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Trabajo Fin de Máster

Control de un exoesqueleto de brazo para rehabilitación de pacientes de ictus basado en EEG

EEG-based control of an upper-limb exoskeleton for stroke rehabilitation

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DECLARACIÓN DE AUTORÍA Y ORIGINALIDAD

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Resumen

El ictus es la principal causa de discapacidad entre adultos en todo el mundo. Aunque la terapia física es el método más utilizado para rehabilitación, entre tres y seis meses después de la lesión más de la mitad de los pacientes continúan con algún grado de discapacidad motora. Es por ello que en la actualidad existe un gran interés en optimizar estas terapias de rehabilitación. En este marco, las Interfaces Cerebro-Computador (BCI, del sus siglas en inglés, Brain-Computer Interfaces) han surgido como una prometedora herramienta en rehabilitación debido a que pueden promover la generaración neuroplasticidad cerrando el bucle entre la actividad cerebral y los movimientos del miembro parético.

La eficacia de estas terapias basadas en una BCI que controla un exoesqueleto de brazo ha sido demostrada en pacientes de ictus severo en varios estudios, por ejemplo, Ramos-Murguialday et atl, 2013. Estos estudios basan la terapia en un feedback predefinido (por ejemplo, mover o no mover el brazo robótico) y han mostrado que, un feedback mas preciso, asociado con la actividad cerebral, produce un mejor aprendizaje motor. De esta forma, si somos capaces de discriminar las activaciones cerebrales asociadas a distintas tareas motoras, podremos dar un feedback más preciso al paciente, mejorando así los resultados de la rehabilitación.

Estas señales cerebrales pueden ser grabadas a través de técnicas no invasivas, como electroencefalograma (EEG), y posteriormente procesadas y traducidas en comandos motores que permitan controlar un efector, como puede ser un brazo robótico o un exoesqueleto de pierna. A pesar de que la decodificación de intención motora se ha realizado con una precisión razonablemente alta en los ultimos años, la decodificación de distintos movimientos del mismo miembro utilizando EEG es un problema más complejo. Recientemete, varios análisis offline han mostrado prometedores resultados. Sin embargo, un decodificador basado en EEG que pueda ser implementado en una aplicación en tiempo real es todavía una problema abierto.

El principal objetivo de este Trabajo Fin de Master es proponer un decodificador basado en EEG que sea capaz de discriminar entre movimientos de brazo en distintas direcciones y evaluarlo en un escenario que imite las condiciones de un entorno en tiempo real. Para ello, propodremos e implementaremos un decodificador; posteriormente se evaluará su comportamiento utilizando un conjuto de datos de seis sujetos sanos grabados en la Universidad de Tubinga (Alemania).

Abstract

Stroke is the most common cause of disability among adults in the world. Although physical therapy is the preferred method for rehabilitation, three to six months after the injury, more than half of the patients remain with some degree of disability. Hence, there is a growing interest in optimizing the rehabilitation process. In this context, Brain-Computer interfaces have been proposed as a promising rehabilitation tool, since they can promote neuroplasticity closing the loop between brain activity and paretic limb movements.

The efficacy of BCI controlling a robotic exoskeleton for rehabilitation of severely paralyzed stroke patients has been demonstrated in several studies, i.e., Ramos-Murguialday et al., 2013. These studies used a predefined feedback, i.e., go vs no-go, and showed that an accurate feedback, linked with the brain activity, promotes better motor learning. Therefore, if we are able to discriminate the brain activations associated to different motor tasks, we could give a more accurate feedback to the patient, enhancing the rehabilitative outcome.

These brain signals can be recorded using non-invasive techniques, such the electroencephalogram (EEG), and then, processed and translated into commands that control an effector, such as an arm exoskeleton. Although the motor intention decoding has been achieved with a reasonably good accuracy in the last years, the decoding of different movements from the same limb using EEG signals remains challenging. Recently, several offline analyses showed promising results. However, an EEG-decoder that could be implemented in a real-time application is still an open question.

The main objective of this master thesis is to propose an EEG-based decoder that discriminates different arm movement directions and test it in a pseudo-online scenario. For that, we will propose and implement a decoder; Then, we will evaluate the performance of this decoder using a dataset of six healthy subjects recorded at the University of Tubingen (Germany).

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1. Introduction

1.1 Motivation

Up to 17 million people suffer a stroke each year and about 80 % of the survivors acquire motor impairments, resulting in the most common cause of disability among adults in the world. This leads to a series of important changes in the lives of the patients and their families, since the new condition of these patients will require from a support that can vary from occasional to full time assistance. Furthermore, the initial and long-term treatments for these conditions have associated enormous economic costs for the families and the health care systems ([Lee et al., 2010]).

Physical therapy is the most used method for rehabilitation of stroke patients. Thus, different approaches have been proposed including passive mobilization, promotion of alternative movement, intense task-directed training and many others. Despite the rehabilitation efforts, three to six months after the injury, the 55-75 % of the patients remain with some degree of disability ([Feys et al., 1998]). Hence, there is a growing interest in optimizing the rehabilitation process in order to maximize the outcome of the rehabilitation. Thus, several strategies based on neurophysiological learning mechanisms to promote neuroplasticity appeared recently as robot-assisted therapy or reinforced feedback exercises in a virtual environment (RFVE) [Silvoni et al., 2011].

The neuroplasticity was described by Donald Hebb who proposed that correlated patterns of synaptic activity lead to synaptic and structural plasticity. This mechanism was popularly summarized by the phrase “cells that fire together wire together”. Thus, correlating brain networks with sensory feedback will promote neuroplasticity, which has been shown as a mechanism that boosts motor learning/recovery ([Ang and Guan, 2013], [Daly and Wolpaw, 2008]). In this context, Brain-Computer Interfaces (BCI) have been proposed recently for rehabilitation, since they can promote neuroplasticity closing the loop between paretic limb movements and brain signals, eliciting the learning effects and strengthening the connection between movement intention and the consequence of a real movement ([Ramos-Murguialday et al., 2012]). .

A Brain-Computer Interface (BCI) is a device that translates the neural activity recorded from the brain into commands for conrolling an external device (i.e prothesis, computer, robot, wheelchair etc [Iturrate et al., 2009, López-Larraz et al., 2016, Escolano et al., 2012]). Brain signals can be recorded non-invasively at the scalp (electroencephalogram –EEG), or invasively at the cortical surface (electrocorticogram–ECoG) or within the brain (local field potentials–LFPs– and neuronal action potentials). Invasive methods offer a better spatial resolution as well as a wider frequency range (the skull acts as a natural low-pass filter [Nunez and Srinivasan, 2006]), but they require the implantation of electrodes on the cortical surface or within the brain. On the other hand, non-invasive methods are simpler but have a poor signal-to-noise ratio (SNR). In addition, a non-invasive BCI is cheaper and safer, which makes them a potential tool for rehabilitative applications ([Millán et al., 2010, Wolpaw et al., 2002]).

The efficacy of BCI controlling a robotic exoskeleton for rehabilitation of severely paralyzed stroke patients has been demonstrated in a randomized double-blind controlled study ([Ramos-Murguialday et al., 2013]). Posteriorly, these findings have been confirmed by other studies ([Ang et al., 2014], [Ono et al., 2014], [Pichiorri et al., 2015]). However, the main limitation in the current state of the art of non-invasive BCI systems for rehabilitation is the low number of movements that can be controlled, as these therapies generally train one type of movement, such as grasping or reaching. These studies have evidenced the importance of coincident feedback between brain activity and peripheral stimulation to promote cortical plasticity. Studies using a sham feedback, in which stimulation may or may not coincide with brain activity showed that those patients improved less than patients in which stimulation was associated to the degree of brain activation. This demonstrates that an accurate feedback promotes better motor learning, and suggests that the more accurate the feedback, the higher the learning. Therefore, if we could discriminate the brain activations associated to different motor tasks, we could link the activation of those different neural populations to the movements they control, maximizing Hebbian plasticity and motor learning. There is evidence showing that different neural populations modulate movements of the arm in different directions ([Georgopoulos et al., 1986]), and recent invasive studies have shown that the brain activity of different movements from the same limb can be decoded ([Collinger et al., 2013], [Spüler et al., 2014]). For this reason, groups worldwide are making a great effort towards the improvement of methodologies to decode several degrees of freedom from EEG ([Shiman et al., 2015], [Iturrate et al., 2016], [Ofner et al., 2016]), so that they can be integrated in BMI therapies in the short term.

1.2 State of the art

An important problem in EEG is obtaining clean data, free of external interferences (also known as artifacts). These artifacts can be from electrical (i.e., interferences, electrode movements or power line noise) or physiological origin (i.e., eye movements, head motions or muscle activations), which modify the recorded brain activity. Hence, detecting artifacts is an important problem in EEG signal processing and several works investigate the artifacts and try to characterize them ([Islam, 2015, Sweeney et al., 2012]). According to these studies, eye-movement activity is generally located at frequencies bellow 5 Hz, and are most prominent over the anterior head regions ([McFarland et al., 1997]). In contrast, the electromyographic (EMG) activity has a wide frequency range being maximal at frequencies over 30 Hz ([Anderer et al., 1999]). Additionally the, relatively, slow arm or head movements can produce low frequency harmonics and contamine the delta activity.

Although avoiding motion, blinks and eye movements during the recording can substantially reduce these artifacts it is not a realistic aproach in a rehabilitative eviroment. Nevertheless, several signal processing methods have been proposed to reduce the influence of these artifacts on the EEG, i.e regression-based methods, Principal component analysis PCA([Jung et al., 2000]), Blind source separation BSS([Belouchrani et al., 1997]) or Independent component analysis ICA ([Delorme et al., 2007]). ICA methods are commonly used as an artifact removal technique but a recent study has demostrated that they can produce an amplitude variation in low frequency components and introduce variation across the data, [Pontifex et al., 2016]. Thus, as we can not remove these motion artifacts without altering the low frequency brain signals, this study includes a section in which we will evaluate the influence of these artifacts in the EEG data recorded.

The signals produced naturally in the brain when a subject performs a movement can be used to decode motion information, since they allow a simple and intuitive control for subject ([Millán et al., 2010]). These include the event-related synchronization/desynchronizations of sensorimotor rhythms (ERS/ERD) and the motor related cortical potentials (MRCP). The ERS/ERD refers to the increase/decrease of subband power due to the more/less synchronous neural activations produced when a motor action (execution, imagery, or attempt by paralyzed patients) occurs ([Pfurtscheller and Da Silva, 1999]). These are observed in the alpha and beta frequency bands (8-30 Hz) and are widely studied and used in this field ([Ang et al., 2008, López-Larraz et al., 2014]). MRCPs are slow (0.1-1 Hz) changes in the amplitude produced up to 1.5 s before the execution and imagination of the voluntary movement [Shibasaki and Hallett, 2006] and are also broadly used in the motor intention decoding ([Niazi et al., 2011], [López-Larraz et al., 2014], [Jiang et al., 2015]).

Even though the motor intention has been succesfully decoding in the last years, the decoding of different movements from the same limb using EEG signals remains challenging due to their poor SNR, together with the close spatial representation on the motor cortex area presented for the different movements from the same limb [Rickert et al., 2005]. Several invasive studies have shown that the information related to arm movement direction can be extracted and classified [Waldert et al., 2008] and [Ball et al., 2009]. Those studies showed that this directional information can be extracted from the low-frequency components (LFC), $<$4 Hz, and the power in gamma band (62-87 Hz) but not from the ERD bands (alpha and beta). As mentioned above, the EEG decoding of different movements from the same limb has become a growing field of interest and some works in the last years ([Shiman et al., 2015], [Iturrate et al., 2016], [Ofner et al., 2016]) showed promising results in offline analyses (using non-causal techniques, like zero-phase filters). However, an EEG-decoder that could be implemented in a real-time application remains an open question.

1.3 Objectives and scope of the work

Several studies based on a specific task (i.e grasp or reaching) have already demostrated significant positive result in standard motor impairment scales for stroke patients, such as the Fugl-Meyer scale ([Ramos-Murguialday et al., 2013, Barsi et al., 2008, Sabut et al., 2010]). However, we strongly believe that a more accurate feedback (more specific tasks) will promote better rehabilitation outcomes. Thus, the main objective of this thesis is to propose an EEG-decoder for different arm movements using techniques that can be implemented in real-time. To achieve this goal, the work has been divided into five steps:

- **Search and study of the bibliography**: this allows the autor to acquire the required background to begin the development of the work. Thus, not only solid skills on biological signal processing and machine learning are important, but also some neuroscience concepts will be valuable during the development of the mentioned decoder.
- **Design of the EEG-based decoder** based on previous research and several offline tests (i.e different features or classifiers evaluation). A deep study of the state of the art will bring us usefull information about the neural signatures related to differents arm movements that will be used in this dessign. In addition, the most common signal processing and machine learning techniques used in BCI applications will be tested.
- **Implementation of the decoder**. Once the methods (signal processing, features, classifiers...) are defined, the objective will be implement this EEG-decoder using Matlab (The MathWorks, Inc.).
- **Test the accuracy of the designed decoder in a pseudo-online scenario** in order to test the proposed decoder we will compute a pseudo-online classification in which the EEG signal will be procesed as it would be done in a real-time setup.
- **Evaluate the influence of the artifacts** present in the recorded EEG data. This analysis will help us to verify that the obtained results are due to a brain signal decodification and not to the influence of external artifacts related to the movement

1.4 Thesis layout

This section lists the structure of this master thesis document. The chapters of this study will be presented as follows:

1. The first chapter presents the motivation, state of the art, and objectives of this thesis.
2. In chapter two, the dataset used in this study and the methods are explained.
3. The obtained results are shown in the third chapter.
4. Chapter four presents the discussion and future work lines. In addition, a short summary of the work done by the student is presented.
5. The relevant bibliography is listed

Additionally the annexes will be presented in a different document.

2. Methods

In this section, we will explain both the dataset used in this study[1] and the methods, including signal processing and machine learning techniques, used for the translation of the brain signals into commands for a rehabilitative exoskeleton.

2.1 Dataset

2.1.1 Subjects

Six healthy right-handed subjects without any neurologic disease history (three males and three females, mean age 24 years) participated in one recording session. Subjects were informed about the experimental procedure and signed a written consent form. This study was approved by the ethical committee of the Faculty of Medicine, University of Tübingen, Germany.

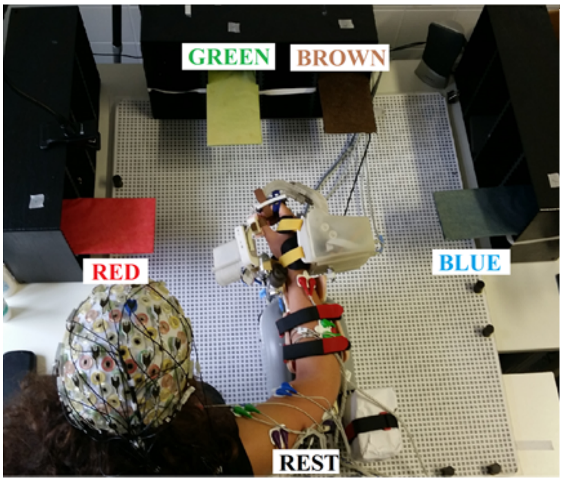
2.1.2 Experimental Setup

Subjects were seated in a comfortable chair with their right arm and hand wearing a 7 degrees of freedom (DoF) Exoskeleton (Tecnalia, San Sebastian, Spain) and an EEG cap with 32 electrodes. Additionally, electrodes were placed in order to record the electromyographic (EMG), activity, and the electrooculogram (EOG),to measure eye movements.

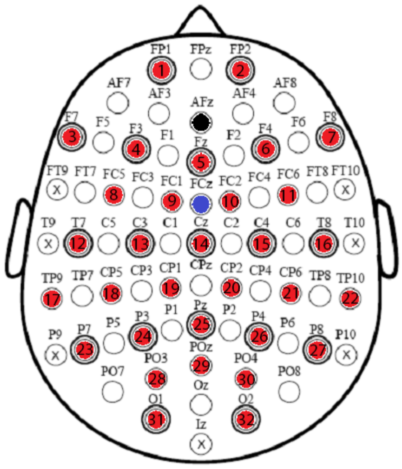
The task consisted of a center-out reaching movement, from a starting position (rest position) towards one of four different target colors (see Figure 2.1a). Upon the presentation of an imperative auditory cue specifying the target, participants were asked to perform the movement and return to the starting position at a comfortable pace but within 3 seconds. The auditory cues and the EEG data were presented and acquired using BCI2000 software.

[1]Although the recording of the data was not part of this study, it is explained in this section for a better understanding of the results and conclusions obtained.

The experiment was divided in 5 runs of 40 trials, i.e., (50 trials per class). Each of these trials consists of a rest period of a random length between 2-4 seconds, in wich the subjects were asked to relax and try not to move. Right after that, an auditory cue (one of the four differents target colors) was presented and the subject had to prepare the movement. After 2 seconds, a GO cue was reproduced, and the subject had 3 seconds to reach the target and go back to the initial position (see Figure 2.1c).



(a) Setup



(b) EEG cap

(c) Trial structure

2.1.3 Data adquisition

Brain activity was recorded with multi-channel EEG amplifiers (Brain Products GmbH, Germany) using 32 channels at a sampling frequency of 2500 Hz. The cap contained the electrodes FP1, FP2, F7, F3, Fz, F4, F8, FC5, FC1, FC2, FC6, T7, C3, Cz, C4, T8, TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, Pz, P4, P8, PO9, O1, Oz, O2 and PO10, using AFz and FCz as ground and reference respectively (see Figure 2.1b). Kinematic data of the 7 DOFs Exoskeleton was recorded at 18 Hz and then resampled to 2500 Hz using cubic interpolation to match the EEG signals. Additionally surface EMG at the right forearm, as well as horizontal and vertical EOG signals, were recorded.

2.2 EEG data analysis

2.2.1 Preprocessing

In order to reduce the computational cost, EEG data were first filtered with a Butterworth 4th order low-pass filter at 45 Hz and then downsampled to 100 Hz. After that, an automated method for reducing EOG artifacts [Schlögl et al., 2007] was applied. This method creates a linear model with the EOG components (see equation 2.1):

$$X(t, ch) = S(t, ch) + [EOG1(t), EOG2(t)] \cdot [b_1(ch), b_2(ch)]^T \tag{2.1}$$

where $X(t, ch)$ is the recorded EEG at time t for channel ch, S is the source without artifact contamination, $[EOG1(t), EOG2(t)]$ is the noise source based on the EOG components and $b(ch)$ the weight vector of the EOG artifacts for each EEG channel ch. Thus, once the model is created ($b(ch)$ coeficients), we can obtain the cleaned signal for every new sample of data by:

$$S(t, ch) = X(t, ch) - [EOG1(t), EOG2(t)] \cdot [b_1(ch), b_2(ch)]^T \tag{2.2}$$

Finally, in order to re-reference the EEG signals, we applied a common average reference (CAR), where the average across all the motor cortex channels (FC5, FC1, FC2, FC6, C3, Cz, C4, CP5, CP1, CP2, CP6) is substracted for each channel independently for each sample time (see equation 2.3). In addition, since we only want to classify brain signals related to movement, the only channels used in the following steps will be those located over the contra-lateral motor cortex (FC5, FC1, C3, Cz, CP5, CP1).

$$X(t, ch)_{CAR} = X(t, ch) - \bar{X}(t) \tag{2.3}$$

whereby $\bar{X}(t)$ is the average across the channels for each sample time t.

2.2.2 Trial extraction

For the posterior analysis, we divided the signal (a continuous EEG recording) into the different trials (task repetitions). This can be done according to the auditory cue (the time when the cue is presented to the subject). This method might introduce a time latency due to the variable time response of the subject across the experiment (time between the cue and the start of the movement). Hence, we obtained the time when the kinematics of the exoskeleton show the start of the movement and we extracted the trials corresponding to [-6, +2] s, being 0 this kinematic onset.

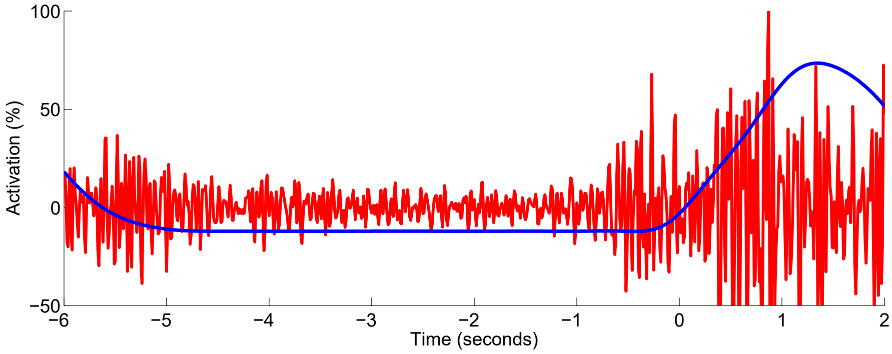


Figure 2.1: EMG activity of the biceps (red) and Kinematic activation (blue).

Figure 2.1 shows the average of all the aligned kinematic activation. EEG and EMG signals were aligned according to this kinematic onset. Thus, from now on, all temporal values mentioned in this study will correspond to this kinematic onset as value t = 0 seconds.

2.2.3 Feature extraction

To classify the preprocessed EEG signals into the commands for the exoskeleton we trained a hierarchical classifier (similar to the one used in [Hotson et al., 2016]), using two different features. First, a binary classifier, based on ERD, was used to determine if a movement is occurring. If the movement is detected these preprocessed EEG signals are evaluated by a second classifier (multiclass classifier), based on the low-frequency components (LFC) described by [Ball et al., 2009, Waldert et al., 2008], in order to determine the target of that movement (see Figure 2.2).

Before computing the features, one-second epochs were extracted from the six contralateral channels mentioned above based on the kinematic onset. Thus, the signal from -5 to -4 secs (being 0 the kinematic onset) will be used for characterizing the rest brain state and signal from -1 to 0 for the movement intention state. Thus, training with the one-second epoch rigth before the starting we minimize the motion artifact influence and we achieve a better temporal accuracy ([Millán et al., 2010]).

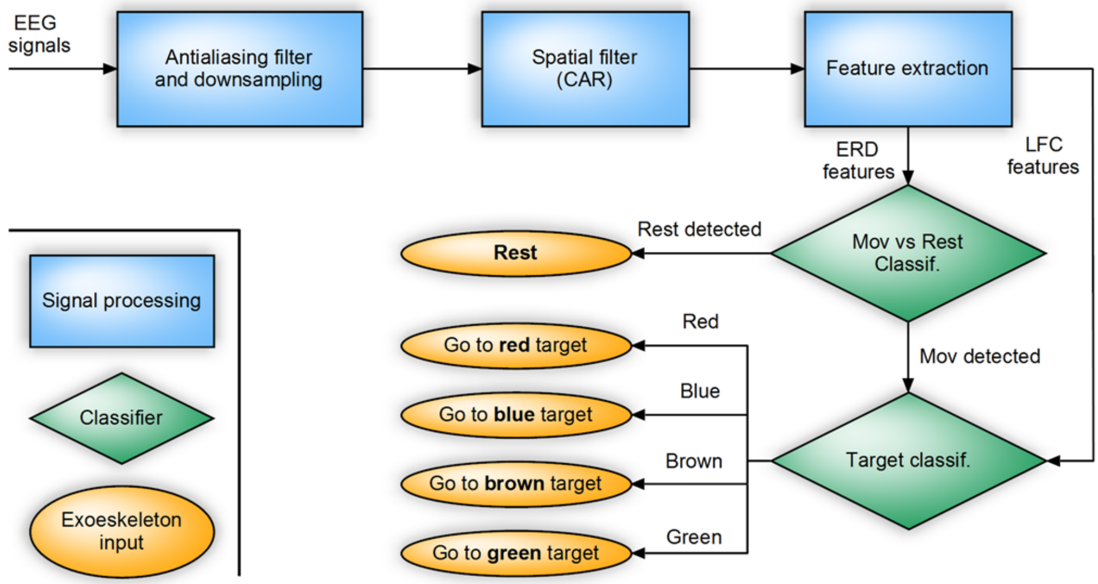


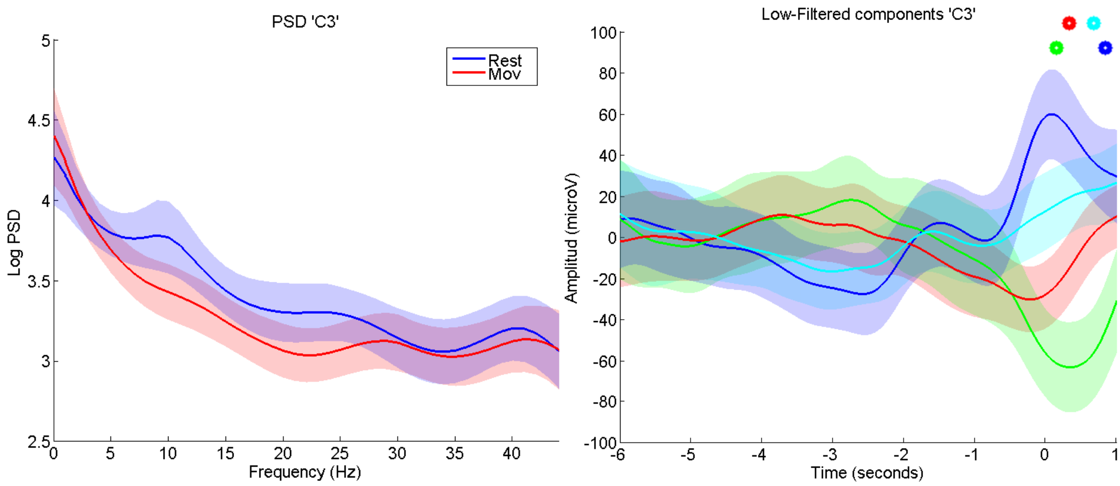
Figure 2.2: Flow diagram of the proposed decoder.

As we have described previously, ERDs are event-related desynchronizations which occur in alpha and beta frequency bands right before the movement and result in a power decrease between the rest and motion states (see Figure 2.3a). Thereby, the power spectrum density (PSD) for each epoch, one-second length and windowed with a Hamming function, was estimated using an autoregressive model of order 20 with Burg's method. After that, the mean log-power in delta (1-6 Hz), alpha (7-13 Hz) and beta (14-25 Hz) were computed for each channel resulting in a set of 18 features (6 channels x 3 features per channel).

For the LFC features (see Figure 2.3b), the preprocessed EEG data were band-pass filtered with a Butterworth first order filter at 0.05 - 4 Hz and downsampled to 10 Hz, which means a set of 60 features (6 channels x 10 features per channel).

After that, the feature vector was standardized according to the z-score procedure: first, the mean of each feature was substracted and then those features were divided by the standard deviation (see equation 2.4). This is a common method used in machine learnig in order to rescale the features. Thus, after that, the feature vector will have he properties of a standard normal distribution ($\mu = 0, \sigma = 1$).

$$Z - score = \frac{X - \bar{X}}{std(X)} \tag{2.4}$$



(a) (b)

Figure 2.3: Figure (a) Example of PSD during Rest (blue) and Movement (red) brain states, correspondig to the ERD. Shaded areas show the standard error. Figure (b) Example of Low-Filtered Components (LFC). Colored lines represent the grand average of the different LFC for each movement direction (from left to right: green, red, blue and dark blue). Shaded areas show the standard error.

2.2.4 Classifiers

For both, binary (Rest vs Mov) and multiclass (Target) classifiers, we used a support vector machine (SVM), which has been shown as a robust classification method that has good generalization properties in BCI applications ([Lotte et al., 2007]). Furthermore, a Gaussian kernel and a regularization parameter (the same as we used in [Bibián, 2015]) were used in the SVM. Thus, the binary classifier was trained using the rest and movement epochs. Then, we removed the Rest epochs and all the movement ones were used to train the multiclass classifier.

2.2.5 Pseudo-online classification

In order to evaluate the performance of this decoding algorithm in a realistic environment, we simulated a pseudo-online scenario, where the decoding accuracy was validated using a 5-fold cross-validation (each subject performed 5 runs of trials). Thereby, in each iteration four runs were used to train the classifiers, as described above, and the remaining one was used to evaluate the proposed system with sliding windows that simulate the real-time output of a BCI controlling the robotic arm.

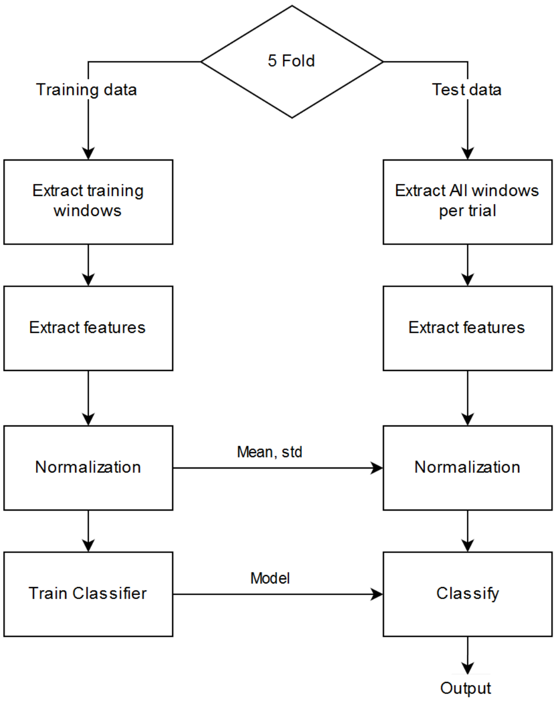


Figure 2.4: Pipeline of the 5-Fold cross-validation computed in the pseudo-online classification.

Thus, in this pseudo-online procedure, we extract one-second length epochs with a sliding step of 50 ms (as our real platform would work in real conditions). However, in order to determinate the performance of the classifier in each movement execution, we consider a trial, [-6, +1] seconds, and we used only the epochs contained in those trials. After that, we classify those epochs using the decoding system (Feature extraction methods and classifiers) built previously resulting in an output (exoskeleton input) each 50 ms for every single trial.

2.2.6 Metrics

Although the purpose of the proposed scheme is to decode different movements and rest from the brain signals, in order to determine how well both classifiers work we tested them separately.

For the binary classifier, we computed the percentage of outputs decoded as movement in the whole trial. In the rest phase we would expect this value to be zero (i.e., all the samples decoded as rest), and in the movement phase we would expect this value to be 100% (i.e., all the movement samples correctly decoded).

Regarding the multiclass classifier performance, we used the decoding accuracy (DA). The DA used in this study (similar to the one used in [Lew et al., 2014]) shows the relationship between the real class label and the predicted output. Thus, the DA is the ratio between the correct predictions divided by the total number of epochs classified.

2.2.7 Metrics

The epochs used to train the classifiers are right before the kinematic onset, before the movement starts. However, the EMG activation and some small arm movements can be produced before the exoskeleton starts the movement so, in order to avoid the existence of these artifacts in the data and their influence on the classification results, we train the classifier with a different epoch, this time right before the EMG activation.

2.3 Analysis of potential artifacts

EEG signals recorded in a rehabilitative environment are mainly contaminated by eye artifacts and movement-related artifacts, both muscular and motion artifacts. As described in 2.2.1, we used a correlation-based method for reducing EOG artifacts ([Schlögl et al., 2007]). Regarding the movement-related artifacts, EMG activity contaminates frequencies over 30 Hz ([Anderer et al., 1999]). EMG artifacts were no considered in this study due to the fact that we are not interested in the frequencies above 25 Hz. However, the movement direction decoder proposed is based in frequencies bellow 4 Hz so these motion artifacts, that mainly affect low frequencies should be carefully taken into account.

Only signals from the channels placed over the contra-lateral motor cortex are used for the decoding, however, in order to further identify the information contained in each single channel we computed the DA for the entire set of channels. Thus, a high DA in most of the channels would imply a strongly contaminated data. Nevertheless, in a clean dataset the most discriminative channels, those with the highest DA, should be mainly placed over the contra-lateral motor cortex.

Brain signals recorded from EEG are often of a magnitude several times smaller than the artifacts and motion artifacts usually affect several channels, if not all of them. That is why if motion artifacts are polluting the data, a high correlation between channels is expected. In order to test the existence of these motion artifacts we computed the Pearson correlation for all the channel and kinematics combinations to the raw signals for the 2 seconds epoch from 0 to 2s where the subject was executing the task, resulting in the confusion matrix of the 32 channels and the kinematics.

3. Results

3.1 Decoding movement intention

Figure 3.1 shows the mean (red line) and standard error (red shaded area) of the outputs decoded as movement (in %) averaged for all the subjects and trials. The black line shows the theoretical chance level (50% for two classes) and the grey shaded area corresponds to the 95% confidence interval, ± 2.82%, computed according to [Müller-Putz et al., 2008].

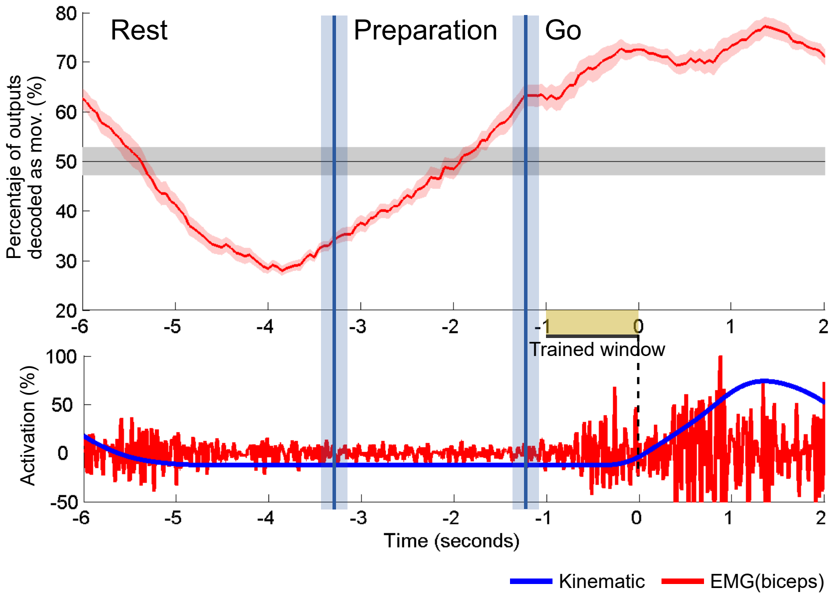


Figure 3.1: Average outputs decoded as movement (%) across subjects (red line) and standar error (red shaded area) in the top figure and the Kinematic (blue) and EMG, biceps, (red) in the bottom. Blue vertical lines show the times when the cues were shown (Notice that these times are not fixed because the trials are aligned to the kinematic onset. Blue shaded areas represent this variability). Additionally, in the x-axis of the top figure, the window (epoch) used for training the classifier is shown as a yellow shaded area.

During the rest time, the percentage stays bellow 35 % between -5 and -3 seconds. Then, it rises above the chance level at around -1.6 seconds, and stays at high values until 2 seconds, indicating that the desynchronization remains during the movement execution and can be decoded ([Ramos-Murguialday and Birbaumer, 2015]). However, the fact that the motion is detected 1,6 seconds before the kinematic onset may seem surprising. This is due to the following two reasons: first, the auditory cue was presented 2 seconds before the movement cue (around 3 seconds before the kinematic onset) so that the subject could be planning the movement during this time. On the other hand, although the exoskeleton is fixed to the arm, it allows some slight arm movements before the exoskeleton really starts moving (in Figure 3.1, we notice that the muscular activation occurs around 800 ms before the kinematic onset).

Thus, percentage of outputs decoded as movement rises above the chance level after -2 s yielding a 78 % during the motor execution. Finally, the times before -5 seconds shows the end of the previous trial. It may therefore not be surprising that the DA shows levels above the chance level before those -5 seconds.

3.2 Decoding movement direction

As we mentioned above, the one-second epoch right before the kinematic activation was used for characterize the movement brain state. However, the EMG activation is produced, in average, 800 ms before the kinematic onset. This movement might lead to possible motion artifacts that affect the signals and might unnaturally boost our classification performance (artifacts are much more discriminable than brain signatures). For this reason, we computed the decoding accuracy of the decoder trained with the epoch right before kinematic activation and, additionally, with the decoder trained with the epoch right before EMG activation. This procedure can provide a robust way to make sure that the classified signals do not come from arm-movement artifacts, since the movement has not yet occurred in the interval used to train the classifier.

3.2.1 Training before the kinematic onset

Figure 3.2 shows the average DA of movement direction decoding from LFC for all the subjects. Blue, red, green and dark blue represent the DA computed only in the trials corresponding to each target (the spatial distribution of the targets is shown in the top-right corner). The thin black line and grey shaded area show the theoretical chance level (0.25 for four classes) and the 95% confidence interval, respectively.

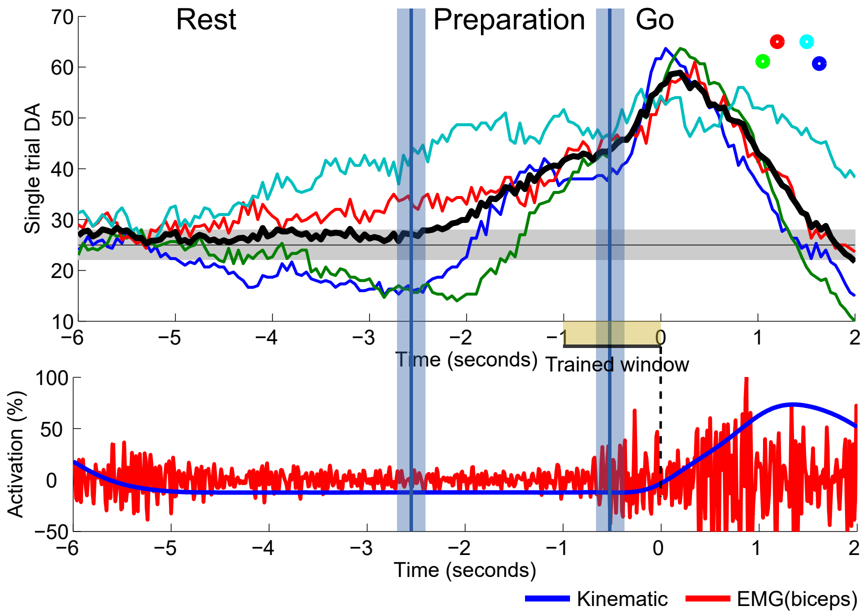


Figure 3.2: Average DA, training with the epoch right before the Kinematic onset, across subjects (black line) and target-specific DA (colored lines) in the top figure. Top-right corner shows the spatial distribution of the targets. Kinematic (blue) and EMG, biceps, (red) in the bottom. Blue vertical lines show the times when the cues were shown (Notice that these times are not fixed because the trials are aligned to the kinematic onset. Blue shaded areas represent this variability). Additionally, in the x-axis of the top figure, the window (epoch) used for training the classifier is shown as a yellow shaded area.

The multiclass DA climbs above chance level around 2 seconds before the kinematic activation, in the same way as the binary DA does, and stays above the chance level during the task execution. Between -0.5 and 0.5, when the MRCP peak is expected ([Shibasaki and Hallett, 2006]), the DA reaches the highest DA (58.92 %). After 1,2 seconds, when the subjects return to the rest position, the performance decreases to chance level. Finally, blue, red, green and dark blue lines, illustrate that all the targets were decoded properly and the target specific DA stays above the chance level during the task execution.

3.2.2 Training before the EMG onset

As mentioned above, in order to avoid possible motion artifacts in the training set, the classifier was also trained using the epochs right before average EMG activation (between [-1.8, -0.8] s, being 0 the kinematic onset). Thus, Figure 3.3 illustrates the corresponding DA wich is slightly lower (50.1 %) but quite above the chance level during the movement planification and execution.

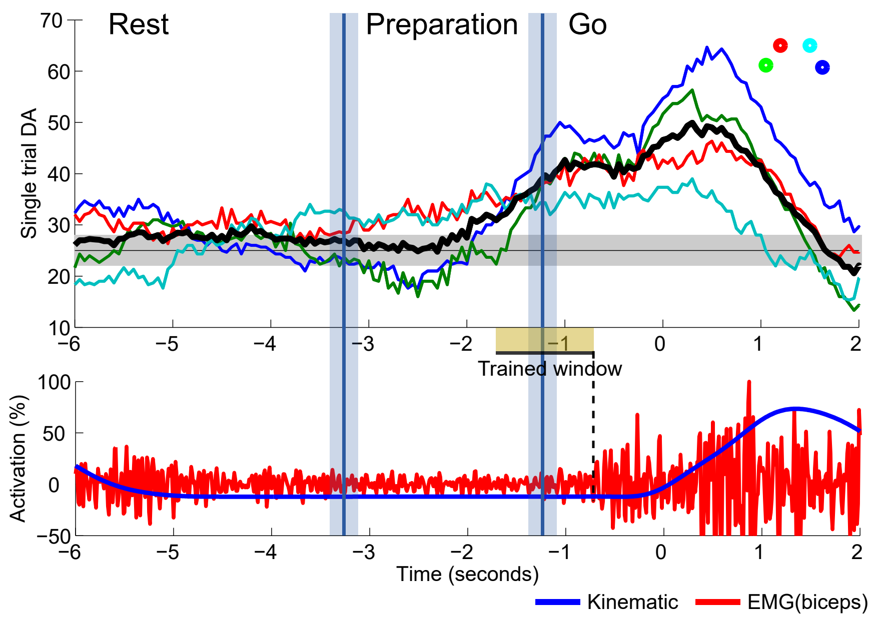


Figure 3.3: Average DA, training with the epoch right before the EMG activation, across subjects (black line) and target-specific DA (colored lines) in the top figure. Top-right corner shows the spatial distribution of the targets. Kinematic (blue) and EMG, biceps, (red) in the bottom. Blue vertical lines show the times when the cues were shown (Notice that these times are not fixed because the trials are aligned to the kinematic onset. Blue shaded areas represent this variability). Additionally, in the x-axis of the top figure, the window (epoch) used for training the classifier is shown as a yellow shaded area.

3.3 Analysis of potential artifacts

Finally, the influence of the potential artifacts in the recorded data was evaluated. For that, we computed the DA for the entire set of channels independently. Thus, Figure 3.4 illustrates the DA for each channel and some representative time points in the interval between -3 and 1 second. PreKin and PreEMG refer to the epoch used in the training (the one-second epoch right before the kinematic activation and the one-second epoch right before the average EMG activation (-0.8 seconds before the kinematic onset, respectively). In both cases, the channels with the highest performance are the ones placed over the contra-lateral motor cortex. Interestingly, before the movement execution (before -1 s) only the contra-lateral channels show performances above the chance level (25 %, dark blue).

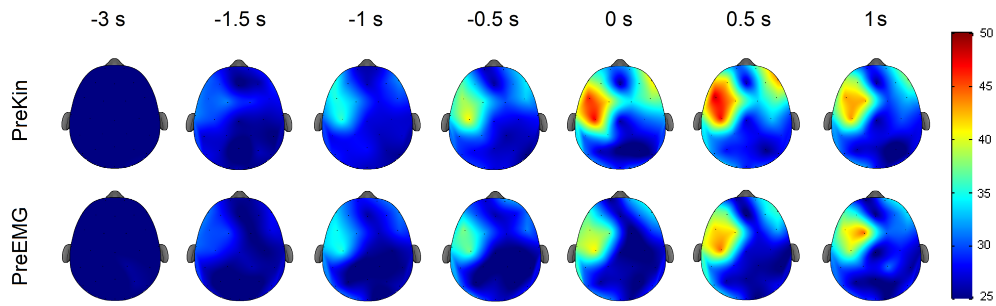


Figure 3.4: Single channel DA for each channel during the trial. Times correspond to the end point of the one second epoch classified. PreKin and PreEMG refer to the epoch using in the training

We computed the correlation matrix of the 32 EEG channels and the kinematic during the [0,2s], when the motion artifacts could be contaminating the signal. Figure 3.5 shows the correlation of the most representative channels: those placed over the contra-lateral motor cortex (used in the decoding), peripheral ones, F7, T7, Fp2 or T8, (more prone to be affected by motion artifacts) and the kinematic signal. There is a high correlation in the contra-lateral channels. On the other hand, peripheral channels show a low correlation with the others and, especially with the contra-lateral ones which means that they are not sharing too much information as in a strongly artifacted data would happen.

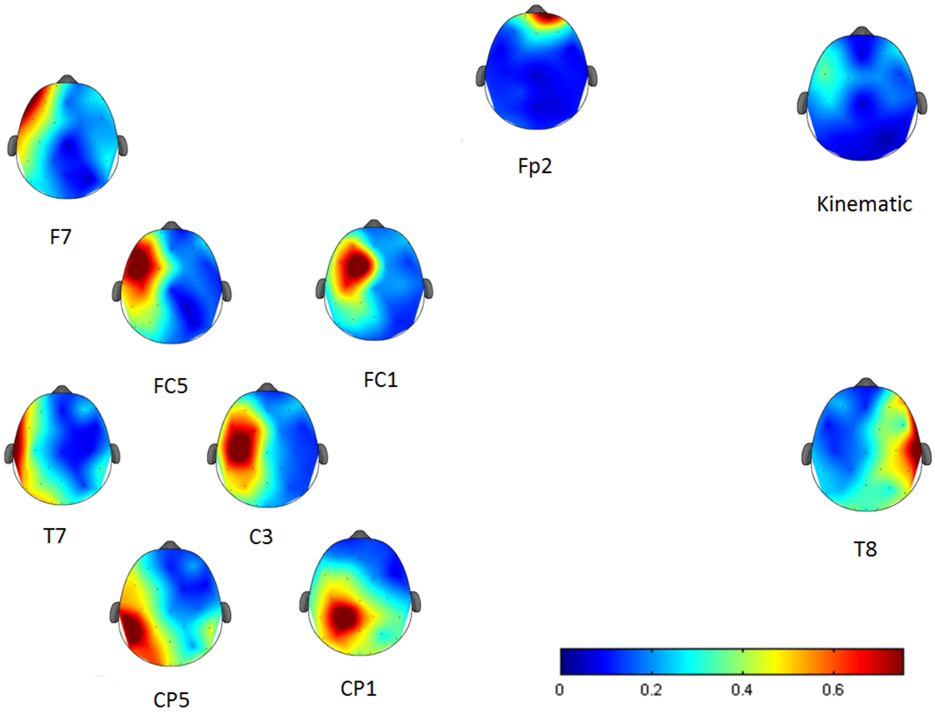


Figure 3.5: Correlation of the channels(in a their original place of the head) and the kinematic (placed in the top-right corner), during the motor execution [0, +2] s, being 0 the kinematic onset.

4. Conclusions and Future Work

4.1 Conclusions

In the present study, we confirmed the feasibility of decoding four different reaching directions from EEG. A hierarchical scheme was proposed with a first classifier identifying when the subjects want to move, and a second one decoding the exact movement to be performed. The results obtained are promising and show the proposed decoder as a potential tool for being included in future BCI-based rehabilitation therapies. This is also, to our best knowledge, the first EEG-decoder for different arm movements proposed that could be implemented in a real-time application.

Several studies had shown a hight performance classifying different movements of the same limb using invasive methods of recording (i.e, ECoG ([Ball et al., 2009]) or LFP ([Rickert et al., 2005])). Regarding non-invasive methods, recent studies present an acceptable performance classifying different wrist ([Vuckovic and Sepulveda, 2008]) or finger movements ([Liao et al., 2014]). However, different arm-movements decoding seems to be more difficult since the cortical representation area for the arm is smaller than that for the hand/wrist ([Gu, 2009]). More recently, a few preliminary works on decoding different arm movements showed promising results in offline analysis ([Iturrate et al., 2016, Shiman et al., 2015, Ofner et al., 2016]). Compared to these works, our proposed decoder achieves a slightly lower decoding accuracy. However, it is difficult to do a fair comparison since these works use non-causal methods which lead to a significant performance increase ([Bibián, 2015]).

The proposed hierarchical decoder, based on [Hotson et al., 2016], presents two different classifier layers. Once the EEG signal is processed, a binary SVM based on ERD features discriminates between rest and movement intention brain states. After that, if this movement intention was detected, a second SVM classifier, this time based on LFC features (<4 Hz), classifies the EEG signal into the different arm movements. The results obtained for both classifiers, discussed below, demonstrate the feasibility of the proposed decoder for driving an arm exoskeleton o any other external rehabilitative device.

The movement intention results show a decoding accuracy (DA) slightly above the chance level during the motor preparation (-1.5 seconds before the movement starts) and climb to 78% during the movement execution. This results shows a good temporal resolution of the proposed decoder, since it is able to decode de movement consistently one before the movement starts. In addition, this DA remains constant during the execution time, showing a smooth and reasonably high DA due to the fact that the desynchronization occurs during the entire execution time ([Ramos-Murguialday and Birbaumer, 2015]). This result presents the ERD features used as reliable brain signatures for controlling an arm exoskeleton.

Results for four classes show a DA, significantly above chance level during the preparation time, 43%, and rises to 59% during the movement execution time. Thus, this results obtained using the <4 Hz band in different arm movements classification, confirm the findings presented in [Ball et al., 2009, Waldert et al., 2008]. However, this low-frequency band is frequently strongly polluted with motion artifacts [Islam, 2015] so that the directional movement information found in the low-frequency can also contain some non-EEG information (i.e., motion artifacts).

Even though most of the studies apply some artifact filtering techniques before analyzing or classifying EEG signal, we decide not to apply these methods based on [Pontifex et al., 2016] findings: these methods could produce an amplitude variation in low-frequency components and introduce variation across the data. Alternatively, we propose some test in order to evaluate if the EEG data is somehow contaminated by artifacts. According to the results obtained in these tests we strongly believe that the information used in the movement direction classification is due to the brain signatures presented by [Ball et al., 2009] and [Waldert et al., 2008] and not to motion artifacts.

In summary, in this study we have demonstrated that different arm movements can be classified from EEG in healthy subjects. During the motor execution, the decoding accuracy achieved is over 78 % for the movement intention and around 59 % for the movement direction decoding. Although this analysis was performed offline, all the methods applied as well as the performance evaluation were implemented as they would be in a real-time application.

However, these results were achieved in healthy subjects, so that, a further investigation in paralized patients is required. These patients suffer a cortical reorganization ([López-Larraz et al., 2015, Tangwiriyasakul et al., 2014]) which might lead to a less accurate decoder. Thus, several methods can be introduced in the decoding scheme in order to improve the accuracy (i.e., EMG signals [Ramos-Murguialday et al., 2015]). Finally, even though this study was focused on stroke patients, the platform can be also used for spinal cord injury (SCI) patients ([López-Larraz et al., 2014]).

4.2 Future Work

Once we have demonstrated the feasibility of the proposed decoder in a pseudo-online evaluation, the next natural step would be to implement the platform to translate the information from the brain into motor commands for driving an arm exoskeleton. However, the output of the proposed decoder is a target (direction of the movement, if any) each 50 ms which, most of the time, would result in twitching movements. Smoothing the decoder output applying a time filter could solve this problem ([Sarasola-Sanz et al., 2017]).

Although the decoder was trained using signal before the actual movement starts, during the movement execution, EEG signals are usually corrupted by motion artifacts. Thus, additional experiments can be done in order to test the presence of artifacts during the movememnt period. Hence, the experiments could be replicated, but adding an accelerometer fixed in the EEG cap. A recent study, [Castermans et al., 2014], demonstrated that EEG and accelerometer signal exhibit similar time-frequency properties and is specially focused in low delta band. Thus, based on the methods proposed by [Castermans et al., 2014], these new recordings would allow us to check the correlation between the acceleration data and the low-frequencies EEG.

The aim of this study was to propose a real-time implementable EEG decoder that could potentially enhance the rehabilitative outcomes. Thus, the last and expected step would be to perform experiments with stroke patients. In these experiments, we would be able not only to test the platform itself but also to investigate the best configuration to promote motor recovery in severely paralized patients.

4.3 Work implemented by the student

The work implemented during this study is detailed bellow:

- Analysis of the state of the art and bibliography.
- Implementation of the scripts needed for loading and synchronize the EEG, EMG and Kinematic data.
- Implementation of the scripts for the signal processing: frequential and spatial filters and spectral density estimation methods.
- Implementation and evaluation of different machine learning algorithms.
- Implementation of the script used for test the pseudo-online performance of the proposed decoder.

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