EVALUATION OF EMOTIONAL COMPONENTS TO IMPROVE SSVEP-BCI

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Abstract—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. Recent decades have seen BCI applications as a novel and promising new channel of communication, control and entertainment for disabled and healthy people. However, BCI technology can be prone to errors due to the basic emotional state of the user: the performance of reactive and active BCIs decreases when user becomes stressed or bored, for example. Passive-BCI is a recent approach that fuses BCI technology with cognitive monitoring, providing valuable information about the user’s intentions, the situational interpretations and mainly the emotional state. In order to improve the accuracy of BCIs, subjects can perform simultaneous or sequential tasks typically used in two BCI approaches in a hybrid condition that combines both BCIs. In this work, a system composed of a passive-BCI co-working with a reactive-BCI, with the aim of improving the performance of the reactive-BCI is proposed. Thus the possibility of adjusting recognition characteristics of SSVEP-BCIs using a passive-BCI output is evaluated.

Keywords—Emotional components, passive-BCI, reactive-BCI, SSVEP-based BCI, asymmetry index

1 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 (Wolpaw et al., 2002). 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. Distinct mental states can be associated with physical actions, such as sending the command “turn right” to a wheelchair robot just imagining the movement of the right hand (Ferreira et al., 2010). Although presenting many advantages, most current BCIs are highly susceptible to emotional states experienced by its users, since emotions indicate what is important and what you care about (Picard, 2010). However, the BCIs have the advantage of direct access to brain activity, being able to provide meaningful information about the user’s emotional state. Such information may be used in two forms (Molina et al., 2009): 1) Knowledge of the influence of emotional state in the patterns of brain activity allows the BCI to adapt their recognition algorithms so that the user’s intent is still interpreted correctly despite signal changes induced by the emotional state of the user. 2) The ability to correctly recognize emotions in BCIs that can be used to provide the user a more natural and intuitive way to control the BCI in affective modulation. In the present work, a passive-BCI able to co-work with a specific reactive-BCI, is evaluated in order to improve the performance of the BCI by evaluating emotional components. Experimental results are shown and the proposal seems effective.

1.1 BCI categorization

According to the categorization proposed in (Zander and Kothe, 2011), active-BCIs have outputs derived from brain activity, which is directly and consciously controlled by the user, therefore being independent of external events (Wolpaw et al., 1991); and reactive-BCIs have outputs derived from brain activity arising in reaction to external stimulation, which is indirectly modulated by the user (Muller, Celeste, Bastos and Sarcinelli, 2010). 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 human-environment interaction or human-machine interaction.

1.2 Reactive-BCI based on SSVEP

An event related potential (ERP) used in many BCI systems is the visual evoked response (VEP).
This potential, occurring involuntarily in response to a visual stimulus, can be measured over occipital brain areas. Steady-State VEP (SSVEP) is a periodic response elicited by repetitive presentation of a visual stimulus, with the same fundamental frequency as that of the flickering stimulus as well as its harmonics (Middendorf et al., 2000), (Sutter, 1992), (Muller, Bastos and Sarcinelli, 2010). In a typical SSVEP-based BCI system, multiple stimuli flickering at different frequencies are shown to the subject. The increase in the SSVEP amplitude can be detected in the electroencephalographic (EEG) signal, which are further processed, classified and translated into control commands (Wang et al., 2006), (Gao et al., 2003), (Cheng et al., 2002), (Muller-Putz et al., 2005).

### 1.3 Passive-BCI based on Emotion Components

A Passive-BCI 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. Emotions can be defined as a subjective, conscious experience characterized primarily by psycho-physiological expressions, biological reactions, and mental state (Kleinginna and Kleinginna, 1981). Affective computing studies techniques that recognize, interpret, and process human emotions (Picard, 2003). Asymmetry of the frontal lobe, given by the variation of the alpha band power of the EEG signals, is significantly associated with human emotional states; in which, high alpha band power in the right hemisphere is associated to negative emotional states while high power in the left hemisphere is associated with positive emotional states (Davidson, 1992).

### 1.4 Hybrid BCI

In order to improve the accuracy of BCIs, subjects can perform simultaneous or sequential tasks typically used in two BCI approaches. A hybrid BCI is assembled by a collection of systems that work together to provide a communication pathway between the human brain and a computer (machine). A hybrid BCI based on two different could combines active, reactive, and passive BCIs.

### 1.5 Assessment

Recently, a new perspective on BCI has emerged (Nijboer et al., 2009), which suggests that 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). It is assumed that relevant features from these involuntary signals (also referred to as passive signals) can be extracted and used to adapt the recognition algorithms of the BCI. In sum, the knowledge of the emotional state influence in brain activity patterns allows the BCI to adapt its recognition algorithms with the aim that the user intentions would be interpreted efficiently.

In the present work, a passive-BCI monitors emotional component of the BCI user with the aim improving a SSVEP-BCI performance is evaluated. The increase of the SSVEP amplitude can be detected in the EEG signals and translated into control commands. However, stimuli flickering could cause a stress-related emotional state or loss of attention, as reported in (Muller, Bastos and Sarcinelli, 2010). In order to accommodate this issue, we propose a system in which passive-BCI co-works with a SSVEP-BCI, whose schematic overview is shown in Figure 1. The SSVEP-BCI detects the elicited evoked potential from EEG signals registered at occipital electrodes. At the same time, the passive-BCI identifies emotional components of user mental state from EEG signals on the frontal brain region. The system is then switched to a “stress mode” when specific component of emotional state, like stress, is detected and consequently the success rate of SSVEP decreases. In this mode, the passive-BCI output modules the reactive-BCI characteristics aiming to maintain the success rate.

EEG signals of one subject were employed. Two flickering stimuli were used to evoke the SSVEP potential. Spectral density of signal is computed using Hilbert Transform. Two ways of become the SSVEP more robust were evaluated: adjusting the amplitude response and adjusting the frequency response. Asymmetry index computed of the alpha band from frontal electrodes were used to evaluate the emotional state of the subject.
2 Methods

2.1 Subjects

Due to the preliminary aspects of this work, the evaluation was performed with only one volunteer with no previous history of neurological or psychiatric disorder. The experiment was taken with the understanding and written consent of the subject, who gave informed consent. This study was approved by the research ethics committee of the Federal University of Espírito Santo (Brazil).

2.2 Stimulus

Two stimuli, emitted by two $5 \times 7$ LED arrangements flickering at 5.6 Hz and 6.4 Hz were displayed simultaneously. The subject seated in front of the SSVEP box and was asked to gaze on the target LED for 17 s after a beep tone, then asked to close his eyes for 5 s, ending the trial after a second beep tone. The EEG signal was recorded between seconds 5 and 17 of the trial. Two sessions of 10 trials were performed during the experiment.

2.3 Signal acquisition

BrainNet36 (BNT) was the device used for EEG acquisition with a cap of integrated wet electrodes. EEG signals from 19 electrodes positioned according to the international 10-20 system were registered (Figure 2). The grounding electrode was positioned on the subject forehead and the bi-auricular reference was adopted. The EEG was acquired at a sampling rate of 200 Hz. BNT is a device for clinical purposes that does not export data in on-line mode. Therefore, a TCP-IP based sniffer programmed in ANSI C was developed to export these data, allowing the on-line processing, which was performed on MATLAB.

![Figure 2: International 10-20 system for electrode placement.](image)

2.4 Preprocessing

Signals were filtered employing an elliptic bandpass (4 Hz - 50 Hz). Signals from O1 and O2 electrodes were used to verify the SSVEP responses; other channels were employed to perform common average reference (CAR) spatial filtering, in order to reduce the correlation between channels originated by external noise. CAR filter is given by:

$$\hat{\mu}_i^{\text{CAR}} = \mu_i^{\text{ER}} - \frac{1}{n} \sum_{j=1}^{n} \mu_j^{\text{ER}},$$  \hspace{1cm} (1)

where $\hat{\mu}_i^{\text{CAR}}$ is the filtered signal and $\mu_i^{\text{ER}}$ is the potential between the $i$-th electrode and the reference electrode.

2.5 Spectral density of an analytical signal

In rhythm modulation-based BCIs, the input of a BCI system is the modulated brain rhythms with embedded control intentions. Brain rhythm modulation is realized by executing task-related activities, e.g., attending to one of several visual stimuli. Demodulation of brain rhythms can extract the embedded information, which will be 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 $g(t)$ is a complex function defined as:

$$g(t) = s(t) + j\hat{s}(t),$$ \hspace{1cm} (2)

where $\hat{s}(t)$ is the Hilbert transform of $s(t)$, defined as:

$$\hat{s}(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{s(t)}{t-\tau} d\tau.$$ \hspace{1cm} (3)

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

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

where $G(f)$ is the Fourier transform of $g(t)$ and $\hat{G}(f)^*$ denotes the complex conjugate of $G(f)$. The analytic signal has no power at negative frequencies.

2.6 Adjusting of Amplitude of the Response

The amplitude of the SSVEP response of the EEG signals depends on the quantity of samples employed to perform the FFT transform. Normalized amplitude spectrum is calculated by:

$$P^{\text{norm}}(f) = \frac{P(f)}{\sum P(f)},$$ \hspace{1cm} (5)

where $P(f)$ is spectral energy density of the analytical signal. $\sum P(f)$ denotes a summation over the total frequency points of a spectrum. The response becomes more robust when more samples are considered.
2.7 Adjusting the Frequency of the Response

The frequency corresponding to amplitude of peaks in the frequency domain is compared with stimuli flickering frequencies to determine which stimulus was chosen by the subject. However, it is common that the frequency of the peak (fundamental or harmonic) is slightly different to the stimulus frequency, or other peaks appear at frequency domain. To solve this problem, Power Spectral Density Analysis (PSDA), which involves processing in the frequency domain, was used to perform automatic recognition of SSVEP responses of the target stimulus.

If there is a peak in the same frequency of the stimulus, the error will be zero. If the error is not zero, the ratio will be small if the amplitude is high, and at different frequencies, the error will be small. In this case, \( f_k \) and \( f_h \) could be adjusted. The power spectral density analysis around the stimulus frequency is given by:

\[
S_k = \frac{mP(f_k)}{\sum_{i=-m/2}^{m/2} P(f_k + if_r)},
\]

usually expressed in dB; \( m \) is number of samples around the stimulus frequency, and \( f_r \) is the frequency resolution which depends on the Fourier transformation. \( P(f_k + if_r) \) is the power density around the stimulus frequency. In this study \( m = 60 \) was considered.

So, given \( k \)-th stimulus frequency \( f_k \), the closer peak response frequency \( f_h \), and the magnitude of the peak frequency \( P(f_k) \), the following ratio of proportion was used:

\[
\text{Ratio} = \frac{|f_k - f_h|}{P(f_k)},
\]

2.8 Asymmetry index

The index of asymmetry of alpha band can be computed by comparing the power of contralateral frontal electrodes, in order to identify component of stress-related emotional states. Frontal cortex asymmetry has provided evidence that greater right frontal activity seems to be more highly related to negative emotional states. This index, that has a value between -1 and 1, can be employed as a switch to shift the system to the "stress mode" (Davidson, 1992). The most commonly reported of the indexes is computed by subtracting the left hemisphere alpha power (\( P_{lh} \)) from the right hemisphere alpha power (\( P_{rh} \)):

\[
\text{Assymetry} = \frac{P_{lh} - P_{rh}}{P_{lh} + P_{rh}},
\]

where \( P_{lh} \) and \( P_{rh} \) were estimated by computing the Power Spectral Density.

3 Results

As mentioned above, the subject was asked to choose one specific target between two stimuli flickering at 5.6 Hz and 6.4 Hz. A particular mental state, such as stress, can affect the frequency or the amplitude of this potential. Therefore, a technique based on adjusting the number of samples employed to perform the FFT transform and/or a technique based on the enlarge the ratio of searching of the peak response to compensate the frequency and amplitude of evoked potentials, respectively. Hence, elicited SSVEP potential response and asymmetry index when the subject was stimulated emotionally are presented in this section.

3.1 Elicited SSVEP potential results

Hilbert transform was used to compute the SSVEP spectral responses shown in the Figures 3 and 4.

![Figure 3](image-url)

Figure 3: Normalized amplitude spectra corresponding to different length. (a) For the stimulus flickering with 5.6 Hz. (b) For the stimulus flickering with 6.4 Hz.

Figures 3(a) and 3(b) show the normalized amplitude spectra corresponding to four different data lengths. If the data length is \( n = 200 \) samples, corresponding to 1 s of signal; then, the amplitude of the response is weak. The response becomes more robust when more samples are considered. Thus, SSVEP response peak will be strong when \( n = 800 \) samples that corresponds to 4 s of signal. Hence, responses that were computed with few data are affected with changes in the subject mental states. In this sense, one way to maintain
the SSVEP potential amplitude could be achieved through adjusting the data length of each trial. The number of samples increases the data and the processing time, so this assessment maintains the success rate, but reduces the information transfer rate (ITR). In practice, the length of the samples are determined by a window function.

Figures 4(a) and 4(b) show the normalized amplitude spectra of the SSVEP response of the electrode O2 corresponding to ten trials (gray curves) and the average curve (black curve). The response to stimulus flickering with 5.6 Hz presents weaker amplitude than its second harmonic frequency (11.2 Hz); concurrently the peak at 5.6 Hz is wider. In cases like this, the peak detection using a threshold becomes inefficient. Thus, adjusting of frequency of the response method can be a good alternative. On the other hand, for 6.4 Hz the SSVEP response presents peaks at fundamental and second and third harmonic frequencies.

Topographic maps of all position of the subject’s scalp is showed in the Figure: The two stimulation frequencies (5.6 Hz and 6.4 Hz) and the second (11.2 Hz and 12.8) and third (16.8 Hz and 19.2 Hz) harmonics of each. Note that these maps present data derived with different frequencies. It is clear from both stimulation frequencies the topographies show occipital activity characteristic of SSVEP. Only the topography of second harmonic presents occipital activity on the right side. Finally, topography of the third harmonic presents slight occipital activity.

3.2 Asymmetry Index results

The alpha power of the contralateral electrodes F3 and F4 was estimated by computing the Power Spectral Density based on the modified periodogram. The absolute value of Fast Fourier Transformation provides the amount of information contained at a given frequency, and the square of the absolute value is considered the power of the signal. In order to compute the asymmetry of alpha band power at frontal lobe from contralateral electrodes F3 and F4, One-minute signal was considered for the analysis. One-second segments the trial signal were taken into account to perform the analysis; thus, for each trial, the CAR filtering, the wavelet frequency band decomposition, and the frequency band power estimation were performed. Computing the asymmetry was realized when subject was listening to unpleasant sounds while he was asked to gaze at an SSVEP stimulus. Four types of sound stimuli were selected to elicit an emotional state: 1) Nothing, 2) ruler on a bottle, 3) dental drill, and 4) baby laughing. In (Kumar et al., 2012), stimuli (2) and 4) were rated as one of the most unpleasant sounds and the of the least unpleasant sounds, respectively.

The box plot was used to show the distribution of results (See Figure 6). It can be seen that, in all cases the value of the median of the index was negative. However, a clear difference between the sounds 2) and 4) is showed. It is evident that the results shows that the sound 3) has the least index for the subject. It indicates that a stress re-
lated emotional state was elicited on the subject, because high alpha band power in the right hemisphere is associated to negative emotional states while high power in the left hemisphere is associated to positive emotional states. Finally, the effect of the stimulus 4) was the same that the “stimulus nothing”.

Figure 6: boxplot with 90th percentile (10% and 90%) of the results of asymmetry index computing.

4 Conclusion

The method of recognizing the fundamental frequency of an SSVEP elicited response described in Sections 2.6 and 2.7 can maintain the error rate by adjusting two parameters \( f_k \) and \( f_h \), that determine the window width around the stimulus frequency. Thus, it can be concluded that the searching limits of evoked potential peaks and the number of samples used to compute the FFT transformation can be adjusted to improve the search of the SSVEP potential’s frequency. Those results are promising because they show that passive-BCIs could improve or maintain the accuracy rate despite of BCI user’s emotional states, such as stress. In the Section 2.8, although the assessment reduces the information transfer rate, it maintains the error rate of the reactive-BCI. Since the asymmetry or energy in alpha band can be used to identify emotional components of the BCI user, the next step in this work will be to integrate the passive-BCI and the reactive-BCI showed in the Figure 1 in order to develop a more robust BCI.

The index is used to modulate the reactive-BCI characteristics by using two adjustable parameters using a specific emotional component such as asymmetry index: 1) the number of samples to compute the FFT Transform and 2) the search range around the stimulus frequency at the spectral domain. Although the ITR decreases because the first adjustment increases the samples and the time between two trials, and the second adjustment increases the SSVEP peak searching time, this assessment could improve the interaction between the user and the reactive-BCI because it maintains the success rate.

Alpha power has been found to be more reliably related to task performance compared to other frequency bands, when the tasks compared carefully match on psychometric properties. Alpha power asymmetry may be considered a gradient of power that exists between the two homologous electrodes in the pair, with the slope of the gradient being towards the electrode with the greatest amount of power in this frequency band.

The next step in this research will be to compute the asymmetry index and to propose a linear equation that ties in this index with SSVEP-based BCI parameters. It is well known that BCIs, like SSVEP-based BCIs, are not suitable for all users (Guger et al., 2012). The causes for this inefficiency have not yet been satisfactorily described. Few studies exist that explicitly investigated the predictive value of internal (user related) and external (BCI related) factors on the BCI performance. The accuracy of SSVEP can be monitored by a Reclassifier, which evaluate a number of consecutive results. The Re-classifier is able to activate a switch if the accuracy is not being recovered. In this case, an autonomous interface can be implemented in order to take control of the machine. Commands like “Stop the machine”, “Return to previous stage” or “Return to the starting point” can be sent to a control system, as shown in the Figure 7.

Figure 7: Schematic overview human-machine interface composed by a passive-reactive hybrid BCI and an autonomous interface.

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References


