# EEG Signal Synchronization Patterns During Hand Laterality Judgment Task

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*Abstract*— **Motor imagery is a mental stimulation that triggers oscillatory events in sensorimotor rhythms often used in brain-computer interface applications, as well as a stimulus used to understand brain activity and improve the rehabilitation process of spinal cord injury people. Using the data extracted from an electronic game designed for a rehabilitation purpose, this paper describes the steps to extract the EEG synchronization patterns during the Hand Laterality Judgment Task that stimulates motor imagery processes, i.e., implicit motor imagery. As result, we obtained the curves of synchronization, in $dB$ values, that showed different levels of synchronization between alpha and beta bands and an activity mostly distributed over centro-parietal and parietal regions.**

*Keywords*— **Mental Rotation, Hand Laterality, ERD/ERS**

## I. Introduction

The decrease and increase in synchronization of the sensorimotor rhythms (SMR) are called event-related desynchronization (ERD) and event-related synchronization (ERS), respectively [1]. ERD/ERS phenomena are also known as an event-related spectral perturbation (ERSP) and it occurs during the motor imagery (MI) process, in which the subject imagines the movements of their body parts, commonly the hands, but also involving the foot and tongue, performed in repetitive trials. In the hand actual or motor imagery activity, the ERD patterns are, preponderantly, contralateral in the function of the hand imagined whilst the ERS are ipsilateral [2].

Electroencephalography (EEG) is an important tool to investigate brain activities, due to it is a noninvasive technique, relatively low-cost, and high temporal resolution [3]. Therefore, works using EEG data to estimate ERD/ERS patterns have been documented in the literature, focusing on classification problems, which is a fundamental step to the Brain-Computer Interface (BCI) systems application [4, 5]. For MI, the time-frequency analysis has key-role in the detection and estimating of the ERD/ERS values [3], since the motor imagery task induces events that modulate the ongoing alpha ($8-12$ Hz) and beta ($13-30$ Hz) activities [2], frequencies that compound the SMR. The modulation of the alpha and beta bands can be express, for instance, in relative change (unit in %), power ration (unit in $dB$), and subtraction (unit in $\mu V^2/Hz$) [3].

The methods for ERD/ERS estimation have importance to BCIs based on motor imagery also called MI-BCI. MI is extensively used in BCI systems due to discriminative stimulus proprieties, translated into EEG synchronization values, and also to involve a not expensive signal acquisition [6]. The experimental paradigm for motor imagery stimulated with a cue, in repetitive trials for each class, has been reported in research, with the goal to enhance MI-BCI systems accuracy [7, 8]. When the motor imagery is stimulated in an indirect way, we have implicit motor imagery. For instance, the hand mental rotation engages motor imagery processes, because the subject imagines their hand rotating for a position. This protocol is often used when the goal is to identify hand laterality presented on a screen, that can be called Hand Laterality Judment Task (HLJT) [9]. Osuagwu *et al* (2017) reported a classification performance of $83\pm3\%$ for implicit motor imagery of the left and right hand, whilst for explicitly stimulated motor imagery the performance was $81\pm8\%$ [10], showing the possibility to use implicit motor imagery for BCI application, until little described in the literature.

In the present study, a method to extract ERD/ERS values during HLJT was implemented. The research investigated how the task influence the oscillatory activity in SMR of the subjects performing a rehabilitation electronic game, described in the pioneer work [11], and called Alice in Land of the Hand, or only ALICE game.

## II. Methodology

### A. Participants

To perform ALICE game, twenty-three subjects participated (age: $25.65\pm3.88$ years), identified as $S_1, S_2, ..., S_{23}$. According to Edinburgh Lateral Dominance Inventory, 95% of the subjects were right-handed. One of the participants declared mixed preference. According to Mini-Mental State Examination (MMSE) all participants had no cognitive impairment. Furthermore, all subjects had no medical or neurological disorders and they hand-signed the Free and Informed Consent to participate of the experiment. The project was approved by the Ethics Committee of the University Hospital Onofre Lopes (HUOL/UFRN), released with CAAE number (Brazil Platform): 34478214.0.0000.5292 and appreciation number: 821294. We prejudged the subject's performance and in this step, the data from the $S_5$, $S_{17}$, and $S_{20}$ subjects were eliminated. $S_5$ closed their eyes as a technique to response, increasing the amplitude of the alpha band. $S_{17}$ was eliminated due to be left-handed and, in the research context, the hemisphere dominance difference is not a desirable feature. $S_{20}$ failed in 104 trials of the 288 trials. Thus, the data from 20 subjects were used in the present work.

### *B. Experimental Paradigm*

The game was development in collaboration between Brain Institute and the Department of Informatic and Applied Mathematics (DIMAP), both of the Federal University of Rio Grande do Norte (UFRN) [11], and the game was programmed in C language with the XNA Microsoft framework.

In the game world, a robot from the ALICE family disputes with an enemy robot on an electronic board game setting, and to take advantage over it, the participants should answer correctly the hand laterality that appears above the ALICE robot, inside circles. To perform the game, the subjects were seated on a comfortable chair, located 50 cm away from a monitor (Figure 1). Then, they were asked to analyze and judge if the hand presented on the screen was left or right (HLJT) and then, press down the respective pedal (left or right) using their respective foot (left or right). The final score for each trial was based on reaction time (RT), i.e., the time from the stimulus shown on screen until the subject pressed down the pedal. The main goal was to be accurate with the shortest RT.

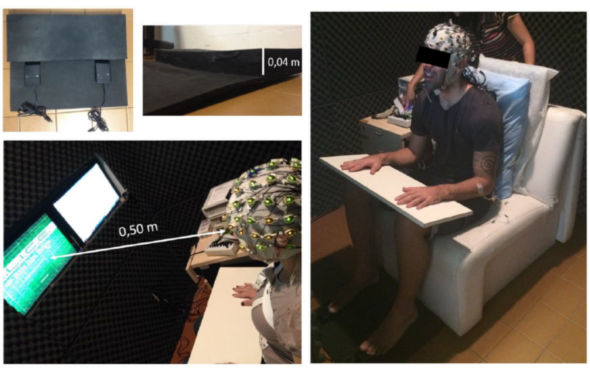


Fig. 1: Environment setting to perform ALICE game.

The hand presented have four features: laterality (left and right), orientation ($0°, 60°, 120°, 180°, 240°, 300°$), view (back-view and palm-view), and posture (extension and flexion), in which the flexion posture was presented in three different conditions. These features are shown in Figure 2 (A). So, there were 96 types of stimuli: left/right (2) $\times$ view (4) $\times$ orientation (6) $\times$ posture (2), but in this work, only trials with hand in back and palm-view were selected. The orientations $0°, 60°, 120°$ are classified as comfortable, due to being biomechanically easy to execute, and the orientations $180°, 240°, 300°$ are labeled as uncomfortable, being difficult to perform [12]. In total, 288 trials were performed by the participants, divided into three blocks. As seen in Figure 2(B), the trial begins with a cross on the screen. $1500\,ms$ later, the image of the hand is shown and stays on the monitor until the subject responds. Next, the robot gives the feedback with a score based on RT. This feedback remains for $1000\,ms$ and it is the final part of the trial.

### *C. EEG signal acquisition and Preprocessing*

The EEG signals were recorded at a sample rate of 1000 Hz with 64-channel ActiCap$^{TM}$ (Brain Products GmbH, Munich, Germany) and using the Vision Recorder (Version 1.20.0506, Brain Products GmbH, Munich, Germany). All electrodes were referenced to FCz, with impedance less than $10k\Omega$ and after EEG recording, the signals were re-referenced to the average of the left (TP9) and right (TP10) mastoids. Ocular artifacts were removed using the automated correction method of EOG based on regression analysis, using the BIOSIG toolbox [13], and three electrooculogram (EOG) electrodes were placed. The EEG data were digitally filtered with a 0.5-40 Hz band-pass FIR (Finite Impulse Response) filter and signal amplitude values exceeding $\pm 100\mu V$ were automatically detected and rejected. The preprocessed EEG data were segmented into epochs defined in $[-500\,ms, 1500\,ms]$, i.e., $500\,ms$ pre-stimulus and $1500\,ms$ after the visual stimulus, that is the average of the RT for all subjects. The $500\,ms$ pre-stimulus, of each trial, was used as baseline period, to compare the power changes after the visual stimulus.

### *D. ERD/ERS Estimation*

To quantify the synchronization levels in alpha and beta bands, in decibel ($dB$), the following equation was used in each trial:

$$ERD/ERS = 10 \times \log_{10}\left(\frac{|F(f,t)|^2}{|\bar{F}(f,t)_{baseline}|^2)}\right) \qquad (1)$$

where $|F(f,t)|^2$ is the power extracted after the visual stim-

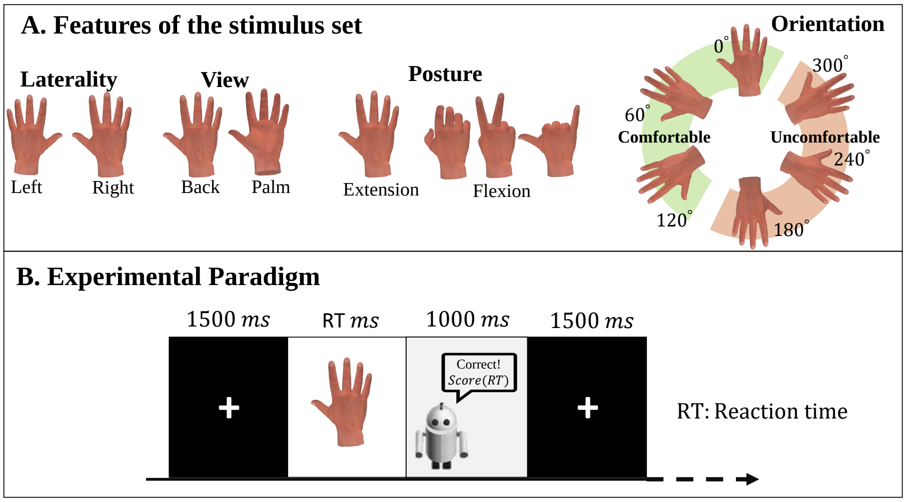


Fig. 2: A. Features of the stimulus. B. The experimental design of the game, involving the HLJT.

ulus and immediately before the act of press down on the response pedal, and $|\bar{F}(f,t)_{baseline}|^2$ is the power during the rest interval (baseline period) [3]. The Welch's method [14] was used to estimate the periodogram, i.e., the power spectral density (PSD) [3].

To implement the method, the epoch $[-500ms, 1500ms]$ was segmented using a rectangular window with length of $N = 500$ samples and step of 250 samples. The segment of $N$ samples was divided in $L = 250$ parts, with $D = 125$ overlapping samples, following the Welch's method, and resulting in $x_k(l) = x(l + (K-1)D)$, where $l = 0, 1, ..., L-1$. So, we have $k = 1, 2, ..., K$ segments, i.e., $x_1(l), x_2(l), ..., x_K(l)$. For each $k = 1, 2, ..., K$ segment, the Fast Fourier Transform (FFT) $A_k(n)$ was extracted, with the signal windowed by Hanning function [15, 16]. Then, the modified periodogram given by:

$$I_k(f_n) = \frac{L}{U}|A_k(n)|^2 \tag{2}$$

is estimated for each segment, where $f_n = n/L$ and $U$ is the window normalization factor, given by

$$U = \frac{1}{L}\sum_{l=0}^{L-1} w^2(l) \tag{3}$$

where $w(l)$ is the Hanning window. As result, we have $K$ modified periodograms $I_k(f_n)$. Thus, a mean is calculated among these periodograms, resulting in

$$\widehat{P}_k(f_n) = \frac{1}{K}\sum_{k=1}^{K} I_k(f_n) \tag{4}$$

i.e., the mean modified periodogram.

Trials with incorrect response, with hand movement detection during the RT [17, 18], without markers, with RT greater than $3500ms$ or smaller than $500ms$ [19], or EEG signal amplitude saturation $(\pm 100\mu V)$ were automatically removed.

## E. Region of Interest

The ERD/ERS patterns were analyzed in nine different regions: Full-montage, Reduced-montage, Simplified-areas, Frontal, Fronto-central, Central, Centro-parietal, Parietal and Occipital (see Board 1 and Figure 3). The goal was to investigate the activity of each brain region during the HLJT and the synchronization pattern.

Board 1: Regions of Interest and EEG channels selection.

| Region | EEG channels |
|---|---|
| Full-montage | 62 channels |
| Reduced-montage | 32 channels |
| Simplified-areas | F3, F4, FC3, FC4, C3, C4, CP3, CP4 P3, P4, PO3, and PO4 |
| Frontal | F1, F2, F3, F4, F5, and F6 |
| Fronto-central | FC1, FC2, FC3, FC4, FC5, and FC6 |
| Central | C1, C2, C3, C4, C5 and C6 |
| Centro-parietal | CP1, CP2, CP3, CP4, CP5, and CP6 |
| Parietal | P1, P2, P3, P4, P5, and P6 |
| Occipital | PO3, PO4, PO7, PO8, O1, and O2 |

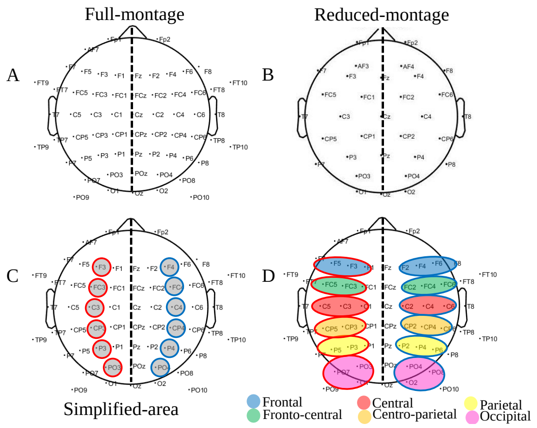

Fig. 3: Regions of Interest.

### *F. Statistical Analysis*

Two statistic steps were performed, in order to confirm the main region(s) involved during the HLJT. In the first step, the main factors were HEMISPHERE (Left and Right), REGION (Frontal, Fronto-central, Central, Centro-parietal, Parietal, and Occipital), and FREQUENCY (alpha and beta), with the dependent variable being the mean ERSP. After the first step and following the results, the second analysis was performed including the hand features (LATERALITY, VIEW, ORIENTATION, POSTURE) and the average values of the ERSP, in order to analyze the influence of the features on ERD/ERS values. To perform the statistic, the Generalized Estimating Equation (GEE) method was used [20, 21] and the significance level is $p = 0.05$.

## III. Results

The ERD/ERS resulty curves, in $dB$, are shown in Figure 4, for alpha and beta bands, respectively, including the features of the stimuli (orientation, view and posture), for each region of analysis (Board 1). The synchronization changes are more evident in alpha frequency than in beta frequency. An increase in alpha band is detected during the first $500\,ms$ after the visual stimulus (see Figure 5), following by an accentuated desynchronization, more evident in the alpha band and in parietal and occipital lobes, that include the central, parietal, and occipital regions, but also in frontal region. The ERD/ERS distribution during the HLJT, differently in explicit motor imagery, has a distributuion more uniform over the cortex, mainly over parietal and occipital lobes. Also, we can see in Figure 5 that the desynchronization is present in both bands.

The first statistical analysis showed significant main effect of REGION ($\chi^2(5) = 562.497$; $p < 0.001$), with the Centro-parietal and Parietal regions obtaining the largest mean ERD: $-1.80\,dB$ and $-1.78\,dB$, respectively. These regions did not show any significant differences between them. The interaction HEMISPHERE $\times$ REGION and REGION $\times$ FREQUENCY were significant, but without differences of hemisphere and frequency to the same region. So, the factors HEMISPHERE and FREQUENCY were considered for the step.

In the second statistical analysis, there were no significant main effects on the HEMISPHERE, FREQUENCY, LATERALITY, VIEW, POSTURE, and ORIENTATION factors. But, there was significant main effect of HEMISPHERE $\times$ LATERALITY ($\chi^2(3) = 7.501$; $p = 0.05$) interaction, in which the right-hand judgment generated a higher ERD in the left hemisphere (mean $-2.02\,dB$) than in the right hemisphere (mean $-1.72\,dB$).

## IV. Discussion

In the present work, we implemented a method to extract ERD/ERS patterns during the Hand Laterality Judgment Task - HLJT, that engages motor imagery processes [9]. The EEG data from 20 subjects was used. The results showed largest changes in the alpha band than in the eta band, as also reported by Chen *et al* (2013). The increase in alpha rhythm during the first $500\,ms$ of the reaction time is due to the visual stimulation, that enhances the activity over the posterior cortex. Also, the hand mental rotation is able to generate an activation over the post-central gyros (M1 region), superior and inferior parietal lobes, and in the primary visual cortex (occipital lobe) [22]. The synchronization of the frontal cortex is related to the attention so requested during the game performance [23]. Furthermore, during the implicit motor imagery, the distribution of the ERD over the cortex is lower lateralized than in explicit motor imagery [2] and besides, is more uniformly distributed over the parietal and occipital regions. The Hand Laterality Judgment Task it is not an easy activity to perform, due to be a multifaceted task, due to involves skills as visual codification, mental rotate capability, judge and also the attention [24].

## V. Conclusion

This paper implemented a method to extract the ERD/ERS patterns during the Hand Laterality Judgment Task, used by a rehabilitation gaming system. This task engages motor imagery processes in an implicit way since the stimulus is part of the body. The method proposed includes Welch's method

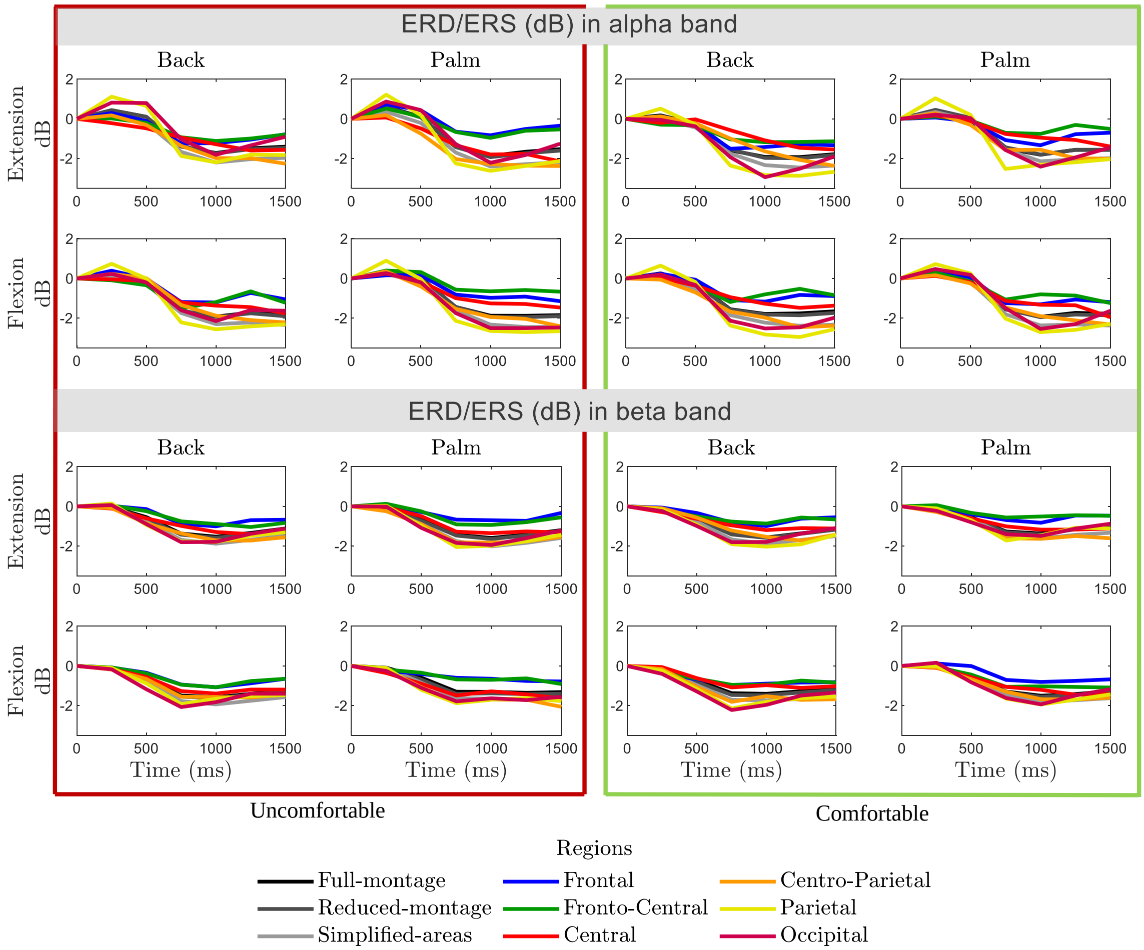


Fig. 4: Average of the alpha and beta synchronization patterns over trials and subject means, for each region of analysis and features of the stimulus.

using the Hanning window with a sliding approach. The results showed the synchronization levels in SMR, predominantly in the alpha band, and uniform distribution over the left and right hemispheres, in the centro-parietal and parietal brain regions. The method used to extract ERD/ERS and the experimental design can be used for BCI system.

## Conflict of Interest

The authors declare that they have no conflict of interest.

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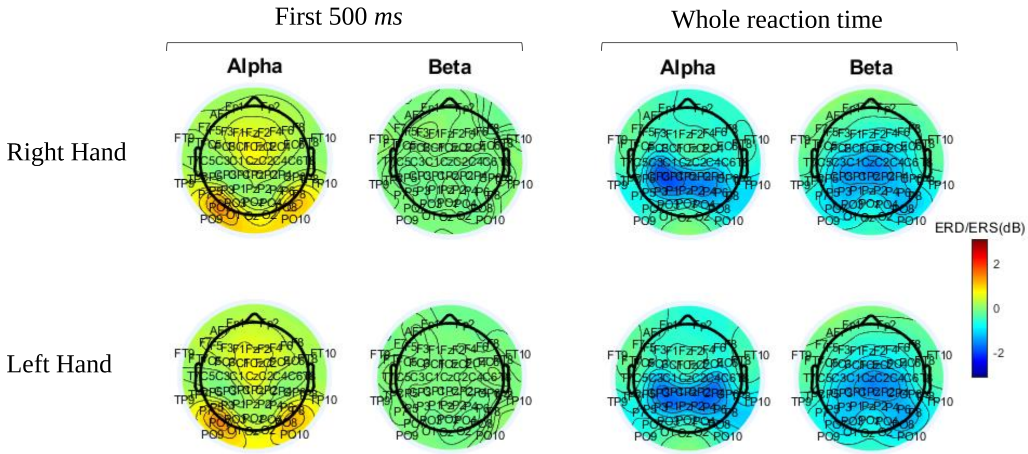


Fig. 5: ERD/ERS topography characteristic during the **first** 500*ms* **after the stimulus** of each hand that appears on the screen, in the alpha and beta bands; and the topography during the whole reaction time, for each hand laterality and frequency range.


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