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User-centered design of brain-computer interfaces: OpenBCI.pl and BCI Appliance

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Abstract. Brain-Computer Interface (BCI) allows for non-muscular communication with external world, which may be the only way of communication for patients in a locked-in state. This paper presents a complete software framework for BCI, a novel hardware solution for stimuli rendering in BCIs based on Steady State Visual Evoked Potentials (SSVEP), and a univariate algorithm for detection of SSVEP in the EEG time series.

OpenBCI is a complete software framework for brain-computer interfaces. Owing to an open license and modular architecture, it allows for flexible implementations of different communication channels in the serial or parallel hybrid mode, minimization of costs and improvements of stability and efficiency. Complete software is freely available from http://openbci.pl.

BCI Appliance is a hardware solution that allows for dynamic control of menus with stable generation of stimuli for the SSVEP paradigm. The novelty consists of a design, whereby the LCD screen is illuminated from behind using an array of LEDs.

Design pioneers also proposed a new line of thought about the user-centered design of BCI systems: a simple box with one on/off button, minimum embedded software, wireless connections to domotic and EEG acquisition devices, and user-controlled mode switching in a hybrid BCI.

Key words: brain-computer interface, BCI, steady-state Visual Evoked Potentials, SSVEP, eyetracker, assistive technologies.

1. Introduction

Jean-Dominique Bauby was an editor of the French fashion magazine ELLE. In 1995 he suffered a massive stroke, which left him in the Locked-In State: his mental facilities remained intact but most of the body was paralyzed—he could only blink his left eyelid. Despite his condition, he wrote the book The Diving Bell and the Butterfly [1] – describing his experiences from the hospital and memories – by blinking when the correct letter was reached by a person slowly reciting the alphabet over and over again.

Nowadays, Bauby could be assisted by the state of the art brain-computer interfaces (BCI, see next section), extending his ability of limited communication with the external world also outside the working hours of the dedicated person reading his eye blinks. But in spite of the progress, this new and advanced technology is still available only to the very few lucky or privileged patients. To cope with this problem, this paper introduces user-centered hardware design in the form of a BCI Appliance as opposed to "proof of concept" approach to experimental BCI systems, and a complete GPL-based software framework for BCI. Together, these elements pave the way towards making the BCI technology widely available.

2. Brain-Computer Interfaces

A Brain-Computer Interface (BCI) is a communication system that allows users to send messages to the external world without passing through the normal pathways of nerves and muscles [2]. In other words, they realize An old dream: liberate the brain from the constraints imposed by the body and make it capable of using virtual, electronic and mechanical tools to control the physical world. Just by thinking [3].

However, communication via BCI does not involve direct mind-reading, as such devices remain in the domain of science-fiction. There are only few mental tasks, known to generate cerebral activity that we know how to detect from measurable signals. These signals include functional MRI (fMRI), near-infrared spectroscopy (NIRS), magnetoencephalography (MEG) and electrocorticogram (ECoG, recorded intracranially), but if we consider non-invasiveness, time resolution, cost and portability, the best signal for contemporary BCIs is electroecephalogram (EEG), that is a trace of the electrical activity of the brain recorded from the surface of the head.

Currently, there are three major paradigms (tasks) used in implementations of EEG-based BCIs:

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P300 Evoked potentials such as P300 are deflections present in an average of EEG responses time-locked to a stimulus. The selectivity of attention is revealed in the fact, that these potentials occur only in response to the stimuli that the subject pays attention to (e.g. by counting the occurrences). The conscious concentration on one of the stimuli appearing randomly can be read by the computer as selection.

SSVEP exposure to a flickering light of given frequency (e.g. 17 Hz) causes appearance of oscillations with the same frequency in the visual cortex. The selective attention comes into play when there is more than one frequency in the receptive field, e.g. symbol "0" flickering at 17 Hz and "1" at 23 Hz. Concentration on "1" could be read from the occipital EEG derivations located over the visual cortex as the 23 Hz oscillation appearing in EEG, called SSVEP (for a recent review of SSVEP c.f. [4]). Detection of this response is far from trivial, especially in higher frequencies. On the other hand, higher frequencies (above 40 Hz) are much less tiring to the subject and do not pose danger of inducing photoepileptic attack. Complete mathematics designed and tested for detection of the SSVEP response in EEG, employed in the OpenBCI system, is described in Appendix A.

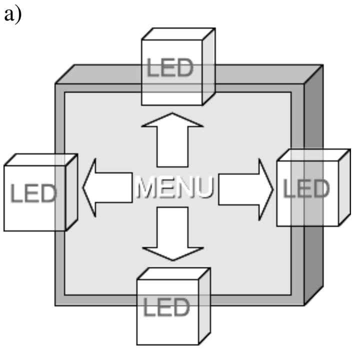
Motor imagery (ERD/ERS) relies on the event-related desynchronization and synchronization occurring in EEG in the course of movement planning and execution, also imaginary. Reading these phenomena from EEG is much more difficult than in the other two paradigms, proper imagery also requires prior subject training, but currently it is the only paradigm that does not engage the vision.

3. SSVEP stimulus rendering

Visual stimuli in current SSVEP-based BCIs are rendered either on a computer screen (by subsequent changes of a selected area of the screen driven by software) or using LEDs driven by hardware frequency generators. Using a computer screen offers high flexibility in terms of shape and color of the visual stimuli but they are limited by their refresh rate and non-realtime nature of the contemporary operating systems. On the contrary, LEDs driven by hardware generators are not limited in frequency, but have limitations in terms of shape, color, and patterns that can be rendered – basically, a fixed menu with fixed symbols must be hardwired into the design of the stimulator. Variation of this scheme, based upon alternate half-field stimulation, was proposed in [5].

The most common solution to this problem is based upon the interface setup of ATM (automated teller machine, cash dispenser), where the central LCD screen is used to display the dynamically changing sets of labels, tagging the buttons on the side of the screen with functions corresponding to the current menu depth. In similarly constructed SSVEP-based BCI systems, the central screen is controlled by a general purpose computer, allowing for creation of menus, assigning dynamically different meanings to the LEDs – functionally corresponding to the ATM buttons – placed around the screen (Fig. 1). However, in such a setup the subject must redirect attention from the symbol to the relevant LED, which is much less natural than just concentrating on a flickering symbol.

a)



b)

Fig. 1. a) scheme of an ATM-like approach to SSVEP-based BCI; b) implementation with LEDs in separate boxes on the sides of LCD and a separate controller in the black box.

4. BCI Appliance

To overcome these limitations, we proposed the setup presented in Fig. 2. Array of LEDs is placed behind the LCD screen in a frame, in such a way, that each box of the frame limits the area highlighted by contained LED to a well defined rectangle. These LEDs are operated by a microcontroller (we used ATmega16 chip). Commands determinating the frequencies of flickering of LEDs are sent to the microcontroller from the OpenBCI software via USB port. Knowing the coordinates of these rectangles, we can display icons or texts in the corresponding area of the LCD, at the same time controlling their flicker with high accuracy. In such a way, we obtain a highly flexible and accurate framework for dynamic creation of SSVEP-based interfaces, which operates as follows:

1. OpenBCI (Sec. 5) sends to the controller commands that flash subsequent LEDs with different frequencies, possibly outside the alpha band and its harmonics – for example 12, 13, 15, 16, 17, 18, 19 and 23 Hz.
2. At the same time, relevant symbols—for example letters "A", "B", "C"... "H" – are drawn in the corresponding areas of the LCD.
3. EEG recorded from parietal derivation (above the visual cortex) is analyzed in real time; if the function described in Appendix A determines that, for example, 12 Hz is statistically dominant in the EEG, then the system concludes that the user concentrated his or her attention on the symbol "A".

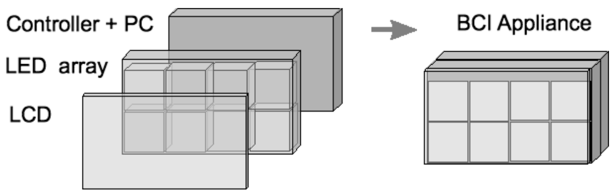


Fig. 2. Proposed solution for a stable delivery of SSVEP stimuli via LED array highlighting designated areas of an LCD – the BCI Appliance

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This design required construction of certain dedicated hardware. Using this opportunity, we implemented also several ideas about how the practical BCI systems should look like and operate, as opposed to the “proofs of concept“ from laboratory research environments. The main assumptions were ease of use, compact design, possibly low cost and wireless connections to the domotic appliances and the EEG amplifier. These assumptions were also included into the design of the software. Owing to the distributed architecture of the OpenBCI framework (Sec. 5), we may run any of the diagnostic modules – like e.g. the online display of the EEG signal, c.f. Fig. 3 – in parallel on another computer during normal operation of the Appliance. Therefore, the Appliance can be equipped with only a minimal set of system modules and custom kernel, according to the JeOS (just enough operating system) idea. This cuts down the hardware requirements, and increases stability and battery life.

Fig. 3. BCI Appliance running speller; EEG is transferred via bluetooth from the small blue amplifier (5-channel Mobi by TMSI, http://tmsi.com) to the Appliance (box on the right) running OpenBCI (Sec. 5). Laptop on the left is connected to the Appliance via WiFi, which allows for online display of EEG in the Svarog.pl viewer, connected as an OpenBCI module (Fig. 4)

5. OpenBCI software framework

OpenBCI is a complete software framework for brain-computer interfaces. Since online communication with signal acquisition hardware is an indispensable part of such a system, when combined with a graphical system for signal review – in our case Svarog, http://svarog.pl – it provides also a complete software EEG recording. Svarog stands for “Signal Viewer, Analyzer and Recorder On GPL”.

Architecture design of the OpenBCI framework is similar to the one described in [6] in the general concept of modularity. However, there is a major difference in terms of the data flow model: we replaced the linear data flow by a centralized approach to modularity (Fig. 4). Centralized data flow greatly facilitates exchangeability of the modules (also “on the fly”) and sharing data between them.

The central module handling the data flow is Multiplexer [7]; it is capable of communication with modules written in Python, Java, and C++. For example, currently we implement data analysis in Python and C++, while the graphical module displaying the signal (Svarog) is written in Java.

Setup of a particular OpenBCI instance, controlling given external devices in given scenarios, is facilitated by modules controlling GUI and logics. Therefore, creating a BCI with new functionality in most cases is just an issue of configuring a matrix representing a graph of states and screens of the application, and adding commands for operating external devices – is transparent to the rest of the system.

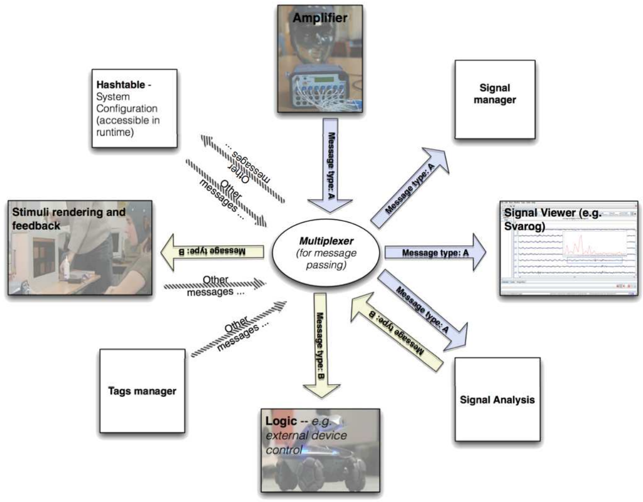

Fig. 4. General scheme of communication between OpenBCI modules

6. Hybrid BCI

Decoding the commands directly from the brain activity is usually slower and less robust than interface built on any muscular activity. The issue of hybrid BCIs has been raised recently (c.f. [8, 9, 10]) – partly because of the slow progress in the information transfer rate of contemporary BCIs. In our case the interest was driven by the actual needs of the patients – most of them have some remaining control of certain muscles, and the interface build upon it will be in most cases not only faster, but also significantly cheaper.

A hybrid BCI is usually defined either as a BCI system using either more than one of the “pure” BCI paradigms relying on direct decoding brain signals, or one of these paradigms in combination with input from different, non-BCI type of assistive devices. These hybrids can operate in parallel or sequentially.

In concordance with the principle of simplicity, advocated by the target group of disabled users, in the OpenBCI system we implemented the serial mode, that is possibility of switching between different modes of input – at the moment SSVEP, P300, eyetracking and muscular switches – within the same menu structure, based upon the 2x4 design of the BCI Appliance (see Fig. 5). Such possibility of switching between the modes reduces the tiredness and negative effects of prolonged use of any of the modalities alone. However, the architecture of OpenBCI makes also implementation of parallel hybrids straightforward, and such studies are planned in the close future.

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Fig. 5. User-controlled menu of a serial hybrid BCI. Available modes of communication are SSVEP and P300-based BCIs (ERD/S is in the works), eyetracker (ETR) and switch-based interaction. Interface is operating in the fallback SWITCH mode, subsequently highlighting options selectable by a muscular switch

7. Discussion

Interest in assistive technologies other than BCI, like eyetrackers, was driven by the needs of people who contacted our group. BCI research described in previous sections raised hopes of many people living in Poland with dramatically reduced communication capabilities. In most of these cases the BCI was not the assistive technology of choice, since with any remaining muscular activity a much simpler, more robust and cheaper to implement communication channel is enough.

Apart from purely scientific issues, we should also keep in mind the huge gap between the possibilities offered by the cutting edge technologies and those available to the most needing target users. We are spending hundreds of millions on advanced medical research, while at the same time availability of simple 50-dollar wheelchairs would change lives of thousands disabled people in Africa. Classical mode of cooperation between Academia and Industry is of course targeted at maximizing profit from cooperation and patents, but some important issues are often left aside in this race.

BCI Appliance was developped as the flagship implementation of the available technology, with user-centered and cost-effective design principles. Subsequent versions of the Appliance were used in several public presentations since 2008, operating on 4, 8 or 9 adjacent fields (first prototype was based on 3×3 array of LEDs) with dynamic menus. Detection function described in Appendix A provided robust operation also for most of the volunteers from the audience, although we did not implement the necessary pre-operation screening of subject's SSVEP responses characteristics.

Strength of the SSVEP response is known to depend significantly on the frequency [11, 12]. Less documented fact relates to its variability between the subjects – because of that, the frequencies used in the SSVEP BCI should be adjusted individually. A systematic study of the inter-subject variability of SSVEP responses in relation to the frequencies, colors and sizes of the stimuli is under way, exploring some of the unique research possibilities opened by the BCI Appliance, combining stable flickering with full flexibility of the stimuli shapes and colors. As for the efficiency of the presented simple scheme of SSVEP detection, it can be increased e.g. by using more than one derivation with Common Spatial Patterns [13], as well as other advanced statistical and signal processing techniques (c.f. [4, 14]).

8. Information sharing statement

OpenBCI, a complete software environment for creation of brain-computer interfaces, is freely available on terms of the GNU General Public License from http://openbci.pl.

Appendix

A. Detection of the SSVEP in one EEG derivation

In line with the idea of using possibly small and lightweight wireless EEG amplifiers with minimum number of channels, we designed a simple function for detection of the SSVEP responses from a single EEG derivation (channel). So far it worked very well even in the difficult conditions of public presentations. However, in terms of the information transfer rate, it should be outperformed by most of the recently proposed advanced multichannel techniques. Nevertheless, we provide a mathematical description to share our initial experiences with those wishing to implement a simple and monochannel approach. Source code of this function in Python is a part of the OpenBCI system.

A.1. General idea. We have NS stimuli flickering with frequencies $f_{s,s=1\ldots\mathrm{NS}}$. For each analyzed epoch we compute spectral power estimates $P(f_i)$ in NF frequencies $f_{i,i=1\ldots\mathrm{NF}}$. In the design stage, we adjust the stimulation frequencies f_s, the length of the analyzed epoch, and the sampling frequency in such a way, that the stimulation frequencies f_s – and hence also the expected frequencies of the SSVEP responses – correspond exactly to some of the frequencies f_i, in which the spectral power $P(f_i)$ is estimated.

In such a setup, detection of the SSVEP response can be done by simply selecting from the stimulation frequencies f_s the one with the largest value of spectral power $P(f)$. In the following, we optimize this scheme by adding simple corrections for:

1. Non-uniform frequency distribution of the EEG background.
2. Harmonics and subharmonics of the response.
3. Statistics.
4. Persistence of the response.

A.2. Background removal. Assuming that signal components unrelated to the stimulation change slowly with frequency, we replace the powers $P(f_i)$ estimated for each frequency f_i by their the second derivatives, approximated by three-point formula as the difference between the power in the corresponding frequency bin $P(f_i)$ minus the average of powers

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in the two neighboring bins $P(f_i - \Delta f)$ and $P(f_i + \Delta f)$:

$$\begin{aligned}\frac{\partial^2}{\partial f^2} P(f_i) &\equiv P''(f_i) \\ &\approx -P(f_i - \Delta f) + 2P(f_i) - P(f_i + \Delta f).\end{aligned} \tag{1}$$

This operation results also in quite good normalization of the distributions.

A.3. Harmonics. For each stimulation frequency f_i we consider NH possible harmonics and subharmonics at $f_i^{j, j=1\ldots\mathrm{NH}}$. As the power $Q(f_i)$, representing the response to the stimulation at frequency f_i, we take the average of $Persistence(f_i)$ for all the considered harmonics and subharmonics:

$$Q(f_i) = \frac{1}{\mathrm{NH}} \sum_{j=1}^{\mathrm{NH}} P''(f_i^j). \tag{2}$$

A.4. Statistics. To quantify the power of the response at a "candidate" frequency f_γ, we compute the difference of $Q(f_\gamma)$ and the average of $Q(f_i)$ for all the other frequencies, with except of frequency f_γ

$$R(f_\gamma) = Q(f_\gamma) - \frac{1}{\mathrm{NS - 1}} \sum_{i=1, i\neq\gamma}^{\mathrm{NS}} Q(f_i). \tag{3}$$

As a candidate for the detected SSVEP frequency, the maximum response is taken:

$$f_\delta = \arg\max R(f_\gamma). \tag{4}$$

To set the threshold for choosing only the statistically significant $R(f_\delta)$, mean μ_R and variance σ_R of $R(f)$ under the null hypothesis of no significant response is estimated from the same spectrum, using the number of NK = NS frequencies f_k at which there was no stimulation – that is, in between the stimulation frequencies:

$$\mu_R \approx \frac{1}{NK} \sum_{k=1}^{NK} R(f_k), \tag{5}$$

$$\sigma_R \approx \sqrt{\frac{1}{NK-1} \sum_{k=1}^{NK} (R(f_k) - \mu_R)^2}. \tag{6}$$

Response detection at frequency f_δ occurs if estimated response $R(f_\delta)$ exceeds the above threshold, multiplied by experimentally adjusted factor K:

$$\frac{(R(f_\delta) - \mu_R)}{\sigma_R} > K. \tag{7}$$

A.5. Persistence. Even if the response detected in the previous step was indeed a statistically significant event, it may have resulted e.g. from an unintentional gaze. To compensate for this effect and increase the robustness of the whole systems operation we may introduce an additional parameter, that will be the number of repetitions of response's detection before the system takes the actual action. Alternatively, we may say that the final detection of a response at f_δ is scored only if the above procedure returned the same "winning" frequency f_δ in NR consecutive epochs.

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