ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/305909794

# Brain-computer interface based on steady-state visual evoked potentials

**Conference Paper** · May 2016

DOI: 10.1109/MIPRO.2016.7522174

CITATIONS
4

READS
82

**3 authors**, including:

Krešimir Friganović
University of Zagreb
**14** PUBLICATIONS **36** CITATIONS

SEE PROFILE

Mario Cifrek
University of Zagreb
**124** PUBLICATIONS **1,265** CITATIONS

SEE PROFILE

**Some of the authors of this publication are also working on these related projects:**

Project MULTISAB View project

Project Intrabody Communication as a Key Technology for Internet of Things in Health Applications View project

All content following this page was uploaded by Krešimir Friganović on 19 August 2019.

The user has requested enhancement of the downloaded file.

# Brain-computer Interface Based on Steady-state Visual Evoked Potentials

K. Friganović*, M. Medved* and M. Cifrek*
* University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia
kresimir.friganovic@fer.hr

**Abstract - Brain computer interface (BCI) can establish communication between human brain and a computer which is independent from normal neuromuscular pathways. This allows giving instructions to the computer without the use of standard communication channels, such as a mouse or keyboard. This paper describes the development of a steady-state visual evoked potential (SSVEP) based BCI system. EEG amplifier with one bipolar channel is designed for the acquisition of raw EEG data from the posterior region of the head over the occipital lobe. The three white LED chessboards with programmable flicker frequencies are used as stimulation to induce different SSVEPs. For feature extraction, the Fourier transform of autocorrelation of the EEG signal is used. In MATLAB, a graphical user interface (GUI) application is implemented, showing the EEG signal in time and frequency domain, both in real time. Simple game of turning on and off the three light bulbs, while looking at different LED chessboard, is also implemented in GUI.**

**Keywords: brain-computer interface (BCI), steady-state visual evoked potentials (SSVEP), EEG amplifier**

## I. INTRODUCTION

Brain computer interfaces (BCI) can establish communication between human and computers. This communication is independent from the normal neuromuscular pathways and allows the subject to give instructions to computer by paying a bit of attention or thinking a single thought [1].

Bioelectrical brain activity is measured and used to detect specific patterns in activity. Brain activity can be measured invasive, when electrodes are placed on the surface of the brain (electrocorticography, ECoG). Signals measured with this method have greater amplitude and better signal to noise ratio (SNR) than signals measured from the surface of the scalp (electroencephalography, EEG) do [2]. However, due to the non-invasive procedure of EEG recording, the EEG method is mostly used in the brain-computer interfaces.

The EEG is used to measure and detect specific patterns in the bioelectrical brain activity, called event-related potentials (ERPs). The three most used ERPs in BCI systems are: P300, SSVEP and motor imagery potentials. In this paper SSVEP are used to establish communication.

SSVEPs are manifested as a periodic response of the bioelectrical brain activity over the occipital lobe. They occur when subject is focusing on the continuous flickering visual stimulus. The frequency of SSVEP is equal to the flicker frequency of the stimulus. Fig. 1 shows a diagram of the BCI system based on the SSVEP.

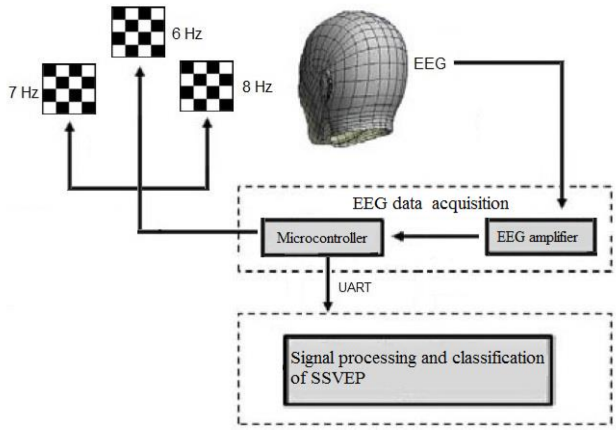


Figure 1. A Block diagram of SSVEP based BCI system

Algorithms for extraction and classification of SSVEPs can be found in related works ([3] - [5]). Design of EEG amplifier, including preamplifier and noise reduction circuitry is represented in the relevant works ([6] - [9]).

In our research, we have developed and designed both hardware and software components of SSVEP BCI system, using only one bipolar EEG channel recording from the posterior region of the head over the occipital lobe (electrodes are placed over position O1 from 10-20 system) and three LED stimuli.

## II. HARDWARE

### A. EEG Amplifier

Hardware design is an important part of the measurement system because all digital signal processing methods depend on the quality of the analog preprocessing. An interference affecting the EEG signal determines the design of an EEG amplifier. The main interferences are from the power lines (50 Hz common mode interference) and the human body signals that don't belong to the EEG signal spectrum. Additional factors that affect the quality of the EEG signal are the impedance and voltage offsets, created by inadequate preparation of the skin-electrode interface. Key parameters in design of EEG signal measuring system are:

- The input impedance of the preamplifier must be high, so that the interference could be rejected.

- A differential amplifier with the high common mode rejection ratio (CMRR) is required to suppress common mode interference.
- The amplifier must have a low noise with gain higher than $10^4$, due to the small EEG signals amplitude.
- The frequency spectrum of a desired EEG signal is lower than 40 Hz, and, therefore, higher frequencies need to be suppressed.

The amplifier consists of the several stages in a cascade. A block diagram of the whole EEG amplifier is shown at Fig. 2. The first stage begins with a RFI filter that suppresses unnecessary high frequency signals from the input. An instrumentation amplifier is a preamplifier with high input impedance, low voltage drift, low current consumption, low noise and high CMRR. A shield driving circuit is used to additionally eliminate common mode interferences that are engaged in the measuring circuit. The third cascade stage is a high pass that is needed to suppress the DC frequency component so that non-inverting amplifier does not amplify unneeded signal component. A low pass filter is realized as the fourth order by using operational amplifier circuit sections to eliminate high frequencies before the final amplification. At the end of the cascade is a programmable gain amplifier (PGA). This amplifier is an advantage, since it allows for the signal to be aligned to operating range of different analog-digital converters (ADC).

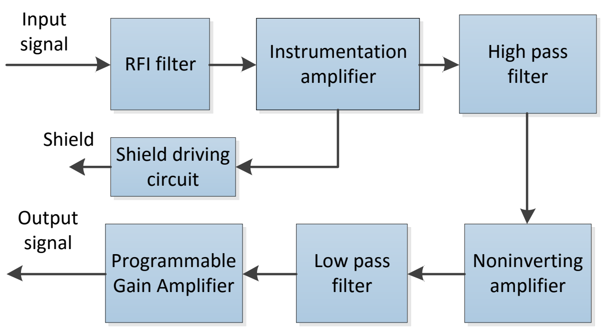


Figure 2. Block diagram of EEG amplifier

The RFI low pass filter is implemented by two resistors and three capacitors as it is shown at Fig. 3. The filter is designed to bypass differential signals lower than 419 Hz, and common signals lower than 39.8 kHz. Most of unwanted high frequencies are eliminated by this filter.

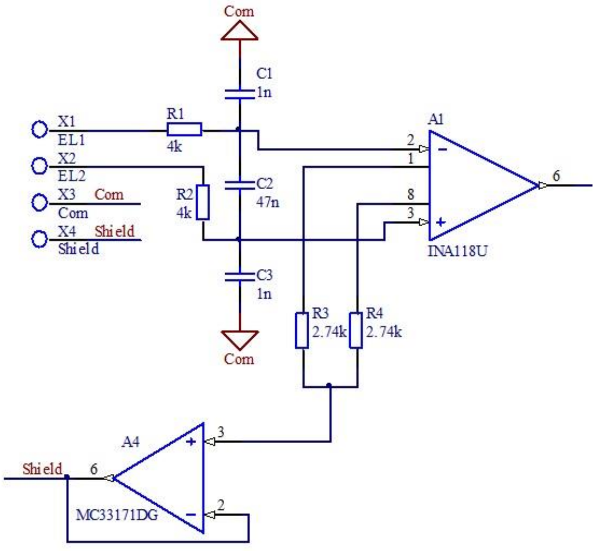


Figure 3. Schematic of EEG amplifier input stage

An instrumentation amplifier INA118U is used as the first stage amplifier. The gain is set to 10 by resistors $R_3 = R_4 = 2.74\ \mathrm{k\Omega}$ and it can be calculated by (1).

$$G = 1 + 50\mathrm{k} / (R3 + R4) \tag{1}$$

Main features of this amplifier are high CMRR (110 dB), low offset voltage ±50 µV, 1 nA input bias current, offset drift around ±2.1 µV/°C and input impedance about 3 GΩ [10]. The gain of differential signal shouldn't be too high because offset voltage is also amplified, as well as unwanted, especially in this application.

To suppress the common signal, which is coupled to the amplifier circuit, a shield drive circuit is used. The composition of the circuit is made by the operation amplifier MC33171DG. Therefore, common signal is passed to cable shields and its influence on the measured signal is reduced.

The next cascade section is a high pass filter to eliminate the DC component. The cut-off frequency is set to 0.8 Hz by selecting capacitor 470 nF and resistor 422 kΩ. Consequently, the signal is more stable and accurate so it can be amplified again.

The non-inverting amplifier is implemented using the operation amplifier OPA2277UA which has low power consumption (0.9 mA) and low input voltage offset (±50 µV). Signal may still contain unwanted components at higher frequencies. Therefore, gain is set to 40 in order to decrease amplification of signal.

The low pass filter is used as antialiasing filter which has the cut-off frequency 37.2 Hz. It is implemented as the Butterworth $4^{th}$ order filter using two Sallen-Key sections. This enables sampling frequencies higher than 100 samples per second and the suppression of 50 Hz signal for at least 9 dB.

The final stage of the EEG amplifier is a programmable gain amplifier. This section is shown at Fig 4. Different gains are realized by jumpers because the speed of switching is not important. Special topology is chosen where the jumper properties do not affect the gain and resistors do not load amplifier output. Gains implemented by this configuration are 1.001, 10.01, 101.

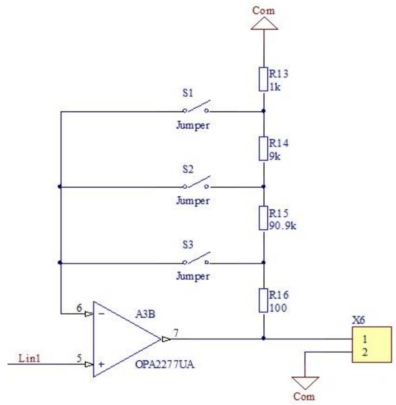


Figure 4. Programmable Gain Amplifier

### B. *Signal adjustment and data acquisition*

The EEG amplifier is made ts one printed circuit board (PCB) and connected at bipolar battery supply ±5V. Before the signal is brought to ADC, it needs to be adjusted by special circuitry to fit the ADC unipolar voltage range 0-5 V. Circuitry is shown on Fig 4. When using PGA gain of 100 times, the final gain of the whole cascade is 40600. Since the highest expected input signal amplitude is 60 µV, then in total gain the signal is amplified to the value of around 2.5 V. The amplified signal in range of ±2.5 V is shifted by 2.5 V to meet the ADC bipolar supply requirements.

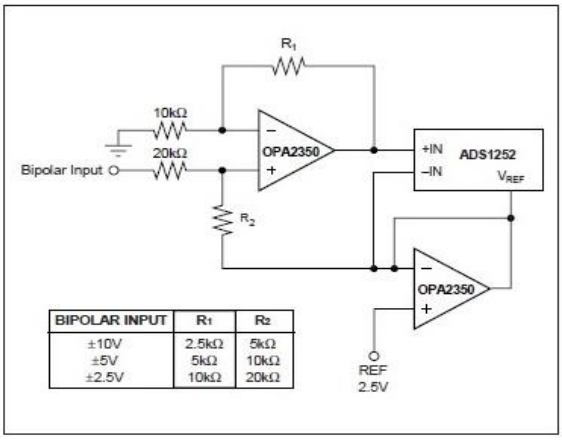


Figure 5. Signal adjusting circuitry [11]

As its shown at Fig 5., ADC used is ADS1252, which is chosen because of 24-bit resolution. Selected sampling rate is 200 S/s which is more than enough for EEG signals.

A microcontroller collects data by serial peripheral interface (SPI) and transmits them to PC by UART. Signals are received and processed in real time using MATLAB.

### C. *Stimuli*

Flickering stimuli for SSVEP based BCI system must have stable frequency to insure less SSVEP jitter in frequency domain of EEG data. Three LED chessboards (Fig 6.) are designed for this purpose. They are powered by +5 V output from the microcontroller. Flickering frequencies are controlled by microcontroller PWM signals and can be changed within MATLAB GUI application.

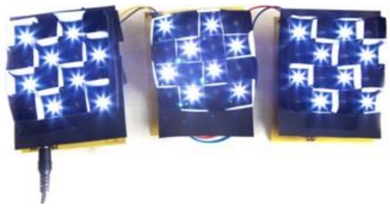

Figure 6. LED chessboard stimuli

## III. SOFTWARE

### A. *Signal processing*

After obtaining the raw EEG signal from the occipital lobe, three steps of signal processing were done to extract relevant information. The first step is the preprocessing of the signal, the second is analyzing it and the third is the feature extraction and classification of the features. Those three steps are done in MATLAB.

During the real time measurement, EEG is constantly recorded. In the preprocessing step, a 4 seconds long block of raw EEG data is acquired every 0.5 seconds. This block is then filtered with the bandpass Butterworth filter of the 4$^{th}$ order with cutoff frequencies at 4 and 30 Hz. Filtering is needed to reduce noise from artefacts. The filtered block is then analyzed.

Spectrum components of the EEG signal containing SSVEPs are first processed with autocorrelation (2). Autocorrelation of the periodic signal is a periodic function of the same frequency and autocorrelation of aperiodic signal tends to zero [12]. Therefore, the periodic SSVEP signals are enhanced and background EEG activity is reduced.

$$R_{ff}(\tau) = \lim_{T\to\infty} \frac{1}{2T} \int_{-T}^{T} f(t)f(t-\tau)dt \qquad (2)$$

For spectrum analysis of auto-correlated EEG data, a fast Fourier transform is used, due to the fast execution performance necessary for real time systems.

### B. *Feature extraction and classification*

To determine on which chessboard the subject is focusing on, the amplitude of the EEG spectrum on flickering frequencies ($f_1$, $f_2$, $f_3$) and their first and second harmonics are examined. The maximum sum of amplitudes is then chosen for classification feature $F$:

$$F(f1, f2, f3) = \max_{f=f_1,f_2,f_3} \{X(f) + X(f \cdot 2) + X(f \cdot 3)\} \tag{3}$$

If the maximum $F$ is larger than threshold $T$, $F$ is classified to classes LED1, LED2 or LED3 (corresponding to one of the three chessboard stimuli). The threshold $T$ is determinate as a mean of the calculated EEG spectrum.

### C. Application

To demonstrate the usage of SSVEP based BCI system, we simulated a real life application of turning lights on and off in the MATLAB GUI application (Fig 7).

The subject's task was to turn on one of the three light bulbs (by personal choice), while focusing on the corresponding flickering chessboard stimuli. Also, the EEG signal is shown in real time, both in time and frequency domain.

## IV. Experiment

The experimental task was to turn on every light bulb in the application. Two healthy subjects with normal to corrected vision, averagely age 23, were tested. Subjects were in a room with dim lights, comfortably seated 1 m from the computer screen and the LED chessboards stimuli (Fig 8).

Three electrodes were placed on the subject's scalp. Two electrodes for the bipolar channel were set over position O1 and one referent ground electrode was stick to the forehead (position Fpz). Flickering frequencies were set to 6, 7 and 8 Hz. The subjects tried to turn each light bulb 10 times. Each successful task is marked as TP (true positive detection). False positive (FP) detections are also marked. Fig 9. shows results for both subjects.

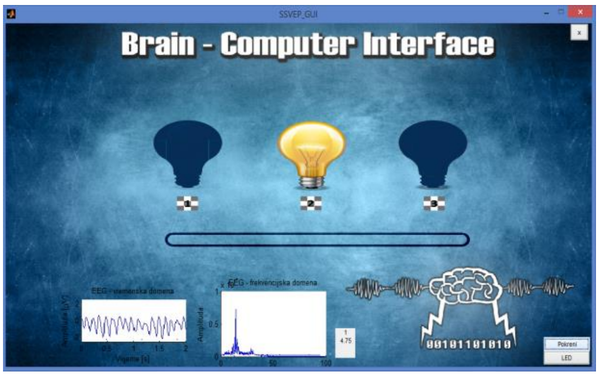


Figure 7. MATLAB GUI application; down left: time domain EEG signal – alpha waves; down middle: spectrum

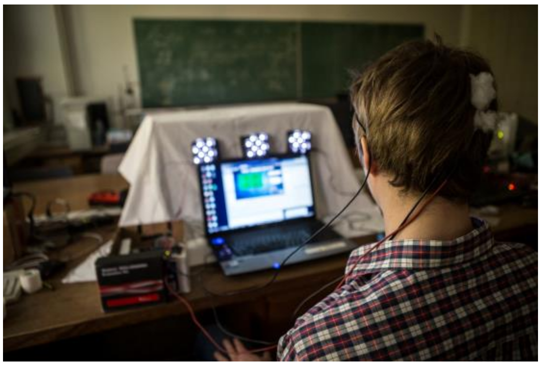

Figure 8. The subject during experimental task

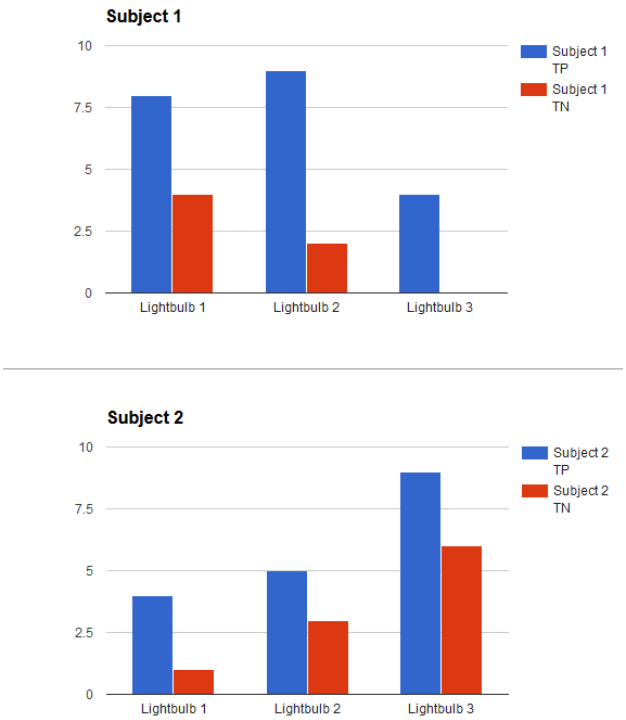


Figure 9. True positive and true negative detections for each stimulus

## V. Conclusion

In this paper we have developed a BCI system based on SSVEPs. We propose a small, portable system that uses only one bipolar channel. Three LED chessboards are used to control simple application of turning light bulbs on and off, which can be easily implemented in to homes. The results show good detection for specific stimulus frequency. The methodology was tested for future work. Improvements of system focuses on frequency calibration for each subject and machine learning classification to improve robustness and accuracy.

## REFERENCES


[1] Sanei S.,Chambers J.A. „EEG Signal Processing“, John Wiley & Sons Ltd., Sveučilište Cardiff, 2007.

[2] Šefer A.B. „Obrada elektroencefalografskog signala u svrhu ostvarivanja sučelja mozak-računalo“, Postgraduate doctoral study coursework, Univeristy of Zagreb, 2011.

[3] Hsiang-Chih C. Et al. Real-Time Control of an SSVEP-Actuated Remote-Controlled Car, SICE Annual Conference, 2010, pp. 1884-1887.

[4] Chun-Shu W. Et al. Detection of Steady-state Visual-evoked Potential Using Differential Canonical Correlation Analysis, 6th Annual International IEEE EMBS Conference on Neural Engineering, 2013, pp 57-60.

[5] Guangyu B. Et al. The SSVEP Topographic Scalp Maps by Canonical Correlation Analysis, 30th Annual International IEEE EMBS Conference, 2008, pp. 3759-3762.

[6] I. Krois, "Measurement System for Neurophysiological Functions Monitoring," *Doctoral Thesis*, University of Zagreb, 2001.

[7] Whitchurch A. K., Abraham J. K., Lonkar M.A., Varadan V. K., „Design of a compact amplifier and signal conditioning module for wireless EEG monitoring “, IEEE Region 5 Tehnical Conference, 2007., pp. 153 156.

[8] Zhang L., Guo X., Wu X, Zhou B. „Low-cost circuit design of EEG signal acquisition for the brain computer interface system “, IEEE BMEI 6th International Conference, 2013., pp. 245-250.

[9] Tan Y. Q., Ibrahim F., Moghavvemi, „Two Electrodes Low Voltage Input EEG Amplifier for Brain-Computer-Interface “, ICIAS 2007, pp. 315-320.

[10] Blurr-Brown Application Guide, „Precision, Low Power Instrumentation Amplifier “

[11] Blurr-Brown Application Guide, „24-Bit, 40kHz Analog-To-Digital Converter, ADS1252“

[12] Lončarić, S., „Random processes in systems – lectures “, Faculty of Electrical Engineering and Computing, Zagreb, 2008.


View publication stats