High-Speed Noninvasive Brain-Computer Interfaces

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Abstract. Brain computer interface (BCI) systems allow interaction with machines through a channel that does not involve the traditional motor pathways of the human nervous system. Thus they can be used by people with severe motor disabilities or those whose limbs are occupied with other tasks. In BCI systems that recently showed greatest interest of researchers, electrical brain activity is measured on the scalp, thus basically they are noninvasive. Using the EEG measurements as the input to the BCI offers the advantages of low cost and high time resolution. However, due to small amplitude of the signal components, relatively high power of noise and poor spatial resolution, achieving large speed, accuracy and the number of targets is a challenge. At present, the steady-state visual evoked potential (SSVEP) BCI paradigm is believed to provide the most promising way of optimizing the BCI performance in that sense. A review of the SSVEP BCI projects is presented, including studies of biodiversity of human EEG response to visual excitation, as well as the design of techniques for visual stimulation, EEG signal acquisition and analysis for best BCI performance. The review is based both on the literature and results of own teamwork.

Keywords: Brain-computer interface (BCI), Steady-state visual evoked potentials (SSVEP), Alternate half-field stimulation.

I. INTRODUCTION

The number of “smart” devices and appliances around us grows quickly in the last decades. Not even computers, tablets, cellular phones do comprise a processor with a complex program. Operation and performance of cars, home appliances, such as washing machine, microwave oven, TV set, etc. strongly depend on the computational power and quality of software of the digital electronic systems embedded in it. The growth of the number of various applications of computers to daily life situations is tremendous and continues beyond imagination. Still, it seems the rate of progress in the performance of the computational systems is not accompanied by an equally fast development of the interfaces necessary for information exchange between machines and their users. As an example, for more than 40 years the standard man-machine interfaces for a personal computer are keyboard, LCD text/graphics display and a mouse. Especially the keyboard, whose principle of operation has not changed much since the invention of typewriter in the middle 19th century, does not meet users expectations. Even in its touchable version, the keyboard requires from its user a special training (which in most cases is not performed, in fact) and the speed of transferring the information from human to computer through this channel has not increased for the last 150 years. (May be there is a little increase in the speed of entering the plain text or commands – with the use of prompt dictionaries.) Anyway, using the keyboard requires unnatural repetitive movements of fingers. Computer use has been associated with musculoskeletal problems of the upper extremities: neck, shoulders, arms, etc. Several postures and behaviors have been suggested as related to these disorders, including position in which the hands are held, neck and shoulder position, wrist posture and hyperextension of the fingers, to name a few [1].

Research work on alternative man–computer interfaces, better utilizing natural ways of human communication are then very well justified, if not urgently needed. It is expected the new approaches will provide better functionality and speed, as well as will be easier to use and its usage will not cause severe disorders of the organs of the human body. Examples of the devices of this type are joystick, graphics tablet and touchpad, with software to recognize hands multi-touch and gestures. One should notice that almost all of the new interfaces (except perhaps speech recognition and text-to-speech software) require movements of the user limbs or fingers. However, there are groups of users who are not able to make such movements. There are fighter pilots or car drivers, whose limbs are occupied with some tasks. There are motor-impaired people, or persons paralyzed after accidents or neurological diseases who cannot move their limbs, cannot speak, but whose mind operates normally and they need ways of communication with the external world.

Thus, there is a need to develop interfaces that would allow users to enter data into computers without involving the traditional motor pathways of the human nervous system. A solution is a brain–computer interface (BCI) [2]. Operation of a BCI is based on analysis of the activity of the brain and is independent of an activity of muscles or other nerves. In those interfaces, the intention/will of a user is not expressed by any movement, gesture or command; it is rather “guessed” by the analysis of some measured signals that reflect the brain activity.

Research projects aimed at development of BCI started about 40 years ago. Some of them have already brought spectacular results, such as mind-controlled prosthesis developed at Technical University Graz [3]. Still, the BCI functionality is far from the expectations. This gives
motivation to further research on the interface performance improvement. The key factors of focus are speed, number of independent symbols that can be transmitted over the interface channel and accuracy (lowest error rate).

II. BRAIN-COMPUTER INTERFACES

A. Outline

The BC interfaces are considered the most modern devices designed to help humans in communication with computers. In the literature they are known also as Brain Machine Interface (BMI) or Direct Brain Interface (DBI), which indicate more general applicability to communication with machines of any type, not computers only. The definition [2] does not specify how the brain activity is to be monitored. In theory, a BCI can use electric field (EEG), magnetic field (MEG), functional magnetic resonance (fMRI), positron emission tomography (PET) or functional near-field infrared spectroscopy (fNIR) [4]. In practice, most of the research efforts are concerned with noninvasive measurement of EEG signals – with the use of electrodes placed on the skin of users’ skull. This choice leads to low cost of the measurement setup and high signal resolution in the time domain. The drawback of this approach is in low spatial resolution – the EEG signal from a single electrode represents average electrical activity of the top brain cortex located in the area of about a few cm². The other methods, despite their excellent spatial resolution, are not considered often, due to demanding technical requirements, high cost of implementation and poor resolution in time. The fNIR technique is considered very promising as a basis for future BCI [5].

The core element of the BCI operation is detection of an assumed activity of a specified brain region, e.g. regions linked to motor functions or regions responding to external stimulation, such as light or sound. Any particular activity is attributed to a unique symbol transmitted through the interface. The present technological advancement limits applications of the BCIs to a simple cellular phone keyboard with a dozen or so keys or a few-command manipulator for control of a prosthetic or a virtual reality game. The main beneficiaries of the interface are now handicapped persons. It is expected, as BCIs become sufficiently fast, reliable and easy to use, the range of their future applications will encompass many other groups of users.

B. Brain bioelectrical activity

Brain is the most complex organ of a human body, a part of the central nervous system. Its basic structural and functional element is neuron. The function of a neuron is to transmit electric pulses, so called functional potentials. Typically, the cerebral cortex is estimated to contain more than 10 billion neurons, each connected by synapses to several thousand other neurons. In a second, the brain processes billions of pulses collected from the peripheral nervous system – to provide contact with human environment and to control all the body functions [6].

Most of the phenomena observed in EEG recordings originate in surface layers of the organ cortex, schematically shown in Fig. 1, where majority of neurons are positioned perpendicularly to the surface. Due to large number of mutual connections of the cortex neurons, the subsequent waves of depolarization/polarization of their cellular membranes cause synchronization of their activity. The synchronous activity of a population of nervous cells leads to changes of electric potential on the surface of the cortex, and consequently, on the surface of the skin.

Fig. 1. Regions of the human brain. Especially important for BCI are primary motor cortex, primary somatosensory cortex and occipital lobe (under Creative Commons Attribution Share-Alike 2.5 License, http://sciencealive.wikispaces.com/Human+Brain).

The recording of EEG signals is performed by measuring differences of electric potential between selected points defined on the surface of the human head. Example of standardized locations of the electrodes, defined in 1958 [7] to make the measurement points independent of the actual size of the skull is the “ten-twenty” system shown in Fig. 2.

Fig. 2. International “10-20” scheme of EEG electrodes placement (http://www.bem.fi/book/, under permission granted in “Info” Section of the book).

The potential measured on an electrode is a sum of potentials generated by millions of neurons. These potentials are the result of a large number of neuronal phenomena. Thus the measured signals are an average of signals from individual neurons located over some area of the cortex. That is why EEG features poor spatial resolution. Moreover, the potentials of individual neurons have to pass the regions filled with cerebrospinal fluid, bones of the skull and through the skin until finally they reach the electrodes. This causes severe attenuation of the functional waves. The EEG signal that represents electrical brain activity is very weak, its values are in the range of tens of microvolts.
Moreover, the measured signal contains not only the brain activity components of interest. There are other, sometimes many times larger components present (in the order of milivolts), called artifacts. Their sources are of technical (e.g. interference from the power supply, thermal noise) or biological (other than nervous cells, e.g. muscles, operation of the heart muscle, varying impedance of electrodes due to their movement across the skin surface and sweat/sebum secretion, etc.) origin.

The fact that the EEG signal components that carry the information about the brain activity are weak and are buried in large-amplitude noise makes detection of the BCI user intention difficult. This is the main drawback of the EEG-based brain-computer interfaces. Significant efforts have been taken to design and build EEG measurement devices that would suppress the artifacts and reduce the power of noise relative to the brain signal components of interest [8]. One of the latest projects along these lines is described in [9]. Advanced signal processing algorithms is another means that leads to reliable detection of the components generated with users intentions. This will be illustrated by results obtained in the authors laboratory, in Section IV.

C. EEG signal components

The brain processing an event (e.g. stimulation of a sense – vision, hearing, etc.) generates a characteristic functional potential (short-term disturbance of the EEG signal), called as Event Related Potential (ERP) [6]. This is an example of a noninvasive electrophysiological signal source that can be used in BCI. Other sources include event-related synchronization/desynchronization (ERS/ERD), visual evoked potentials (VEP), steady-state visual evoked potentials (SSVEP), slow cortical potentials (SCP), P300 evoked potentials and μ and β rhythms [10]. Of particular attention and importance are SSVEP-based BCIs because they can provide relatively higher bit rates, e.g. 70 bits/min while require limited training [11]. When user focuses his/her attention on a light source of a specified frequency, EEG signals especially from above primary visual primary cortex include components of the same frequency and/or its harmonics [13]. Since SSVEPs can be elicited by repetitive visual stimuli at frequencies in the relatively wide range from 1 to 100 Hz, this potentially gives room for a large number of different symbols transferred via the interface.

D. BCI types

In a brain–computer interface system, users perform mental tasks that invoke specific patterns of brain activity. Those may be invoked by an external stimulation or a mental effort of user solely (Fig. 3). The EEG signals is measured, and its relevant features extracted, after necessary preprocessing. A pattern recognition system determines which brain activity pattern a user’s brain is producing and thereby infers the user’s mental task, thus allowing users to send messages or commands through their intentional brain activity alone.

Four basic categories of noninvasive BCIs have been described in the literature. These categories are related to the brain electrical activity that is invoked, detected and used for sending messages or commands to machine [13]. Accordingly, the BCIs use P300 potentials [14], [15], SSVEP [16], [17], [18], slow cortical potentials [19] and event-related desynchronization (ERD) [20].

To compare performance of different BCI systems, one should use some standard evaluation criteria [21]

1) Detection time (a time period between the moment user starts to express their intention to the moment of taking decision by the system).
2) Classification accuracy (a ratio of true positive classifications to the sum of true positive, false positive and false negative ones).
3) Information transfer rate (bit rate, a parameter used to estimate a theoretical rate of information transfer to the computer) [22], [23].

There has been a steadily growing number of laboratory BCI systems reported worldwide for the last 15 years. They allow data transfer to computer with a bit rate approaching 100 bit/s, with an accuracy of about 90%. One of the latest reviews of BCI system is presented in [24].

The most promising type of the BCI is based on steady-state visual evoked potentials (SSVEP). Relatively large information transfer rate and the number of distinct messages are achieved with the use of the SSVEP BCI. At the same time, high accuracy and speed are obtained at rather small training effort of the user. Thus this type of BCI is the subject of research results discussed in the next Sections.

III. BRAIN-COMPUTER INTERFACES

A. SSVEP BCI operation

Most of the SSVEP BCI systems use frequency encoding of the messages. Therefore, detection of potentials generated in result of user’s intention is usually based on amplitude or power spectrum analysis (Fig. 4).

Referring to Fig. 4, the user (2) concentrates his/her sight on one element (intended to be selected – a target) of the photo-stimulator (1). Each target is a light source flickering with a unique frequency. There is a message or command attributed to each frequency, so the stimulator plays a role of a virtual keyboard [25]. The EEG signal is measured over the user’s skull and its amplitude spectrum (3) computed. In the example illustrated by Fig. 4, the user was looking at the stimulator element that was flickering with
the frequency of 7 Hz. The SSVEP response was composed of the fundamental frequency, its second and third harmonic, 7 Hz, 14 Hz and 21 Hz, respectively.

![Stimulation diagram](image)

**Fig. 4** An SSVEP BCI system with frequency encoding.

For each stimulation frequency, the signal to background ratio (SBR) is computed from the EEG spectrum with the use of Fast Fourier Transform. The background noise could be e.g. the total power of spectrum components in a neighborhood of a given frequency [26]. When the SBR ratio exceed a predefined threshold, a symbol attributed to that frequency of stimulation [27], [28], [16], [29]. In some works, the amplitude of the SBR coefficient is considered a signal feature and then classified with the use of linear discriminant analysis [30]. Other methods include autoregressive spectral analysis [31] and wavelet decomposition [32]. These methods allow shortening the width of analysis window in the time domain, which speeds up the interface. On the other hand, they are computationally more demanding than the FFT, so they need some acceleration to be implemented in real time.

**B. Visual stimulation**

The signal-to-background ratio is an essential characteristic of the SSVEP signal. Larger values of SBR lead to shorter time of taking decision and increase the BCI accuracy. Thus it is worthwhile to optimize the visual stimulation to increase the difference between the power of the SSVEP and noise. Typical stimulators have a form of rectangular fields displayed on an LCD computer screen, each flickering with a different frequency [17].

One of the approaches that actually increases the power of the SSVEP with respect to noise is based on alternate stimulation of the halves of visual fields of the user retina [33]. An example target of this type is shown in Fig. 5a, along with an experimental 5-target stimulator in Fig. 5b. The light-emitting (LED) diodes SL and SR in Fig. 5a flicker with the same frequency, but with opposite phases. The F diode is a fixation point. When the user wants to select a given element, he/she focuses their sight on the fixation diode. Then, the SL and SR diodes stimulate the left and right visual half-field of the retina. Locating alternatively flashing light sources in the left and right halves of the visual field will lead to SSVEP responses in the right and left hemisphere part of the visual cortex, respectively. The neuron bundles from the left and right half of the retina go to optical chiasm where they are directed, respectively, to the right and left half of the brain visual cortex. The two SSVEP waveforms have opposite phases and be strongly and negatively correlated. Therefore, taking a difference of the two signals from the hemispheres will enhance SSVEP, reduce the noise components (which are positively correlated if the electrodes are located close to each other). The efficiency of the technique has been confirmed by numerous experiments. The half-field stimulation was used for multi-command BCI system with a single flickering source [34]. A survey of stimulation methods for SSVEP-based BCI is presented in [11].

![Stimulator diagram](image)

**Fig. 5** A single stimulator element (target) (a) and a five different-color-target, experimental stimulator array (b)

Another important aspect of the stimulus design is the diversity of users’ responses to visual stimulus [35], considering e.g. individual dependence on color and frequency of the flickering lights. The multiple-color LED stimulator of 27 frequencies in the 7 - 47 Hz range (Fig. 5) was used in experiments with 21 users (Fig. 6). We postulate, the promising strategy of SSVEP-based BCI system optimization for best performance can be through stimulus adjustment to each individual user [36].

Among the attempts to increase the BCI capacity (the number of different messages), phase encoding is one of the techniques that are being explored [37], [38].

**C. EEG signal analysis for SSVEP BCI**

Even in the stimulus has been optimized and care has been taken to design measurement equipment as to obtain high signal-to-noise ratio, still the EEG signal is weak and noisy. Then, further signal processing and advanced VEP detection techniques are needed to ensure high accuracy, speed and capacity (i.e. the number of different messages sent over the interface). Taking into account individual anatomical and psycho-physiological differences between users, it is difficult to tell in advance what is the right position for the EEG electrodes to capture most of the information related to BCI users intention. On the other hand, it is impractical to use, say 22 electrodes covering densely the whole skin area on the head. Thus, as a compromise, a limited number of channels (say, 8 electrodes) is considered representative to the problem. The multichannel measurements is a standard now.

It is hypothesized in most research projects that some linear or nonlinear combinations of the channels, individualized for each user, carry the information which is searched for [39]. An example of obtaining a linear
combination (spatial filtering) of the multichannel EEG recordings is shown in Fig. 7.

![Image](image1.png)

Fig. 6 Measurement setup [35]: photo-stimulator (1), a user (2), EEG recording device based on g.tec, Graz Austria (3) and a technician (4).

The optimum linear spatial filter of Fig. 7 should produce new “channels” S for which a ratio of the power of the signal of interest to the noise power is maximum. Among different goals of this procedure, there are Best Bipolar Combination (BBC) [40], Minimal Energy Combination (of noise), Maximum Contrast Combination (MCC) [41] and Canonical Correlation [42], [43].

![Image](image2.png)

Fig. 7 The concept of spatial filtering of EEG signals.

A novel, Cluster Analysis of Canonical Correlation Coefficients (CACC) method for detecting steady-state visual evoked potentials (SSVEP) using multiple channel electroencephalogram (EEG) data has been developed in [44], [45]. Accurate asynchronous detection, high speed and high information transfer rate can be achieved with CACC after a short calibration session. Spatial filtering based on the Canonical Correlation Analysis method proposed in [42] was used for identifying optimal combinations of electrode signals that cancel strong interference signals in the EEG. Data from a test group consisting of 21 subjects were used to evaluate the new method performance and to compare results to standard spectrum analysis approach. Conducted research, for different length of signal segments and five visual target frequencies, showed improvement of both classification accuracy and detection speed (Table 1, Table 2). Group A denotes 5 subjects who had earlier experience with a BCI, while Group B were 11 subjects who were not familiar with the BCI but actively participated in the experiments.

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In yet other set of experiments, it was demonstrated that the developed CACC method allows compensation for the electrode set rotation in the range of ±25° and displacement of ±3 cm, on top of the subject’s head. This shows its potential to account for individual user anatomical and physiological characteristics.

IV. CONCLUSION

It has been shown the SSVEP is a promising paradigm for fast and accurate brain-computer interfaces. Since some users may not exhibit the VEP responses at all, or require long training, further work on tuning the stimulus, measurement and signal processing techniques to individual user characteristics could remove some limits in BCI applications. Optimization of SSVEP detection algorithms and their hardware/software implementation for real time SSVEP detection is an important research avenue. Finally, the BCI research and its various possible applications raise important ethical issues that need to be discussed in different communities to promote acceptance and develop adequate policies [46].

REFERENCES

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