EEG Analysis for Joint Momentum Control

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A ABSTRACT

Since the beginning of engineering, this field of study has based its progressions on the mimicking of and inspiration on the biological systems.

In the field of robotics, the desire for better and more capable system models and designs have motivated countless engineers to pursuit the optimal systems.

One of the current studies, is to improve the joint momentum control in manipulator robotics.

In this paper two approaches will be developed in order to better understand the biological mechanisms behind the human joint momentum control.

First, the Event-Related Desynchronization and Event-Related Synchronization of the mu rhythms associated with the flexion or extension of the elbow's joint were studied.

Second, a Neural Network classifier was developed in order to better understand the relation between the cerebral cortex's patterns and the decision to flex or extended the elbow's joint.

The obtained results for the Event-Related Desynchronization and Event-Related Synchronization were not the desired although not surprising.

The obtained results for the Neural Network classifier were, in fact, motivational as an accuracy of 61.3% (higher than chance) was achieved for a data set comprising the neurological data of two volunteers.

With this study one can realise that field of Brain-Computer Interfaces and the possibility of understanding a finer layer of our brains systems is still achievable through modern day technology.

B PROBLEM AND MOTIVATION

The evolution of engineering has an underlying inspiration in the countless biological systems that surround the human being. From the ability to fly, based on the natural mechanisms of the birds, to meta-heuristic algorithms which mimic the interactions of single cell organisms or the behaviour of animals in a hive, engineering lies on the observation of and inspiration by these biological systems.

One, rather recent, field of engineering, that has been expanding its limits in the past years, is the Robotics field. In this field, we try to transpose human abilities to electrical-mechanical mechanisms, such as the capability to walk, to grasp or to identify frames of interest.

In the field of Manipulator Robots, significant advances have been made in recent years but there is still room for improvement. One can divide the performance of the desired tasks into positioning control, joint momentum (force) control and joint impedance control.

In this paper, an attempt to improve the current control models of joint momentum will be made by analysing the dynamics between the cerebral cortex and the joint momentum of the elbow.

For this, the electroencephalogram (EEG) *Meditron Vertex SC 823* was chosen, which is a 23 channel device based on the international 10-20 System for the positioning of the electrodes[1].

To obtain the information referent to the applied joint momentum, a dynamometer was used, the *Biodex Isokinetic Dynamometer*.

In order to exalt the cerebral cortex's dynamics of joint momentum, an isokinetic procedure with 3 load levels for the extension of the elbow and another 3 for the flexion of the elbow, was developed. Also, 3 different joint amplitudes were analysed for each cycle of loads.

The results of the two proposed solutions were somewhat not the desired.

In the case of the Event Related Desynchronization of the mu rhythms, these were not observable.

In the case of the Convolutional Neural Network classifier, an accuracy score of 58% (higher than by chance) was considered a good result has it derives from the usage of the data of two volunteers and allows for some interpretations that are explored latter in this paper.

C BACKGROUND AND RELATED WORK

One way to understand the cerebral cortex's patterns in order to decode the information relative to body movement is by the observation of Event Related Desynchronization and of Event Related Synchronization.

A study was developed in this area in order to understand the effects of Brain-Computer Interfaces (BCIs) with Virtual Reality Neurofeedback[2].

In this study, chronic stroke patients were able to control a small, narrow watercraft (Kayak), in a virtual reality environment. This was managed, although the impairment in one of the patients arms, through motor imagery. Motor imagery is the mental execution of a movement without any actual movement or without any peripheral (muscle) activation. It has been shown that motor imagery leads to the activation of the same, or adjacent, brain areas as actual movement[3].

The same order of though can be applied in the case of actual body movement rather than motor imagery.

One other article that, in one complete diferent way, tackles the same questions is the The Muscle Activation Method[4].

In this study, the objective is to, via a BCI, control the applied momentum by a robotic manipulator. An adult female monkey (Macaca mulatta) was implanted with four arrays containing 32 microwires each (with 1-mm separation between each wire) in the motor cortex (M1: 64 electrodes), sensory motor cortex (S1: 32 electrodes) and the premotor cortex (PMd: 32 electrodes) of the left hemisphere. The monkey was trained to do center-out tasks to 12 targets (7–15 cm), while seated in a KINARM exoskeleton.

The paradigm of this paper was to find out if the combination of a Neural Network associated with a Hill's muscle model, would lead to better results than the more traditional linear filter.

Indeed the designed model lead to a higher accuracy than the linear filter and, also, allowed for the extrapolation of data, being the system capable of predicting values 5 times lower than the ones found in the training data set.

This paper will be used as an inspiration for the second approach developed in this study.

D APPROACH AND UNIQUENES

D.1 Material

D.1.1 Meditron Vertex SC 823

The *Meditron Vertex SC 823* guarantees a sampling rate of 256 Hz which, by the Nyquist Sampling Theorem, allows for the recording of signals with frequencies not higher than 128 Hz. Since the frequency spectrum of interest is in the range of 0.1 Hz to 40 Hz, this device is capable of performing the desired tasks.

The aforementioned 10-20 System, by which the cap of the EEG device was designed, is shown in detail Figure 1 and led to electrodes placed over the motor areas of the cerebral cortex (areas of major interest): C3, Cz, C4. The electrodes were referenced and grounded to the right and left mastoid processes, and the electrode impedance was kept at less than 10 kOhms. Finally, the EEG system was connected via USB to the dedicated desktop computer for raw signal acquisition and processing.

The signals that exit the EEG amplifier are made digitally available with the Somnium software. This clinical software allows for the visualization of the signals and for the exportation of the raw signals via the European Data Format (EDF), which is a standard file format designed for exchange and storage of medical time series. These signals were then uploaded to *Matlab*.

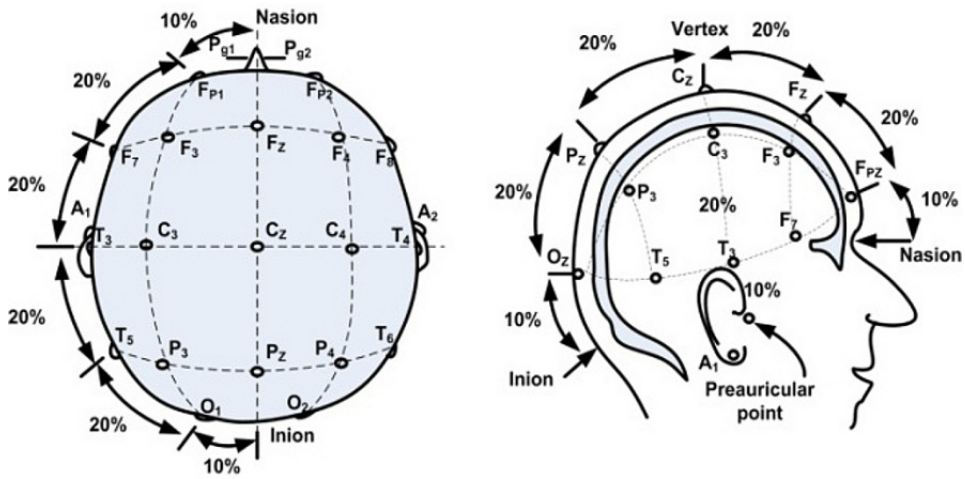

Figure 1: Informative sketch of the positioning of the electrodes by the 10-20 System

D.1.2 Biodex Isokinetic Dynamometer

The Biodex Isokinetic Dynamometer, with a sampling rate of 1000 Hz, was chosen to perform the task of recording the applied momentum, at each given instant, while also providing visual feedback to the volunteer through a graphical display.

The Biodex Isokinetic Dynamometer communicates with the Acqknowlede software, allowing for the exportation of the data through it's specific format *.acq*.

D.1.3 Data and Protocol

The *Matlab* programming platform was used to integrate and process the gathered data.

The used data was made available by the participation of two volunteers. Two male subjects with 23 and 25 years of age, similar height and weight and both right handed were asked to participate in the study.

The same procedure was applied to both volunteers. These, were asked to apply 3 different, isokinetic load levels: 6, 8 and 10 kg for flexion and 4, 5.3 and 6.6 Kg for extension. A ratio between the load levels for the flexion and extension was applied in order to reflect the average contraction capability of the arm muscles responsible for the flexion and extension of the elbow's joint, which is around 2/3 [5].

This measure was used as to minimize muscle fatigue. Also, the procedure was designed as not to exceed the duration of 30 minutes after the EEG cap was place as an extended period of usage can lead to discomfort which can alter and corrupt the cerebral cortex's signals.

The same load levels were applied in three different joint amplitudes: 0, 25 and 50º made by the forearm arm with the horizontal, with a constant 120º of the arm with the horizontal. During the acquisition, the volunteers were asked not to move their head or any other part of their body.

Each sampling event had the duration of 10 seconds after the volunteer reached a stable muscle contraction.

The final data set was achieved by applying a high-pass filter at 1 Hz, used to remove the "baseline drift" followed by a linenoise and harmonics removal at 50 Hz with a notch filter applied in the frequency of 50 Hz, with a Q factor of 20, as the electric fields produced by the 50 Hz activity in the environment contaminates the EEG.

A bandpass filter was, also, applied to attenuate frequencies higher than 40 Hz and lower than 4 Hz as the biological signals of the brain, the brain waves of interest, lay on this frequency spectrum.

Figures 2 and 3 show the brain and load signals, respectively, of one of the volunteers.

D.2 Methods

D.2.1 Event-Related Desynchronization (ERD) and Synchronization (ERS)

The event-related and frequency-band specific power decrease and increase are known as event-related desynchronization and synchronization ,

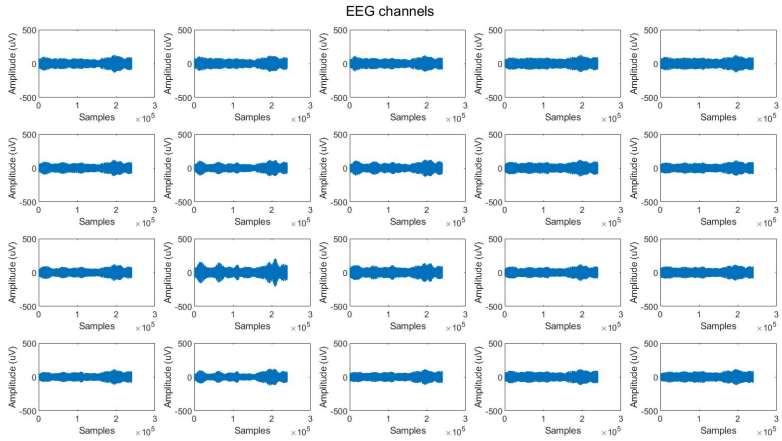

Figure 2: Plot of 20 EEG channels

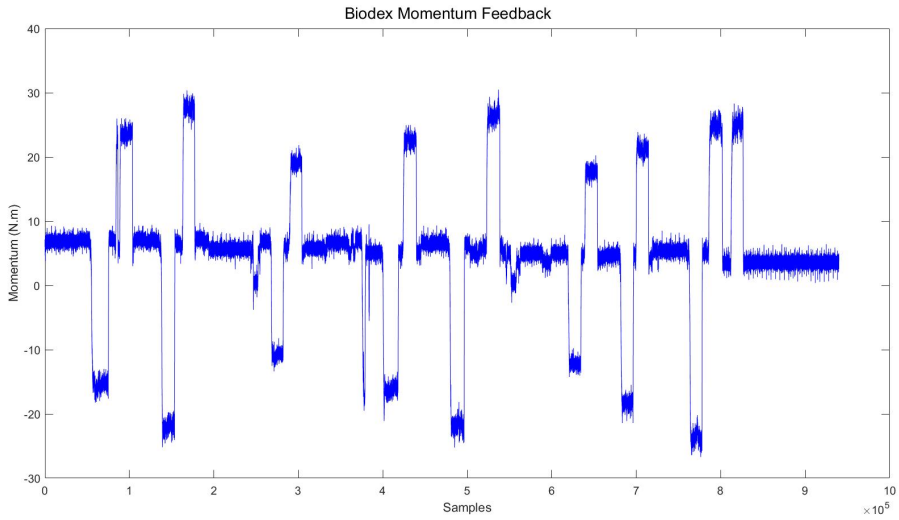

Figure 3: Plot of the momentum feedback recordings

respectively. For the practical use of brain computer interfaces, attempts to decode the oscillatory activities associated with human sensorimotor processes in noninvasive manner have been intensively investigated[6].

Those research are mainly focused on the ERD/ERS in alpha and beta brain waves. The salient brain oscillations in alpha band (8–13 Hz) over the sensorimotor area is known as mu-rhythm, which is desynchronized during motor planning, execution and imagery of hand/finger movements, even when one observes the movement by others. The sensorimotor beta power (14–30 Hz) is totally consistent with invasive studies and it is attenuated by a voluntary execution and imagery of hand/foot movements, and even passive movements, but it prominently increases after movement offset (known as beta rebound) and during steady contractions.

In figure 4, in the display of the Alpha and Beta waves bands, it is possible to visualize the event related desynchronization happening in the motor cortex (C3 and C4, dark blue).

The aforementioned study ,that was conducted to analyse the effects of BCIs with Virtual Reality neurofeedback, can be set as an example of what is expected to obtain in the frequency-time maps of the alpha and beta bands during the flexion or extension of the elbow's joint. In figure 5 it is possible to visualize the event related desynchronization during the task of imagining arm movement.

The images shown in figure 5 allow us to visualise the ERD present in the imagining of left and right arm movement, C4 and C3, respectively.

The dark blue colors, in the motor action area, represent the desynchronized alpha and beta mu rhythms. With an enough number of events and correct syncronization between them, it is expected to obtain similar information as in figure 5.

D.2.2 Neural Network Classifier

A second method to analyse the behavioural patterns of the cerebral cortex was chosen as the ability to train a Neural Network in order to identify if the act of flexion or extension of the elbow's joint is coded in these brain areas or if this is decided downstream from the cerebral cortex.

D.3 Proposed solution

D.3.1 Event-Related Desynchronization (ERD) and Synchronization (ERS)

The collected data had to be processed and reorganized as to fit the desired objective.

One definite variable that will determine the quality of the detection of the desynchronization and synchronization of the mu rhythms is the number of similar EEG events recorded.

A number of recent experimental studies suggested that the minimum number of trials for estimating motor evoked potentials (MEP) amplitude would be around 30 trials. In another study, a data set with 100 recorded MEP trials was used to estimate the amplitude of recorded MEP. The desired target was met with an estimation error of MEP amplitude below 20%. One can assume that the optimal number of recorded events of EEG motor data would be in between those two values. [7]

As a matter of fact, the recorded data for this study lies short of that value. Even joining the data for both volunteers, one can only obtain 15 events for the flexion of elbow's joint and 16 events for the extension of the same joint.

Due to this paradigm, the analysis of the data was divided into subsets:

- 1) Inter-volunteer, consider every action (31 events)
- 2) Inter-volunteer, considering flexion and extension (maximum of 16 events)
- 3) Intra-volunteer, consider every action (maximum of 16 events)
- 4) Intra-volunteer, considering flexion and extension (maximum of 8 events)
- 5) Intra-volunteer, considering each separate load (maximum of 3 events)

The different subsets will be composed by a EEG time series containing 7 second data. The 7 seconds are composed by two seconds recorded before the action, followed by 5 seconds of activity (flexion or extension). These define the baseline and the motor action.

Each time series is the summation and later averaging of the correct time series, according to the aforementioned subset generation.

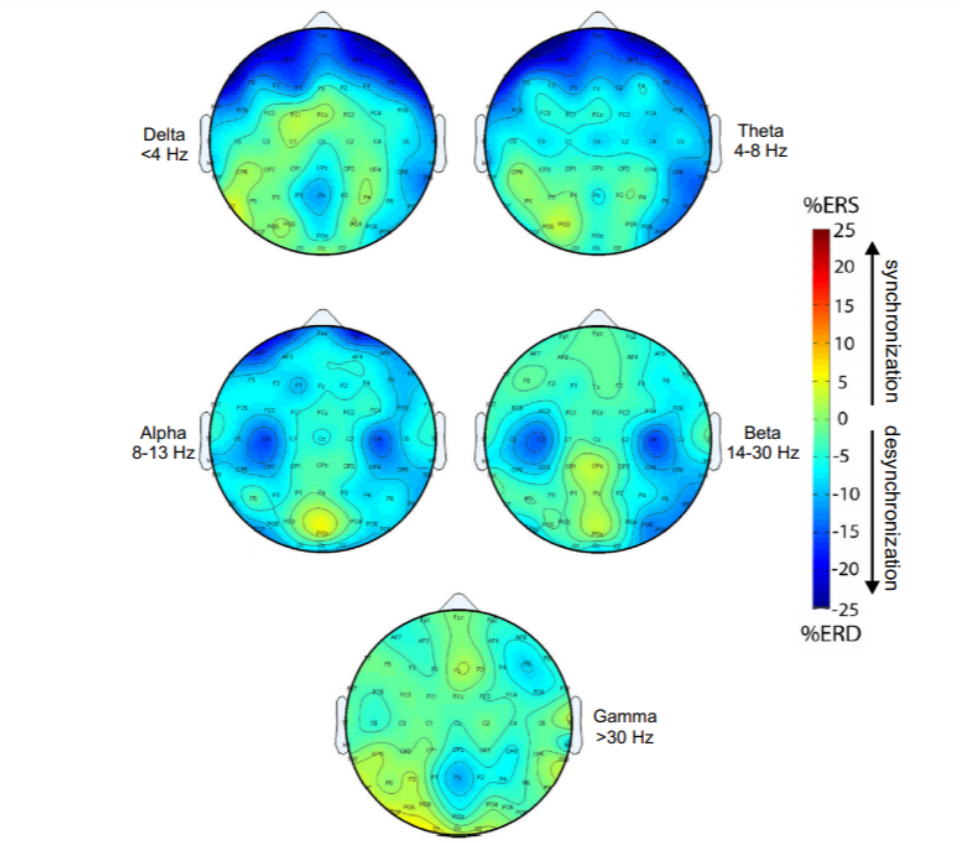

Figure 4: Informative display of the desynchronization obtained in the aforementioned study.

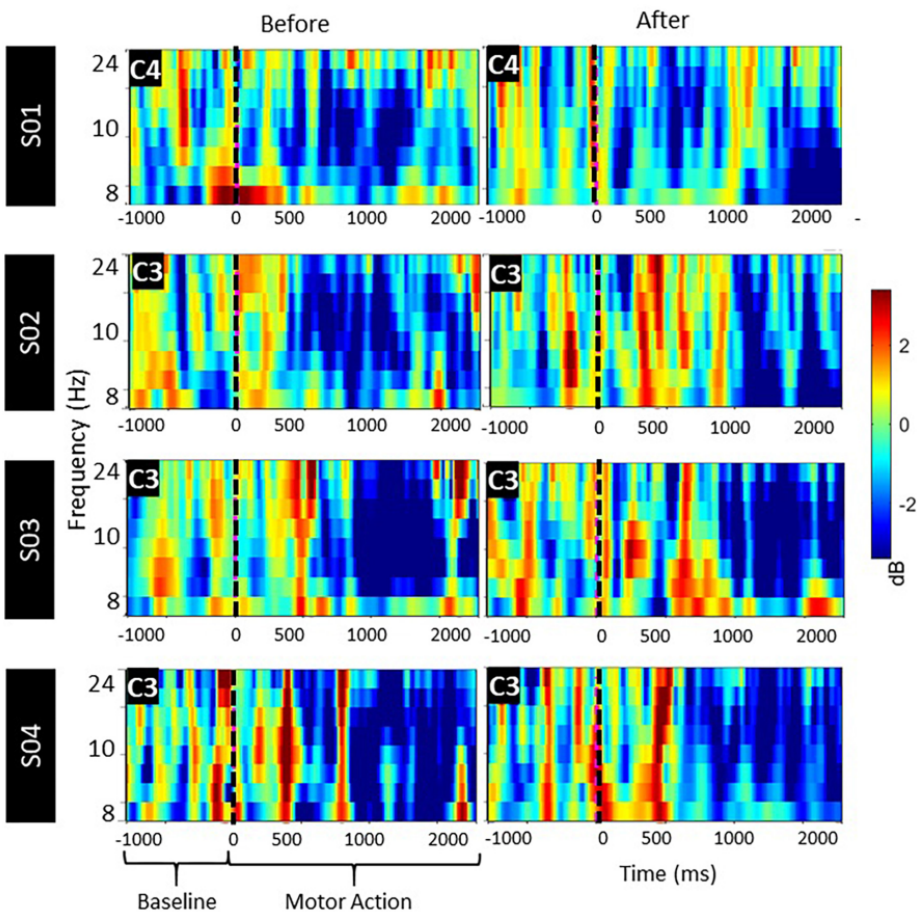

Figure 5: Frequency-time maps of four volunteers in motor imaging

D.3.2 Neural Network Classifier

For this analysis a Convolutional Neural Network (CNN) was developed as this is a rather successful aproach to EEG data classification[8].

In order to extent the data over the 31 recorded examples, a data mining procedure was applied. Of the 10 second stable load application time series, the 7 middle seconds were selected to guarantee synchronization. A time window of 1,25 seconds swiped the 7 seconds time series in order to obtain 10 new time series of each 7 seconds time series, which amounted for 310 input-output pairs.

In order to maximize the use of the collected data, the K-folds Cross-Validation technique was applied. With this technique, a part of the data is chosen to train the model while the rest is used for testing the model. One can choose how many times (how many folds) this is done until the end of the loop.

In the end, the mean accuracy of all folds is calculated and the final accuracy is achieved.

A grafical visualization of the aforementioned technique is shown in figure 6.

The shape of the input data of the CNN was 22x326x1 which translates into a intensity image in which each row is an electrode's signal, each with 326 samples. As said before, the signal passed to the classifier was correctly filtered and selected.

The CNN was built with two sequences of convolutional 2D layers, each followed by a 2D Max-pooling layer. The first convolutional layer had a filter size of 32 and the second layer a filter size of 64.

After this, a flatten layer was used and 3 dense layers followed. In all layers expect the last, a "relu" activation function was used. For the last layer, in order to obtain an answer of which class does the analysed signal belong to, a "softmax" activation function was applied.

This particular network organization lead to 3229090 trainable parameters.

The network's optimizer chosen was "Adam", with a loss function of binary cross entropy and a evaluation metrics of accuracy.

E RESULTS AND CONTRIBUTIONS

E.0.1 Event-Related Desynchronization (ERD) and Synchronization (ERS)

Figure 7 to 11 present the results obtained in the search for the visualization of the ERD/ERS.

E.0.2 Neural Network Classifier

The best accuracy score of CNN network was around 61.3% with a batch size of 1 image, 20 epochs per fold and 5 folds.

F DISCUSSIONS AND CONCLUSIONS

The results obtained were not near optimal but not surprising. Although, in the experimental procedure the load level were repeated, only one event for each specific background condition (action + load + amplitude + volunteer) was recorded. This is far from an optimal condition for a proper ERD/ERS evaluation, as shown before.

Even so, the division of the data into other reorganized subsets could lead to some interpretations.

If the event related desynchronization were to be observed though the data of the subset 1, this would mean that the desynchronization's properties were the same for the two volunteers, independently of the action being made (flexion or extension), the forearm's position or the load being apllied. The event-specific waves would vary only in amplitude, not in phase or delay.

If this assumption was verified, this would lead to the best analysis due to lack of same event repetition in the recorded data.

If the desynchronization were to be observed though the data of the subset 2, this would mean that the shape of the different desynchronization waves were the same for each action (flexion or extension), independently of the volunteer.

The same logic of though applies to the third subset. If the desynchronization were to be observed in this subset's data, this would indicate that the properties of the desynchronization depends only of the person being examined.

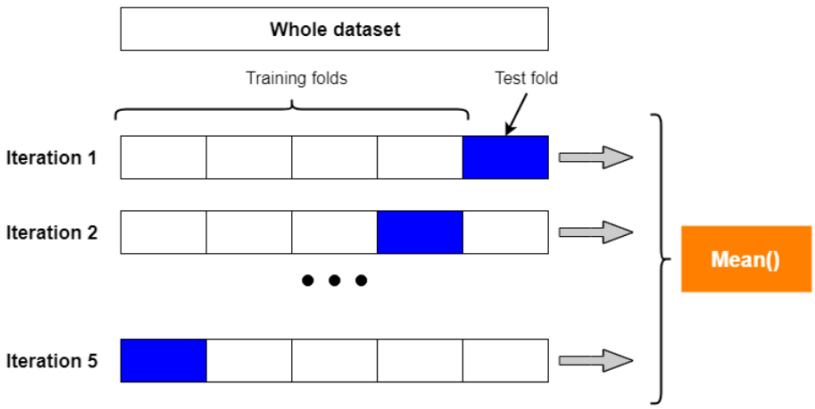

Figure 6: K-Folds Cross-Validation technique

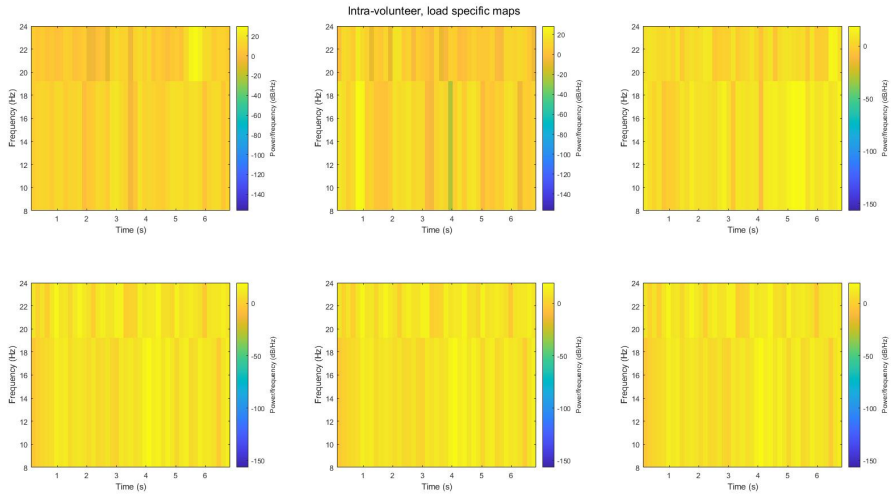

Figure 7: Frequency-time maps of one volunteer: top and bottom line are flexion and extension, respectively, in ascending order of load

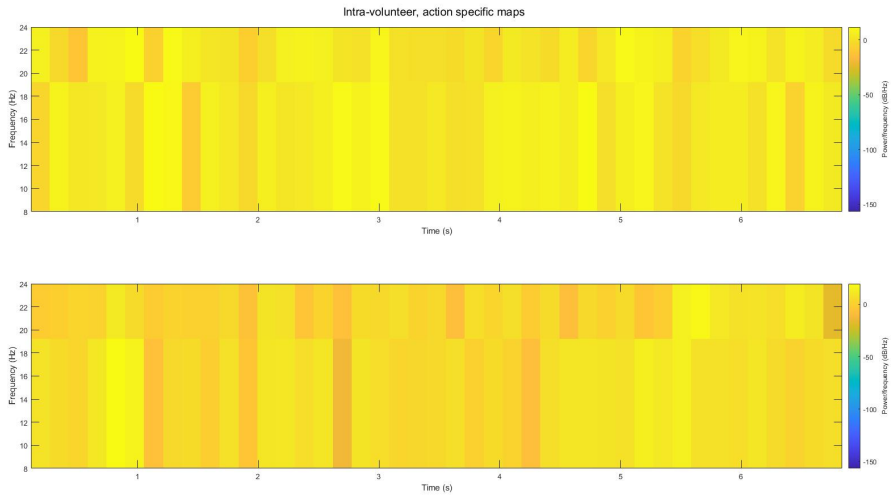

Figure 8: Frequency-time maps of one volunteer: top and bottom line are flexion and extension, respectively

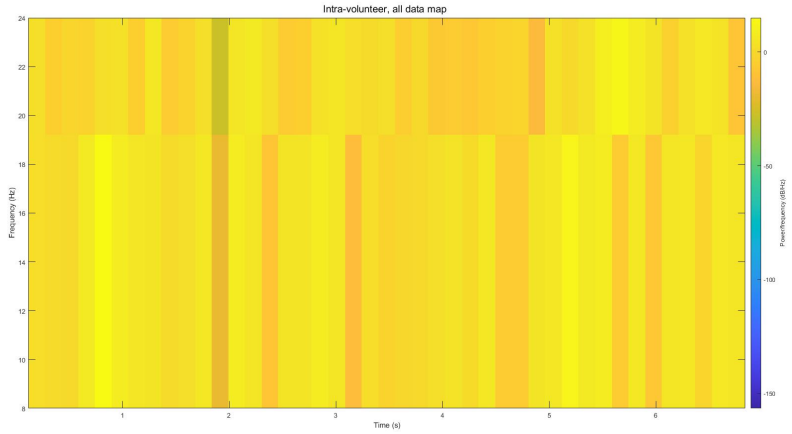

Figure 9: Frequency-time map of all data of one volunteer

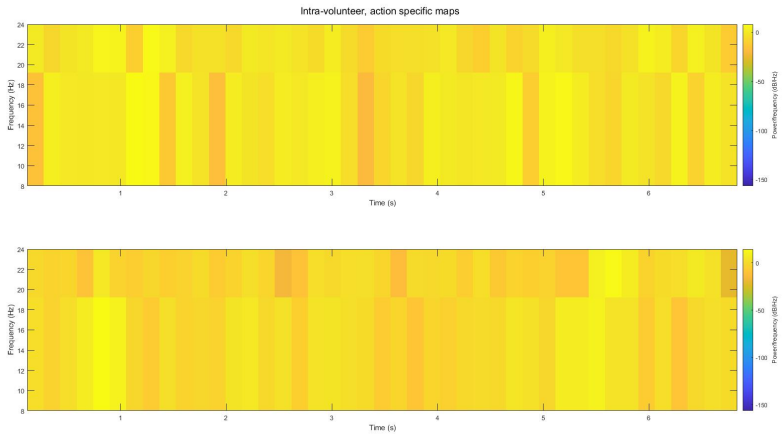

Figure 10: Frequency-time maps of joint data of both volunteer: top and bottom line are flexion and extension, respectively

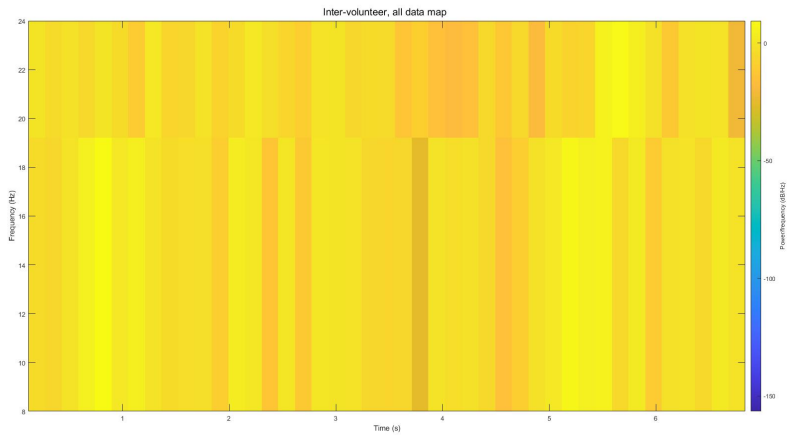

Figure 11: Frequency-time map of all joint data of both volunteers

Also, if the desyncronization were to be observed in the data from subset 4, this would translate in a fact that the properties of the desyncronization depend on the volunteer and the action being performed.

Finally, the data from the final subset, if had evidenced the ERD, would mean that the properties of the desyncronization depend on the subject performing the task and the task itself: either flexion or extension.

On the topic of the second approach to understand the underlying patterns of the cerebral cortex, the CNN classifier, the accuracy score being higher than chance (50%) allows for the assumption that the decision of flexion or extension of a body's joint is already determined before reaching the downstream reflex arcs located in the spinal cord.

Also, this result was achieved used data from both volunteers which leads to the conclusion that different people can have similar cerebral responses to same motor events. This has a great impact in the BCI paradigm as it means that, with finer network tunning, it can be possible to develop a "plug and play" device suitable to a large range of people, rather than having the individual train the network through an extension of examples.

G Limitations and Future Work

After the elaboration of this research paper it became clear some alterations that have to be done to the experimental protocol. In fact, this data gathering was originally designed for a pilot study with the objective to better understand the expected procedures for this type of data collection (EEG data through visual feedback).

Also, although the data had the information for 31 EEG events, this study was limited by its specific sample size, meaning that no specific event was recorded more than once in the data collection for each volunteer. Furthermore, increasing number of sessions per subject could also have resulted in more positive resulted.

One other detail that can be changed, for the future data collection of this topic, is to, instead of asking the volunteer to apply force when is feeling comfortable, guarantee a 10 second baseline before the action. This duration is necessary because event-related changes need time to develop and then recover and thus the inter-event interval between two consecutive motor events should be at least 10s[9].

One interesting choice of experimental protocol would be to chose only one volunteer, with data collection throughout a higher number of sessions. This is would, with a high level of certainty, improve the CNN's accuracy scores.

Finally, after some research, the use of a Filter Banks Common Spactial Patterns (FBCSP) filter, could help to maximize the CNN's ability to differentiate between the two classes. This technique has become a standard tool in the use of MI-based BCIs [10]. The main idea is to use a linear transform to project the multi-channel EEG data into a low-dimensional spatial subspace with a projection matrix, of which each row consists of weights for channels. This transformation can maximize the variance of two-class signal matrices. FBCSP method is based on the simultaneous diagonalization of the covariance matrices of both classes[11].

H References

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