TOWARDS THE PORTABILITY OF AN INDEPENDENT-BCI BASED ON SSVEP

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Abstract: This paper presents a comparison between two different technologies of visual stimulation (check-erboards presented on LCD monitor and LED matrix) for an Independent-BCI based on Steady-State Visual Evoked Potential (SSVEP). Two stimuli separated by a viewing angle < 1º, the least angle subtended by the eye showed in the literature for this mode were used. Multivariate Synchronization Index (MSI) technique was used as feature extractor and five subjects participated in the experiments. The commands (targets) are obtained through a criterion of maxima. The flicker stimuli were modulated at frequency of 8.0 and 13.0 Hz. Stimulation via LCD showed better results, obtaining the highest value, of accuracy (96.67%) and the highest ITR (35.18 bits/min).

Keywords: Steady-State Visual Evoked Potential (SSVEP), Multivariate Synchronization Index (MSI), Brain Computer Interfaces (BCIs).

Introduction

The traditional SSVEP-BCI main idea is activating commands through gaze control. The general idea is to use flickering stimuli in order to induce SSVEP: when the user wants to select one of the commands, he/she focuses at one of the stimuli. Then, by analyzing the generated SSVEP, the BCI tries to infer which stimulus the user selected [1].

Researchers have developed various techniques for the optimization of the classification performance in terms of extraction of features, such as Power Spectral Density Analysis (PSDA), Spectral F-Test (SFT), Empirical Mode Decomposition (EMD), Minimum Energy Combination (MEC), Canonical Correlation Analysis (CCA), Least Absolute Shrinkage and Selection Operator (LASSO) and Multivariate Synchronization Index (MSI); these methods were reviewed in [2]. According to previous results of our research group, it was found that the MSI technique obtains the best performance [2]. Thus, this feature extractor is here used.

Nevertheless, some SSVEP-based BCI approaches do not depend on gaze control [3-6], defining a type de BCI named Independent-BCI, which is controlled by subject's attentions without requiring head neuromuscular control or eye movements. This is a very important aspect of SSVEP-BCIs, because independent-BCIs have specific users. For instance, possible end-users of BCI systems are patients with Amyotrophic Lateral Sclerosis (ALS) and locked-in syndrome, who may not control their eye movements and therefore not be able to use dependent BCI systems. However, an Independent-BCI can be used for applications in daily life, such as the use of a portable system able to select a command on the screen of a smartphone, even having a reduced screen.

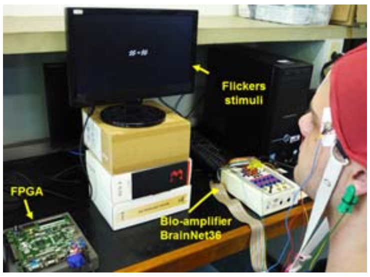
Initially, in [7] the effect of spatial attention on SSVEP was studied. In the work performed by [3], it was shown that there was a reduction in 20% of precision when a volunteer does not perform eye movements compared to another who does it. In that study, the terms attended or unattended mean overt and covert attention. Also, feature extraction based on Power Spectrum Density and LDA (Linear Discriminants Analysis) classifier was used. In [4], a similar work was performed using flickering letters in a CRT monitor. Six out of eleven physically and neurologically healthy subjects demonstrate reliable control in binary decision-making, achieving at least 75% of correct selections in at least one of only five sessions, each of approximately 12 min duration. In [5], the hypothesis that overlapping stimuli can evoke changes in SSVEP was evaluated to control a BCI. Finally, in [6] the modulation effects of SSVEP amplitude and phase response for covert shifts of attention was investigated to one of two dot sets with distinct colors.

In other hand, in [8] the visual stimuli on the LCD screen based on its vertical refresh rate offer the best recognition rate for the classification of SSVEP responses using MEC technique compared to LEDs. The selection of stimulator (LCDs or LEDs) mainly depends on the complexity of the BCI system, and other parameters such as frequency can also influence this selection [9], it is for this reason that this paper is not intended to determine a standard of stimulation. However, this work attempts to demonstrate the feasibility of using an independent-BCI with these technologies and the degree of selectivity to very small viewing angles. This independent-BCI is based on covert attention. The results can determine which stimulation system is more recommended to command a robotic wheelchair using a BCI independent.

Methods

Subjects and EEG preparation– Five male subjects, ages from 27 to 33 years old, were recruited to participate in this study. The mean and standard deviation of the ages was 29.8 and 2.17, respectively.

The experiments were performed according to the rules of the ethics committee of the UFES/Brazil, under registration number CEP-048/08. Figure 1(a) shows a volunteer being stimulated with LCD monitor and Figure 1(b) through LED matrix.



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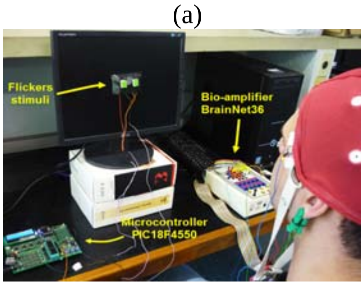

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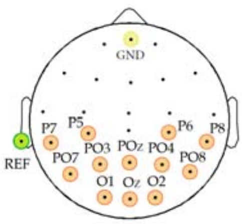
Figure 1: (a) Acquisition system with flickering stimuli presented on a LCD screen; (b) Acquisition system with the flickering stimuli generated by LEDs.

System architecture and visual stimulus– For the development of the BCI, 12 channels of EEG signal with the reference at the left ear lobe were recorded at 600 samples/s, with 1 to 100 Hz pass-band. The GND was placed on the forehead. Using the extended international 10-20 system, the electrode positions were P7, PO7, PO5, PO3, POz, PO4, PO6, PO8, P8, O1, O2 and Oz. Additionally two channels of EOG (EOG-R and EOG-L) were used to confirm that the volunteers performed the tasks effectively without muscle strain on the eyes (Figure 2).



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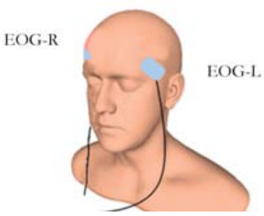

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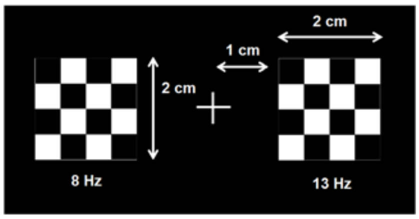
Figure 2: (a) Electrode placement on the scalp during the experiments; (b) position of the EOG channels used.

The equipment used for EEG signal recording was the BrainNet-36, manufactured by Lynx Tecnologia Ltd. The volunteers sat on a comfortable chair, in front of a 17-in LCD display, 70 cm far from it.

The participants were asked to watch a stimulation screen generated by an FPGA-based subsystem (Xilinx Spartan3E). Such stimulation screen consists of two checkerboard stripes presented simultaneously to the user. In the other stimulation system, the timing of the two flickering matrix (type 7 × 5) is controlled by a microcontroller (PIC18F4550, Microchip Technology Inc., USA) with 50/50 % on-off duties. Two LEDs (part number: HS-757BG/NCM85415020, luminous intensity from 0.9 to 2.5 mcd) of green color were used. The dimensions of each stimulator element are specified in Figure 3. For both stimulation system, the flickering frequencies were 8.0 Hz (left) and 13.0 Hz (right).



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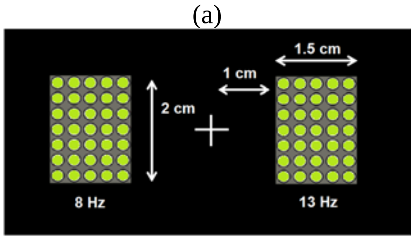


(b)

Figure 3: Dimensions of each stimulator element. (a) Checkerboards or reverse pattern (LCD); and (b) LED matrix.

Figure 4 shows the visuals angles subtended for each type of stimulator during the selection of a target.

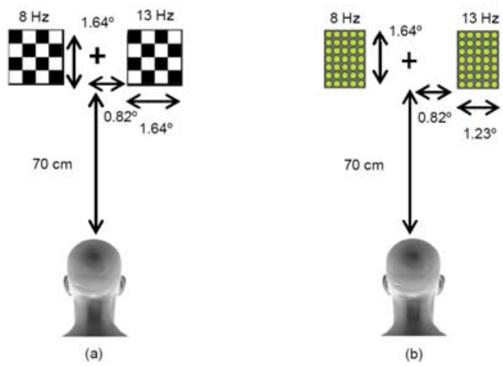


Figure 4: Visuals angles subtended for each type of stimulator during the selection of a target.

Experimental Tasks– The experiments were performed in an offline way. During the first five seconds a cross fixed on the screen is shown to the volunteers. Before finishing the five seconds, a beep is issued and the volunteer has to fix his/her attention on the stimulus located on the left side for thirty seconds. Then the volunteer takes five seconds for a break, and in the next thirty seconds, he/she fixes his/her attention to the right side, ending in 70 seconds. The EOG signals were acquired from each volunteer (Figure 5), confirming that effectively the volunteers did not have exceeded the limit of 1o of visual range, important requirement of an Independent-BCI.

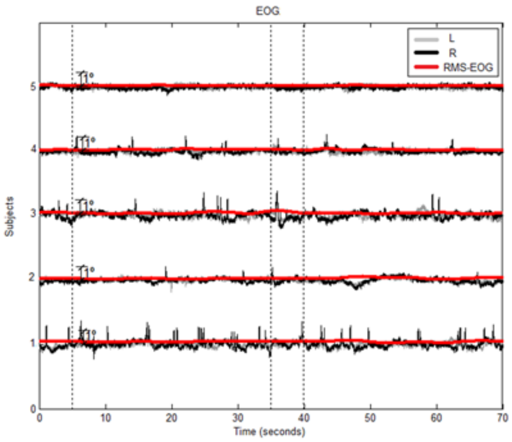


Figure 5: EOG analysis of each volunteer.

Data Analysis

The data from twelve EEG channels were segmented and windowed. The window lengths were 1, 2, 4 and 6s, each one with an overlapping of 50 %. Subsequently, a spatial filtering was applied using a Common Average Reference (CAR) filter, and a band-pass filter between 3-60 Hz was also applied for the twelve electrodes.

Although the twelve EEG channels were used during the spatial filtering process, just the three occipital channels (O1, O2 and Oz) were used in the evoked potential detection analysis (feature extraction and classification). According to previous results of our research group, it was found that the MSI provides the best performance to extract EEG signal features related to SSVEP [2].

MSI is a method to estimate the synchronization between mixed signals and reference signals, which provides a potential index for recognizing the stimulus frequency. For more details, see [10]. We used N_h = 3 harmonics were used in the EEG signal analysis. The synchronization index between the signals from the occipital electrodes (O_1, O_2 and O_Z) and each reference signal was calculated. Then, k indices or classes ($S_1, S_2, \ldots, S_k$) were obtained. Finally, the class was obtained through a criterion of maxima.

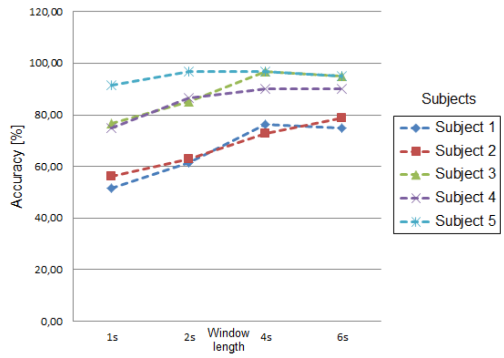
Experimental Results

In addition to the accuracy rate, the Command Transfer Interval (CTI) and Information Transfer Rate (ITR) were also computed. The CTI was defined as the total experimental time (Ttotal) divided by the number of total output digits or letters (Ntotal), i.e., Ttotal/Ntotal. Thus, it follows that the values of CTI represent the sizes of window length (1, 2, 4 and 6s) for each case. The most common measure to assess the performance of a BCI system is the Shannon's Information Transfer Rate (ITR) [1].

Figure 6 represents the accuracy of the classification evaluated using stimulation by LCD and LEDs, respectively.

From Figure 6, it can be inferred that the accuracy in the classification through stimulation via reversal pattern is slightly higher than the classification through LED arrays. As expected, the classification accuracy improves with the increase of three window length. However, it also leads to an increase of time to determine a classified command. Tables 1 and 2 show the quantified data for better visualization together with the ITR values calculated for each window length analyzed. Also, these tables represent the quantification of the values expressed in Figure 6.

Table 3 presents confusion matrices of the classification accuracy for both LCD and LEDs for each subject. The window length used is 4s.



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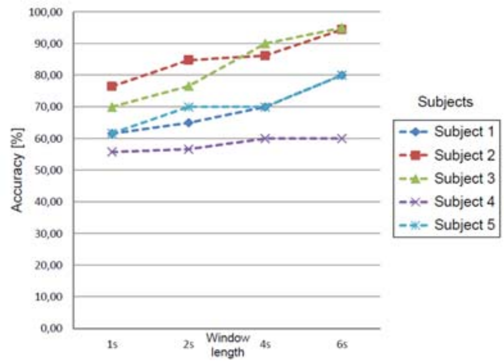

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Figure 6: (a) Accuracy of the classification evaluated using stimulation by LCD; (b) Corresponding for stimulation by LEDs.

Table 3: Comparative of classification expressed in confusion matrices between stimulation generated by LCD and LEDs for time window length of 4s.

	LCD (Condition)			**LEDs** (Condition)	
Subject 1	**8 Hz**	**13 Hz**	Subject 1	**8 Hz**	**13 Hz**
8 Hz	92.86%	40.00%	**8 Hz**	100.00%	60.00%
13 Hz	7.14%	60.00%	**13 Hz**	0.00%	40.00%
Subject 2	**8 Hz**	**13 Hz**	Subject 2	**8 Hz**	**13 Hz**
8 Hz	78.57%	33.33%	**8 Hz**	85.71%	13.33%
13 Hz	21.43%	66.67%	**13 Hz**	14.29%	86.67%

Subject 3	**8 Hz**	**13 Hz**	Subject 3	**8 Hz**	**13 Hz**
8 Hz	100.00%	6.67%	**8 Hz**	100.00%	20.00%
13 Hz	0.00%	93.33%	**13 Hz**	0.00%	80.00%
Subject 4	**8 Hz**	**13 Hz**	Subject 4	**8 Hz**	**13 Hz**
8 Hz	100.00%	20.00%	**8 Hz**	100.00%	80.00%
13 Hz	0.00%	80.00%	**13 Hz**	0.00%	20.00%
Subject 5	**8 Hz**	**13 Hz**	Subject 5	**8 Hz**	**13 Hz**
8 Hz	100.00%	6.67%	**8 Hz**	100.00%	60.00%
13 Hz	0.00%	93.33%	**13 Hz**	0.00%	40.00%

Discussions and Conclusions

The results have clearly shown that it is possible to obtain an acceptable degree of classification for the usability of an Independent-BCI with stimuli very close (viewing angle < 1º), using the feature extractor most current and most accurate from the literature (MSI). The SSVEP response is undoubtedly affected by both frequency and by the type of the stimuli, but it also is inter-variable between subjects. Subject 3 and subject 5 were both stimulated by checkerboards, obtaining the highest hit rates and confirming the excellent level of attention during the experiments (see Table 3). On the other hand, subject 2 and subject 3 that were stimulated by LEDs, obtained acceptable results for this case (see Table 3). The best results were obtained in the case of stimulation via LCD (according Figure 6). The highest value of accuracy was 96.67% and the highest ITR was 35.18 bits/min in all cases analyzed.

Acknowledgment

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Table 1: ITR [bits/min] with the corresponding accuracies [%] and differents window lengths using LCD screen.

Window length	**1s**		**2s**		**4s**		**6s**	
Subjects	Acc(%)	ITR	Acc(%)	ITR	Acc(%)	ITR	Acc(%)	ITR
1	51.52	0.05	61.55	1.17	76.43	3.18	75.00	1.89
2	56.29	0.69	62.76	1.43	72.62	2.30	78.89	2.57
3	76.66	12.97	85.00	11.71	96.67	11.84	95.00	7.14
4	74.95	11.28	86.67	13.01	90.00	7.97	90.00	5.31
5	91.67	35.18	96.67	23.68	96.67	11.84	95.00	7.14
Mean ± std	70.21 ± 16.34	12.03 ± 14.22	78.53 ± 15.60	10.20 ± 9.36	86.48 ± 11.32	7.43 ± 4.57	86.78 ± 9.31	4.81 ± 2.48

Table 2: ITR [bits/min] with the corresponding accuracies [%] and differents window lengths using LEDs.

Window length	**1s**		**2s**		**4s**		**6s**	
Subjects	Acc(%)	ITR	Acc(%)	ITR	Acc(%)	ITR	Acc(%)	ITR
1	61.57	2.35	64.94	1.97	70.00	1.78	80.00	2.78
2	76.47	12.78	84.77	11.54	86.19	6.31	94.45	6.91
3	69.97	7.11	76.55	6.43	90.00	7.97	95.00	7.14
4	55.75	0.58	56.61	0.38	60.00	0.44	60.00	0.29
5	61.67	2.39	70.00	3.57	70.00	1.78	80.00	2.78
Mean ± std	65.09 ± 8.13	5.04 ± 4.96	70.57 ± 10.77	4.78 ± 4.39	75.24 ± 12.50	3.66 ± 3.28	81.89 ± 14.28	3.98 ± 2.96