4 Training the CNN

3.4.1 CNN architecture

The used convolutional neuronal network has a architecture that consists in seven layer:

1. **Input layer:** That takes as input a image of size [224 x 224 x 3]
2. **Convolution layer:** That has a number of 16 filters with a size of [3 x 3]
3. **ReLU:** Activation function that introduces nonlinearities into the model
4. **Max pooling:** Downsampling operation on feature maps
5. **Fully connected layer:** Processes the extracted features
6. **Softmax layer:** Outputs a probability distribution
7. **Output layer:** Provides the predicted class

3.4.2 Training options

1. **Optimization algorithm:** Stochastic gradient descent with momentum (*sgdm*)
2. **Constant learning rate:** 0.0001
3. **Shuffle data:** every epoch
4. **Validation data:** 20% from data will be reserved for validation
5. **Validation frequency:** every 5 epochs
6. **Validation Patience:** 10 validations

The validation has the role to avoid overfitting on the training data by evaluating, on every 5 epochs in this case, the accuracy of the model and if it does not find another minimum in 10 validations the training will stop.

The data was split into training data that represents 60% of the total data, testing data with 20% and validation data with 20%.

3.4.3 Single subject attempt

As studies have shown a trained model is subject independent, keeping that in mind the first attempt in training a model has data only from a subject. In figure 3.8 the training progress over time is graphically represented.

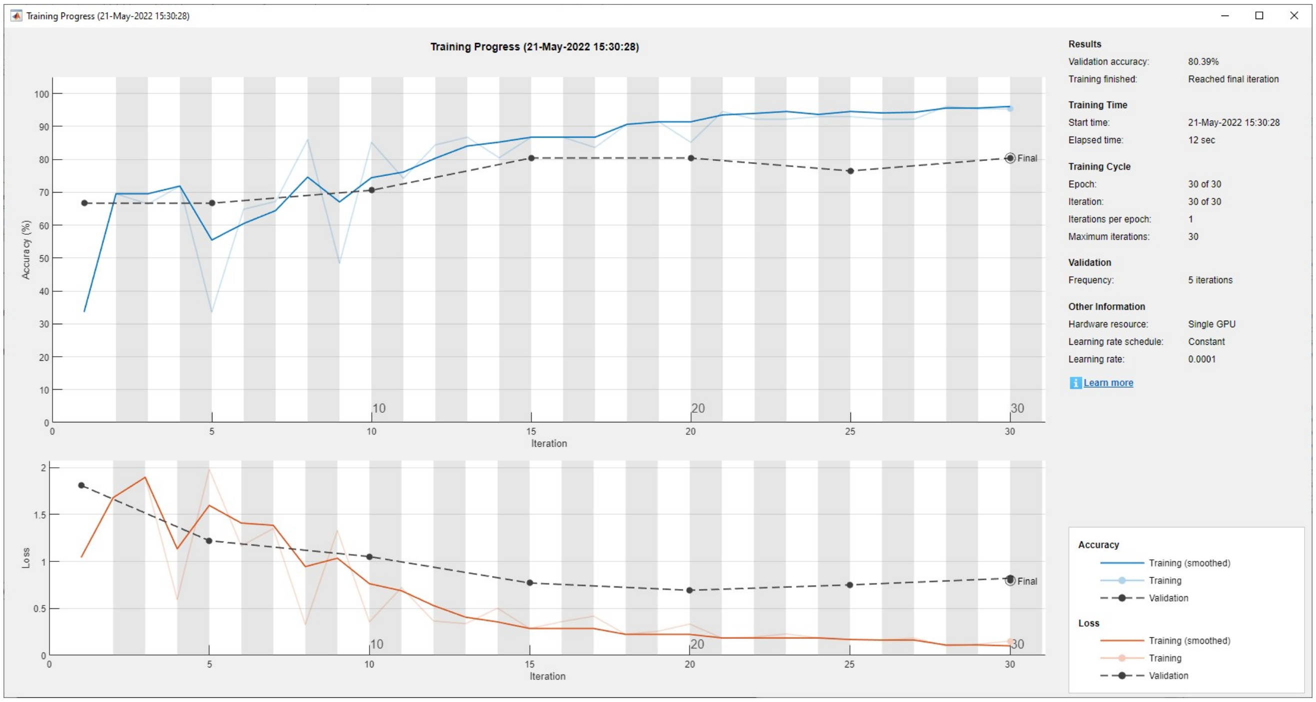

Figure 3.8: Single subject training progress plot

The model obtained after training has a accuracy of 78% on the testing data, the corresponding confusion chart is represented in figure 3.9.

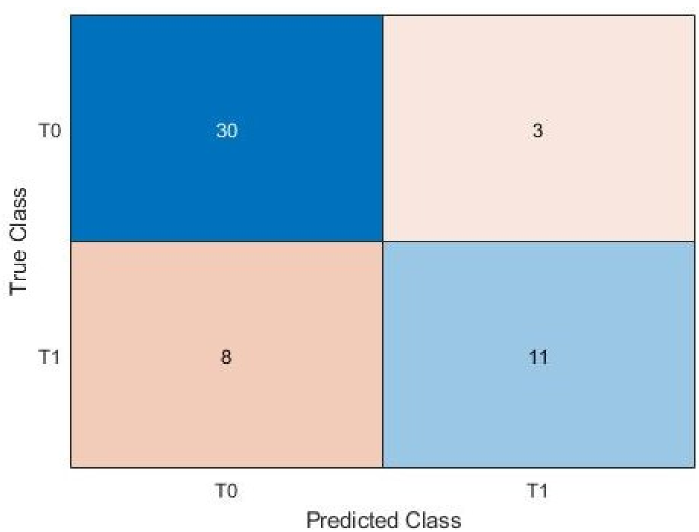

Figure 3.9: Single subject confusion chart

3.4.4 Multiple subjects attempt

The training data used for this attempt comes from ten different subjects. The training progress plot is shown in figure 3.10

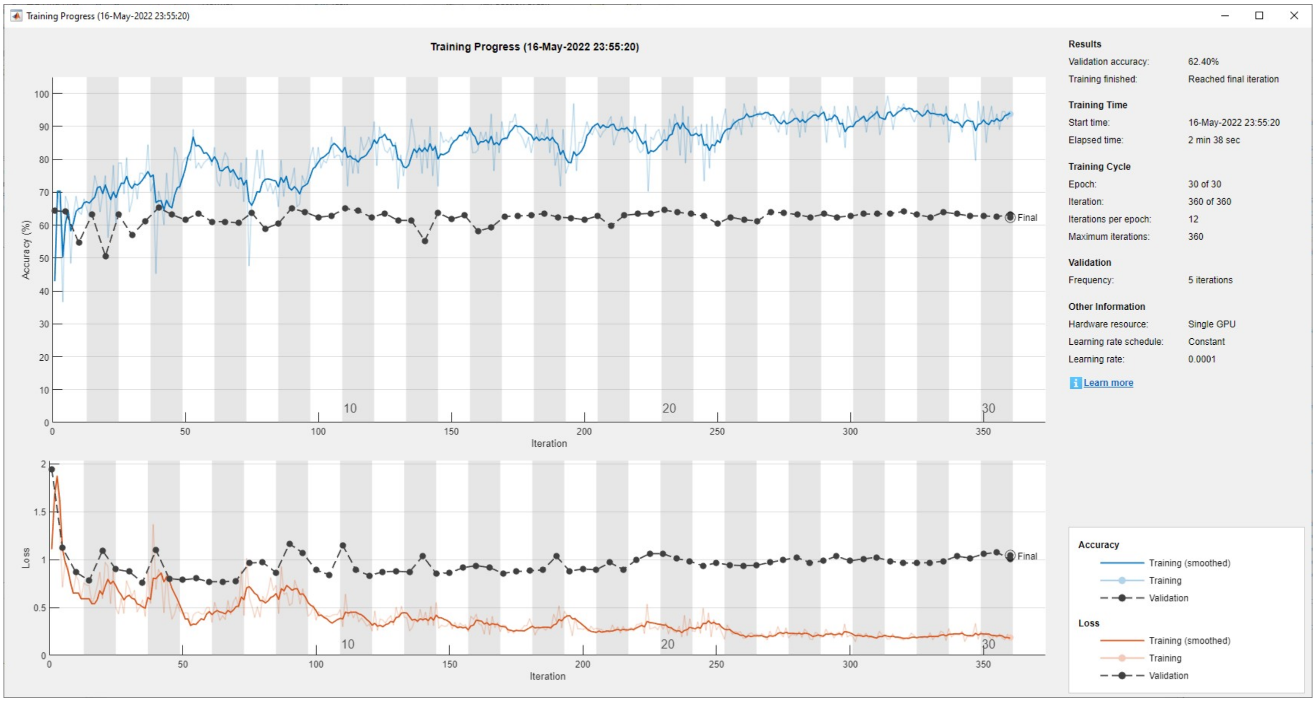

Figure 3.10: Multiple subjects training progress plot

The model obtained after training has a accuracy of 70% on the testing data, the corresponding confusion chart is represented in figure 3.11.

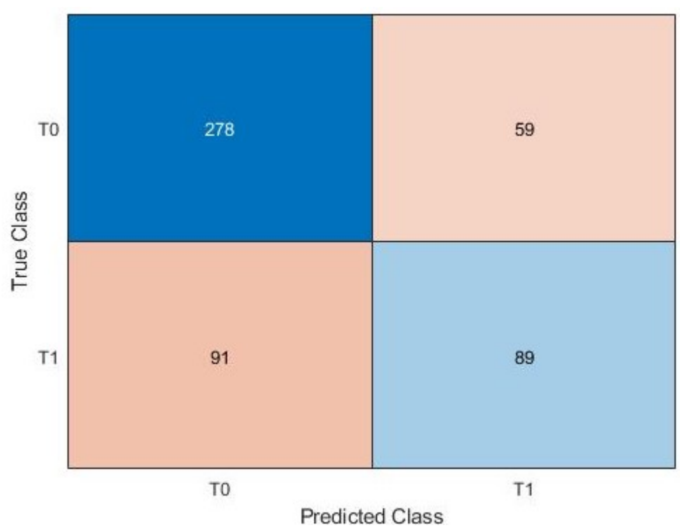

Figure 3.11: Multiple subjects confusion chart

3.4.5 Model applied on different subjects

As a summary the best accuracy was achieved training a model based only on data from a single person, when the data comes from multiple subjects it tends to lose some accuracy but another question might be how will a already trained model, with data from a single person, perform on other persons.

To answer to this question the best model achieved, witch had 78% accuracy on the test data, was used to classify EEG recording data from another person. As a result the model predicted on the another person EEG recordings with a accuracy of 50%, a considerable downgrade that in a actual BCI system could make the difference.

In figure 3.12 the confusion chart obtained from the predictions of a model trained with data from a single person that classified EEG data from another person, can be observed.

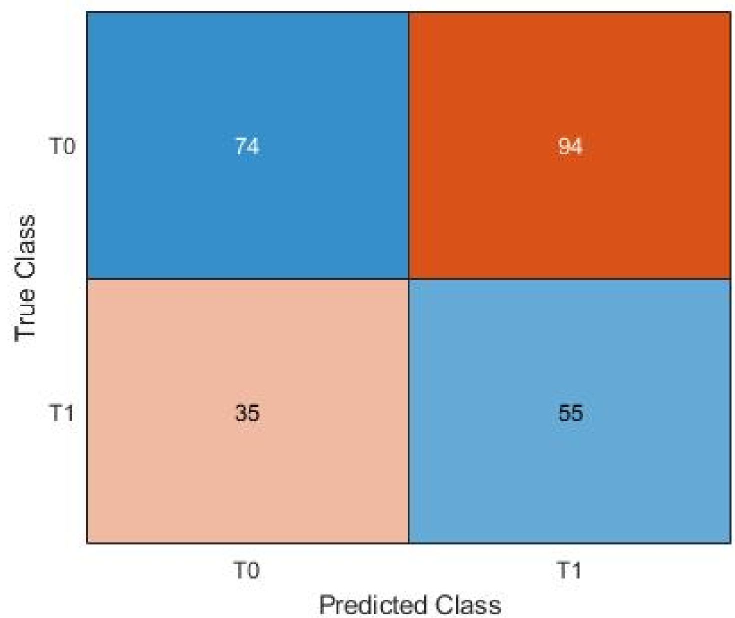

Figure 3.12: Different subject confusion chart

Chapter 4

Conclusion

4.1 Project results

Considering that this project was done in order to approach the idea of a BCI(*Brain Computer Interface*) system, the obtained results, in terms of accuracy are not practical, if we consider the other research done on this topic the presented results does not have any improvements.

On the positive side the results of this project confirmed that EEG based motor imagery classification is a subject independent problem.

The three staked channels of two dimensional vectors, obtained after applying the Wavelet Transform, using just relevant motor imagery related task electrodes in such a way to obtain a valid input for a CNN network was my contribution for this project, not a great one as it seems but at least others will know to approach the problem in a different way, or maybe the idea needs more refinement.

4.2 Future research possibilities

This topic remains of great interest and it shows much potential in the future. As I see it, the future directions should focus in tackling the problem of subject independence and making a solution that is invariant to multiple subjects.

Another interesting direction could be trying to emphasize event related potential(*ERP*) and see how it can be relevant for the classification problem.

If the main goal is to achieve a BCI(*Brain Computer Interface*) then a severe problem needs to be taken in consideration. A fast responsive BCI system needs to respond in real time and that brings the problem of the classification speed. There is a considerable amount of information that needs to be passed to the trained model, for example as in this project 3 seconds worth of signal, this delay is not wanted in a fast responsive BCI system so some attention needs to be focused on the classification speed.