STATISTICAL SPECTRAL POWER EVALUATION OF ALPHA RHYTHMS FOR HYBRID-BCI

Anibal Cotrina*, Javier Castillo*, Alessandro Benevides*, Berthil Borges**
André Ferreira*, and Teodiano Bastos-Filho*,**

*Post Graduate Program in Electrical Engineering, Federal University of Espirito Santo,
**Post Graduate Program in Biotechnology, Federal University of Espírito Santo,
Vitoria-ES, Brazil
e-mail: anibal.atencio@ufes.br

Abstract: *This work aims at investigating the existence of variation in the anterior cortical response, more specifically in the alpha band signal of the frontal area, to evaluate the differences in power spectrum between contra-lateral electrodes F3 and F3 in order to study the passive response caused by performing repetitive tasks in a BCI. Thus, statistical spectral power evaluation of alpha rhythms is executed before and after the user performing a specific BCI repetitive task. Visual stimuli (SSVEP) are used during the user's electroencephalographic recording. The sampling distribution of Spectral F test and Wilcoxon test are here investigated.*

Keywords: *BCI, SSVEP, Reactive-BCI, Passive-BCI, Hybrid-BCI, Spectral f Test, Wilcoxon Test.*

Introduction

A Brain-Computer Interface (BCI) provides a direct connection between the user’s brain signals and a computer, generating an alternative channel of communication that does not involve the traditional way as muscles and nerves [1]. Hence, a BCI defines a new input modality for human-machine interaction (HMI), which could substitute or add up to other input modalities like manual input. BCIs can be categorized as active, reactive and passive [2]. Active-BCIs have outputs derived from brain activity, which is directly and consciously controlled by the user, therefore being independent of external events [3]. Reactive-BCIs have outputs derived from brain activity arising in reaction to external stimulation, which is indirectly modulated by the user. And Passive-BCIs have outputs derived from implicit information on the actual user mental state, which arises arbitrarily without the purpose of voluntary control. The first two categories derive their outputs for controlling an application, and the last one derive its output to improve the human-environment interaction or human-machine interaction.

A Reactive-BCI is given, for example, by a BCI based on steady-state visual evoked response (SSVEP). Visual evoked potentials, that occur involuntarily in response to visual stimuli, are measured by recording electroencephalographic (EEG) signals over the brain occipital region. SSVEP is a periodic response elicited by flickering visual stimuli, which have the same fundamental frequency as that of the flickering stimuli as well as its harmonics. These signals are processed, classified and translated into control commands [4]. However, flickering stimuli could cause a stress-related emotional state or loss of attention, as reported in [5]. Consequently, stress decreases the performance of a SSVEP-BCI.

In order to improve the usability of this technology, users can perform simultaneous or sequential tasks employing systems based on two or more BCI systems. A hybrid BCI is assembled by a collection of systems that work together to provide a robust communication pathway between the human brain and a computer [6], [7]. A hybrid BCI based on two different ones could combines active, reactive, and passive BCIs. A specific passive-BCI based on emotional components identification could be combined with the reactive-BCI based on SSVEP, because not only voluntary self-regulated signals can be used as input, but also involuntary signals might tell us something about the state of the BCI user, e.g. the emotional and cognitive state [8]. Involuntary responses (also referred to as passive signals) can be extracted and used to adapt the recognition algorithms of a BCI.

Emotions can be defined as a subjective, conscious experience characterized primarily by psycho-physiological expressions, biological reactions, and mental state [9]. Passive-BCI based on emotional components is a recent approach that fuses BCI technology with cognitive monitoring, providing the computer information about the user’s intentions, the situational interpretations and mainly the emotional state. Affective computing studies techniques that recognize, interpret, and process human emotions [10]. Frontal cortex has provided evidence that greater right frontal activity seems to be more highly related to negative emotional states. Thus, high alpha band power in the right hemisphere is associated with negative emotional states while high power in the left hemisphere is associated with positive emotional states [11]. This asymmetry can be computed by subtracting the alpha power from of left hemisphere and right hemisphere.

Figure 1 shows a hybrid-BCI that combines a Reactive-BCI and Passive-BCI sequentially. The Reactive BCI based on SSVEP detects the elicited evoked potential from EEG signals registered at occipital electrodes, and the passive-BCI identifies emotional components of user's mental state from EEG

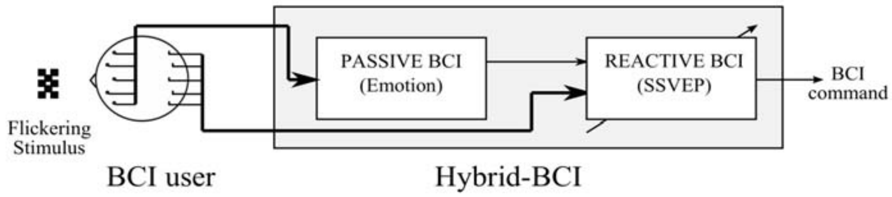


Fig. 1. Schematic overview of a passive-reactive Hybrid BCI.

signals on the frontal brain region. Asymmetry of the frontal cortex associated with a specific emotional state can make changes in detection settings of SSVEP in order to maintain the BCI accuracy.

Because of spectral tests are being used to investigate the existence of cortical changes in motor imagery [12] and SSVEP [13], the present work aims at investigating the existence of variation in the anterior cortical response, more specifically in the alpha band signal of the frontal area, to evaluate the differences in power spectrum between contralateral electrodes F3 and F4. Since stress is one of the emotional state of the subject caused by repetitive tasks, statistical spectral power evaluation in the alpha rhythm is realized using electroencephalographic (EEG) signals recorded before and after the user performed a repetitive task. For that, the user is sit in front of SSVEP stimuli during the EEG recording. For adequate quantitative evaluation of the emotional effects, changes on frontal areas should be assessed on a statistical basis. With this aim, the sampling distribution of spectral F test and Wilcoxon test is here investigated.

Spectral Analysis

In rhythm modulation-based BCIs, the input of a BCI system are the modulated brain rhythms with embedded control intentions. Brain rhythm modulation is realized by executing task-related activities, e.g., gazing to one of several visual stimuli. Demodulation of brain rhythms can extract the embedded information, which is converted into a control signal. The brain rhythm modulations could be sorted into the following three classes: power modulation, frequency modulation, and phase modulation. For a signal $s(t)$ its analytical signal is a complex function $g(t) = s(t) + j\hat{s}(t)$, where $\hat{s}(t)$, that is the Hilbert transform of $s(t)$, is defined as:

$$\hat{s}(t) = \frac{1}{\pi}\int_{-\infty}^{\infty} \frac{s(\tau)}{t-\tau} d\tau. \quad (1)$$

Due to the $\hat{s}(t)$ has the same energy as $s(t)$, energy spectral density is given by:

$$P(f) = \frac{1}{4}\hat{G}(f)\hat{G}(f)^*, \quad (2)$$

where $\hat{G}(f)$ is the Hilbert transform of $g(t)$, and $\hat{G}(f)*$ denotes the complex conjugate of $\hat{G}(f)$. Power spectrum computing by this method has no negative frequencies values. After subdividing each experiment into M epochs, the power spectral density (PSD) is then estimated using the Bartlett periodogram technique with hamming window, denoted by:

$$\hat{P}_B(f) = \frac{1}{M}\sum_{m=0}^{M-1} \tilde{P}_{xx}^{(m)}(f), \quad (3)$$

where $\hat{P}_B(f)$ is the PSD of the epoch, M is the number of epochs of *x[n]*, and $\tilde{P}(m)_{xx}(f)$ is the estimated spectrum of *m*-th segment. The Spectral F test (SFT) for the discrete-time signals *y[k]* (here assumed to represent an EEG during or after emotional stimulation) and *x[k]* (EEG signal immediately before stimulation) can be defined as:

$$SFT = \frac{\hat{P}_{xx}(f)}{\hat{P}_{yy}(f)} = \frac{\dfrac{1}{M_x}\sum_{m=0}^{M_x-1}\tilde{P}_{xx}^{(m)}(f)}{\dfrac{1}{M_y}\sum_{m=0}^{M_y-1}\tilde{P}_{xx}^{(m)}(f)}. \quad (4)$$

For $M = M_x = M_y$ the SFT is expressed as $\hat{\phi}_{xy}(f)$. Assuming that *x[k]* and *y[k]* have Gaussian distributions, it reflects the null hypothesis H_0, under which is known to be distributed as:

$$\hat{\phi}_{yx}(f)|_{H_0} \sim F_{2M,2M}, \quad (5)$$

where $F_{2M,2M}$ is the Fisher distribution with *2M* and *2M* degrees of freedom. Thus, for a given significance level, if it is greater than the critical value of the F-distribution, the hypothesis of absence of cortical response can be rejected. Figure 2 shows a block diagram illustrating the computing sequence.

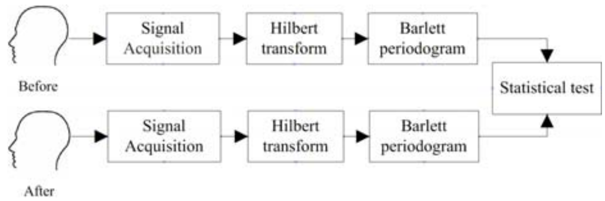


Figure 2. block diagram of the computing sequence.

Materials and Methods

One healthy subject without any experience with BCI experiments were considered in this preliminary study. The experiment was conducted with the understanding and written consent of the subject. This study was approved by the research ethics committee of the Federal University of Espirito Santo (Brazil). EEG signals from 14 electrodes (Fz, F3, F4, C3, Cz, C4, T7, T8, P3, P4, Pz, Oz, O1, and O2) were registered. The ground electrode was positioned on the user forehead and two reference electrodes were adopted; the first one was placed at FCz and the second one placed between

Pz and CPz. An modified EEG equipment based on Emotiv Epoc equipment was used. It has 14-channel wireless with 128 Hz sampling rate and 0.16-45 Hz band-pass. The subject was instructed to sit with his hands resting on his legs, to stay as still as possible and to observe the center of the screen. A LCD monitor was placed on a table 70 cm away from the subject. The experiment was divided in three parts of 200 seconds each one. In the first and third parts the subject realized the SSVEP task, in which an alternating checkerboard was displayed in the middle of the monitor. In the second part the subject was asked to perform a repetitive task (rise his index finger). EEG recorded only during the SSVEP tasks were sectioned into 5-seconds epochs. An automatic trial rejection counted the number of contaminated samples in each trial to provide the percentage of samples with artifacts or outliers.

Signals from O1 and O2 electrodes were used to verify the SSVEP responses, and channels P3, P4, Pz, Oz, O1, and, O2 were employed to perform common average reference (CAR) spatial filtering at the anterior region of the brain. Next, they were filtered employing an elliptic band-pass (4 Hz - 50 Hz) filter. On the other hand, signals from F3 and F4 were used to perform the spectral analysis of the alpha rhythm. Previously, CAR filtering at the anterior region of the brain was performed using channels Fz, F3, F4, C3 and, Cz. After, EEG signals were filtered using an equiripple band-pass (8 - 12 Hz) filter. The power spectra of the EEG before and after the repetitive task was estimated using the periodogram of Bartlett based on the Hilbert transform (frequency resolution of 0.5 Hz). Spectral F test was computed using the power spectrum of EEG signals recorded before and after the repetitive task in the numerator and denominator of expression (1), respectively. The critical value for the null hypothesis of absence of response was determined by setting a 5% percentage of significance ($\alpha = 0.05$). Two experiments were realized; in the first the frequency of alternating checkerboard was 5.4 Hz, and in the second, that frequency was 8.0 Hz. Also, the Wilcoxon (paired, non-parametric) test ($\alpha = 0.05$) was used to evaluate the differences in power spectrum between the same derivation (F3, F4, and F3-F4) before and after the repetitive task, by comparing their medians.

Results

Results obtained by comparing the power density in the alpha band between EEG captured before and after the repetitive task are presented in this section. Figure 2 shows the energy spectral density computed by using Hilbert transform of $M = 10$ epochs (gray curves) and the power spectral density estimated using the Bartlett periodogram technique (black curves). Figure 2(a) and Figure 2(b) corresponds to SSVEP tasks performed before and after performing the repetitive task, respectively. Figure 3 shows the SFT (frequency resolution of 0.5 Hz). Figure 3(a) corresponds to the checkerboard frequency of 6.4 Hz for $M_x = 10$ and $M_y = 14$ epochs acquired before and after the repetitive task, respectively.

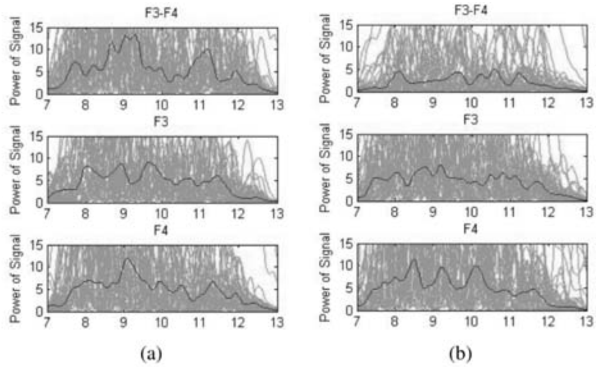
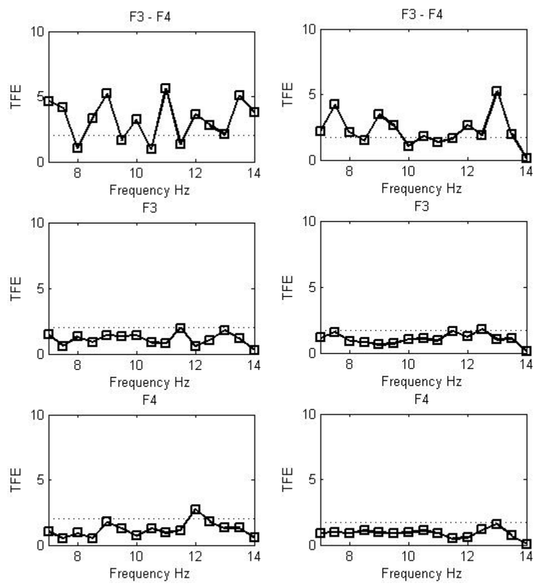


Figure 2: Barlett periodogram for F3, F4 and F3-F4 derivations. (a) Before the repetitive task. (b) After the repetitive task.

The critical value $SFT_{critic} \sim F_{(2Mx\,,2My\,,\alpha=0.05)} = 2.03$ is shown in the horizontal doted lines. It can be noticed in both F3 and F4 separated electrodes that SFT did not exceed the critical value at the alpha band. However, in the case of the derivation F3-F4, the response exceeded the critical value, which is in accordance with the literature on negative emotions and EEG, since the frontal cortex asymmetry has provided evidence that greater right frontal activity seems to be more highly related to negative emotional states. Figure 3(b) corresponds to checkerboard frequency of 8.0 Hz. In this case, the SFT critic was 1.68, and F3 and F4 also did not reach this critic value. On the other hand, the bipolar F3-F4 derivation arises the threshold. In F3 and F4 electrodes, no statistical difference was found between signals recorded before and after the repetitive task. However, the difference is clearer in F3-F4 derivation. Since the EEG power can hardly be described as a Gaussian distribution, the Wilcoxon (paired, non-parametric) test ($\alpha = 0.05$) was used to



(a) (b)

Figure 3. Spectral F test for F3, F4 and F3-F4 derivations. (a) Experiment of 6.4 Hz: $M_x = 10$, $M_y = 14$, $\alpha = 0.05$; (b) Experiment of 8.0 Hz: $M_x = 13$, $M_y = 11$, $\alpha = 0.05$.

evaluate the differences in power spectrum between the same derivation (F3, F4, and F3-F4) before and after the repetitive task, by comparing their medians. Table 1 shows the results for all analysis with p-values obtained in Wilcoxon tests. The comparison between sequences taken before and after the repetitive task reveals significant difference only for in F3-F4 derivation ($p < 0.05$).

	6.4 Hz before x after		8.0 Hz before x after	
F3	p = 0.6232	h = 0	p = 0.4307	h = 0
F4	p = 0.6776	h = 0	p = 0.8438	h = 0
F3 - F4	p = 0.0018	h = 1	p = 0.0010	h = 1

Table 1. Wilcoxon test for electrodes F3 and F4 , and for F3-F4 derivation.

In order to check that the BCI based on SSVEP is working properly, Figure 4 shows the normalized amplitude spectra of the average of these trials when the user is stimulated with 8.0 Hz of flickering frequency. The curves were generated using the SSVEP trials, plotted with frequency at the *X* axis and amplitude at the *Y* axis. The three different lines plotted represent signals for O1, O2 and Oz electrodes.

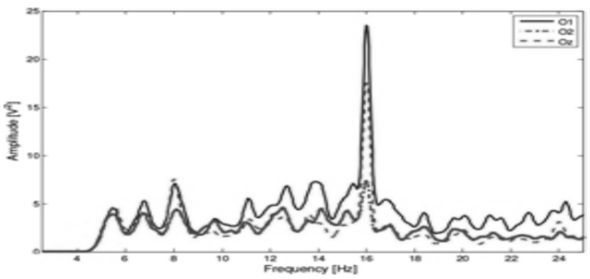


Figure 4. Normalized amplitude spectra SSVEP responses for electrodes Oz, O1 and, O2.

Conclusion

For adequate quantitative evaluation of the emotional effects, changes on frontal areas were assessed on a statistical basis. The application of Spectral F-Test allows detecting energy variations at electrodes F3 and F4. Moreover, using alternative hypothesis of the presence of response and 95% confidence interval makes possible to apply a statistical technique as an indicator of the strength of energy variation. Thus, statistical tests can be used to compare the strength of responses in the same electrode but in different time. Results showed that, although no significant variations was found in aislate F3 and F4 electrodes, the F3-F4 derivation shows variation before and after the user performed the repetitive task. In this sense, the next step of this work is to make a quantitative analysis of asymmetry for more volunteers, in order to obtain a unidimensional value to propose a linear equation that relates this index to the BCI based on SSVEP settings. Although results is from just one individual, they are promising because show that passive-BCIs could improve the success rate despite of the user's emotional states, such as stress. Tests with a larger data corpus will be necessary to confirm those results.

Acknowledgment

The authors would like to acknowledge the financial funding from CAPES and FAPES/CNPq.

References

[1] J. R. Wolpaw, N. Birbaumer, D. McFarland, G. Pfurtscheller, and T. Vaughan, “Brain-computer interfaces for communication and control,” Clinical Neurophysiology, vol. 113, no. 6, pp. 767–791, 2002.
[2] T. O. Zander and C. Kothe, “Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general,” Journal of Neural Engineering, vol. 8, no. 2, 2011.
[3] J. Wolpaw, M. Neat, and C. Forneris, “An eeg-based brain-computer interface for cursor control.” Electroencephalography and clinical neurophysiology, vol. 78, no. 3, pp. 252–259, 1991.
[4] M. Middendorf, G. Calhoun, and K. Jones, “Brain-computer interfaces based on the steady-state visual-evoked response.” IEEE transactions on rehabilitation engineering vol. 8, no. 2, pp. 211-214, 2000.
[5] S. Muller, T. Bastos-Filho, and M. Sarcinelli-Filho, “Incremental ssvep analysis for bci implementation,” in Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE.
[6] G. Muller-Putz, R. Leeb, J. D. R. Millan, P. Horki, A. Kreilinger, G. Bauernfeind, B. Allison, C. Brunner, and R. Scherer, “Principles of hybrid brain-computer interfaces,” Eds. Springer Berlin Heidelberg, 2013.
[7] G. Pfurtscheller, B. Allison, C. Brunner, G. Bauernfeind, S. Teodoro, R. Scherer, T. Zander, M. Gernot, C. Neuper, and N. Birbaumer, “The hybrid bci.” Frontiers in neuroscience, vol. 4, 2010.
[8] F. Nijboer, S. Carmien, E. Leon, F. Morin, R. Koene, and U. Hoffmann, “Affective brain-computer interfaces: Psychophysiological markers of emotion in healthy persons and in persons with amyotrophic lateral sclerosis,” in Affective Computing and Intelligent Interaction and Workshops, 2009. pp. 1–11.
[9] P. Kleinginna and A. Kleinginna, “A categorized list of emotion definitions, with suggestions for a consensual definition,” Motivation and Emotion, 1981.
[10] R. W. Picard, “Affective computing: challenges,” International Journal of Human-Computer Studies, 2003.
[11] R. Davidson, “Anterior cerebral asymmetry and the nature of emotion.” Brain and cognition, vol. 20, no. 1, pp. 125–151, 1992.
[12] M. V. Stecklow, A. F. C. Infantosi, and M. Cagy, “EEG changes during sequences of visual and kinesthetic motor imagery,” Arquivos de Neuro-Psiquiatria, vol. 68, pp. 556 – 561, 08 2010.
[13] A. de Sa, M. Cagy, V. Lazarev, and A. Infantosi, “Spectral F-Test power evaluation in the EEG during intermittent photic stimulaton,” Arquivos de Neuro-Psiquiatria, vol. 64, pp. 228 – 232, 2006.