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Preface

For this edition of the Brazilian Conference on Biomedical Engineering (CBEB2020 – Congresso Brasileiro de Engenharia Biomédica), 665 papers were submitted, composed of 564 scientific articles (4-6 pages) and 101 Scientific Communications (Abstracts up to 2 pages). After the first round of reviews, 595 papers were accepted (514 full papers and 81 scientific communication). These 595 articles underwent a second review round, and at the end 551 papers (478 full papers and 73 scientific papers) were accepted to be presented at CBEB2020.

CBEB is promoted by the Brazilian Society of Biomedical Engineering (SBEB), with biannual periodicity, organized by researchers linked to a local research institution, with the collaboration of the entire scientific community linked to the area of Biomedical Engineering in Brazil. CBEB2020 was held on October 26-30, 2020 in Vitória (Brazil) and was organized in the following tracks:

- Clinical Engineering and Health Technology Assessment
- Biomaterials
- Tissue Engineering and Artificial Organs
- Bioengineering
- Biomedical Devices and Instrumentation
- Biomechanics and Rehabilitation
- Neuroengineering
- Biomedical Signal and Image Processing
- Biomedical Robotics, Assistive Technologies, and Health Informatics
- Biomedical Optics and Systems and Technologies for Therapy and Diagnosis
- Basic Industrial Technology in Health
- Special Topics

We would like to thank the sponsors CNPq and FAPES for making it possible to celebrate this event in times of uncertainty due to the COVID-19 pandemics.

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Analysis and Classification of EEG Signals from Passive Mobilization in ICU Sedated Patients and Non-sedated Volunteers

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Abstract— **Electroencephalography (EEG) has been the focus of research and advances for many years, yet there are several tasks to be explore and methods to be tested to improve analysis and classification. Event-Related Potential (ERP) is one of the brain responses measured with EEG, resulting from motor tasks usually are related to motor imagery or real movement. This study aims to analyze and classify event-related desynchronization (ERD) and event-related synchronization (ERS) occurred in tasks involving passive mobilization in Intensive Care Unit (ICU) sedated patients and non-sedated volunteers. Our main goal is to provide preliminary analysis and comparisons between sedated and non-sedated groups based on signal visualization and a classifier. Common Spatial Pattern filtering (CSP) and visual inspection of best band and time were used to verify signal and phenomena. From that, specific features (i.e., Root Mean Square, standard deviation, mean of Welch periodogram and differential entropy) were extracted based on time and frequency to apply a Linear Discriminant Analysis (LDA) classifier. Once the two Intensive Care Unit sedated patients and the two volunteers were analyzed, it was possible to observe the proposed phenomena. Mean accuracy in the best scenario and best person for each group (two people in each group) was found higher than 80% and 77% to sedated and non-sedated participants, respectively. Preliminary results, based on four participants (i.e., two sedated and two non-sedated patients), suggested lateralization in tasks performed with passive mobilization and provided accuracy comparable to previous studies involving motor tasks.**

Keywords— **EEG, Passive Mobilization, Event-Related Potential.**

I. INTRODUCTION

New processing methods and advances in the knowledge of brain functionality with electroencephalography (EEG) employing Brain Computer Interfaces (BCI) have evolved to more complex tasks in biomedical engineering and clinical applications [1]. It is now possible to control prostheses [2], wheelchair [3], consciousness levels [4] and diseases diagnostics [5] using EEG signals. Expected alterations in the EEG signal, such as P300, somatosensory evoked potential (SSEP) and event-related desynchronization (ERD)/event-related synchronization (ERS), therefore can be used to control or activate a device.

The analysis of a specific sensory output, cognitive or motor event allows observation of an Event-Related Potential (ERP) in different parts of the brain [6]. Executing or imagining the movement in both hands cause the phenomena of ERD in the contralateral side before movement and ERS in the ipsilateral side after execution [7]. This phenomena is observable in α and β rhythms [1, 6]. ERD and ERS are analyzed to evaluate the difference between left and right hand movements in passive mobilization in both sedated and non-sedated participants, the use of ERD and ERS are analyzed. The definition of the relative energy, used to identify ERD and ERS was presented in [8].

This study presents a preliminary analysis of ICU sedated patients and non-sedated volunteer's EEG signals during passive mobilization in both hands were used to compare the phenomena and classify different individuals and groups. Such analysis can be applied to observe motor responses in ICU based patients in passive mobilization, allowing in future communication and alteration in state of consciousness analysis. EEG signals are collected with an EPOC electrode cap by *EMOTIV* with 14 electrodes based on 10-20 system [6], this neuroheadset has been already used to ERD/ERS phenomena in [9]. The signal is pre-processed using digital and CSP filtering, features are extracted based in time and frequency. RMS value, standard deviation, mean of Welch periodogram and differential entropy are calculated. Finally, the features are classified in two classes in a Linear Discriminant Analysis (LDA) classifier.

II. METHODOLOGY

A. Experiment Format

Signal acquisition is performed in order to configure a synchronous BCI system, therefore passive movements were carried out by the physiotherapist at specific time. The first two seconds were defined as the pre-stimulus interval, the next

Table 1: Timing in a Trial

Events	Reference	Stimulus	Post-Stimulus
Interval Time (s)	0-2	2-4	4-7

Table 2: Subjects and Respective quantity of Movements

Subject	Non- Sedated 1	Non- Sedated 2	Sedated 1	Sedated 2
Movements	100	100	50	100

two seconds were movement time interval performed by the physiotherapist and the last three seconds were defined as the post-stimulus period, time intervals presented in Table 1. EEG signal are collected throughout the experiment. Each trial consists of a randomly defined movement representing the flexion of the left or right arm. Each section consists of 10 trials and *n* sections were performed per participant (10 sections for the two Non-Sedated and for 'Sedated 2', and 5 to 'Sedated 1'). Table 2 indicates the number of movements performed by each subject. Total number of trials is balanced between right and left movements.

Signal acquisition is done using an *Emotiv Epoc* cap via an interface with *Labview 13*, running in a laptop with *Windows 10*, at a rate of 128 Hz. Time intervals and a random sequence of movements were generated in *Labview*. All data, channel-acquired signals, and stimuli performed (setting the value '1' for the subject's left arm stimulus and '2' for the right) were saved in *.lvm* files. All the remaining signal processing was done in *Matlab 2012b* running on *Windows 10*.

The Sedated Patient admitted to the ICU had to comply with the following inclusion criteria:

- Adult patients of both genders;
- Patients over 18 years old;
- Patients using continuous sedoanalgesia with Richmond Agitation Sedation Scale (RASS) -3 to -5;
- Patients on invasive mechanical ventilation between 48 and 72 hours;

For the control group, inclusion criteria was adult volunteers without previous neuromuscular disorders. The procedure is performed to simulate the environment of an ICU, therefore, the volunteer keeps their eyes closed while lying down with neck support. A physiotherapist performed the movements for both groups.

All procedures performed in the acquisition of this dataset which involved human participants followed the ethical standards of the institutional review board and the 1964 Helsinki declaration and its later amendments or comparable ethical standards. All procedures performed were approved by the institutional research committee under the Certificate of Presentation for Ethical Appreciation (number: 11253312.8.0000.5347).

Other comparable trials stimuli formats can be found in [7, 10, 11, 12, 13].

B. Emotiv Epoc Neuroheadset

An *Emotiv Epoc* neuroheadset was employed in the present study. This is a commercially available EEG portable cap based in 10-20 system, with 14 signal electrodes and two reference electrodes, 14-bit, 1 LSB resolution. Positioning was based on standard 75 electrodes, acquisition rate was 128 Hz. Signal was digitally filtered from 0.2 to 45Hz, notch filtered at 50 and 60 Hz and range from 8400 uV.

C. Preprocessing

First, signal was filtered at the frequencies relative to the analyzed phenomena. A fourth order digital Butterworth filter in the 8 to 30 Hz range applying the *filtfilt* function was implemented. The *filftfilt* function does not contribute to phase changes in the data, only attenuates the signal in amplitude. Second, the filter was centered in a frequency specific for each subject, which was based on visual inspection of lateralization index in the frequency domain. This was selected using a Welch periodogram in channels FC5 and FC6 (channels next to motor cortex). Time window was set based on the lateralization in these channels. This was a two-second time window, which was set between "second 2" and "second 5", at movement start and one second after movement end (see Table 3). Lateralization in frequency and time domain based analysis was implemented in [11, 13].

The next step was to apply the CSP filter in all left and right hand trials in all electrodes. CSP filters are commonly used in EEG experiments to minimize the effect of unwanted signals captured from other regions of scalp which are not of interest. So, the filter was applied to maximize discrimination from a sample space transformation, facilitating differentiation between two classes. The filter application was performed by a function developed in Matlab based on [14]. Two CSP channels with the largest discrimination between classes were chosen after filtering and were defined as CSP1 and CSP2. This selection of two channels are used to compare results with analysis of channels FC5 and FC6 without CSP filter applied.

D. Feature Extraction

After Preprocessing we start with a Feature Extraction to utilizy in classifier. Our signal classification characteristics were based on previous work [15], which performed classification with these features, but applied in a non-combined way. Thus, the characteristics extracted presented non-combined high hit rates when used in BCI systems, namely: RMS value, standard deviation, power spectral density (PSD) and differential entropy (DE). These features are calculated on signal preprocessed with digital filters and for the selected channels processed with CSP filter.

RMS was calculated for each track using the *rms* function and the standard deviation using the *std* statistics function. The use of standard deviation and RMS values is interesting when applying ERD / ERS detection, since these phenomena alter the amplitudes more sharply on one side of the brain.

PSD was estimated using the Welch periodogram method, Fourier transform dependent method. This method uses overlapping windows and is commonly used for EEG signals because it is not stationary in time but can be considered stationary in short periods of time (i.e., 1 to 2 s), so from the overlapping window it is possible to decrease the random error for windows up to 50 % overlay [16, 17]. We applied the function *pwelch*, with Hamming window function and frequency one sided with interval [0, fs/2] (cycles/unit time), available in *Matlab* and performed the average magnitude in frequency.

The differential entropy method measures the complexity of a continuous variable with a stochastic character. It is shown in [18] that the EEG signal can be related to a Gaussian distribution, from which DE can be roughly calculated by the expression in (1). DE is used to extract characteristics that are harder to find by using statistical metrics such as mean and standard deviation.

$$DE = \frac{1}{2} log\left(2\pi e \sigma_i^2\right) \tag{1}$$

E. Classification

An LDA classifier with cross-validation utilizing 10 folds was used for signal classification. Cross-validation was applied over the feature set, which randomly select a feature set for training. Average test error over all folds was calculated. For each subject the classifier was trained 100 times. Mean and standard deviation for all trials during training was obtained. A LDA classifier is commonly utilized to classify this type of EEG data and presents good results [19].

III. Results and Discussion

A. Preprocessing and Signal Visualization

For the proposed experiment and dataset, when compared with others datasets using the same preprocessing and visualization [10, 11, 13], the ERD and ERS was not so clear to observe in α rhythms for all participants before CSP filters. Fig. 1 shows the lateralization in channels (the *Emotiv* electrodes FC5 and FC6 and the CSP generated channels CSP1 and CSP2) for each movement and subject. It is evident that the channels generated by CSP filter are better to find the phenomena. Therefore, CSP filter works well to maximize the difference between these two classes of signal. When analyzing lateralization, in frequency and time domains, the result in CSP shows evident occurrence of these phenomena. The electrodes positioning in the Emotiv Cap can be a reason for the difficulty in finding the characteristics of ERD/ERS in FC5 and FC6 channels. When analyzing the signal after all preprocessing is possible to observe the phenomena in both groups (sedated and non-sedated subjects).

Table 3 displays mean and standard deviation of central frequency and time for each group defined after visual inspection and signal analysis. Statistical analysis showed that there was no significant difference between non-sedated and sedated participants.

B. Classifier

Classification accuracy results are presented in Table 4. Mean of all 100 loops using different random training groups in classifier was calculated for each subject. The method with and without frequency and time windows selection was also tested.

Sedated Subject 2 showed the best result, with 80.1±0.95 % average accuracy using the selected frequency and time windows. All means were higher than 60% without the specific time and frequency and higher than 71% when used the specific time and frequency windows. When comparing the

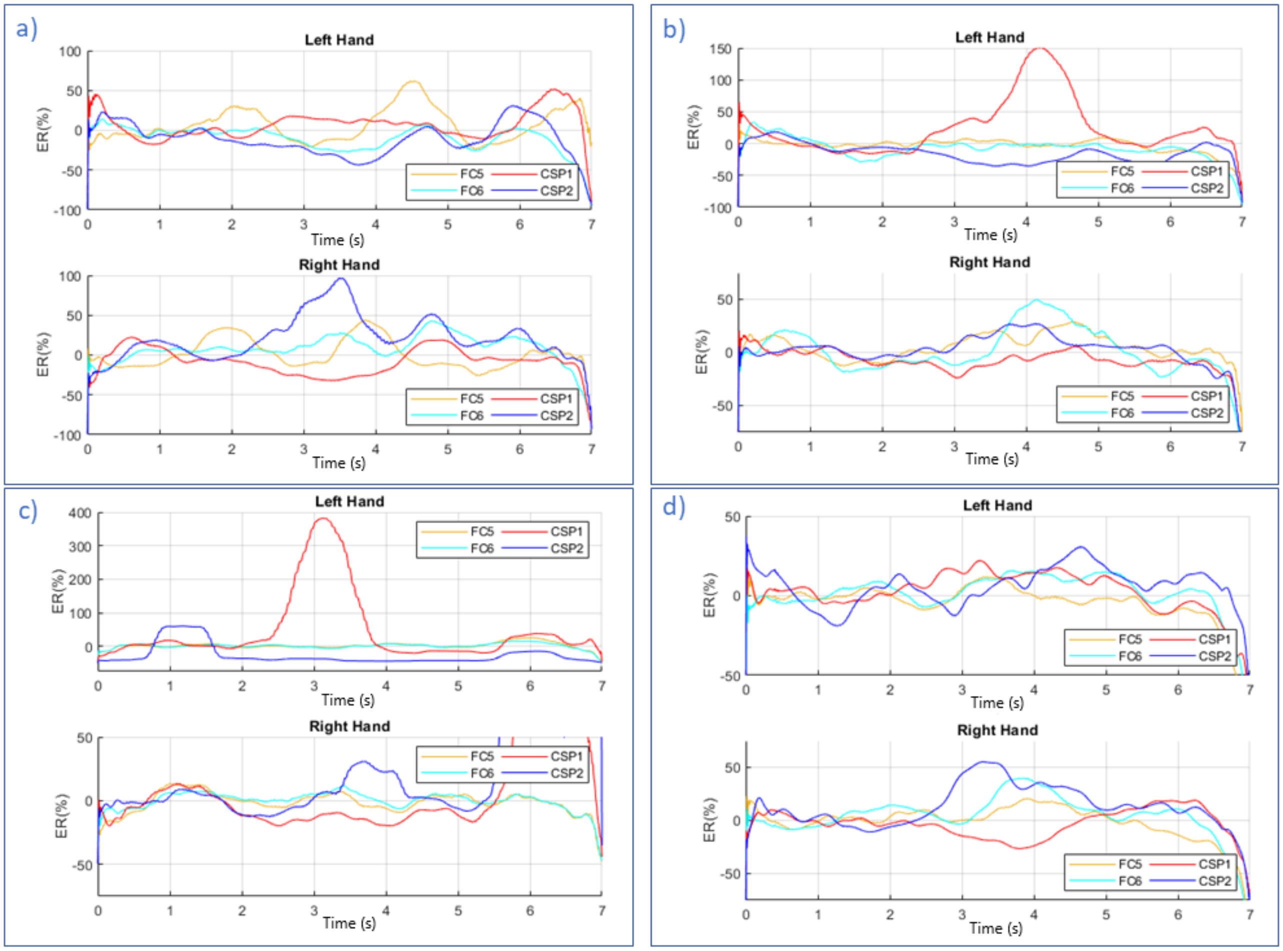

Fig. 1: Mean of Relative energy for all trials for each movement using channels: FC5,FC6, CSP1 (CSP channels with the largest discrimination for class left) and CSP2 (CSP channels with the largest discrimination for class right) for: a) Non-Sedated Subject 1 (50 movements each hand), b) Non-Sedated Subject 2 (50 movements each hand), c) Sedated Subject 1(25 movements each hand) and d) Sedated Subject 2 (50 movements each hand). Movements starts at second 2 and ends at second 4

two groups all average accuracy was compatible to experiments employing motor imagery or real movements. They are also compatible with each other.

Visualization of ERD and ERS and accuracy are improved when analyzing signal and accuracy in the specified best time and best frequency for each subject. This suggests that setting these parameters is necessary. Frequency and time window comparison for all subjects were significant parameters to classify movements.

IV. Conclusions

The proposed method using CSP filter, frequency and time windows analysis, RMS, standard deviation, PSD and DE like features and LDA as classifier allowed ERD/ERS visual analysis and classification for passive movements in the studied groups. Results of signal analysis and classification are comparable to previous research [11, 12, 13].

More specifically, when comparing accuracy rates with previous studies [7] using Emotiv headset and motor imagery. Better results were around 85% for BCI Competition Dataset II (motor imagery experiment datasets with 280 trials and one volunteer) and 79% with two volunteers (motor imagery experiment with 140 trials per volunteer), when applying CSP filters to select two CSP channels and a Naive Bayes classifier.

Based on the characteristics of signal and the difficulty to analyze and classify, this kind of dataset and method can be used for many other studies to improve the classification or visualization of phenomena. For example, monitoring EEG

Table 3: Mean Frequency and Time Window defined for each group

Group	Initial Frequency (Hz)	Final Frequency (Hz)	Initial Time (s)	Final Time (s)
Non-Sedated	11.5 ± 2.12	16.5 ± 2.12	2.25 ± 0.35	4.25 ± 0.35
Sedated	10.5 ± 3.54	15.5 ± 3.54	2.5 ± 0.35	4.5 ± 0.35

Table 4: Accuracy rate for each Subject

Subject	Non-Sedated 1	Non-Sedated 2	Sedated 1	Sedated 2
Accuracy without Frequency and Time Windows selected (%)	67.7±1.1	60.5±1.0	64.9±2.7	69.5±1.6
Accuracy with Frequency and Time Windows selected (%)	77.8±0.6	71.6±1.0	74.9±1.5	80.1±0.95

signals in ICU or surgery settings, and physiotherapy protocol analysis (i.e., passive mobilization in sedated and non-sedated patients).

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