Non-Parametric digital methods for EEG spectral analysis for Mental Effort recognition

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***Abstract* — The purpose of this study was to identify some patterns that differentiates the EEG during mental effort from resting, to understand the involvement of different brain areas during the cognitive task. The work was based on the study of the EEG recordings of a small sample of subjects, extracted from data used in Seleznov et al. (2019). Therefore, the focus was on the analysis of individual signals rather than on a statistical quantification of the dynamics. Recordings were obtained both at rest and under cognitive workload using a standardized stress-inducing protocol based on mental arithmetic calculations. On top of the brainwave sub-band division approach, the study focused mainly on analyzing the variation of key indicators, regarded in literature as related to mental activity, in the two conditions.**

***Keywords* — EEG, power spectral analysis, theta/beta ratio, theta/alpha ratio, cognitive task, mental effort, brain areas**

I. INTRODUCTION

The human brain activity has been studied for many years and it still fascinates researchers from all over the world. One of the main fields of study involves the activity of the brain during mental effort or emotional stimuli. Power Spectral Density analysis with brainwave sub-bands division and Coherence Analysis have been proven to be the most effective tools in quantitative characterization of brain activity. However, this area of study is still open and in literature does not emerge a specific and generally agreed pattern on how brain waves change from rest to mental effort activation. Nonetheless, in many study cases it emerged that the aroused state is often characterized by mid-high frequency brain waves and that while performing mental effort, math calculations and tasks requiring "active" intelligence, very high alpha or low/mid beta activity arises. [2, 3] Moreover, a growing number of studies suggest that the theta/beta ratio is related to different aspects of cognitive control and motivated decision making and that it can be an effective marker of cognitive processing capacity and concentration. [5, 6] Specifically, there is evidence that the sum of two specific beta sub-bands, the sensorimotor rhythm (SMR @12–14.99 Hz) and mid-Beta (Mid-B @15–19.99 Hz) waves, divided by Theta waves can be used as an EEG index to determine the concentration state. The purpose of our project is to use power spectral analysis to study pre-recorded and pre-processed EEGs to show the differences in the spectrum between a rest state and during serial subtraction. To achieve our goal, we plan to use different methods of analysis and indicators that could reveal those differences.

II. MATERIALS AND METHODS

1) Data Description

This study focused on a small sample of EEG recordings selected from data used in Seleznov et al. (2019), related to 6 subjects, all assessed as "Good Counters" (Group B). The EEGs were recorded using electrodes placed on the scalp according to the International 10/20 scheme, obtaining the traditional 19 derivations: anterior frontal (Fp1, Fp2), frontal (F3, F4, Fz, F7, F8), central (C3, C4, Cz) parietal (P3, P4, Pz), occipital (O1, O2) and temporal (T3, T4, T5, T6). The sample rate was 500 Hz per channel. A high-pass filter with 0.5 Hz cut-off frequency, low pass filter with 45 Hz cut-off frequency band and a power line notch filter (50 Hz) were applied. In Seleznov et al. (2019), during EEG recording, subjects were first induced to relax and then were asked to count mentally without speaking and using finger movements, accurately, and quickly in the rhythm they had reached. The consequential subtractions last for 4 minutes, but only the first minute was considered to grasp the change of the emotional state of the participants on intellectual overload onset.
In the end, for each subject have been collected 2 time series for each derivation: about 3 minutes at rest state (182 s * 500 samples = 91 000 samples) and about 1 minute during intensive cognitive task (62 s * 500 samples = 31 000 samples). Seleznov et al. (2019) also applied some strategies to evaluate the subtraction correctness and the difficulty level experienced by the subjects in managing the task. According to those criteria they divided the subjects in Good and Bad counters, but in the present study the difference among the two groups hasn't been taken into account on purpose, selecting a sample of all good counters.

2) Study Design and Data Processing

This study focused on the analysis of the dynamics of activation of different brain areas during the cognitive tasks in the frequency domain, hence the PSD estimation has been the first processing step performed. In the study design initial phase, both parametric and non-parametric approaches have been considered for PSD estimation. Although, it was immediately verified that the complexity of the EEG signal makes the parametric method not suitable for this analysis, at least with model orders consistent with the available data. Therefore, the focus of the study shifted on non-parametric methods. Multiple approaches, namely Bartlett, Welch and indirect estimation, with varying parameters and different windows both in terms of shape and dimension, have been compered. In the end, the Welch approach resulted to be the optimal choice to obtain a power spectral density with an acceptable trade-off between variance and informative content. Hence, we decided to choose this method to proceed with PSD estimation.

Then we analyzed which was the optimal choice for windowing, in terms of the number of windows (K) and the window's shape, also to identify the best trade-off between variance and resolution frequency. First, we defined the minimum acceptable resolution for the study case around 0.1 Hz. Then we identified the minimum number of samples for each window to get that spectral resolution.

$$\Delta f = \frac{f_s}{M} \ \leq \ 0.1\, Hz\,,\ fs = 500Hz \ \rightarrow \ M \geq \frac{500}{0.1} = 5000$$

Considering the different length of the EEG recordings in the two conditions, we identified two possible paths to proceed: either extracting two segments of the same length from both recordings or use all data provided but averaging the rest signal on more segments of M samples. The two approaches have been attempted and compared. To be more specific, at first the PSD was esteemed on both signals considered in a defined time-window of around 1 minute (31000 samples), and further divided into subsets of M samples, where M has been identified according to the required spectral resolution.

$$M = 5000 \ \rightarrow K = \frac{N}{M} = \frac{31000}{5000} = 6.2 \ \rightarrow \ K = 6$$
$$\rightarrow \ \Delta f = f_s/(N/K) = 500 * 631000 = 0.0968\, Hz$$

Then, all data provided have been used esteeming the PSD on both signals, still further divided into subsets of about M samples to get the spectra with similar spectral resolution, but this time resulting in different numbers of segments to average (18 ($\Delta f \cong 0.099$) and 6 ($\Delta f \cong 0.097$) segments respectively on recordings at rest and during counting). As expected, averaging on more windows provided smoother results. However, since the core of the analysis is the comparison among signals in the two conditions, the more comparable the results the better. Therefore, in the end we decided to take the first path. In addition, upon deeper analysis, it was found that the window's shape wasn't so influential, but the hamming window provided a more informative spectrum at fixed K. Therefore, in the end, we used the Welch method with 6 Hamming window on signals considered in a defined time-window of around 1 minute for the PSD estimation.

Once we had defined the basis of our signal processing, we proceeded by analyzing in frequency domain the differences between rest and counting for each subject.

We analyzed the spectrum of all derivations for each subject in comparison among the two conditions taking as reference the following frequency bands: delta (0.5-4 Hz), theta (4-8 Hz), further divided in low theta (4-5.99 Hz) and high theta (6-8 Hz), alpha (8-12 Hz), beta (12-32 Hz), further divided in SMR (12–14.99 Hz), Mid-B (15–19.99), and high-Beta (20–32 Hz) and gamma (> 32 Hz). From the spectral analysis, over the whole set of subjects, two main findings emerged in the first place. Firstly, in both conditions a lot of energy is carried by the components at very low frequencies. Secondly, the components that change the most when mental activation is on-set with respect to the background are the ones in the range (5-15) Hz. The latter aspect is the most relevant. Whereas the former is an expected result consistent with literature, but not relevant in this case of study, since delta waves have been proven to be relevant in deep sleep stages, consciousness, and some diseases analysis, but quite uncorrelated with active cognitive effort.

To deeper investigate those variations, multiple indices have been analyzed to identify mental effort characterization. The energy carried by components in Alpha, Theta and Beta bands has been analyzed in comparison between rest and counting, both in absolute form and as a percentage of the total power. The inspection of the results has been performed both subject-by-subject and on the average trend, minding the inter-subject variance. Then 3 indices have been identified as relevant for the Rest/Counting comparison: the Theta/Beta ratio (the sum of Beta waves divided by Theta waves), the SMR+MidB/Theta ratio (the sum of sensorimotor rhythm (SMR) and mid-Beta (Mid-B) waves divided by Theta waves) and the Theta/Alpha ratio (the sum of Alpha waves divided by Theta waves). Those parameters have been computed for all subjects and the average trend has been analyzed, still keeping in mind the inter-subject variance.

III. RESULTS

By performing the Rest/Counting comparison in terms of power of Alpha, Theta, and Beta bands both in absolute values (Figure 1.a) and as percentages of the total power carried by the signal (Figure 1.b), it emerged that Beta and Theta waves strongly increase during counting, even reaching in many areas of the brain a level of power comparable to Alpha waves' one. Moreover, by visualizing the difference between the key indices during the task and at rest (index at count minus index at rest) (Figure 2), it's possible to clearly identify how parameters change during the mental task with respect to the background: a positive bar depicts a higher value of the index during counting and a negative bar the opposite. In addition, comparing the indices on the scalp map (Figure 3), it's also more intuitively visible that while counting the Theta/Beta ratio increases considerably, especially in the frontal and central location.

IV. DISCUSSION AND CONCLUSION

In conclusion, the spectral analysis applied on available data managed to show the differences in the spectrum between the rest state and the cognitive effort. In particular, the Power Spectral Density analysis with brainwaves sub-bands division revealed a sort of pattern when the subject shifts from relax to the mental task performance. This trend seems to be driven by two main factors: an increase of the energy carried by the components in the Theta and Beta bands, producing a shift in the portion of energy carried by the overall signal from Alpha waves to Theta and low/mid Beta waves, especially in the frontal and in the occipital areas of the brain. Overall, it emerged that it is relevant to analyze Theta and Beta waves, taking as reference their more specific sub bands, to characterize mental effort during cognitive task.

V. FIGURES

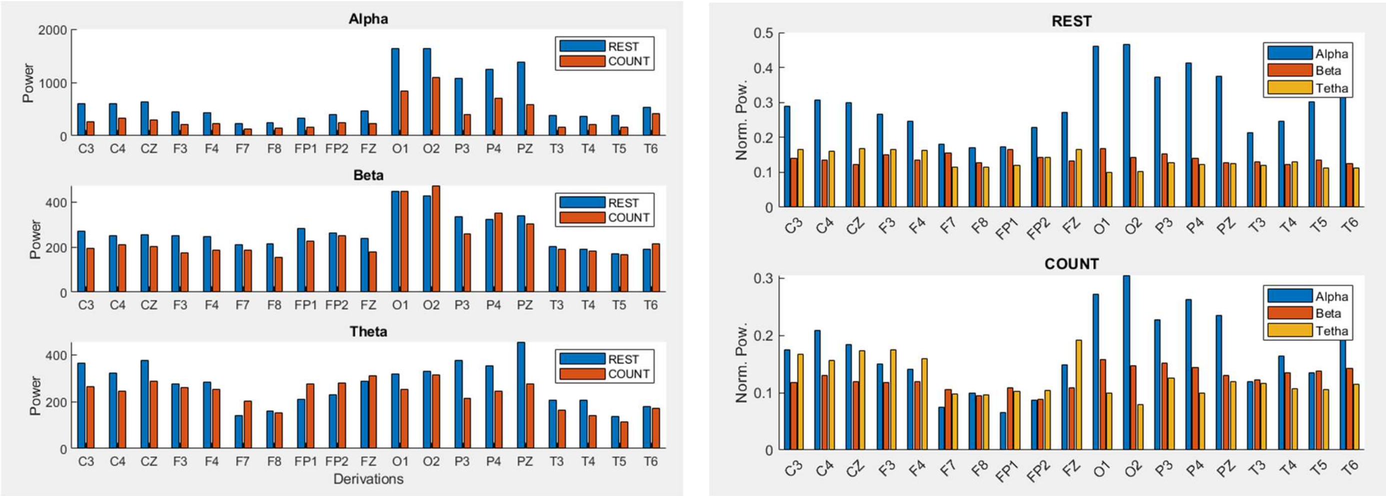

Figure 1. Power of Alpha, Beta and Theta waves at rest and during the cognitive task, respectively in absolute values (a) and expressed as percentage of the total power carried by the EEG signal (b)

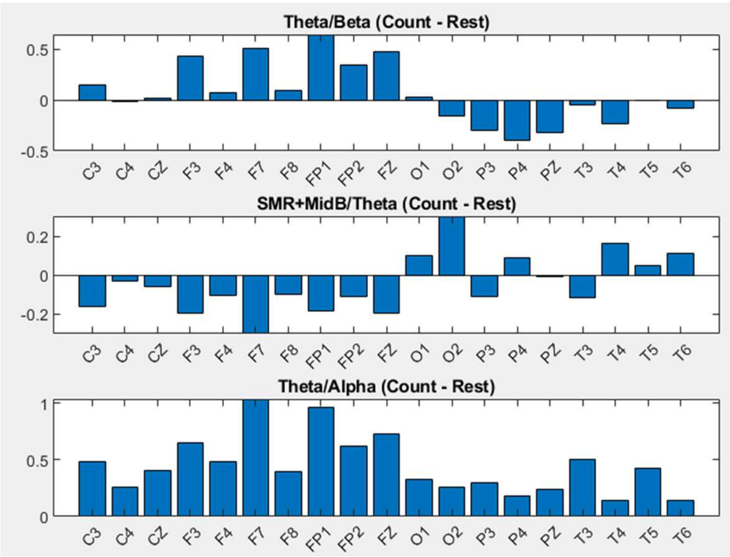

Figure 2. The 3 key indices: Theta/Beta ratio, SMR+MidB/Theta ratio and Theta/Alpha ratio, all expressed as the difference between the index value at counting and the index value at rest

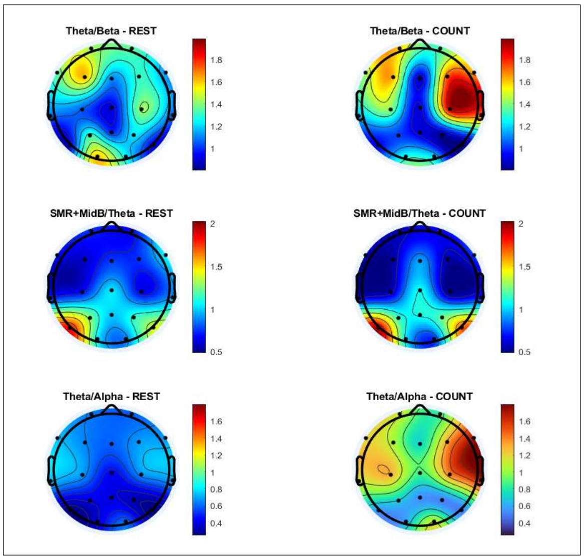

Figure 3. The 3 key indices: Theta/Beta ratio, SMR+MidB/Theta ratio and Theta/Alpha ratio respectively at rest and during the mental task, reported on the scalp map, obtained with the topoplot function

VI. REFERENCES

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