Towards an Architecture of a Hybrid BCI Based on SSVEP-BCI and Passive-BCI

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Abstract— **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 decrease 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 this work, an architecture composed by passive-BCI co-working with SSVEP-BCI is proposed, with the aim of improving the performance of the reactive-BCI. The possibility of adjusting recognition characteristics of SSVEP-BCIs using a passive-BCI output is evaluated. In this sense, two ways to recover the accuracy of SSVEP are presented in this paper: 1) Adjusting of Amplitude of the SSVEP and 2) Adjusting of Frequency of the SSVEP response. The results are promising, because accuracy of SSVEP-BCI can be recovered in the case that it was reduced by the BCI user's emotional state.**

I. 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]. According to the categorization proposed in [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]; and reactive-BCIs have outputs derived from brain activity arising in reaction to external stimulation, which is indirectly modulated by the user [4]. On the other hand, 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.

A Passive-BCI is a recent approach that fuses BCI technology with cognitive monitoring, providing to the computer valuable 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 psychophysiological expressions, biological reactions, and mental state [5]. But, how can a computer recognize human emotional states? Affective computing studies and develops systems that recognize, interpret, and process human emotions [6]. Currently, many affective computing techniques are being developed to recognize human emotions based on face expressions [7], physiological reactions like skin conductance [8] or electroencephalography (EEG) [9], [10], [11]. In the case of EEG signals, the asymmetry of the frontal lobe, given by the variation of the alpha band power, 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 [12], [13].

It is well known that BCIs, like SSVEP-based BCIs, are not suitable for all users [14], [15], [16]. 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. An integration of the existing knowledge about factors that influence a BCI performance into a model of BCI-control was presented in [17]. Four different aspects that contribute for BCI-control were suggested: 1) individual characteristics of the BCI user which include physiological, neurological and psychological factors; 2) characteristics of the BCI that comprises hardware and software components; 3) type of feedback and instruction, including feedback modality, presentation within each modality and instruction that is provided prior to the training; and 4) the BCI-controlled application, which can range from simple two-choice to multiple-choice paradigms for communication, neuro-prosthetic control, and clinical applications. Recently, a new perspective on BCI has emerged [18], 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 influences brain activity patterns allowing the BCI system to adapt its recognition algorithms with aiming the efficient interpretation of the user's intentions.

In the present work, an architecture composed by passive-

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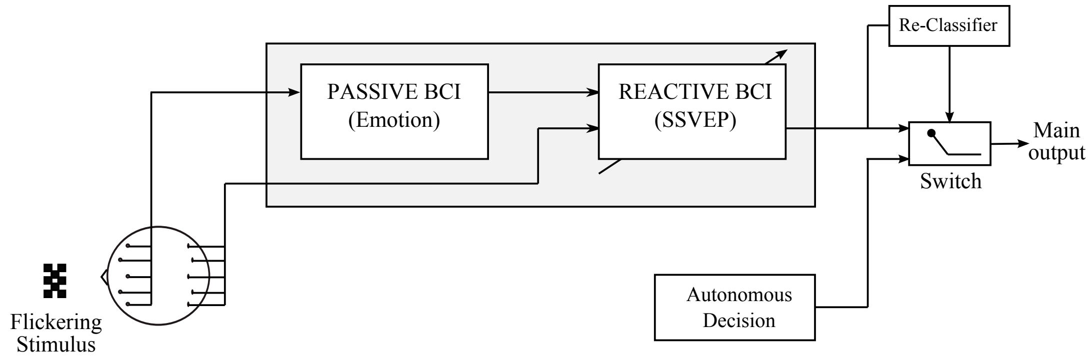


Fig. 1. Architecture of Hybrid BCI composed by passive-BCI co-working with reactive-BCI based on SSVEP.

BCI co-working with a reactive-BCI (SSVEP-based BCI) is proposed. In a typical SSVEP-based BCI system, multiple stimuli flickering at different frequencies are shown to the subject [19], [20], [21]. 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 [22]. In this architecture, which is shown in the Figure 1 the SSVEP-based BCI detects and translates the elicited evoked potential from EEG signals registered at occipital electrodes into a command. At the same time, the passive-BCI provides to the computer information about the emotional state by monitoring EEG signals on the frontal brain region. The system is then switched to a "passive mode" when the success rate of SSVEP decreases caused by the emergence of an specific component of emotional state, like stress. In this mode, the passive-BCI output is able to adjust some parameters of SSVEP-BCI with the aim of recovering the accuracy. The accuracy of SSVEP is monitored by a Re-classifier, 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 control system will take control of the machine. Commands like "stop the machine", "return to previous stage", or "call for help" can be sent by the autonomous decision making to control the system.

Two ways to recover the accuracy of SSVEP are presented in this paper: 1) Adjusting the Amplitude of the SSVEP and 2) Adjusting the Frequency of the SSVEP response.

II. Materials and Methods

A. Subject

One healthy subject without any experience with BCI experiments was initially considered in the study. 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 Espirito Santo (Brazil).

B. Stimulus

Two flicker stimuli was displayed simultaneously on two 5×7 LED arranges. Stimuli frequency of 5.6 Hz and 6.4 Hz were generated by analog signal generators. The subject seated in front of the SSVEP box and asked to focus 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.

C. Signal acquisition

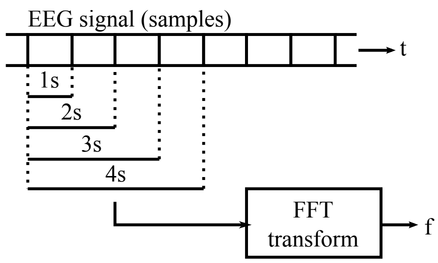
BrainNet36 (BNT) was the device used for EEG acquisition with a cap of integrated electrodes from Electro-cap company. EEG signals from 19 electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1 and O2) positioned according to the international 10-20 system were registered. The grounding electrode was positioned on the user forehead and the bi-auricular reference was adopted. The EEG was acquired at a sampling rate of 200 Hz. Signals were filtered employing elliptic band-pass (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.

III. Proposed Architecture

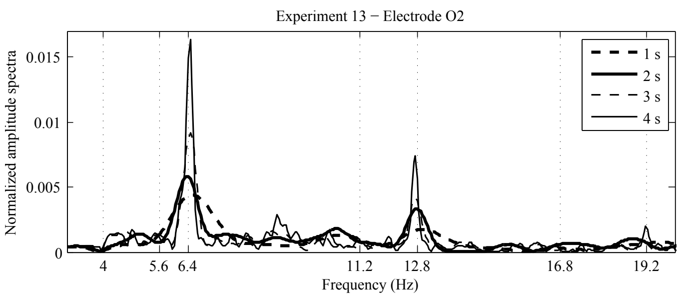
As mentioned above, the user was asked to choose one specific target between two stimuli flickering at 5.6 Hz and 6.4 Hz. Results corresponding to SSVEP potential response elicited by 6.4 Hz are presented and analyzed in this section. A particular mental state, such as stress, can affect the frequency or the amplitude of this potential. Therefore, a technique based on adjusting the number of samples and a technique based on the range of search were evaluated to compensate the frequency and amplitude of evoked potentials, respectively.

A. Adjusting the 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. Figure 2(a) shows four different ways to take a sample for computing the spectra. 2(b) shows the normalized amplitude spectra corresponding to these different ways. If $n = 200$ samples (corresponding to 1 s of data length) are considered, then the amplitude of the response is weak. So, this kind of response will be more affected with changes in the user mental states. The response becomes more robust when more samples are considered. Thus, SSVEP response peak will be strong when 800 samples (corresponding to 4 s) are employed. In this sense, one way to maintain the SSVEP potential amplitude could be achieved through adjusting the data length of each trial.



(a)



(b)

Fig. 2. (a) Length of FFT transformation window; (b) Normalized amplitude spectra corresponding to different data lengths for one subject.

The number of samples increases the data and the processing time, so this assessment maintains the success rate, but reduces the ITR. In practice, the EEG amplitude spectra was calculated by using a FFT-based Periodogram with Hamming windowing.

B. Adjusting the Frequency of the Response

Figure 3 shows the normalized amplitude spectra corresponding to the average of responses of ten trials of one subject SSVEP (gray) and the average of this trials for electrodes O1 and O2 when the user was stimulated with 6.4 Hz flickering frequency (black). Electrode O1 presents this potential at the fundamental frequency of 6.4 Hz without any other representative peak in the second or third harmonics (12.8 and 19.2 Hz), while O2 on the other hand, presents strong responses in the fundamental frequency and in the second harmonic and a weak potential in the third harmonic.

The frequency corresponding to peaks of amplitude in frequency domain is compared with stimuli flickering frequencies to determine which stimulus was chosen by the user. However, it is common that the frequency of the peak (fundamental or harmonic) is slightly different of 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.

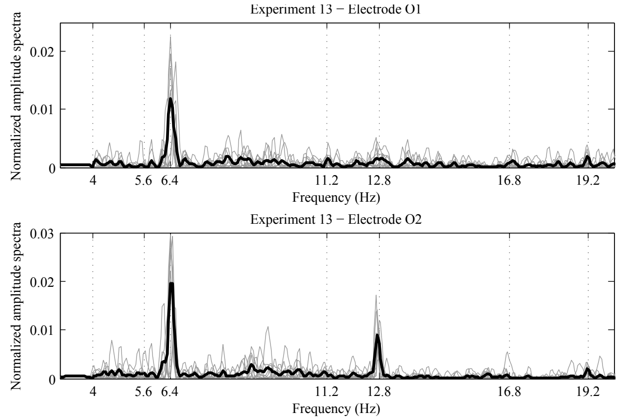


Fig. 3. Normalized amplitude spectra SSVEP responses corresponding ten trials (gray) and the average (black) of this trials for electrodes O1 and O2.

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:

$$Ratio = \frac{|f_k - f_h|}{P(f_k)}. \tag{1}$$

So, 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:

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

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.

IV. Discussion

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. Since the alpha power is inversely related to activation, blocking of or decreases in alpha are seen when underlying cortical systems engage in active processing. Thus the 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 [12], [13]. The most commonly reported of the indexes is computed using the frontal electrodes by subtracting the left hemisphere alpha power (P_{lh}) of channel F3 from the right hemisphere alpha power (P_{rh}) of channel F4, as given by,

$$Assymetry = \frac{P_{lh} - P_{rh}}{P_{lh} + P_{rh}}. \tag{3}$$

This approach results in an unidimensional scale representing the relative activity of the right and left hemispheres, with the middle point of the scale equaling zero or symmetrical activity. Interpreting this scale, high scores indicate relative grater left frontal activity whereas lower scores indicate relatively greater right frontal activity. Since asymmetry index is the output of a passive-BCI, it can scale by multiplying parameters such as the closer peak response frequency f_h (See equation 2) and window length n (See Section III-A) of a reactive-BCI to maintain the success rate. Regarding the computation of the alpha band asymmetry, our preliminary results shown in [23] indicates that asymmetry in the frontal lobe is significantly associated with human emotion reactivity [12]. The next step in this research will be to compute the asymmetry index and to propose a linear equation that relates this index with SSVEP-based BCI parameters.

V. Conclusion

The method of recognizing the fundamental frequency of an SSVEP elicited response described in the Section III-B 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 limits of the search range of frequency of the evoked potential 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 this show that passive-BCIs could improve or maintain the accuracy rate despite of BCI user's emotional states, such as stress. In the Section III-A, 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 all components of the architecture proposed given by the passive-BCI, the SSVEP-BCI, the Re-classifier and the Autonomous decision making showed in the Figure 1 in order to develop a more robust BCI.

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