A High Frequency Steady-State Visually Evoked Potential Based Brain Computer Interface Using Consumer-grade EEG Headset

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***Abstract*— This work evaluates a possibility of creating a high-frequency, SSVEP-based brain computer interface using a low cost EEG recording hardware - an Emotiv EEG Neuroheadset. Both above aspects are crucial to enable deploying the BCI technology in the consumer market. High frequencies can be used to create a non-tiring and more pleasant interface. Commercial EEG systems, as the Emotiv EEG, although demonstrating large underperformance, are much more affordable than standard, clinical-grade EEG amplifiers. A system classifying between two stimuli and rest is designed and tested in two experiments: on five and ten subject respectively. First, the accuracy of the system is compared for frequencies in lower range (17Hz, 19Hz, 23Hz, 25Hz) and higher range (31Hz, 33Hz, 37Hz, 40Hz). The mean online accuracy is $80\% \pm 15\%$ for the former and $67\% \pm 12\%$ for the latter. Second, a more thorough investigation is done by evaluating the system for frequencies within a set of 35Hz–40Hz. Although the mean accuracy, $64\% \pm 22\%$, is relatively low, most of the users were able to achieve satisfying accuracy, with the mean reaching $82\% \pm 5\%$, which would allow for an efficient, and yet pleasant, usage of the BCI system. In each case a user dependent approach is applied, with a calibration session lasting about five minutes. EEG feature extraction is done using common spatial pattern (CSP) filtering, canonical correlation analysis (CCA), and linear discrimination analysis (LDA).**

I. INTRODUCTION

A Brain-Computer Interface (BCI) is an artificial system that allows expression of user's intent by directly measuring and interpreting brain activity, bypassing the body's natural efferent pathways (peripheral nerves and muscles). This provides an alternative channel for communication and control [1]. Although different methods of utilizing EEG signal's features have been proposed for the use with BCI systems, the steady-state visually evoked potentials (SSVEPs) have obtained increased attention. This is mainly because with no extensive training needed, system still shows high information transfer rate[2].

The SSVEP is the response of the brain to the flickering visual stimulation presented with a repetition rate from 4Hz up to 90Hz [3]. It is usually classified into three ranges: low (up to 12Hz), medium (12-30Hz), and high (above 30Hz).

The amplitude of brain response for lower frequencies is larger than for higher [4], making it easier to detect and analyze. Using lower frequencies, however, seems rather tiring and annoying [5]. It can also be harmful, as it carries additional risk of inducing epileptic seizures for photosensitive users [6].

Researchers proved the performance of the SSVEP-based BCI systems during many laboratory studies, mainly focusing on the 5–30Hz range [7]. However, in order to introduce BCI systems to the consumer market, some real-life issues still have to be overcome: the stimulus must be unobtrusive, the system must be easy enough to use, and utilize a low cost hardware. As for the latter, although EEG amplifiers and recorders are still, on average, less expensive than the equipment used in other neuroimaging methods, most of them are not suitable for the commercial use.

So far only a few studies utilizing low-cost EEG equipment have been performed. In [8], [9], and [10] an accuracy of 95%, 80% and 75% respectively was obtained for detecting frequencies below 15Hz. [11] evaluated 54 users applying frequencies in 6–24Hz range, and reported a maximum classification accuracy of 85% for the stimulus pair 8Hz and 10Hz. However, for frequencies higher than 20Hz, the accuracy did not exceed 60%.

This study, therefore, concentrates on a consumer-grade, portable EEG recorder, i.e. Emotiv EEG Neuroheadset[1]. A high frequency stimulus ($>$ 30Hz) significantly decreasing user's visual fatigue, is applied.

The rest of this paper is organized as follows: section II describes the equipment used during recordings; section III presents the calibration paradigm and signal analysis methods. Section III-C.4 describes tests of the system. Section IV presents results, and Section V contains conclusions.

II. EQUIPMENT

A. The stimulus

The stimulus for this study was provided by a set of LED diodes. It consisted of a 8cm by 8cm square panel of 64 white, LED diodes, with a dispersive screen in front of them. The flicker frequency control was performed by an Atmega 328p microcontroller mounted on an Arduino UNO[2] evaluation board, and based on a hardware, 16bit timer.

B. EEG Recording

The EEG signal was recorded with Emotiv EEG Neuroheadset. It has already proved its usability in many experiments (e.g. [12], [10], [13], [14]) and the price (about

[1] http://emotiv.com/eeg
[2] http://www.arduino.cc

700USD) is much more affordable than clinical-grade amplifiers (thousands of USD).

The cap was put backwards, so that more electrodes were placed over the visual cortex. The signal was collected with 128Hz sampling frequency. It was gathered from 8 electrodes corresponding to O1, O2, P7, P3, P4, P8, CP5, and CP6 in the international 10-20 system. Two reference electrodes were located at F3 and F4[15]. Each channel was filtered by a hardware band-pass filter with cut-off frequencies at 0.2Hz and 45Hz, and two notch filters at 50Hz and 60Hz.

III. METHODS

This section describes the data acquisition and further analysis of EEG signals.

The acquisition consists of two parts. First, calibration is performed. During this stage spatial filters (CSP) are calculated, and classifiers trained for each user and selected frequencies. Second, an evaluation of the trained system is performed.

The system itself consists of two stimuli, each flickering at a constant rate. User's objective is to focus on one of them. The system aims to detect the SSVEP generated by this stimulus. Proper detection enables basic control: if two different functions are assigned to each of the frequencies, detecting on which stimulus user is concentrating can evoke one of these functions.

A. Subjects

15 subjects (including 3 females) participated in the experiment. All subjects were fully informed about the possible health risks concerning participation in the experiments, and gave their consent. Ethical approval was granted by the institutional ethics committee.

B. Calibration paradigm

The user is seated in front of a computer screen, at the distance of about 1.5m. Two LED panels are attached to the sides of the monitor, one on each side.

Each session consists of 40 trials, each lasting four seconds. During each trial two stimuli are displayed; the frequencies of stimuli are randomly chosen from a given, constant set. User is to focus on one of the stimuli specified by a marker (a green square displayed on the screen next to the selected stimulus). The position of the marker is also random in each trial. There is a two second break after each trial, during which no stimuli are displayed, only the marker showing the next focus point. A basic scheme of the system used in the calibration process is presented on Fig. 1.

The randomization algorithm is designed so that during each session the user concentrates 10 times on each of the frequencies from the set.

After the calibration, the collected EEG data is written to a file along with tags specifying when the stimulation occurred, and on which frequency the user was concentrating.

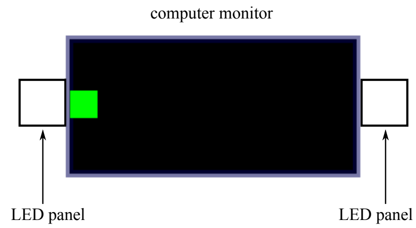

Fig. 1. The scheme of calibration process. Two LED panels are used as stimuli, each flickering at different frequency. Green marker, displayed on the monitor, shows at which stimuli user should be focusing.

C. Calibrating the system

1) Spatial filtering: Initially, the recorded EEG consists of eight channels. A common spatial patterns method [16], [4] provides a way of reducing the dimension of this signal to the one that contains the most information. Essentially, this method looks for a linear combination of channels that, for given two time series (two conditions), maximizes variance (energy) in one of the time series and, simultaneously, minimizes variance in the second one.

2) Canonical correlation: The feature calculation is done by the canonical correlation method [17]. This procedure allows for calculation of correlation between two sets of signals. Here it is applied to the spatially filtered signal and a matrix which two rows contain a sine and cosine wave of specific frequency. As the SSVEP is phase locked, using both sine and cosine wave will automatically choose the phase that gives the highest correlation.

3) Choosing the best frequencies: Although the system is designed to work with two stimuli, more frequencies are used for stimulation during the calibration stage. As the SSVEP response to different frequencies changes from person to person, this approach enables choosing the best stimuli pair for the given user. The procedure is as follows:

1) For each frequency f_i a CSP filter is calculated following procedure described in [4].
2) A pair of frequencies f_i and f_j is chosen.
3) Signal is filtered twice: once using the CSP filter calculated for frequency f_i, and then using the filter calculated for frequency f_j. From the filtered signals, only channels with the highest energy during a stimulation (corresponding to the largest eigenvalue) are chosen producing signals s_{fi} and s_{fj} respectively.
4) Signals s_{fi} and s_{fj} are divided into parts, s^k_{fi} and s^k_{fj} for $k = 1, \ldots, 40$, each corresponding to one stimulation trial.
5) For signal s^k_{fi} (for each k), a canonical correlation is calculated with a signal consisting of sine wave in one channel and cosine in the other channel, both with frequencies f_i. This yields a correlation feature ρ^k_{fi}. It is expected that the correlation is high when the stimulation frequency during the corresponding trial was f_i, and low otherwise.
6) The same is done for signal s^k_{fj} (for each k), only frequency of sine/cosine signal is f_j.
7) The signal is now characterized by two sets of features: ρ^k_{fi} and ρ^k_{fj} for $k = 1, \ldots, 40$. Each part of the signal can be represented in a two-dimensional space – a correlation space, i.e. $\rho^k_{ij} = (\rho^k_{fi}, \rho^k_{fj})$.

8) Each point in the correlation space, ρ_{ij}^k, can be assigned to one of three sets depending on the stimulation frequency during the corresponding trial: if k corresponds to the trial in which the stimulation frequency was f_i, point is assigned to class C_{fi}. If k corresponds to the trial in which the stimulation frequency was f_j, point is assigned to class C_{fj}. Otherwise it is assigned to a class C_{rest}.
9) For each pair of classes: C_{fi} and C_{rest}, C_{fj} and C_{rest}, and C_{fi} and C_{fj}, Fisher's Linear Discrimination Analysis (LDA) is applied. This results in a number λ_{ij}^l for $l = 1,2,3$, that describes the separation between the classes from the corresponding pairs after the LDA projection - λ_{ij}^l is the largest eigenvalue that is calculated during the LDA procedure.
10) The points 2–8 are repeated for each of the frequency pairs. For each pair f_i, f_j a value S_{ij} is calculated as:

$$S_{ij} = ((\lambda_{ij}^1)^2 + (\lambda_{ij}^2)^2) sin\left(2arctan\left(\frac{\lambda_{ij}^2}{\lambda_{ij}^1}\right)\right) + \lambda_{ij}^3. \quad (1)$$

First part of the equation describes how classes C_{fi} and C_{fj} separate from the C_{rest} class. The $sin\left(2arctan\left(\frac{\lambda_{ij}^2}{\lambda_{ij}^1}\right)\right)$ part assures that cases where λ_{ij}^1 is much higher than λ_{ij}^2 (or vice versa) will be punished (the best case is when $\lambda_{ij}^1 = \lambda_{ij}^2$). The last part increases S_{ij} when there is a good separation between classes C_{fi} and C_{fj}.
11) The frequency pair that has the largest S_{ij} is chosen for further testing; this assumes that the better the LDA separation, the better further classification will be.

4) Classifiers: The previous procedure results in a selection of two frequencies, f_k and f_l, with corresponding spatial filers, CSP_{fk} and CSP_{fl}, three sets of data points in correlation space: class C_{fk}, class C_{fl}, and C_{rest}, and three LDA projection vectors: separating C_{fk} and C_{rest}, separating C_{fl} and C_{rest}, and separating C_{fk} and C_{fl}. On these data three logistic regression classifiers are trained: each for the pair of classes after the LDA projection.

D. Testing procedure

The experimental setup is similar to the one from calibration described in Section III-B. The stimulation frequencies are those chosen during the calibration procedure. The flicker lasts for four seconds and there is a four seconds break between trials.

The subject concentrates on one of three different points: on any of the stimulation fields, or on the center of the monitor. As previously, the instructions where to look are given by a green marker displayed on the screen.

There are 30 trials in total: 10 for each frequency and 10 trials when the user is supposed to look in the middle of the screen. This ensures that the system is tested for a situation when the subject is not using the BCI system.

E. Testing algorithm

The system aims to classify at which stimuli the user is looking during each trial: a two second window is analyzed every 0.5 second. This means that during each four second trial there are seven classifications.

1) Classification procedure: The classification procedure is as follows:

1) The analyzed signal window is filtered with two CSP filters (one for each frequency).
2) Canonical correlation is calculated as described in the Section III.
3) The resulting point in the correlation space is projected using each of LDA vectors.
4) Resulting points are classified by three logistic regression classifiers: first two classify whether the signal belongs to class corresponding to one of the frequencies or the *rest* class. It is possible that these two classifiers will state membership to both frequency classes - in that case, the third classifier is used to distinguish them.
5) If during the last five (out of seven) measurements the system classifies 3 times positively, i.e. the detected frequency is the same as the one user is focusing on, then it is assumed that during this trial classification was successful. Based on this, the accuracy of the system is calculated as a ratio of the number of positively classified trials to the number of all trials.

IV. RESULTS

A. Comparing high and low frequencies

The first experiment was designed in order to compare accuracies of the system for low and high frequencies. The test consisted of two separate measurements for two sets of frequencies: low - 17Hz, 19Hz, 23Hz, 25Hz, and high - 31Hz, 33Hz, 37Hz, 40Hz. During each test two frequencies from each group were selected as described in Section III. The results are presented in Table I. The average accuracies were: $80\% \pm 15\%$ for the set of lower frequencies, and $66\% \pm 12\%$ for the set of higher frequencies.

TABLE I
RESULTS OF COMPARISON BETWEEN LOW AND HIGH FREQUENCIES

Subject	Frequencies (Hz)	Accuracy (%)
S0	19, 25	86
	31, 40	60
S1	17, 19	60
	31, 40	60
S2	17, 23	97
	33, 37	60
S3	19, 25	70
	31, 33	63
S4	19, 25	66
	31, 33	60
S5	17, 19	100
	31, 40	93

B. Evaluation of high frequencies

The second experiment aimed at more thorough investigation of the high frequency range. For that purpose a larger set of high frequencies was selected: 35Hz, 36Hz, 37Hz, 38Hz, 39Hz, and 40Hz. As previously, two best frequencies were chosen for each user. Table II presents obtained results. All subjects performed with a mean accuracy of $64\% \pm 22\%$, however six of them reached mean accuracy of $82\% \pm 5\%$.

TABLE II

THE ACCURACY OF THE SYSTEM TESTED ON A LARGER SET OF HIGHER FREQUENCIES

Subject	Frequencies (Hz)	Accuracy(%)
S6	39, 40	87
S7	36, 37	77
S8	35, 36	33
S9	36, 39	40
S10	35, 37	40
S11	38, 40	37
S12	37, 39	80
S13	35, 37	90
S14	35, 36	83
S15	35, 38	77

V. CONCLUSIONS

This paper aimed at researching the ability to utilize a consumer-grade EEG equipment, the Emotiv EEG, to detect high-frequency SSVEP responses. Based on the presented framework, one could imagine building an unobtrusive and affordable BCI system, e.g. used for TV control, where a function changing channel or volume would be assigned to each stimulus.

Presented results show a decline in the accuracy of the system with high-frequency stimuli when compared to the low-frequency settings. This is in line with other experiments: [4] has shown that SSVEP response decreases after about 15Hz, making it harder to detect. [7] stated explicitly that only about 65% of users were able to use BCI when it came to frequencies above 30Hz. This finding is confirmed in the second presented experiment where six out of ten users reached an accuracy of 82%.

The fact that one third of subjects are not able to use high-frequency SSVEP systems is a challenge in designing BCIs. On one hand, those systems should incorporate high-frequencies as the users find them preferable [7]. On the other, BCIs must include lower-frequencies for unresponsive subjects in order to make the system usable. This implies that the application should use both high and low frequencies during the calibration to establish the mode of operation. Moreover, frequencies should be selected from a wide set, as the SSVEP response is very subject dependent. This is visible when comparing tables I and II. Higher accuracy in the second experiment might be due to a larger number of frequencies selected for the calibration.

An interface designed this way, incorporating higher and lower frequencies, and calibrated to a specific user, would enable both good user experience and efficient operation.

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