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SSVEP-BCI Implementation for 37-40 Hz Frequency Range

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Abstract— **This work presents a Brain-Computer Interface (BCI) based on Steady State Visual Evoked Potentials (SSVEP), using higher stimulus frequencies (>30 Hz). Using a statistical test and a decision tree, the real-time EEG registers of six volunteers are analyzed, with the classification result updated each second. The BCI developed does not need any kind of settings or adjustments, which makes it more general. Offline results are presented, which corresponds to a correct classification rate of up to 99% and a Information Transfer Rate (ITR) of up to 114.2 bits/min.**

I. Introduction

Communication can be defined as a process to express and share experiences among people, where the machine can be used as an accessory tool. A new trend for man-machine interaction is use the brain signals to promote a natural interface, which is named Brain-Computer Interface (BCI). Among the paradigms used in a BCI development, one has the Steady-State Visual Evoked Potentials (SSVEP). It means that the fundamental frequency component (and its harmonics) of a flickering visual stimulus will be present in the ElectroEncephaloGram (EEG) signal of the stimulated individual. The BCIs based on these potentials are called SSVEP-BCI and the interest in developing such kind of BCI is mainly due to the robustness of this phenomenon, since this potential is an inherent response of the human brain. This characteristic leads to a fast adaptation of the user to operate the BCI [1], as well as allows to use a great number of stimuli, obtaining a high Information Transfer Rate (ITR) [2].

Several groups working on SSVEP-BCI use low and medium ranges for the stimulus frequencies (<30 Hz) [1], [3], [4], in which the SSVEP is more prominent [5]. At the same time, this frequency range may cause some user discomfort, and then a tiresome for a long time BCI operation. The present work proposes to use the same structure of signal analysis developed in [6] and [7], which was implemented for low stimulus frequencies, and use it for a higher stimulus frequency range.

Some works have used high frequencies for visual stimulation, such as [8]. However, some adjustments are necessary for each volunteer using the BCI. In the present work neither calibration nor baseline signal are required for the BCI operation. The user has just to sit, wear the EEG acquiring system, observe the stimuli and begin to operate the SSVEP-BCI. The approaches used to identify the SSVEPs are a statistical test, responsible for enhancing the evoked peaks, and a decision tree, in charge of selecting the correct peaks among the extracted ones. These topics are presented in the following sections, as well as the database used, the results found and the conclusions obtained.

II. Database

Utilizing the same acquisition structure implemented in [9], the volunteers sat on a comfortable chair in front of a 17-in CRT monitor with four bars on each side, as illustrated in Fig. 1. These bars measure 10 cm x 2.5 cm and are illuminated by high efficiency light-emitting diodes (LEDs). The flickering frequencies were 37.0 Hz (top), 38.0 Hz (right), 39.0 Hz (bottom) and 40.0 Hz (left), which are almost imperceptible by the users. The LEDs flicker is precisely controlled by an FPGA Xilinx Spartan2E.

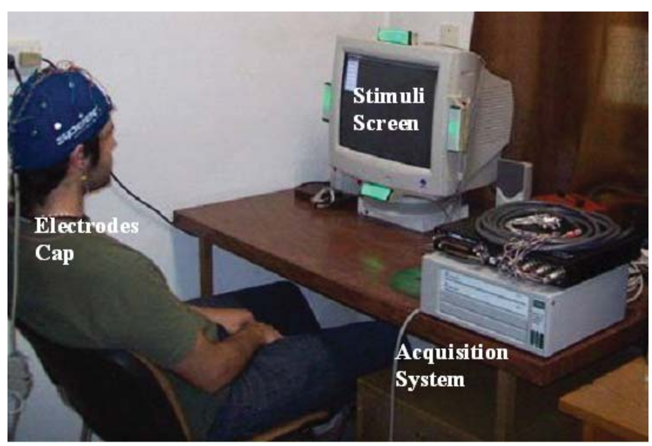

Fig. 1. Acquisition system with four bars flickering simultaneously.

Six EEG channels, with the reference electrode at Fz, grounded at linked A1-A2, sampled at 256 Hz, and with 3 to 100 Hz passband were recorded. Using the international 10-20 system, the locations for the electrodes are O1, Oz, O2, P3, Pz and P4. The EEG signals were acquired in GATEME/UNSJ (Argentina) with a Grass MP15 amplifiers system and digitalized with a NI-DAQPad6015 and a notch filter for 50 Hz was used, for line interference cancellation.

Six healthy volunteers, one female, 32$\pm$3 years old, named *Vol1* to *Vol6*, participated in this study. Each one was asked

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to watch a flickering bar during trials of 10 s. The trial begins with a beep, in t=0 s, and a flickering bar is randomly indicated 2 s later using an arrow shown on the screen. All volunteers participated in four sessions and each session contains 20 trials, with a resting interval of a few minutes between sessions and a few seconds between trials.

III. Feature Extraction

To evaluate syncronyzed spectral changes in the EEG signal recorded during stimulation, $x[k]$, at a given stimulus frequency, f_0, a Spectral F-Test (SFT) is applied as the ratio between the power in such frequency and the average power in L even neighboring frequencies [10]. That is,

$$\hat{\phi}_x(f_0) = \frac{P_{xx}(f_0)}{\frac{1}{L}\sum\limits_{\substack{i=-L/2\\ i\neq 0}}^{i=L/2} P_{xx}(f_i)} \tag{1}$$

where $P_{xx}(f_0)$ is the Power Spectral Density (PSD) of the signal $x[k]$ evaluated at the frequency f_0, and $P_{xx}(f_i)$ are the PSD values at the L neighboring frequencies closest to f_0.

This statistic test has the purpose of determining whether the spectrum at the frequency f_0 is statistically distinct from its neighbors, considering that the spectrum in this neighborhood is white. Equation (1) is also used in [11] to evaluate the Signal-to-Noise Ratio (SNR) of SSVEPs. This was used to help in the choice of the best values of stimulus frequencies. Here, this expression is used to detect the evoked peaks that are rejected by the null hypothesis, H_0, which corresponds to the absence of evoked response. The alternative hypothesis is that the null hypothesis is false, that is, there is evoked response. Under the null hypothesis, $\hat{\phi}_x(f)$ is distributed as [10]

$$\hat{\phi}_x(f_0)\Big|_{H_0} \sim F_{2,2L}, \tag{2}$$

where $F_{2,2L}$ is the F distribution with 2 and $2L$ degrees of freedom. Consequently, H_0 is rejected ($\alpha = 0.05$) using the critical value given by

$$STF_{crit} = F_{(2,2L,\alpha)}. \tag{3}$$

It can be noticed that this last critical value is independent of the length of the analyzed data segment. This lead to a robust threshold to identify the evoked peaks.

IV. Rule-Based Classifier

From the F-test developed in Section III, the input parameters of the classifier should be related to peaks that overshoot the SFT_{crit} value. Considering that there is no metric for the points which is desired to classify, the classifier chosen is based on decision trees. Thus, the parameters were defined as the amplitude of these peaks and the associated frequency value. These parameters are converted in attributes capable of modeling the system suitably.

The decision tree implemented in this work is a little different from the one used in [6]. Some considerations were assumed to implement this new decision tree: (i) the stimulus frequencies of 37.0, 38.0, 39.0 and 40.0 Hz were labeled as Class 1 to Class 4, respectively; (ii) only the fundamental component of each stimulus frequencies was used, since they were in a high value range; (iii) as the sample frequency is 256 Hz, the PSD was estimated using a number of 1024 points, which leads to a frequency resolution of 256/1024 = 0.25 Hz, and; (iv) the exact value of the stimulus frequency plus one point before and after of the exact value were considered in the classification process. For instance, for a stimulus frequency of 37.0 Hz the peaks on the points 36.75, 37.0 and 37.25 Hz were considered to compose the decision tree. Then, two attributes concerning to the first twenty peaks (if there is) that reject H_0 were created.

The first attribute, $A1$, consists of four elements: (i) the amplitude of the peak; (ii) the value of the frequency where the peak occurred; (iii) the information whether this frequency value corresponds or not to the exact value of the stimulus frequency, and; (iv) the class associated to it. If the value of the frequency does not belong to none of the stimulus frequencies, the peak is labeled as an undefined class X.

The second attribute, $A2$, is created from the first one, and has two components related to the class labels different than X. The first component is the information whether the frequency value corresponds or not to the exact value of the stimulus frequency, splitting the peaks in two groups called *Exact Group* and *Approximated Group*. The second component is the peaks ordered in a descending order with respect to their amplitude values, which was performed for the two groups of peaks.

The decision tree developed is shown in Fig. 2. The tree will first search the maximum value for the peaks that belong to the *Exact Group* and, if there is not a peak in this group, it will search in the *Approximated Group*. Observe that when the tree classifies the sample as belonging to the class X it means that the sample was not classified. The training step is unnecessary in this application because the classifier use is straightforward. This represents a great advantage, because the computational cost decreases.

Moreover, the Information Transfer Rate (ITR) is used to measure the quantity of information transmitted per time unit, and it can be determined using the accuracy and speed of the BCI. This rate can be expressed as [12]

$$B = \log_2 N + P\log_2 P + (1-P)\log_2\left(\frac{1-P}{N-1}\right),$$

where N is the number of classes and P is the rate of correct classifications. The unit for ITR is $bits/s$ and can be determined in $bits/min$ multiplying the result by the selection speed, that is, how many selections can be done by the system in a minute.

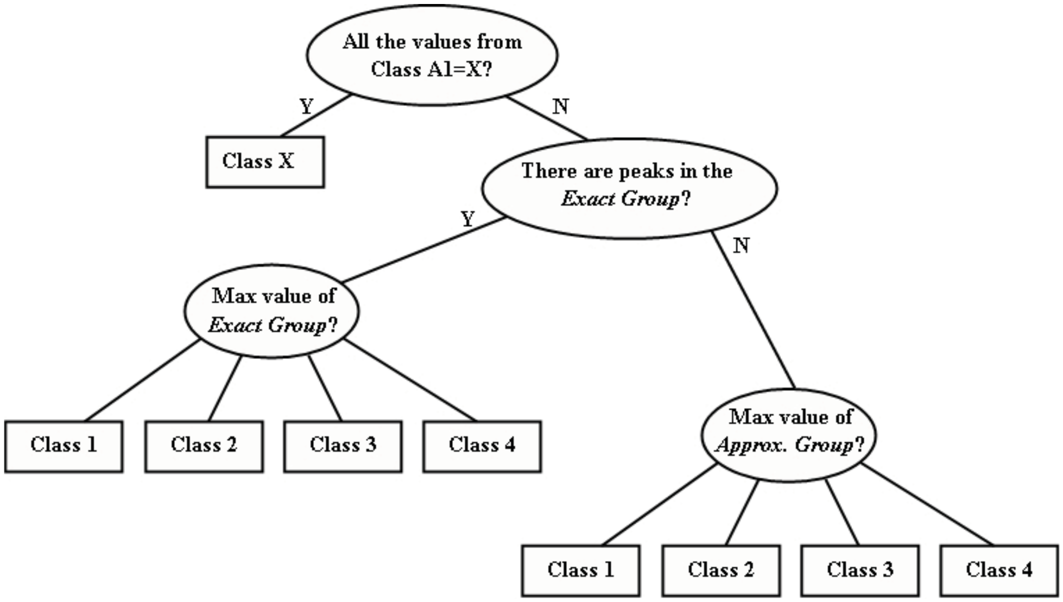

Fig. 2. Decision tree developed.

V. RESULTS

The trials correspondent to each stimulus frequency were concatenated to compose a vector of 200 s of EEG signal. The composed signals of the six channels were spatially filtered using the Common Average Reference (CAR) method. In the CAR, the average value of the entire electrode montage (the common average) is subtracted from the one of the channel of interest [13]. That is,

$$u_i^{CAR} = u_i^{RE} - \frac{1}{n}\sum_{j=1}^{n} u_j^{RE}, \tag{4}$$

onde u_i^{RE} is the potential between the electrode i and the Reference Electrode, and n is the number of electrodes used in the acquiring structure. Even with the assumptions of complete electrode coverage usually not met completely in practice, the CAR provides EEG recording that is nearly reference-free [13].

Two approaches were adopted to apply the steps of feature extraction and rule-based classification on the spatially filtered signals. The first one uses the signal from all six electrodes for the processing. It means that the peaks from the six channels were extracted and used in the decision tree. The second approach uses only the three occipital channels O1, O2 and Oz (chosen empirically), which was implemented to evaluate the system performance using less electrodes. In both cases, the first 2 s of each trial were not considered to estimate the correct classification rate, since the user was not gazing any bar in this interval.

In both approaches the periodogram was determined for the spatially filtered signal, split in intervals of 2 s with overlapping segments of 1 s, which allows to determine one class at each second. The rate of the spectral F-test was done with a significance level of $\alpha = 0.05$ and $L = 32$ neighbor frequencies, which leads to a SFT_{crit} of $F_{(2,64,0.05)} = 3.1404$. The decision tree was performed incrementally for the signal, that is, at each second, new 256 samples were processed and classified by the decision tree.

The results found for each volunteer in the first approach, that is, using six electrodes for classification, are shown in Table I. Note that even with a medium classification rate (71% for Vol4) the ITR is high (40.3 bits/min). This is because the analysis is performed incrementally and the system updates the classification result at each second, so that the BCI is able to take 60 decisions per minute. Although the high values of hit rates (99% for Vol1), some volunteers, such as Vol6, have not adapted to the system.

TABLE I

CLASSIFICATION RATE AND ITR FOR SIX VOLUNTEERS USING SIX EEG CHANNELS.

	Classification Rate	ITR (bits/min)
Vol1	99%	114.2
Vol2	79%	55.5
Vol3	79%	55.5
Vol4	71%	40.3
Vol5	49%	11.5
Vol6	38%	3.6
Average	**69%**	**46.8**

The second approach allowed studying the influence of the reduction of the number of electrodes, and the results are presented in Table II. Although the number of electrodes was reduced during the processing steps, just a slight performance reduction can be observed. This indicates the possibility of developing a SSVEP-BCI with quite few electrodes (three or four).

In terms of comparison, in other works [4], [8], the classification method is generally based on founding a threshold to detect the peaks. In [4], linear discriminants were used as the classifier model, which correspond to calculate a threshold

TABLE II

CLASSIFICATION RATE AND ITR FOR SIX VOLUNTEERS USING THE THREE OCCIPITAL CHANNELS.

	Classification Rate	ITR (bits/min)
Vol1	99%	114.2
Vol2	74%	45.7
Vol3	77%	51.4
Vol4	72%	42.0
Vol5	41%	5.3
Vol6	33%	1.4
Average	**66%**	**43.3**

in one dimension. It has resulted in a classification rate of 90% and a ITR of 43 bits/min. In [8], a method to find the best spatial filtering configuration was shown, which requires some training. The detection rates, for stimulus frequencies in the 30-45 Hz range, were characterized by values of the area under the Region of Convergence from 0.8 to 1.

In this paper, a totally automatic SSVEP-BCI with hit rate up to 99% and ITR up to 114.4 bits/min is shown. Moreover, there is no need of settings, calibration, personalization, adaptation, baseline acquiring or training step. This was the same structure implemented in [3], [6] and [7] for low stimulus frequencies. This work, actually, has proven that it could be used also in high frequency range. It means that using a statistical test is a robust way of detecting evoked peaks. Also, a rule-based classifier, i.e., a decision tree, is enough to discriminate the peaks extracted. Although the trials were performed offline, the trials configuration represents a good characterization of the influence from the other stimuli, once the volunteers gazed on one stimulus while the others were lit on. Moreover the SSVEP-BCI using high stimulus frequencies is more appropriated to be used in long time operation because gazing that stimuli is less tiresome.

VI. CONCLUSIONS

The system presented in this work is very efficient in detecting SSVEP in high frequencies range. The use of higher stimulus frequencies leads to a more comfortable stimulation. The system developed is totally automatic and no adjustment is required. The parameter of the statistic test, L, is not related to the time period of the EEG signal analyzed, but to the number of frequency components analyzed, which leads to a quite robust system. The best results are found using six electrodes, but good results can be found using only three occipital channels during the processing step. This automatic system would be useful to implement an online SSVEP-BCI. Such BCI would be applied to command a robot or even a robotic wheelchair, for instance. Indeed, this last possibility is the one we now working on.

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