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Research Article

Low-cost Brain-Computer Interfaces

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Abstract: This article reviews and establishes the current state of research and technology for low-cost, portable and easy to use Brain Computer Interface (BCI) suitable for non-medical applications such as communication, environmental control, entertainment and gaming. The scope of this research is to analyse all possible technologies that are currently available to enable channel of communication between humans and electronic devices using only cerebral activities. In addition, the EMOTIV Epoc wireless EEG hardware has been reviewed
Keywords: Brain-Computer Interface, electroencephalography, Emotiv EPOC, Steady State Visual Evoked Potential

INTRODUCTION

The purpose of this paper is to review the feasibility of developing a low-cost, portable and easy to use BCI system that might be used in various non-medical applications such as electronic device and computer control, entertainment (gaming) and other assistive technologies, based on the current state of technology and research.

A brain-computer interface (BCI) can be described as a combination of hardware and software producing a system allowing for communication between the human's brain and external devices such as computer only through the use of cerebral activity [1]. There are five distinctive steps required in order for the BCI to work. The first is the signal acquisition [1]. This can be done in various ways through either invasive or noninvasive methods.

Invasive methods are known as Intracortical Neuron Recording and Electrocorticography (ECoG). Noninvasive methods include Electroencephalography (EEG), Magnetoencephalography (MEG), Functional Magnetic Resonance Imaging (fMRI) and Near Infrared Spectroscopy (NIRS) [1]. In order to satisfy the scope of this paper only Electroencephalography (EEG) will be considered for its low cost, portability and relatively easy operation. The second step involves signal preprocessing and enhancement which requires signal amplification and filtration. The third step is responsible for accurate feature extraction with the use of various mathematical algorithms such as Principle Component Analysis (PCA), Independent Component Analysis (ICA) and Common Spatial Pattern (CSP) depending on the complexity of the signals recorded and precision required.

Classification relates to the process of recognizing the subject's intended actions based on the vector information derived from the extracted features. The last step requires building a control interface which depends on the system's intended application [1].

Following the introduction, Section II 'EEG-Electroencephalography' describes the basics of Electroencephalography. Section III 'How EEG works' explains all the elements that make up a typical EEG system and describes the principles of its operation. In Section IV 'Physiological and non-physiological artefacts' the variety of internal and external artefacts that disturb the EEG signal are clarified while Section V 'Other artefacts correcting methods' continues on analyzing, correcting and removing unwanted signal components from the EEG. Section VI '10-20 Electrode placement system' refers to internationally agreed system that unifies the placement of EEG electrodes in relation to the scalp. In Section VII 'Brain waves' rhythmic and transient components of the brain oscillations are briefly reviewed while Section VIII 'EEG rhythmic activity comparison by frequencies' presents an extensive table with all the commonly known brain waves, their band names and characteristics. Section IX 'Various types of electrical brain activities commonly used for EEG based BCI' explains in great detail slow cortical potentials (SCP), sensorimotor rhythms, event related potentials (ERP), oddball paradigm and P300 phenomena and steady state visual-evoked potentials (SSVEP). 'Other types of

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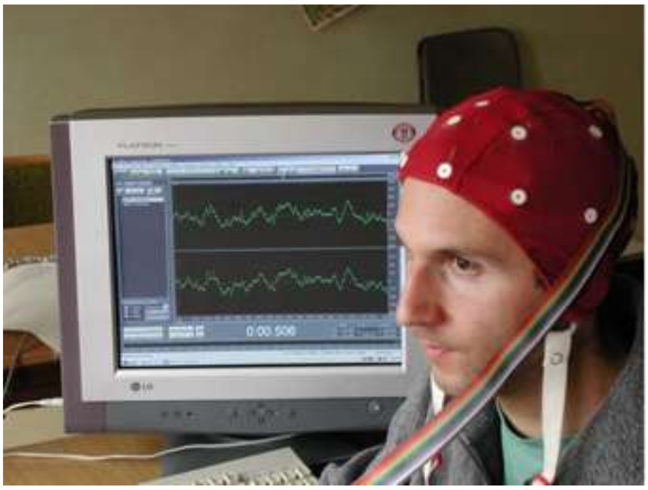
stimuli used in SSVEP' are explained in Section X, where alternative methods of eliciting stimuli related brain oscillations are discussed. Section XI 'BCI classification' categorises BCI systems based on their mode of operation. In Section XII 'EMOTIV Epoc as BCI hardware' the specific model of wireless, low-cost EEG device and its usability in BCI systems are reviewed. Section XIII titled 'BCI mobility' discusses first attempts of using mobile phones and tablets in assembling a truly portable BCI system. Finally Section XIV 'Conclusions' presents a brief summary of all the BCI related topics discussed in the paper.

EEG – Electroencephalography

Electroencephalography (EEG) is an imaging technique used in research and medical applications that records electrical signals emitted by the brain along the scalp. It measures changes in voltage caused by ionic current flowing through the brain neurons which are picked up by metal electrodes often using conductive media such as gels or paste [2]. The signals are so weak that they need to be massively amplified in order to be properly digitised and stored. Digitisation of the analog signals is performed by A/D (analog-to-digital) converters which then are stored and displayed by a PC or other relevant device [3]. A typical EEG equipment consists of a group of electrodes, where at least one of them is an active electrode, one acts as a reference electrode and one as a ground electrode. In multichannel systems there can be as many as 14 up to 256 active electrodes. In such arrangements electrodes are placed on a cap or a headband [3].



(a) Fig-1: Cap with electrodes placed according to 10-20 system [3].

How EEG works

The EEG data acquisition is performed by placing electrodes on the scalp with gel or paste applied to them in order to increase conductivity of the signal. Some systems use electrodes with each electrode attached to an individual wire while other use caps or nets [2, 3]. International 10-20 system is utilized in most research practice where EEG technique is used [4]. It determines electrode's placement and naming which is consistent across laboratories. In most applications 19 recording electrodes are used with addition of grounding and system reference [5]. For more demanding research projects additional electrodes can be added to increase spatial resolution of any given brain area. When caps or nets are used, they usually hold up to 255 electrodes (high density arrays) which can be evenly spaced on the scalp [2].

In order to properly carry a usable signal, each electrode is connected to one input of a differential amplifier. The other input of this amplifier is connected to the reference electrode. The operation of these amplifiers is induced by the voltage difference between the active electrode and the system reference electrode and the voltage gain they provide usually ranges between 60-100 dB. The EEG electrical signal by its nature is analogue and with today's availability of digitising devices it is normally more convenient to transcode it to digital form [3]. First the signal is passed through an anti-aliasing filter and then sent to an analog-to-digital converter. Depending on the research objectives various activities may be used to measure the EEG signal such as light stimulation, eye closure and opening, mental activity [1]. After digitisation the EEG signal can be stored as data for further display or manipulation [3]. In order to properly display the signal a series of filters need to be applied. Those filters include a high-pass filter (frequencies below 0.5-1 Hz) for slow artefacts removal resulting from electro-galvanic signals or movement artefacts, low-pass filter (for frequencies between 35-70 Hz) for high frequency artefacts removal such as electromyographic signals and a notch filter for electrical power line artefact elimination in 50 Hz for Europe or 60 Hz for America [2]. A typical scalp signal amplitude of EEG ranges between 10μV and 100μV [6].

There are numerous advantages to using EEG system for brain signal analysis. EEG is much more affordable [7] and offer lower-cost operation in comparison to other systems such as Electrocorticography (ECoG), Functional Magnetic Resonance Imaging (fMRI), Near Infrared Spectroscopy (NIRS). The other above mentioned methods are also much more bulky and thus considerably more difficult to transport (Nicolas-Alonso, Gomez-Gil, 2012) 1. Mobility can only be yielded from EEG which also guarantees very high temporal resolution in the range of milliseconds. For digitisation of the EEG signal usually 250-2000 Hz sampling rate is used; however for more accurate data sampling systems achieving 20kHz should be used [8]. Another advantage of the EEG system is better handling of the subject's movement and with the proper use of filtration movement artefacts can be further eliminated [9]. By its nature EEG provides silent operation where auditory stimuli can be used. It also doesn't expose the subject to high-intensity magnetic fields allowing EEG to be used by people with metal implants (pacemaker) [10]. While being highly non-invasive recording system, the EEG can read hidden processes that occur in the brain, especially those that don't require subject's response [11]. It is also suitable for subjects who are not able to perform motor responses [12]. Although EEG recording system contains a lot of noise and is prone to artefacts it is the most often used signal acquisition technique in BCI which is reflected in over 80% of published BCI related work [13].

EEG has also disadvantages. The main one is quite low spatial resolution on the surface of the scalp resulting in poor signal-to-noise ratio response compared to other systems. Therefore, a thorough interpretation of the EEG signal and sophisticated data analysis algorithms are required to collect useful data [14, 15]. The EEG exhibits rather poor response to activities found in deeper layers of the brain i.e. the cortex [2]. Also quite long set-up time is required in order for the electrodes to be placed correctly with the use of gels, saline solution or pastes to increase conductivity of the electrodes [2].

Physiological and non-physiological artefacts in EEG signals

Fisch [16] revealed in his publication "Fish and Spehlmann's EEG Primer: Basic Principles of Digital and Analog EEG" that artefacts shown in the EEG signals are of non-cerebral origin and they are one of the main factors confusing and sometimes distorting EEG readout. They can be divided into two main categories which Fisch [16] called physiological artefacts and non-physiological artefacts.

Physiological artefacts are generated by various body activities that are caused by head movement, body or scalp (e.g. pulsations of the scalp arteries) which directly affect the electrode scalp interface. They can also occur as bioelectrical potentials produced by other moving signal sources within the body itself such as eyes, tongue, jaw or stationary sources like the scalp muscles, heart or even sweat glands [16].

For the non-physiological artefacts they distinguish two main sources: external electrical interference originating from other power sources like power lines or electrical equipment located in the same room as the EEG system; and internal electrical defects and malfunctioning of the EEG recording system developing from recording electrodes (electrodes integrity, positioning and application), leads, amplifiers and filters [16].

Later in the book the authors precisely explain the specifics of artefacts generation. For example blinking and eye movements cause potential changes which are mainly picked up by the nearest frontal electrodes; Fp1 and Fp2 for blinking, F7 and F8 for horizontal (lateral) eye movement. Artefacts linked to eye activities are usually identifiable by their frontal distribution, bilateral symmetry and characteristic shape [16]. Muscle artefacts are known to cause very short potential changes which usually recur. Muscle artefacts produced by scalp and face muscles mainly show in the frontal and temporal lobes. Head and body movement artefacts appear even if all the electrodes make good mechanical and electrical contact. Many artefacts associated with movement can be eliminated by simply avoiding body movement during the recording. Heart activity potential changes referred to as ECG (electrocardiogram) are better picked up by the EEG with wider electrode arrangements [16]. Unlike most other artefacts the ECG usually cannot be avoided by simply improving the electrode contact or replacing it [16]. Tongue movement produce intermittent or repetitive slow oscillations in a wide distribution showing their maximum amplitudes in the mid-temporal region. Tongue artefacts can be caused by speaking, swallowing, chewing and coughing [16]. Electrical interference artefacts as externally caused emanate from electrical equipment and power lines. In Europe it is 50 Hz and in the US 60 Hz interference. Wherever an electrical equipment powered by alternating current is used the artefacts will occur regardless if the electrodes are faulty or working properly [16]. These artefacts can be introduced as either electrostatic interference produced by moving charged objects or electromagnetic interference by strong currents flowing through cables and equipment i.e. transformers or electric motors. Both types can be minimised by shielding the offending power cables and by proper wiring of the power cables [16].

Huster et al. [17] agree that the most problematic are the artefacts caused by physiological functions and processes of the body. They can be either corrected or rejected. They also suggest that pronounced cardiac artefacts can be avoided by proper electrode placement while most of the signal power linked to muscle movement occupy higher frequency bands which are usually neglected by the current BCI designs [17]. Huster et al. [17] confirm that simply by instructing the subject not to clench teeth or move the head significantly eliminates all myographic artefacts while stating that no such easy solution is available for the eye movement artefacts. Blinks or eye movement cannot be avoided during longer EEG recording sessions. They also contaminate the frequency bands often used for neurofeedback training. Simply monitoring and rejecting suspiciously high (75 µV) signal amplitudes is the most effective method since eye blinks and horizontal movement generate signals shifts larger than the normal EEG [17].

Other artefact correcting methods

There are various Independent Component Analysis (ICA) techniques available today that can be used to analyse, correct and remove unwanted signal from the EEG system [18, 19]. Their main function is to extract separate components from the EEG signals. Whatever the method used, after determining which part of the signal is usable, the noise is nullified and the remaining components are mixed back together. Some of the methods used in ICA are so advanced that the process of ‘unmixing’, signal purifying and mixing it back together is fully automated [20. As researched in the last few years by comparing EEG data between paralysed and healthy subjects, it has been observed that muscle movement play a significant role in the EEG signal contamination in particular in the range of higher Gamma frequencies above 20 Hz. Surface Laplace operator is one of the methods used in removing muscle artefacts however it works best with EEG systems comprising of at least 64 electrodes [21].

10-20 Electrode placement system

The 10-20 system [3] has been developed to unify the electrode placement for easy comparison and reproducibility of conducted EEG measurements. The ’10-20’ refer to the percentage by which the electrodes are spaced away from one another (20%) and from nasion, inion and both ears (10%). The letters F, T, C, P, and O indicate frontal, temporal, central, parietal and occipital lobes. All electrodes marked as ‘z’ (zero) have been placed in the middle of the skull. Even numbered electrodes such as 2, 4, 6 represent right hemisphere placement while odd numbered electrodes (1, 3, 5) indicate left hemisphere placement [3] as shown in Figure 2.

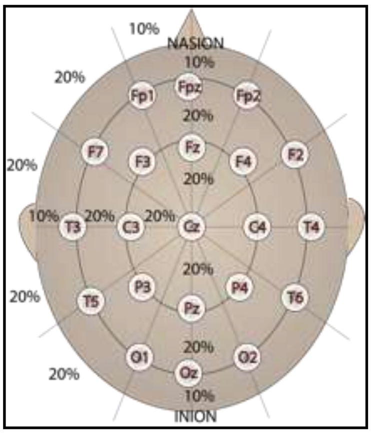


Fig-2: Electrode placement according to international 10-20 system [3].

Brain waves

Brain waves are oscillations that occur naturally in the brain and can be measured by EEG system. The majority of oscillations is within 1-20 Hz and represents rhythmic patterns [2]. There are also transient components that can be observed. These occur as sharp waves and spikes in the waveform and usually are associated with seizure [2]. Vertex waves and sleep spindles seen during sleep are considered normal. There are also so called ‘normal variants’ which although statistically uncommon are not considered as pathology with Mu waves being one of them. Mu waves also known as Mu rhythms occur within 7 Hz - 13 Hz frequency band and can be mainly observed when body is at rest [2]. The EEG patterns vary with age. Young children have slower oscillation than adults. Also state of mind and other individual characteristics have an impact on the EEG patterns [2]. EEG is built of set of signals which are classified and named in relation to their distribution over the scalp, biological function and frequency range. Commonly known frequency bands are called delta [δ], theta [θ], alpha [α], beta [β] and gamma [ɣ] [1] as detailed below in Table-1.

Various types of electrical brain activities commonly used for an EEG based BCI

Slow Cortical Potentials (SCP)

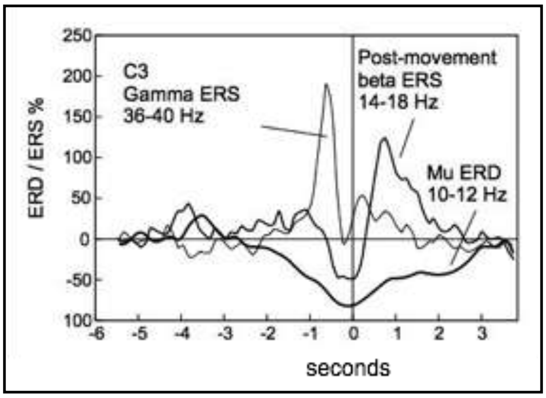
SCP signals are very slow brain waves that mostly occur below 1 Hz. There are negative and positive potentials within this range and they are correlated with increased or decreased brain activities respectively [36]. These self-regulated brain waves can be used to control computer cursor or select different targets on the screen. A thorough user training is necessary to use SCPs effectively. For that purpose thought-translation devise is used [37]. During training this devise equipped with a screen cursor constantly provides the user with feedback showing SCP’s amplitude through cursor’s vertical position [38]. The learning process is heavily dependent on the user’s psychological state, mood or motivation. Therefore, the user's capability to obtain this particular skill has to be determined on individual basis during initial trials [37].

Table 1: EEG rhythmic activity comparison by frequency bands

	Frequency in Hz	**Characteristics/ Location**	**Activity**
Delta [δ]	0.5 - 4	the highest in amplitude the slowest in frequency most prominently occur frontally in adults and posteriorly in children decreases with age can be confused with artefacts [1]	most neonatal brain activity in adults this slow wave represents sleep occasionally recorded during long attention tasks Kirmizi-Alsan et al. [22] large amounts in awake adults is abnormal and suggest neurological deceases [1]
Theta [θ]	4 - 7	locations not related to tasks performed	larger amount observed in young and older children, in adults relate to neurological decease [23] associated with drowsiness or arousal in adults and teenagers [23] also found in states of relaxation, meditation and creativity [24-26]
Alpha [α]	8 - 12	mostly found in the occipital lobe of the brain [27]	found in the state of relaxation and reflection amplitude increases when eyes are closed decreases with open eyes and mental effort [85] mainly associated with visual processing [28]
Beta [β]	13 - 30	low amplitude waves mostly detected at the frontal and central regions of the head [1]	associated with motor activities [1] during real movement and motor imagery Beta oscillations are desynchronised symmetrically distributed with no motor activity [29]
Gamma [ɣ]	30 - 100 Hz	somatosensory cortex	displayed during activity requiring combination of two different senses (ie. smell and taste) [30, 31] related to certain motor functions or perceptions [32] observed during maximal muscle contraction [33] and replaced by Beta rhythms during weaker contractions [34] less common in BCI applications, prone to artefacts related to eye movement and muscle contractions [35]
Mu	7 - 13	sensorimotor cortex band overlaps with other frequencies	related to motor activities may correlate with beta rhythms [27, 87]

Sensorimotor rhythms

Beta rhythms (13-30 Hz) which have symmetrical distribution over the central part of the brain possess harmonic relation to the mu rhythms. Sensorimotor rhythms are a combination of Mu rhythms (7 Hz - 13 Hz) and Beta rhythms (13 Hz - 30 Hz). Mu rhythms also referred to as Mu waves have the form of synchronised patterns of electrical activity that are associated with voluntary movement [2]. Although Mu rhythms are occupying similar frequency band as the Alpha waves they differ in nature. Unlike Alpha waves, which occupy occipital lobe and are associated with the state of relaxation and brain's vision processing activity, Mu rhythms occur in the motor cortex between the ears and are associated with motor action, although physical movement is not actually required for the oscillations to appear. With training such brain waves can be triggered by only mental rehearsal of a motor act which results in a paradigm called imaginary movement [27]. Beta rhythms are also closely linked to motor behaviour and have been observed to attenuate during active movements [39]. Sensorimotor rhythms as the combination of both Mu and Beta oscillations can be used to control a BCI because people can be trained to trigger these voluntary modulations, although it is time consuming and not easy to do [29]. Imaginary movement can be observed as decrease in amplitude and signals desynchronisation within motor cortex along the entire range of Mu and Beta waves (8-30 Hz) [40]. These amplitude changes and desynchronisation can be utilised to successfully control a BCI. There are two types of amplitude modulations found in sensorimotor rhythms. They are Event-Related Desynchronisation (ERD) involved in amplitude suppression and Even-Related Synchronisation (ERS) linked to amplitude enhancement [29].



(b) Fig-3: Example of ERD and ERS desynchronisation [29]. Negative time represents the time before the movement onset.

Figure-3 illustrates the process of desynchronisation during voluntary index finger lifting experiment. In this example ERD (suppression) of Mu wave starts approximately two seconds before the onset of the movement, reaches its maximum at the movement and restores back its original level after three seconds [29]. At the same time we can observe different behaviour of the Beta wave where a short ERD (suppression) occurs at the movement start and then it shows ERS (enhancement) peaking immediately after the movement execution [29]. This is the moment of the maximum desynchronisation where Beta ERS appears while the Mu wave is still being suppressed. In this illustration we can also notice a short ERS peaking of the Gamma wave right before the movement execution. Gamma waves (36-40 Hz) which are fastest brain oscillations registered by the EEG are also known to be linked to human motor activity [29]. In the BCI design sensorimotor rhythms are very useful since they can be generated voluntarily by the brain without the actual movement [41].

Event Related Potential (ERP)

Event Related Potentials (ERP) are very small voltages that can be measure by an EEG system reflecting brain activities which are time locked to and directly induced by specific sensory, cognitive or motor events [42]. Because ERPs can be detected by an EEG they produce opportunity for a noninvasive and safe mode of brain waves research. It is believed that ERPs are generated by thousands to millions of neurones synchronously firing electrical signals when information is being processed by the brain exposed to sensory, cognitive or motor events [86]. There are two categories of ERPs that have been detected in humans. The first wave appears during the first 100 ms after the stimulus and is referred to as ‘sensory’ or ‘exogenous’ since it is directly related to the physical quality of the stimulus. In the next portion of the brain wave, approximately within 200 ms, another signal peak can be observed which is usually termed as ‘cognitive’ or ‘endogenous’ which reflects the subjects attempt to analyse and evaluate the stimulus [42].

Oddball Paradigm and P300 phenomena

Oddball Paradigm refers to an experiment mainly used in Event Related Potential (ERP) research area [43]. It is based on the idea of presenting sequenced repetitive auditory or visual patterns (considered ‘standard’) occasionally interrupted by a stimulus not expected by the subject (called ‘target’). The subject is requested to react to these unexpected elements by either counting them or pressing a button to confirm. The difference between the expected (standard) and unexpected (target) stimuli is that the latter requires a response from the subject [43]. Although each stimuli triggers an ERP, it has been found that the unexpected target signals that required a reaction produce brain waves that occur approximately 300 ms after the stimulus presentation and their amplitude is greater compared to a standard (expected) stimuli. The average 300 ms reaction time and positive (P) deflection of the wave contributed to the name of P300 given to this specific potential [44]. Based on published research it is wise to state that P300 is a distinct brain signal directly related to decision making [44]. It means that rather than being a direct product of physical occurrence of either auditory or visual stimuli, the P300 wave is associated with human’s reaction to it. To be more specific, the P300 is believed to be more dependent on the human’s ability to evaluate and categorise events [44]. The oddball experiment provides perfect mode for eliciting and evaluation of the P300 signal. In electroencephalography (EEG) the P300 shows as a positive peak in voltage with delay ranging between 250 and 500 ms [44].

The two parameters of P300 which are measured are amplitude and latency (delay). Amplitude measured in μV is expressed as the difference between the pre-stimulus baseline voltage level and the greatest registered positive peak of the waveform. The measurement is taken within pre-defined time window of 250-500 ms which matches the length of the usual P300 peak, although it may vary depending on various conditions such as person's age, task intensity. Latency measured in ms is expressed as the time between stimulus onset and the highest registered point in the positive waveform within the same time window [44].

Steady State Visual-Evoked Potential (SSVEP)

SSVEP is one of the easiest methods to trigger brain waves. The brain signals can be elicited by exposing retina to repetitive flickering light or graphic. The frequency of the flicker generates brain waves that carry the same fundamental frequency together with higher order harmonics [45]. Thanks to this phenomena an SSVEP-based BCI can control many parameters through multiple classes which can be achieved without elaborate training. The main advantage of this system is that the user doesn't have to concentrate on motor action simulation which is necessary for other BCI systems. The user only needs to switch his/her eye view between different stimuli sources [46]. In SSVEP system the user can select between different commands where each command needs a separate visual stimulus. Each stimulus must have a distinctive characteristic (frequency or phase). For practical reasons it is best when the display simultaneously presents the user with all stimuli and the user can select each one as required by the application by shifting his/her gaze [45]. The possible range of frequencies that can be elicited in SSVEP system is between 1 to 100 Hz [47]. The strongest signal amplitudes were obtained within 10 Hz range as well as between 16-18 Hz bands while the weakest ones could be observed in the high frequency range (30-60 Hz) [48]. The main concerns in using this method are related to safety and comfort of the user. Due to the nature of the stimuli there is a danger of evoking epileptic seizures, inducing fatigue and weakening the user's vision [49, 45]. It has been determined that the most annoying flicker frequencies for humans are in the low range of 5-25 Hz. Furthermore, the danger of inducing epileptic seizures has been recognised between 15-25 Hz frequency bands [49]. Another problematic issue is associated with the fact that the user needs to be focused on the stimuli at all times in order to maintain the matching oscillation in the brain. In cases where the user wants to control a computer cursor or other moving object the eye contact with the stimulus is lost. One way of mitigating this problem is to program the application in such way that the stimulus will move together with the controlled object [50, 51]. Also Van Vliet et al. [52] experimented with SSVEP visual flicker using EMOTIV Epoc [53] EEG for data recording. In their experiment which was organised during I-Brain & Senses event (18-19 March 2011, Ghent, Belgium) they encouraged 25 users to play their custom designed game which was controlled by only one flickering square placed at the lower left corner of the computer screen. In questionnaires provided afterwards the users contributed their feedback in relation to playability of the game and expressed their enjoyment especially for the parts where they could monitor the brain signal detection process and could see the results of their actions on the computer screen [52].

Other types of stimuli used in SSVEP

Various approaches can be taken in designing visual stimuli. It can be presented as a flickering light, a colour alternating graphic or as a checkerboard [54]. Various devices can also be utilised for the flicker presentation. For light flickers a flash tube, a light bulb or an LED panel will work. For more elaborate graphic elements a CRT/LCD screen should be used. To facilitate portability and tighter integration with the BCI modern portable screens (laptop, tablet, smartphone) will be taken into account in this research. Computer/tablet monitors are more convenient since they offer more opportunities for detailed graphics and feedback presentation as well as target alignment [54]. Nakamishi et al. [55] point out all the advantages of using a computer screen for the flicker presentation. All the stimulation parameters such as the amount, colour, pattern, size and position can be flexibly configured [55]. However, the number of targets is limited by the common 60 Hz refresh rate of most screens available today. In the Alpha range of 8-12 Hz where the SSVEP is most effective the number of available flickers is very limited [56]. For instance, for an effective checkerboard flicker we need constant period graphics meaning an equal amount of black and white frames per period to display a steady stimulus using 60 Hz screen. That leaves us with frequencies such as 7.5 Hz (60 Hz/7.5 Hz gives 8 frames per period, 4 for black and 4 for white fields), 10 Hz (6 frames per period) and 15 Hz (4 frames per period) [55].

Therefore, other solutions must be introduced to expand the available amount of frequencies to increase the number of commands in the resulting BCI. Wang, Y., et al. [57] proposed a method where flickering graphics are created by approximation where variable number of frames are utilised to display frequencies that otherwise could not be shown by a 60 Hz screen. In their example they suggested that an 11 Hz flicker can be approximated by mixing 10 Hz and 12 Hz frequencies, where 5 and 6 frames periods can be interleaved as '1110001110011100011100…' [57]. Figure 4 below shows a graphic representation of this method used to create 6.3 Hz flicker.

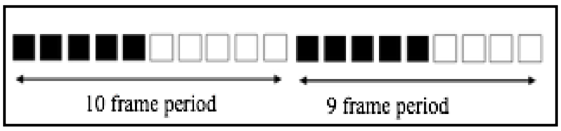


Fig-4: Example of 6.3 Hz flicker with approximated period of 9.5 frames.

This method gives us additional frequencies such as**(d)** 11 Hz (with approximated period of 5.45 frames), 8 Hz (7.5 period), 9.2 Hz (6.52 period), 13.3 Hz (4.5 period), 7.05 Hz (8.5 period) and 6.3 Hz (9.5 periods) that will work with 60 Hz screen refresh rate [55]. Nakamishi et al. [55] in their paper compared the results of their SSVEP based system using both constant period approach and the approximation approach and stated that the results were comparable. They further claimed that the approximation approach for rendering SSVEP-based oscillations may lead to a more practical BCI system requiring large number of user selections such as spelling systems using more than 30 targets. Their only concern for the future work is developing a multi-command, real-time portable BCI with the use of the approximation method in light of the ever growing various display technologies utilizing not only 60 Hz but also 75 Hz and 120 Hz refresh rates [55]. Szalowski and Picovici [58] investigated the robustness of variable period stimuli graphics against the constant period flickers. In their experiment they used Emotiv EPOC headset and two computers. The response of three subjects was tested in a set up where one computer wirelessly registered the EEG signals while the other displayed checkerboard flickering graphics of various frequencies. The tests were performed in two different environments. One was normal office room with fluorescent lighting with regular ambient noise and the other was a quiet dark room with no distractions. They found out that indeed the constant period stimuli graphics produced better overall performance with cleaner signals and less harmonics. Also based on the fact that the same stimuli graphics produced different responses in the three subjects they suggest that individual features of each subject such as eyesight, age, ability to concentrate, might play a significant role in the resulting signal discrepancies. Originality of this approach lays in the fact that Szalowski and Picovici [58] used external professional motion graphics software like Adobe after Effects to produce high quality stimuli graphics. This method allows to free some computing power of the future BCI systems for EEG signal decoding algorithms.

Another method of increasing the possible number of stimuli graphics is through the use of phase feature of the oscillations [54]. In this method a single frequency can be used with varying phase. In the example below 10 Hz flickers have been presented with phase equally shifted by 60° giving six independent flickering graphics [54].

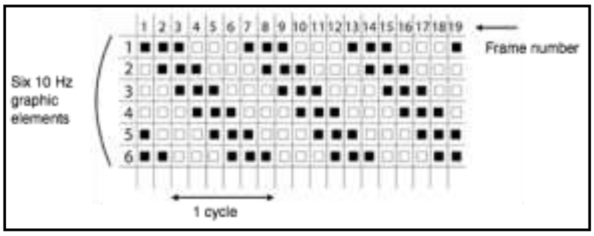


Fig-5: Six independent 10 Hz graphic elements with phase shifted by one frame which equals 60°.

Using phase shift in stimuli design the screen's refresh rate stability are of the utmost importance [54]. As reported by Kluge and Hartmann [59] who used only two phase shifted targets, the online application of this method was not feasible at that time due to increased demand for computational power that was required from the computers to classify them. It will be worth checking though whether current personal computer is able to process online this type of data.

Another important issue is the physical appearance of the stimuli, their sizes and arrangement on the display ([60]. Wu and Lekany [60] investigated the impact of configuration of multi-stimuli presented on a computer monitor for the SSVEP response. They looked over the three distinctive parameters such as the size, the separation distance between the stimuli and the layout that might impact the resulting BCI signal. In their tests they found out that the configuration with bigger size and larger separation between the stimuli gave better results pointing to the layout as having the least impact [60].

An area that lacks in research and presents high opportunity for new discoveries is the SSVEP response to different colours. Colour of the stimulus among other parameters such as size and separation also influences SSVEP signal as it presents different responses to red, blue and yellow light [61]. Singla, Khosla and Jha [62] in their study used four colours (green, red, blue and violet) to investigate the colour influence in SSVEP. In their findings they state that an SSVEP with violet colour showed higher performance than green and red.

The concept of improving SSVEP response with different colour stimuli presentation is based on the fact that SSVEP is heavily dependent on human vision system [63]. The human eye is equipped with two types of photoreceptive cells: rods and cones. There are approximately 120 million rods and only 6-7 million cones in the retina [64]. The rods are over one thousand times more sensitive to light compared to the cones hence they are responsible for the human night-vision. In contrast they are not sensitive to colour and are very slow in response [64]. This can be observed when we enter a dark room and start to see some details after a few minutes. The rods are also better motion sensors especially in the peripheral vision. The cones provide the eye's colour sensitivity and are responsible for high resolution vision. They are less sensitive to light but much faster in response. The cones can be divided into three categories based on their response to different light wavelengths: 'red' cones [64%], 'green' cones [32%] and 'blue' cones [2%] [64]. All this may lead to a conclusion that colour response of the human eye and specifically the anatomy of the retina might have a substantial effect on the signal elicited by SSVEP stimuli graphics.

BCI classification

Based on the various BCI control signal types discussed earlier in this paper it is possible to categorise BCI systems into the following categories: exogenous, endogenous, synchronous (cue-paced) and asynchronous (self-paced) [1]. The first two categories refer to the nature of the signals that the BCI system receives, while the last two depend on the input data processing modality.

In exogenous BCI an external stimulus is required for the specific brain activity to be elicited [1]. Previously discussed SSVEP and P300 are good examples of such BCI systems. There are numerous advantages of the exogenous BCI systems. Among them are minimal to no training required and easy set up of control signals [65]. Another very crucial parameter for any control systems are Information Transfer Rates (ITR) [54]. This determines how many individual commands can be sent through the system during set amount of time. Exogenous BCI systems excel in this area and they can provide up to 60 bits per minute [1]. This means that an average person after minimal training can send 60 different commands per second using this method. In most of the situations it’s more than enough to control any type of domestic device or computer application [65]. Also stimulus based control signals require only one EEG channel which significantly simplifies the system and lowers the overall cost [1]. The list of disadvantages is not very long but they may cause some problems in various situations. First of all this type of BCI requires the user to be constantly focused on the stimulus. This means that if the eye contact is lost also the elicited signal disappears. One way to overcome this problem would be to programme the application in such a way that when the controlled object moves the stimulus moves along with it or the controlled objects are presented as flickers themselves [66]. Also the quality of the flickering graphics and their accuracy in terms of frequency plays an important role in the overall robustness of the system. As indicated by Bakardjian et al. [67], visual graphic employed in BCI systems using SSVEP need the same degree of optimization as the analysis algorithms in order to maximize the brain’s response. As Wang et al. [68] reported, also the number of commands (targets) has a considerable impact on the tiredness of the person using the system. The more flickering graphics will be presented to the user the more discomfort the system will cause. Wang et al. [68] suggested that systems with more targets provide higher transfer rates giving an example of 13-target system versus 2-target system, where the first one operated at 43 bit/minute and the second one at just 10 bits/minute transfer rate. They also pointed out that the number of targets implemented in the BCI needs to be considered as a tradeoff between the performance and user comfort [68]. In summary, the exogenous BCI systems won’t allow the user to freely move a computer cursor or a mechanical arm in any desired direction. Instead it constrains the device’s control by only the choices the stimuli graphics present [1].

In contrast, endogenous BCI systems are operated on the principle of self-regulation and self-control of the brain waves without the use of any kind of external stimulation [65]. Endogenous BCI systems are based on sensorimotor rhythms (Mu band) and the user needs to be trained how to change brain oscillations based on motor imagery [1] or on Slow Cortical Potentials (SCPs) where a though-translation device is used [37]. In this training the user performs certain motor imagery tasks while the EEG records the signal which then further needs to be extracted and classified by comparing to the reference data. Based on the success results a visual feedback is presented to the user enhancing the learning experience [1]. It is a rather time-consuming task and the results are never guaranteed and depend on the individual’s abilities [69]. Another disadvantage of this method is the need to use multichannel EEG systems in order to increase the performance and stability of the system. It also delivers significantly lower bit rate of approximately 20-30 bits/minute compared to exogenous systems. However, the fact that it operates at free will and is stimulation independent makes it a good choice for systems where cursor control is required [1].

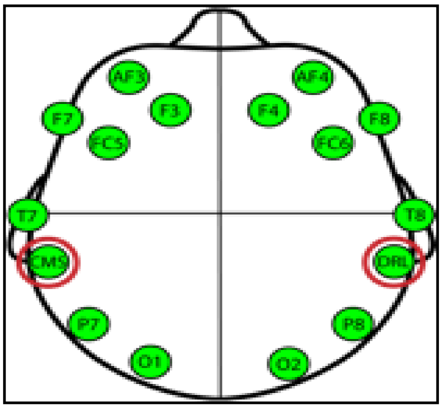
Endogenous systems can further be classified according to the input data processing modality i.e. synchronous and asynchronous. In synchronous systems there are predetermined time slots during which the brain signal is analyzed and recorded. Any brain activities that occur outside this time are ignored. During this predefined time space the user is presented with auditory or visual cues [70]. The most obvious advantage of this method is the ability to simplify the system’s design and brain signal evaluation methods. Also eye blinks, eye movement and most of other biological artefacts can be eliminated since the signal recording is only limited to the allocated time windows and it is easier for the user to focus during this time.

Asynchronous BCI presents more natural mode of interaction where brain signals are recorded at all times. In consequence this approach requires elaborate system where signal evaluation is much more difficult and the demand for computation is much higher [1].

EMOTIV Epoc as BCI hardware

Using standard EEG equipment for popular applications imposes various problems such as high cost, difficult assembly and lack of portability due to sizeable dimensions and wire connections. Therefore, a relatively small device with wireless transmission capability is necessary. Among various devices available on the market that fulfill this requirement are NeuroSky [71],, Mindflex [72] and EMOTIV Epoc [53]. Clear advantage of the latter lays in the number of electrodes and according to Stamps and Hamam [73] it is the most effective low-cost EEG system delivering acceptable performance [73].

(e) Fig-6: Emotiv Epoc headset [53].



(f) Fig-7: Scalp locations covered by Emotiv EPOC according to 10-20 system.

According to the producer's specifications the device is equipped with 14 EEG active electrodes accompanied by 2 reference electrodes (CMS and DRL) as shown in Figure 7. It uses the following EEG locations in accordance with the 10-20 international system for signal acquisition: AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2. It is capable of capturing signal frequencies between 0.16 Hz and 43 Hz with internal sampling rate of 2048 Hz and resolution up to 16 bits (Compare 2015). The signals are internally filtered and down-sampled to 128 or 256 Hz. The sensors are saline soaked felt pads which need to be kept wet while in operation. Epoc EEG connects to any operating system PC via the supplied USB wireless dongle. The supplied software allows for the use of preset mental commands or extract EEG raw data which then can be used in research.

While Emotiv's EPOC appears to be perfectly suited for testing and designing video games, entertainment and neurotherapy [74], numerous researchers report its high usability in scientific research [75, 76, 52, 77]. In this respect it is very useful that the product is accompanied by a dedicated Application Programming Interface (API) which simplifies any potential BCI-based application development [1].

Yue et al. [75] in their paper compared the easy of use, setup time and final results between Emotiv EPOC and the more elaborate g.tec systems. In their results they stated that although EPOC operated noticeably poorer it still delivered useful performance of 95% accuracy using SSVEP stimuli. They also pointed out that EPOC was not only much more affordable but also easier to setup and operate which is an ideal combination for the type of system this paper tries to establish [75].

Duvinage et al. [78] performed a similar comparison between EPOC and a medical-grade system costing in the range of tens of thousands of dollars produced by Advanced Neuro Technology [79] using P-300 paradigm. In their discussion they noted that although EPOC device was able to record EEG data in a satisfying manner it delivered a significantly worse performance pointing out that it should rather be used for non critical applications such as gaming or entertainment.

Stytsenko, Jablonskis and Prahm [76] stated in their EPOC performance comparison paper that in general it delivered comparable EEG data to a more advanced g.tec system with the latter producing clearer and stronger signal. They also observed a drift in recording speed between the devices despite the fact that both operated with 128 samples/second setting. They also suggested possible benefits of using the built-in gyroscope sensors in EPOC presenting potential for developing future software applications that could be used within BCI system augmenting its usability (artefacts reduction, yes/no nodding, etc.).

Van Vliet et al. [52] denoted in their paper that SSVEP detection on EPOC is robust and opens the way to developing commercial BCI-based games that can be fully controlled using only brain commands. They also noticed poorer performance of other BCI paradigms such as P-300 in current state of the research while stating that it might be feasible to employ them in the future using EPOC device [52]. One of the reasons for the EPOC to under perform, especially in comparison to other more advanced systems might be the fact that the electrode placement in EPOC is predetermined, limiting its use in certain BCI paradigms where other arrangement is preferable. For example, in SSVEP an occipital lobe electrode placement is preferred to increase the EEG signal [52].

Therefore, as Manyakov et al. [80] indicate, for successful application of SSVEP in EPOC a reversal of the headset is advised. This enables the electrodes to access specific (occipital lobe) areas of the brain.

AlZu'bi, Al-Zubi and Al-Nuaimy [77] compared the EMOTIV Epoc's performance to a more expensive BrainAmp EEG system using asynchronous BCI tasks and they claim that the inexpensive Epoc can deliver comparable accuracy. They also noted a more natural mode of operation of the Epoc device due to wireless communication with the computer. In summary they recommend using Epoc for further BCI study and application development [77].

BCI mobility

Majority of the BCI systems especially used in research laboratories are based on bulky and wired equipment. This does not translate to easy of use, portability, practicability and ubiquity of the system this paper is attempting to establish. As it has been determined earlier in the paper the signal acquisition should be performed by a non-invasive, easy to set-up and operate, portable, wireless and low-cost device such as the latest generation of EMOTIV Epoc EEG headset. But it still requires equally small and yet powerful device to elicit the signal, process it, ideally in real time, and perform tasks such as web browsing, game control or making a phone call. Modern tablets and smart-phones with multi-core processing power seem to be the best candidates for such mobile system.

One of the first attempts utilising this approach was demonstrated by Wang, Y.T., Wang, Y. and Jung, T.P. [81]. They integrated a cell-phone in a system consisting of a wearable and wireless EEG (Figure 8) implementing SSVEP.

(g) Fig-8: An EEG headband with an embedded data acquisition and wireless telemetry unit [81].

The EEG system used 4 electrodes which acquired the bio-signal form the brain. The signal was then amplified, band-pass filtered and digitized by analog-to-digital 12-bit converters. The digitized EEG signal was then sent to a cell-phone via a Bluetooth module. For the stimulator they used a 21-inch CRT computer screen (140 Hz refresh rate and 800x600 resolutions) that displayed SSVEP flickers representing virtual phone keypad with 0-9 digits, BACKSPACE and ENTER. The stimuli frequencies between 9 Hz and 11.75 Hz were picked (Wang, Y.T., Wang, Y. and Jung, T.P. 2010). Although the bulkiness of the computer screen does not make it for a true portable system, the experiment proved that a cell-phone can be programmed in much the same way a computer is, providing data processing, real-time monitoring and task execution. All subjects participating in this EEG-based phone dialing experiment with an average accuracy of 95.9% in an average time of 88.9 seconds [81]. The average Information Transfer Rate (ITR) was 28.47 bit/minute which can be compared to results achieved on high-end computers [82, 57].

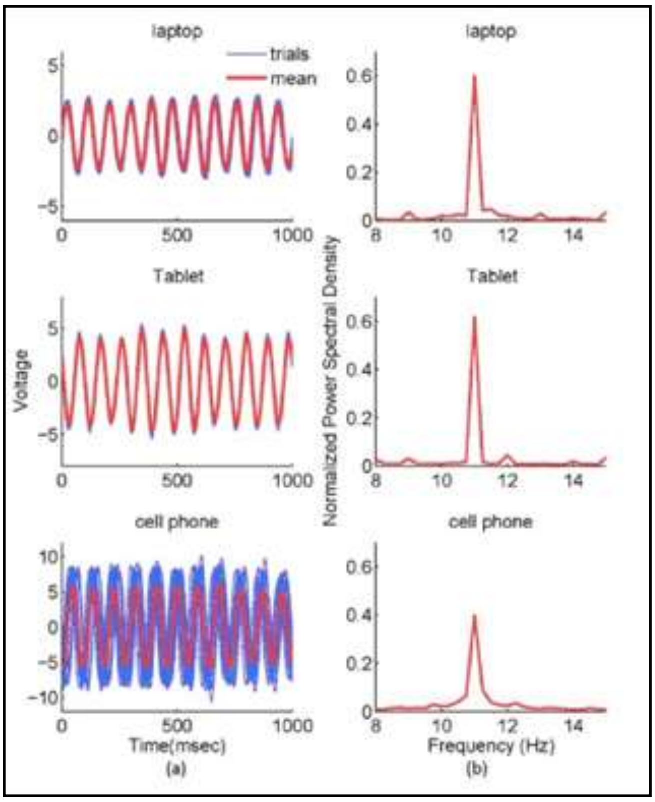
In order to move the complete BCI system from laboratories to real-life applications and environments a more portable and practical system needs to be developed. Ever growing computational speed of the most recent smart phones and tablets leads to a concept of using them as a complete BCI solution. In this respect tablets seem to be the better option due to bigger storage space available for applications, faster processors for data processing and larger screen for flickers presentation.

This approach has been thoroughly examined by Wang et al. [83] by using a laptop, a tablet and a smart-phone for both stimuli display and data processing, achieving much better results and thus increasing functionality and portability of the system. Again SSVEP was used for eliciting the EEG signals due to its robustness and minimal training required. They displayed the flickering graphics through a Lenovo X200S laptop, a Motorola XOOM tablet and a Samsung Galaxy S smart-phone [83].

TABLE-2: Specifications Of The Devices Used In The Experiment [83].

	Lenovo X200s	Motorola XOOM	Samsung Galaxy S
OS	Windows XP SP3	Android 3.0	Android 2.1
CPU	Intel Core 2 Duo 1.4GHz	NVIDIA Tegra 2 Dual-Core 1GHz	ARM Cortex-A8 1 GHz
Software	Direct X	OpenGL ES	OpenGL ES
Screen refresh rate (Hz)	60.375	59.975	55.575
Screen size (inch)	13	10.1	4
Screen resolution (pixels)	800 × 1280	800 × 1280	400 × 800

From the Table 2 above it is evident that in general the computational specifications have been matched between all of the devices. The most obvious differences can be observed in the screen's resolution, size and refresh rate. Wang et al. [83] pointed out that while the refresh rate of the laptop and tablet were comparable and the signal's phase was almost identical in every second, the smart-phone presented a little bit of a challenge while presenting 11 Hz flicker due to phase shifting back and forth. The averaged ITR of the experiment was 33.87 bits/minute which is better when compared to the previous experiment. Despite the refresh rate differences and slight instability of the flicker on the smart-phone, all three devices were able to produce a signal with correct 11 Hz fundamental frequency [83].



(h) Fig-9: The waveforms and power spectra of the stimuli graphics [83].

Figure-9 shows the normalised amplitude of the stimulation as being the smallest on the smart-phone but the frequency is still accurate. Although Wang et al. [83] describe the BCI operation as near real-time it is still very promising for future development.

CONCLUSIONS

As it has been shown in the above sections, most of the technical requirements for a mobile low-cost, easy to set up and operate BCI system can be achieved with today's off the shelf technology.

Starting with the hardware it is essential that it provides quick set-up mode, straightforward operation and wireless connectivity. In order to satisfy these guidelines the latest generation of EMOTIV Epoc EEG headset has been identified.

Based on the literature review SSVEP (Steady State Visual Evoked Potential) has been also identified as the mode of eliciting oscillations in the brain. This methods satisfies the minimal training requirement for the system operation, providing also excellent signal-to-noise ratio (SNR) thus significantly simplifying the signal recognition and classification. SSVEP is also known to produce high information transfer rate (ITR) of up to 60 bits/minute which in conjunction with multi-target operation can increase the possible number of commands that the end user could perform in any given time frame.

As it has been described in section IX of this paper, despite screen refresh rate limitation, the SSVEP stimulation can be successfully presented on various modern displays including laptops, tablets and even smart-phones using either the method of frequency approximation or phase shift. Reportedly a 48-command BCI system using SSVEP has been successfully implemented, although this result was achieved by only one user [84].

Modern displays offer unparalleled possibilities for stimuli presentation in terms of stimuli arrangement and movement, size, resolution, contrast and colour. The quality of the graphic elements serving as stimulators is very important and is directly linked to the robustness of the EEG signal. It has been concluded that one area that lacks in research thus providing opportunity for new development is the SSVEP's response to different colours. It is envisaged that introducing certain colour combinations with varying colour saturation and contrast might greatly reinforce signal strength. This is a niche area that the authors are going to investigate.

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REFERENCES
1. Nicolas-Alonso LF, Gomez-Gil J; Brain Computer Interfaces, a Review, Sensors, 2012; 12(2): 1211-1279.
2. Niedermeyer E, Lopes da Silva FH; Electroencephalography: Basic principles, clinical applications and related fields, 3rd edition, Lippincott, Williams & Wilkins, Philadelphia, 1993.
3. Teplan M ; Fundamentals of EEG measurement. Meas. Sci. Rev, 2002; 2: 1-11.
4. Towle VL, Bolaños J, Suarez D, Tan K, Grzeszczuk R, Levin DN, Cakmur R, Frank SA, Spire JP; The spatial location of EEG electrodes: Locating the best-fitting sphere relative to cortical anatomy. Electroencephalography and Clinical Neurophysiology, 1993; 86(1): 1–6.
5. American Electroencephalographic Society; Guideline seven: a proposal for standard montages to be used in clinical EEG. J Clin Neurophysiol, 11: 30–36.
6. Aurlien H, Gjerde IO, Aarseth JH, Eldøen G, Karlsen B, Skeidsvoll H, Gilhus NE; EEG background activity described by a large computerized database. Clinical Neurophysiology, 2004; 115(3): 665–673.
7. Vespa PM, Nenov V, Nuwer MR; Continuous EEG Monitoring in the Intensive Care Unit: Early Findings and Clinical Efficacy. Journal of Clinical Neurophysiology, 1999; 16(1): 1-13.
8. Hämäläinen M, Hari R, Ilmoniemi RJ, Knuutila J, Lounasmaa OV; Magnetoencephalography-theory, instrumentation, and applications to noninvasive studies of the working human brain. Reviews of Modern Physics, 1993; 65(2): 413–497.
9. O'Regan S, Faul S, Marnane W; Automatic detection of EEG artifacts arising from head movements. 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, 2010; 6353–6356.
10. Schenck JF; The role of magnetic susceptibility in magnetic resonance imaging: MRI magnetic compatibility of the first and second kinds. Medical Physics, 1996; 23(6): 815–850.
11. Mulholland T; (Objective EEG Methods for Studying Covert Shifts of Visual Attention. In McGuigan F. J.; Schoonover, R. A. The Psychophysiology of Thinking: Studies of Covert Processes, 2012; 109–151.
12. Hinterberger T, Kübler A, Kaiser J, Neumann N, Birbaumer N; A brain–computer interface (BCI) for the locked-in: Comparison of different EEG classifications for the thought translation device. Clinical Neurophysiology, 2003; 114(3): 416–425.
13. Carreiras J, Osorio P, Zamith A, Caetano A; Brain Computer Interface (BCI) based on Electroencephalography, 2006.
14. Srinivasan R; Methods to Improve the Spatial Resolution of EEG. International Journal, 1999; 1(1): 102–111.
15. Schlögl A, Slater M, Pfurtscheller G; Presence research and EEG. University of Technology Graz, Austria, 2002.
16. Fisch BJ; Fisch and Spehlmann's EEG Primer: Basic Principles of Digital and Analog EEG, 3e. 3 Edition. Elsevier, 2002.
17. Huster RJ, Mokom ZN, Enriquez-Geppert S, Hermann C; Brain-computer interfaces for EEG neurofeedback: Peculiarities and solutions. International Journal of Psychology, 2014; 91(1): 36-45.
18. Jung TP, Makeig S, Humphries C, Lee TW, McKeown MJ, Iragui V, Sejnowski TJ; Removing electroencephalographic artifacts by blind source separation. Psychophysiology,2000; 37(2): 163–178.
19. Keren AS, Yuval-Greenberg S, Deouell LY; Saccadic spike potentials in gamma-band EEG: Characterization, detection and suppression. NeuroImage, 2010; 49(3): 2248–2263.
20. Nolan H, Whelan R, Reilly RB; FASTER: Fully Automated Statistical Thresholding for EEG artifact Rejection. Journal of Neuroscience Methods, 2010; 192(1): 152–162.
21. Fitzgibbon SP, Lewis TW, Powers DMW, Whitham EM, Willoughby JO, Pope KJ; Surface Laplacian of Central Scalp Electrical Signals is Insensitive to Muscle Contamination. IEEE Transactions on Biomedical Engineering, 2013; 60(1): 4–9.
22. Kirmizi-Alsan E, Bayraktaroglu Z, Gurvit H, Keskin YH, Emre M, Demiralp T; Comparative analysis of event-related potentials during Go/NoGo and CPT: Decomposition of electrophysiological markers of response inhibition and sustained attention. Brain Research, 2006; 1104(1): 114–128.
23. Kübler A, Kotchoubey B, Kaiser J, Wolpaw JR, Birbaumer N; Brain-Computer Communication: Unlocking the Locked in. American Psychological Association: Washington, 2001.
24. Anand BK, Chhina GS, Singh B; Some aspects of electroencephalographic studies in Yogis. Electroencephalogr. Clin. Neurophysiol, 1961; 13: 452–456.
25. Aftanas LI, Golocheikine SA; Human anterior and frontal midline theta and lower alpha reflect emotionally positive state and internalized attention: High-resolution EEG investigation of meditation. Neurosci. Lett, 2001; 310: 57–60.
26. Fernández T, Harmony T, Rodríguez M, Bernal J,

Silva J, Reyes A, Marosi E; EEG activation patterns during the performance of tasks involving different components of mental calculation. Electroencephalogr. Clin. Neurophysiol, 1995; 94, 175–182.
27. Pineda, Jaime A; The functional significance of mu rhythms: Translating 'seeing' and 'hearing' into 'doing'". Brain Research Reviews, 2005; 50(1): 57-68.
28. Klimesch W; EEG-alpha rhythms and memory processes. Int. J. Psychophysiol, 1997; 26: 319–340.
29. Pfurtscheller G, Neuper C; Motor imagery and direct brain-computer communication. Proc. IEEE, 2001; 89: 1123–1134.
30. Kisley MA, Cornwell ZM; Gamma and beta neural activity evoked during a sensory gating paradigm: Effects of auditory, somatosensory and cross-modal stimulation. Clinical Neurophysiology, 2006; 117(11): 2549–2563.
31. Kanayama N, Sato A, Ohira H; Crossmodal effect with rubber hand illusion and gamma-band activity. Psychophysiology, 2007: 44(3): 392–402.
32. Lee KH, Williams LM, Breakspear M, Gordon E; Synchronous Gamma activity: A review and contribution to an integrative neuroscience model of schizophrenia. Brain Res. Rev, 2003; 41: 57–78.
33. Brown P, Salenius S, Rothwell JC, Hari R; Cortical correlate of the piper rhythm in humans. J. Neurophysiol., 1998; 80: 2911–2917.
34. Mima T, Simpkins N, Oluwatimilehin T, Hallett M; Force level modulates human cortical oscillatory activities. Neurosci. Lett., 1999; 275: 77–80.
35. Zhang L, He W, He C, Wang P; Improving Mental task classification by adding high frequency band information. J. Med. Syst., 2010; 34: 51–60.
36. Birbaumer N, Elbert T, Canavan AG, Rockstroh B; Slow potentials of the cerebral cortex and behavior. Physiol. Rev., 1990; 70: 1–41.
37. Hinterberger T, Schmidt S, Neumann N, Mellinger J, Blankertz B, Curio G, Birbaumer N; Brain-computer communication and slow cortical potentials. IEEE Trans. Biomed. Eng., 2004; 51: 1011–1018.
38. Kaiser J; Self-initiation of EEG-based communication in paralyzed patients. Clin. Neurophysiol, 2001; 112: 551–554.
39. Pfurtscheller G, Lopes da Silva FH; Event-related EEG/MEG synchronization and desynchronization: Basic principles. Clin. Neurophysiol., 1999; 110: 1842–1857.
40. Rohani DA, Henning WS, Thomsen CE, Kjaer TW, Puthusserypad, S, Sorensen HBD; BCI using imaginary movements: The simulator. Computer Methods and Programs in Biomedicine , 2013; 111(2): 300 – 307.
41. Pfurtscheller G, Neuper C, Flotzinger D, Pregenzer M; EEG-based discrimination between imagination of right and left hand movement. Electroencephalogr. Clin. Neurophysiol., 1997; 103: 642–651.
42. Sur S, Sinha VK; Event-related potential: an overview. Ind. Psychiatry J, 2009; 18(1): 70-73.
43. Squires NK, Squires KC, Hillyard SA; Two varieties of long-latency positive waves evoked by unpredictable auditory stimuli in man. Electroencephalogr Clin Neurophysiol., 1975; 38(4): 387-401.
44. Polich J; Updating P300: An Integrative theory of P3a and P3b. Clinical Neurophysiology, 2007; 118(10): 2128-2148.
45. Zhu D, Bieger J, Garcia Molina G, Aarts RM; A survey of stimulation methods used in SSVEP-Based BCIs. Comput. Intell. Neurosci, 2010.
46. Muller-Putz GR, Pfurtscheller G; Control of an Electrical Prosthesis With an SSVEP-Based BCI. IEEE Trans. Biomed. Eng., 2008; 55: 361–364.
47. Hermann C S; Human EEG responses to 1-100 Hz flicker: resonance phenomena in visual cortex and their potential correlation to cognitive phenomena. Experimental Brain Research, 2001; 137: 3-4, 346-353.
48. Regan D; Human Brain Electrophysiology: Evoked Potentials and Evoked Magnetic Fields in Science and Medicine. Elsevier, Amsterdam, The Netherlands, 1989.
49. Fisher RS, Harding G, Erba G, Barkley GL, Wilkins A; Photic- and pattern-induced seizures: a review for the epilepsy foundation of america working group. Epilepsia, 2005; 46(9): 1426-1441.
50. Vasquez PM, Bakardjian H, Vallverdu M, Cichocki A; Fast multi-command SSVEP brain machine interface without training. In Proceedings of the 18th International Conference on Artificial Neural Networks, 2008; 300–307.
51. Martinez P, Bakardjian H, Cichocki A; Fully online multicommand brain-computer interface with visual neurofeedback using SSVEP paradigm. Computational Intelligence and Neuroscience, 2007; 2007: 9.
52. Van Vliet M, Robben A, Chumerin N, Manyakov N, Combaz A, Van Hulle M; Designing a brain-computer interface controlled video-game using consumer grade EEG hardware. In Proceedings of the Biosignals and Biorobotics Conference (BRC), ISSNIP,2012; 2012: 1–6.
53. Epoc; Epoc, 2014.
54. Yijun W, Xiaorong G, B, H, Chuan J, Shangkai G; Brain-computer interfaces based on visual evoked potentials. IEEE Eng. Med. Biol. Mag., 2008; 27: 64–71.
55. Nakamishi M, Wang Y, Wang YT, Mitsukura Y, Jung TP; An Approximation Approach for Rendering Visual Flickers in SSVEP-Based BCI Using Monitor Refresh Rate. 35th Annual International Conference of the IEEE EMBS, Osaka, Japan, 2013.
56. Nakamishi M, Wang Y, Wang, YT, Mitsukura Y,

Jung TP; Generating Visual Flickers for Eliciting Robust Steady-State Visual Evoked Potentials at Flexible Frequencies Using Monitor Refresh Rate. Plos ONE, 9, 6, pp. 112, Academic Search Complete, EBSCOhost, 2014.
57. Wang YT, Wang Y, Jung TP; A Cell-Phone Based Brain-Computer Interface for Communication in Daily Life. Artificial Intelligence and Computational Intelligence, Lecture Notes in Computer Science, 2010; 6320: 233-240.
58. Szalowski A; Picovici D; Investigating the robustness of constant and variable period graphics in eliciting steady state visual evoked potential signals using Emotiv EPOC, MATLAB and Adobe After Effects. 2015 26th Irish Signals and Systems Conference (ISSC), 2015.
59. Kluge T, Hartmann M; Phase coherent detection of steady-state evoked potentials: experimental results and application to brain-computer interfaces. In Proc. 3rd Int. IEEE EMBS Neural Engineering Conf, 2007: 425-429.
60. Wu CH, Lekany H; Impact of Stimulus Configuration on Steady State Visual Evoked Potentials (SSVEP) Response. The Fourth International Conference on Advanced Cognitive Technologies and Applications, p. 77-82, Nice, France, 2012.
61. Regan D; An effect of stimulus colour on average steady-state potentials evoked in man. Nature, 1966; 210 (5040): 1056–1057.
62. Singla R, Khosla A, Jha R; Influence of stimuli colour in SSVEP-based BCI wheelchair control using support vector machines. Journal of Medical Engineering & Technology, 2014; 38 (3): 125-134.
63. Wang Y, Wang R, Gao X, Hong B, Gao S; A Practical VEP-Based Brain–Computer. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2006; 14 (2): 234-239.
64. The Rods and Cones of the Human Eye; The Rods and Cones of the Human Eye, 2015.
65. Kleber B, Birbaumer N; Direct brain communication: neuroelectric and metabolic approaches at Tübingen. Cogn. Process, 2005; 6: 65–74.
66. Chumerin N, Manyakov NV, Van Vliet M, Robben A, Combaz A, Van Hulle MM; Processing and Decoding Steady-State Visual Evoked Potentials for Brain-Computer Interfaces. Laboratorium voor Neuro- en Psychofysiologie, KU Leuven, Belgium, River Publishers, An Edited Volume, 2012; 1-33.
67. Bakardjian H, Tanaka T, Cichocki A; Optimisation of SSVEP brain responses with application to eight-command Brain-Computer Interface. Neuroscience Letters, 2010; 469(1): 34-38.
68. Wang Y, Gao X, Hong B, Jia C, Gao S; Brain-Computer Interfaces Based on Visual Evoked Potentials. Feasibility of Practical System Designs. IEEE Engineering In Medicine And Biology Magazine, 2008.
69. Hwang H, Kwon K, Im C; Neurofeedback-based motor imagery training for brain-computer interface (BCI). J. Neurosci. Methods, 2009; 179: 150–156.
70. Tsui C, Gan J; Asynchronous BCI Control of a Robot Simulator with Supervised Online Training. In Intelligent Data Engineering and Automated Learning—IDEAL 2007; Yin, H., Tino, P., Corchado, E., Byrne, W., Yao, X., Eds.; Springer: Berlin, Germany, 2007; 4881: 125–134.
71. EEG Headsets | NeuroSky Store; EEG Headsets | NeuroSky Store, 2014.
72. Mindflex; Mindflex, 2014.
73. Stamps K, Hamam Y; Towards inexpensive BCI control for wheelchair navigation in the enabled environment - a hardware survey. In Proceedings of the 2010 International Conference on Brain Informatics, BI'10. Berlin, Heidelberg: Springer-Verlag, 2010; 336–345.
74. Compare; Compare, 2014.
75. Yue L, Xiao J, Teng C, Feng W, Peng Un, M, Pui-In M, et al.; Implementation of SSVEP based BCI with Emotiv EPOC. Virtual Environments of Human-Computer Interfaces and Measurement Systems (VECIMS), 2012; 34-37.
76. Stytsenko K, Jablonskis E, Prahm C; Evaluation of consumer EEG device Emotiv EPOC. In Proceedings of the MEi CogSci Conference, 2011.
77. AlZu'bi HS, Al-Zubi NS, Al-Nuaimy W; Toward Inexpensive and Practical Brain Computer Interface. in Proc. of Developments in E-systems Engineering (DeSE), 2011; 98-101.
78. Duvinage M, Castermans T, Petieau M, Hoellinger T, Cheron G, Dutoit T; Performance of the Emotiv Epoc headset for P300-based applications. BioMedical Engineering Online, 2013; 12:56.
79. ANT Neuro | Inspiring Technology for the Human Brain; ANT Neuro | Inspiring Technology for the Human Brain, 2015.
80. Manyakov VN, Chumerin N, Combaz A, Robben A, Van Vliet M, De Maziere PA; Brain-Computer Interface Research at Katholieke Universiteit Leuven. Proc. of the 4th Int. Symp. on Appl. Sci. in Biomedical and Commun. Technologies, ACM, 2011.
81. Wang Y, Wang YT, Jung TP; Visual stimulus design for high-rate SSVEP. Electron Lett, 2010; 46: 1057–1058.
82. Cheng M, Gao XR, Gao SG, Xu DF; Design and implementation of a brain- computer interface with high transfer rates. IEEE T. Bio-Med. Eng., 2002; 49: 1181–1186.
83. Wang YT, Wang Y, Cheng CK, Jung TP; Developing stimulus presentation on mobile devices for a truly portable SSVEP-based BCI. Proc 35th Intl IEEE EMBS Conf, 2013; 5271–5274.
84. Gao X, Xu D, Cheng M, Gao S; A BCI-based environmental controller for the motion-disabled.

IEEE Trans. Neural Syst. Rehabil. Eng., 2003; 11: 137–140.
85. Black AH; The Operant Conditioning of Central Nervous System Electrical Activity. In Psychology of Learning and Motivation, Gordon, H.B., Ed.; Academic Press: New York, NY, USA, 1997; 6: 47–95.
86. Peterson NN, Schroeder CE, Arezzo JC; Neural generators of early cortical somatosensory evoked potentials in the awake monkey. Electroencephalography and Clinical Neurophysiology, 1995; 96: 248-260.
87. Pfurtscheller G, Brunner C, Schlögl A, Lopes da Silva FH; Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. Neuroimage, 2006; 31: 153–159.