Brain Computer Interface

(SSVEP-BCI and P300-BCI)

- Neurophysiology and Experimental Examples

by

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20 July 2011

MSc PROJECT IN HUMAN PHYSIOLOGY

Acknowledgements

The work presented in this master thesis was carried out at the Department of Biomedicine, University of Bergen, between November 2010 and July 2011.

First I would like to thank my supervisor Arvid Lundervold for giving me the opportunity to work with the interesting research field of brain computer interface. You have been supportive and encouraging throughout my project, and I really appreciate that you always have given me time when I have asked for it, despite a tight time schedule.

I want to thank Dr. Marcin Byczuk for a thoroughly demonstration of the SSVEP-BCI system developed at his lab.

To my fellow students, who have made these two years memorable. We have shared ups and downs and I appreciate all the moments we have had together.

I will also give my thanks to Pål W. Wallace, Craig Myrum and Øyvind K. Leidland for proof reading and constructive input.

Finally, I would like to thank my family and friends. I'm forever grateful for the long conversations and continuous support you have given me.

Einar Leidland
Bergen, July 2011

Abstract

The last century has seen an incredible leap in human medicine, which has led to an increased life expectancy spanning over all age groups. Despite this development of modern medicine some patient groups do not have any proper treatment except for artificially prolonged life. One such group of patients suffer from neurodegenerative illnesses or spinal chord injuries resulting in a state of complete locked in syndrome (CLiS). Studies have shown that patients suffering from a milder type of locked in syndrome (LiS) highly value the ability to interact with their surroundings and that this interaction is important for their quality of life. The last couple of decades have on the other hand seen the emergence of a new promising technology in such context, namely the brain computer interface (BCI). This technology might give CLiS and LiS patients an improved ability to communicate with their surroundings and consequently improve their quality of life. BCI also give rise to other possibilities such as enhancing otherwise healthy people‘s general performance and introducing a new modality in gaming and entertainment.
BCI represents a new way of communication for the brain, circumventing the normal output pathways of peripheral nerves and muscles. Instead alterations in brain signals are transmitted directly between the brain and a computer, where changes in the signals are detected and associated with a command or user intetion. These commands then let the user control electrical and mechanical devices connected to the system. This process is overseen and controlled through the operating protocol. In short a BCI system is made up of four essential parts: (i) signal acquisition, (ii) signal processing, (iii) command output, and (iv) an operating protocol.

This thesis gives a extensive survey of the BCI field in a biomedical context and also highlights two BCI systems developed by Hoffmann et al. and Materka & Byczuk, respectively. Both systems are based on scalp EEG recordings needing very little training to operate. While Hoffmann and coworkers used P300 evoked potential to operate an environmental controller, Materka & Byczuk used steady state visual evoked potentials (SSVEP) to operate a spelling device.

Even though BCI technology is mainly limited to research settings so far, it has great perspectives for the future - both for improving daily life in clinically targeted groups of patients, in cognitive neuroscience, and entertainment and gaming activities.

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Abbreviations

ADHD	attention-deficit/hyperactivity disorder
ALS	amyotrophic lateral sclerosis
BCI	brain-computer interface
CLiS	completely locked in syndrome
CNS	central nervous system
CSF	cerebrospinal fluid
ECoG	electrocorticography
EEG	electroencephalography
EP	evoked potentials
EPSP	excitatory postsynaptic potential
ERD	event related desynchronization
ERP	event related potentials
ERS	event related synchronization
FES	functional electrical stimulation
fMRI	functional magnetic resonance imaging
fNIRS	functional near infrared spectroscopy
GUI	graphical user interface
Hb	deoxyhemoglobin
Hb0	oxyhemoglobin
IPSP	inhibitory postsynaptic potential
ISI	inter stimulus interval
ITR	information transfer rate
LiS	locked in syndrome
LFP	local field potentials
MEG	magnetoencephalography
P300-BCI	P300 event related potential based brain computer interface
SCI	spinal cord injury
SCP	slow cortical potentials
SSVEP	steady state visual evoked potentials
SNR	signal to noise ratio
SMR	sensorimotoric rhythms
SU	single unit
SSVEP-BCI	steady state visual evoked potential based brain computer interface
TTI	target to target interval
VEP	visual evoked potentials

1 The research field of brain computer interfaces

Humans have long sought ways to increase general health and life expectancy. The last couple of centuries have shown a great leap in medicine with numerous new therapies and drugs, consequently helping a growing number patients suffering from a variety of diseases. Despite an increasing medical understanding and available therapies, some conditions still do not have any good treatments. This is the case for patients suffering from locked in syndrome (LiS) or complete locked in syndrome (CLiS), which renders patients unable to control any muscle, or greatly limiting motor control [9, 64, 106]. Hallmarks of the two conditions are intact sensory and cognitive functions, while interaction with surroundings are severely restricted or impossible. LiS patients, still having some residual muscle control, are often able to express simple responses to questions through external apparatuses (e.g. eye camera, pressure plate), giving them a limited form of communication with their surroundings. Jean-Dominique Bauby, a well known LiS patient, wrote a book about his experience following his hospitalization due to a cortico-subcortico stroke. He woke up 20 days later completely unable to move any muscle except his left eye, but was still aware of his surroundings. He described his experience in the book *The Diving-Bell and the Butterfly* [5]. A book which he was able to write with the help of his speech therapist who would read him the alphabet while he chose a letter by blinking his left eye.

The restricted form of communication available to some LiS patients and the fact that CLiS patients are totally isolated by the lack of normal means of communication, have lead researchers to look into new ways these patients can convey their thoughts and wishes to their surroundings. An emerging research field trying to meet these patients' needs is the **brain computer interface** (BCI) (or brain machine interface, BMI), which over the last decades has gained an increasing momentum. Development of methods and equipment have led to increasing numbers of applications, spanning from recreation (e.g. Mindset [86, 115]) to clinical use for patients suffering severe illnesses leading to varying degrees of motor impairment as illustrated above. Utilization spans from spelling [12] to controlling wheelchairs [116] and the environment [38].

A general definition of BCI was proposed at the first international BCI meeting at Rensselaerville Institute, New York in 2000. *"A brain-computer interface is a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles"* [140]. BCI will in other words introduce an alternative communication pathway which the brain can use to communicate with its surroundings. This communication might go in both directions, as a command output from the brain and/or as a feedback to the brain [65]. Based on the need for muscle control, different BCI systems are divided into two distinct groups, namely dependent and independent BCI systems [139]. Dependent BCI systems rely on the use of muscles to generate necessary brain activity to convey user intent (e.g. BCI system based on visual evoked potentials), while independent BCI systems are totally independent of any muscle control for conveying user intent (e.g. BCI systems based on imaginary movement [μ and β frequency bands]). There are four essential elements required for a functional BCI platform, namely signal acquisition, signal processing, command output and operating protocol [67, 121, 139]. These four components and their interrelations are shown in Fig. 1 and will be explained in more detail later in the thesis.

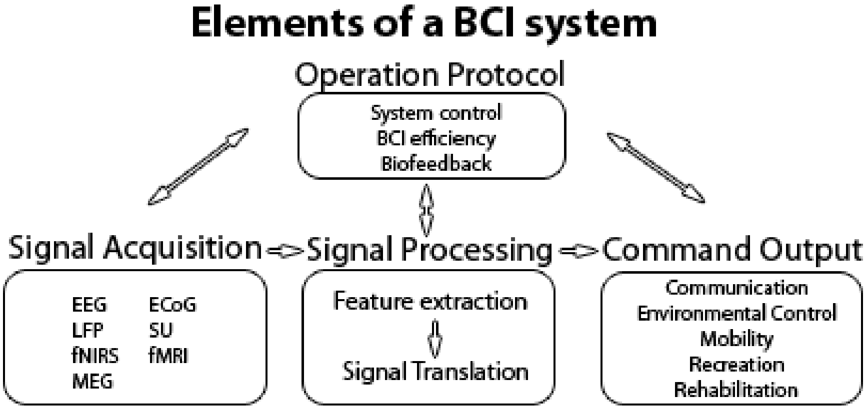

Figure 1: Essential elements of a BCI system.

Aim of this work

This master thesis aims to introduce the research field of BCI, dealing in particular with the methods of **steady state visual evoked potentials** brain computer interface (SSVEP-BCI) and **P300 event related potential** brain computer interface (P300-BCI), including experimental examples. The contribution of this thesis is primarily the physiological exposition and the introduction to the BCI field from the biological side. The author do not know of any extensive ongoing or previous BCI research being conducted in Norway, or other biologically oriented MSc or PhD thesis on BCI coming from a Norwegian educational institution - which makes this MSc project a kind of pioneering regarding biomedical BCI research in Norway.

1.1 Signal acquisition

The first component of any BCI system is signal acquisition, which measures real time changes in the electrophysiological state of the brain [67]. These changes encode the user's intentions, consequently giving the user a way to communicate with the BCI system. After signal acquisition, analog data regarding the electrophysiological state is digitized and sent to signal processing, which is the next element needed to convey user intent and hence the control of a predefined apparatus. To obtain the required amount of data to be able to control a desired apparatus, BCI systems use different approaches, such as scalp electroencephalography (EEG) [25, 61, 90], magnetoencephalography (MEG) [63], local field potentials (LFP) [58], single unit recording (SU) [49] and electrocorticography (ECoG) [68], which all directly measure neuronal activity directly by registering changes in electrical currents (or magnetic fields generated by these electrical currents) in the brain. Another approach is to measure neuronal activity indirectly by measuring hemodynamic (neuro-vascular) changes. This approach is utilized by functional magnetic resonance imaging (fMRI) [128] and functional near infrared spectroscopy (fNIRS) [93].

Based on sensor placement, acquisition methods are normally divided into two groups, invasive and non-invasive (Fig. 2). Recordings made subcranially fall under the category of invasive procedures, while recordings made without surgical procedures are non-invasive techniques. Based on these definitions, MEG, fMRI, fNIRS and scalp EEG recordings are non-invasive techniques, while ECoG (both epidural and subdural), LFP and SU recordings are considered invasive.

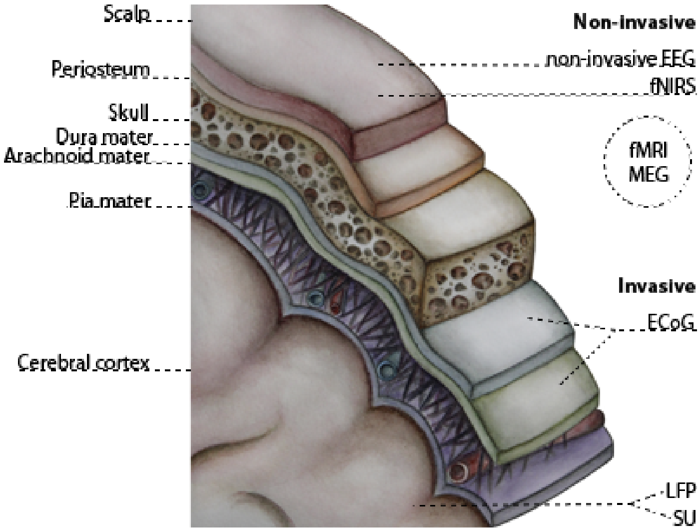

Figure 2: Recording locations of different BCI acquisition methods. (Adapted version printed with permission [113])

1.1.1 Non-invasive recordings

Many positive aspects follow non-invasive signal acquisition techniques, among these is the absence of surgery. Surgery might expose the user to foreign elements leading to infection and local damage to brain tissue, consequently reducing brain functionality or in worst case leading to life threatening disease. In addition to increased user safety, the economical and technical advantages of non-invasiveness are obvious. Not needing surgical expertise will both reduce operation cost and reduce the technical requirements needed to operate the BCI system.

Scalp electroencephalography

Scalp EEG recording is the most used and studied method in a BCI system [65, 67] (Fig. 3A). This is first and foremost due to the fact that it is both cheap and easy to obtain and operate necessary equipment [67]. On the other hand, the scalp EEG signal has a relatively poor temporal and spatial resolution, which is a direct consequence of concerted electric activity contribution by overlapping cortical areas. Another issue is reduced signal amplitude as the scalp EEG signal must traverses meninges, cerebrospinal fluid (CSF) and bones to reach the electrodes. The use of a low pass filter on the recorded EEG signal therefore leads to an increased loss of resolution. The fact that EEG is susceptible to electrooculography (EOG), electromyography (EMG) and mechanical artifacts further complicates the use of the EEG signal in any BCI system. Despite these shortcomings, scalp EEG still gives a good overall basis for a BCI system [65, 67, 91].

Magnetoencephalography

MEG can also be used in BCI systems (Fig. 3B) and measures very small magnetic fields (fT range) generated by active neurons. An advantage of MEG compared to EEG is a better spatiotemporal resolution due to better signal to noise ratio (SNR). This increased SNR is a consequence of magnetic fields being less affected by spatial blurring than electrical fields, an effect generated by bones, meninges and cerebrospinal fluid [63]. A significant issue regarding MEG is immobility, due to the need of magnetic shielding of the subject, which is a consequence of the very small magnetic fields generated by neuronal activity. These very small magnetic fields are affected by the relative large magnetic fields produced by the earth (fT versus μT respectively) [44]. This has led researchers to use MEG as an acquisition method in BCI primarily for training situations and screening, because real-life situations demand more mobility [9, 79]. Another issue is the high cost of MEG systems and their limited availability - in fact, there are no MEG systems in Norway.

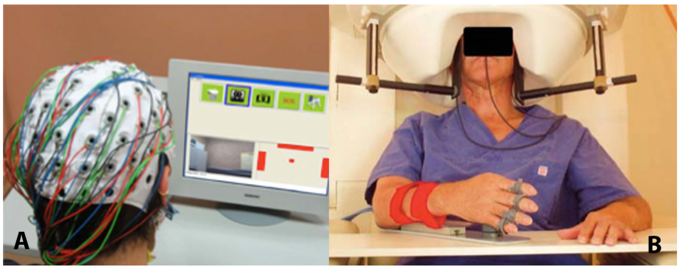

Figure 3: *A:* A scalp EEG based BCI system controlling different electrical devices *B:* A BCI system controlling a flexible hand prosthesis based on MEG (slightly modified from [11, 24]).

Functional magnetic resonance imaging and functional near infrared spectroscopy

An alternative to using EEG is BOLD[1] fMRI and fNIRs. Both techniques have a better spatial resolution than EEG electrodes, but temporal resolution is poorer [39, 48, 122]. This is a consequence of the biological parameters used to measure the brain activity. As EEG measures electrical conductances in the brain, fNIRS and fMRI measure changes in blood oxygen levels [39, 96]. Changes in blood oxygen levels are directly correlated to changes in neuronal activity in a specific region, but this neuro-vascular responses are first observed several seconds after start of neuronal activity [62]. fNIRS and fMRI therefore measure neuronal activity indirectly as opposed to EEG which measures neuronal electrical activity directly. An important difference between fNIRS and fMRI is equipment size and cost (Fig. 4). Although fNIRS has a poorer spatial resolution than fMRI, much smaller and cheaper hardware leads to fNIRS being more portable and easier to use than fMRI [93]. fNIRS technology is still relatively new and its uses in BCI systems are at the moment more limited than for example non-invasive EEG electrodes. Today the best overall solution regarding a functional, economical and mobile BCI system usable for an extended period of time is proviede by fNIRS and scalp EEG [93]. fMRI can on the other hand be used to train users and for method development [128], while a general use in a BCI system is unlikely due to the equipment's large size and cost as it is essentially a complete MRI system.

Figure 4: *A:* A fMRI machine *B:* The latest version of the OTIS system developed by Archinoetics (fNIRS) (slightly modified from [36, 93]).

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[1] Blood Oxygenation Level Dependent contrast

1.1.2 Invasive recordings

Invasive signal acquisition techniques measure signals sub-cranially, giving a big signal recording advantage in comparison to non-invasive techniques. The signal is improved due to the closer proximity to brain tissues and hence the origin of the signal which is measured. The shorter signal travel distance and the fact that it does not need to traverse the meninges, bones and cerebrospinal fluid result in less interference and better spatiotemporal resolution. On the other hand, invasive recordings need surgery, consequently increasing user risk. Another important factor is long-term stability of invasive recordings, which is problematic due to both equipment robustness and biochemical characteristics of the brain. Conducting invasive method studies are also ethically challenging, due to the increased risks associated with surgery and the type of patient groups normally participating in the studies (for further details see Section 1.5). Consequently, most invasive BCI studies have used animal subjects [26].

Electrocorticography

A promising semi-invasive recording technique is ECoG, which might be a good compromise between a good and robust signal quality and the degree of invasiveness [34]. ECoG registration electrodes are placed either subdurally or epidurally and register neuronal activity directly [80] (Fig. 5A). Placement of registration electrodes ensures that ECoG has a better spatial resolution (0.125 cm versus $\approx$3 cm for scalp EEG), a higher signal to noise ratio and a higher frequency bandwidth (0-200 Hz versus 0-40 Hz for EEG), making it less sensitive to artifacts (EMG, EOG) than EEG (reviewed in [21, 66]).

A good quality of ECoG in comparison to other invasive acquisition techniques such as LFP and SU, is that the meninges are kept intact (except for subdural ECoG which penetrates the dura mater) and consequently reducing risk of infections and more severe complications, as well as keeping buffering properties of the meninges intact [80]. The distance between ECoG electrodes and the brain results in ECoG having a relatively poor spatiotemporal resolution in comparison to LFP. The difference in distance between registration electrodes and the brain parenchyma in relation to epidural versus subdural ECoG measurements have very little consequences for the measured signal, due to the good conductivity of dura mater. Studies using ECoG have primarily been conducted with epilepsy patients with intact motor control [67, 123].

Single unit

Another invasive acquisition technique is single unit (SU) recordings. Small microelectrodes are placed inside the brain parenchyma in close proximity to small ensembles of task specific neurons, where single neuron action potentials are measured (Fig. 5B). Spatial resolution of $\approx 100\ \mu$m and temporal resolution of 50-100 Hz give SU-based BCI systems a high level of user control (cf. [67] and [123]). Even if these methods give the best means of control, obstacles have to be overcome, such as difficulties regarding long-term and chronic use.

By today's methods of invasive electrode placement, it is impossible to avoid vascular and neurological damage when placing the electrodes in the parenchyma of the brain [66]. Apart from risk of CNS infection, encapsulation of electrodes is an obstacle that needs to be overcome before robust SU acquisition methods can be used successfully. Electrode encapsulation is initiated by vascular and neuronal damage, which often leads to the migration of microglia and astrocytes to the target area [14]. This process will over time result in signal deterioration and finally lead to electrical insulation of the electrodes, making them useless for their intended purpose. As a result of encapsulation and variability in recorded neuronal ensembles, daily recalibration is often needed to maintain reliable performance [23]. To counteract encapsulation, several groups are looking into new materials and slow drug delivery systems that will hopefully prevent encapsulation [126, 127]. In this context, Bartels et al. [3] have developed neurotrophic electrodes to counteract encapsulation of the electrodes, and report persistent recordings in two individuals for over four years.

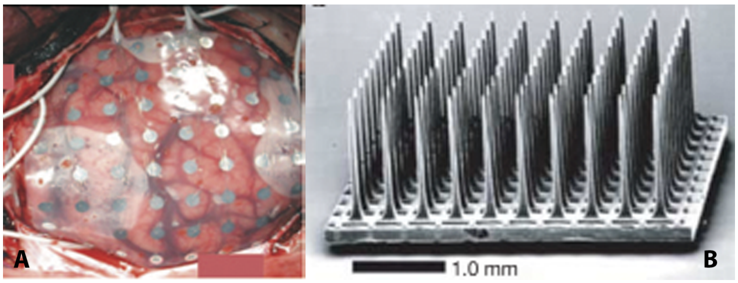

Figure 5: *A:* ECoG electrodes placed sub-durally *B:* An array of 100 SU electrodes used in the Braingate system (slightly modified from [49, 68]).

Local field potential

Another way to counteract encapsulation is to rely on a set of neurons instead of single unit action potentials, consequently increasing the concerted extracellular current measured. This is achieved by changing the passband filter (300 Hz - 10 kHz) to a low pass filter using (<250Hz) and thereby using a lower segment of the signal spectrum compared to SU acquisition [123]. As a result, concerted neuronal activity i.e. local field potentials (LFP) can be measured, which has been shown to correlate with single unit activity (cf. [80]).

1.1.3 Hybrid BCI

One way researchers try to meet accuracy, safety and overall performance requirements of different BCI systems is by combining different BCI modalities ([103]). A known obstacle to the universal use of BCI systems is *BCI illiteracy*, which is a challenge to 15-30% of BCI users (cf. [137]). Although researchers have shown that improved training, subject instructions and signal processing can improve BCI literacy, some are still unable to use BCI systems which only rely on a single method of conveying user intention [2]. BCI illiteracy is a consequence of a user's lack of adequate signals, hence making them unable to convey their intent to the BCI system. Consequently researchers have started to develop BCI systems combining different signal features in hope that every user has at least one signal feature to convey the user intent to the BCI. Another approach used to battle BCI illiteracy has been to combine different signal types (e.g. hemodynamic and electrophysiological signals). Hybrid BCI systems can also benefit from the use of other physiological parameters and external devices giving users new ways to control the system [103]).

1.2 Signal processing - translation of user intent to system action

After signal acquisition, necessary information needs to be extracted from the gross signal and converted to a system command. First, desired signal features containing user intention are extracted from the gross signal in the *feature extraction*. Measured changes in these features are then translated into an output command in the signal translation [67].

1.2.1 Feature extraction

The first step in this process is extraction of featured data from the recorded data, which should be strongly correlated with user intentions [66, 74]. This is a process made possible by complex statistical analysis, which also registers statistically significant changes in extracted data. Depending on acquisition method and type of signal feature targeted, a number of methods are used. From the voltage amplitude measurements, most commonly used feature extraction methods are based on spatial filtering, spectral analyses, or even single-neuron separation (reviewed in [67, 121, 139]). In this same process, artifacts of non-CNS origin (e.g. EMG, EOG), and CNS-originated artifacts are reduced to improve the signal to noise ratio [74]. For further reading regarding feature extraction algorithms, see [4, 73, 78].

Electrophysiological signal features

The most common electrophysiological signals in current BCI systems are: visual evoked potentials (VEP), slow cortical potential (SCP), sensorimotor rhythms (SMR), P300 event related potential (P300) and neuronal action potentials [74, 139]. EEG signals thus contain several signal features used by BCI systems, where the most prominent are presented in this section.

Steady state visual evoked potentials

Visual evoked potentials (VEP) is brain activity in response to visual stimuli, which is most prominent over the occipital areas of the brain. Steady state visual evoked potentials (SSVEP) are continuous signals produced when the stimulus presentation frequency is >6 Hz. The more general and transient VEP is observed at lower stimulus frequencies. A SSVEP signal frequency is an exact multiple integer of the stimuli frequency [117]. A more detailed description of SSVEP is given in Section 2.2.

Slow Cortical Potentials

Slow cortical potentials (SCP) is a low frequency EEG signal feature with potential shifts observed over 0.5-10 s either by spontaneous or voluntary activity changes in large neuron assemblies [61, 139]. Generation of SCP depends on sustained afferent intra- or thalamocortical input to apical dendrites (layer I and II) of pyramidal cells in the cortex and simultaneous depolarization of large assemblies of pyramidal cells [13]. The large field of activity associated with SCP is due to long-distance connection between cortical neurons contributing to the signal.

Negative shifts in SCPs are due to synchronous depolarization by slow excitatory post synaptic potentials (EPSP) at the apical dendrite near or at the soma of an pyramidal cell. A negative shift in SCP reflects a general excitation threshold reduction of neuron assemblies and is associated with an increase in cognitive or motor activity. Positive shifts in SCPs are less well understood, but might be a result of positive outflow in deeper layers of the brain or slow inhibitory post synaptic potentials (IPSP). A positive shift in SCP is associated with reduced cognitive and motor activity [13, 8].

Sensorimotor rhythms

Electrical signals in the brain oscillate and are categorized based on frequency bands. They are primarily a result of active pyramidal cells in the brain cortex. Two of these oscillations denoted μ (8-13 Hz) and β (13-30 Hz) rhythms, respectively, originate in somatosensory and motor areas of the brain and are the bases of the sensorimotor rhythms (SMR) signal feature used in BCI [42]. Preparation or execution of a voluntary movement, both physically executed or imagined, results in a reduction of the μ and β frequency bands, a phenomenon called event related desynchronization (ERD) [104]. ERD starts contra-laterally around 2 s before execution of a movement and becomes bilateral just before execution [4]. The opposite phenomenon, an increase in the μ and β frequency bands, called event related synchronization (ERS), is observed over contralateral sensorimotor areas after movement and during relaxation [102]. An important aspect is that a large portion of cortical layers need to be activated for a measurable desynchronization [42] to take place, and motor tasks can be used to obtain sufficient SNR levels in SMR-based BCI. The most commonly used frequency bands in BCI are μ and β rhythms, but invasive BCI techniques, such as ECoG, can also employ γ rhythms (>30 Hz). γ rhythms increase in amplitude during execution of movement [4], and ERD and ERS are observed with both EEG and MEG [104].

P300 event related Potential

The so-called P300 signal peak is normally found in the EEG signal around 300 ms after visual, somatosensory or auditory stimuli is received [61, 66], elicited by rare events interspersed between more frequent or insignificant events. The more rare the event is, the greater P300 potential is observed. To obtain useful P300 potentials in a BCI system, an *oddball paradigm* [28] is normally used. See section 2.3 for a more detailed description of the P300 signal feature.

Single unit action potential

SU is the measurement of single neuron activity, reflecting the transmembrane currents of a neuron. This type of measurement gives the highest spatiotemporal resolution, but a problem is that single neurons only are active under certain tasks, some even show a non-specific activity [49]. Consequently one is running the risk of a specific neuron not being active under the brain activities one wants to measure. BCI researchers use the fact that task relevant neuron activity is the same for specific motor executions and when a person is imagining the same movement.

Magnetoencephalography

Instead of measuring electrophysiological signal features with EEG-electrodes, the same signal features can be measured with MEG. The difference is that MEG measures magnetic fields while EEG measures electrical fields. Due to their geometrical orientation, pyramidal cells in the *sulci* will contribute the most to the MEG signal. This is in contrast to an EEG signal, where pyramidal cells in the *gyri* contribute the most [72]. Despite MEG having a better spatiotemporal resolution than EEG, widespread use is not an option in today's BCI technology due to equipment requirements [74] (see Section 1.1.1).

Hemodynamic signal features

Alternative methods using hemodynamic measurements to register brain activity are available. Measurements can be conducted either with fMRI or fNIRS. Algorithms are used with the same purpose as in EEG feature extraction. The purpose is to remove artifacts and register an increase in regional cerebral blood flow which is correlated with brain activation [71, 77]. In the case of fNIRS, two methods of feature extraction are studied, either measuring changes in oxygenated hemoglobin (Hb0) concentrations or a combination of changes in Hb0 and deoxygenated hemoglobin (Hb) concentrations. The most promising method is the latter [77].

1.2.2 Signal translation

After extraction and identification of changes in featured data, *translation algorithms* associates these changes with desired functions [67]. A well functioning signal translation algorithm contains three levels of adaptations, namely adaption to (i) a new user's electrophysiological state in terms of signal features, (ii) short- and long-term variation in the user's physiological state, and (iii) the brain's modification of featured signal to optimize BCI operation [139]. It is important to mention that excessive adaptation is unfavorable because of possible negative effect on the overall performance of the BCI system. For more detailed descriptions of signal translation algorithms, see [4, 78].

1.3 Command output - human rehabilitation and BCI applications

A third constituent of any BCI is the *command output* - the actual function of a BCI system. The main motivation for most BCI developments has been to improve communication, environmental control and the ability to move about freely for patients suffering from different motor impairments [74, 124, 81], where the most extreme case being CLiS patients. Motor impairments in locked-in patients are often a result of damage to ventral pons [100], but can also be a result of diseases such amyotrophic lateral sclerosis (ALS) [119]. ALS is a degenerative muscle disease that results in the affected person gradually being unable to control voluntary movement [40]. Patients afflicted by ALS, who choose to artificially prolong their life, will in the last phase of the illness end up with no voluntary muscle control, including muscles controlling eye movement (i.e. CLiS).

Other areas of BCI utilization covered here are recreation and entertainment, entertainment being an area where several commercialized BCI technologies are being developed (e.g. [31, 86]).

1.3.1 Communication

Communication is one of the fundamental aspects of being a human. Without means to communicate, either through body language or spoken language, isolation is a very likely outcome. Restoring communication for people suffering of LiS and CLiS is an area of great interest for the BCI research community and has been the main motivation in BCI development. The last decade has brought much promise, with a variety of BCI system based on a wide range of brain signals. The following are different ways of conveying user intent to a speller through a BCI system.

Speller controlled by slow cortical potentials

BCI has shown potential to be a helpful tool for some persons suffering from CLiS and LiS. One possibility is to train patients to be able to voluntarily change their SCP activity through operant conditioning. This can give the patients the ability to communicate with their surroundings through an external spelling device [10, 12, 47, 61]. Birbaumer and colleagues trained participants to change their SCP to a set value either positive or negative of a baseline. A box of letters was presented on a computer screen which could be chosen on the basis of changes in the SCP of the patient. If the patient opted to choose a box of letters, the box of letters would split in two. The two new boxes of letters would then successively be shown one at a time for a certain amount of time. This continued until the patient chose a box of only one letter, which led to that letter being written. This process continued until the patient made a desired word. Visual feedback was given on the screen in the form of a ball that moved towards or away from the letter box depending on whether the SCP deviated positively or negatively from the baseline [12].

Speller controlled by sensorimotor rhythms

Another type of spelling device is the Hex-O-Spell, which uses SMR to convey user intent to the BCI system. Users are presented with an interface showing a hexagon, used to give necessary visual feedback (shown in Fig. 6). Figure 6A depicts the initial configuration where an arrow is centered in a hexagon surrounded by different groups of signs and letters, which are placed in each of the six corners of the hexagon. The user must then turn the arrow in the center of the hexagon by imagining right hand movement, which turns the arrow clockwise. When the arrow point towards desired group of characters, imagining right foot movement will stop the turning arrow (Fig. 6B). Continuous focus on this mental state extends the arrow towards the outer part of the hexagon and selects the desired group (Fig. 6C). The content of the selected group is then divided into a new hexagon and the process starts over again. Only that this time every hexagon contains one character only. Consequently, choosing one of these characters will result in this character being written (Fig. 6D). Incorrect typing can be corrected by choosing ”<” [15, 16].

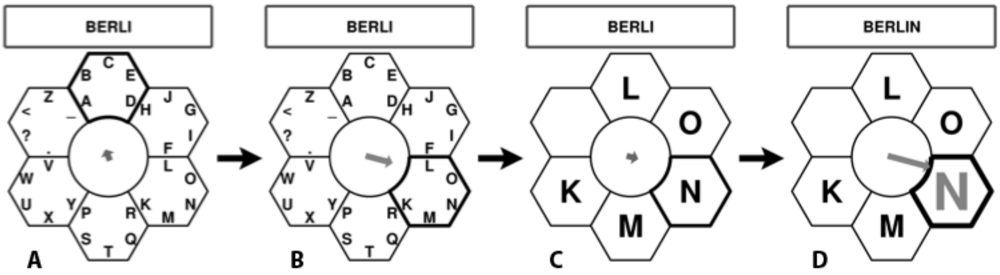

Figure 6: Hex-O-Spell GUI used by Blankertz et al. (2006) [15].

Speller controlled by steady state visual evoked potentials

SSVEP-BCI is characterized by a relatively high information transfer rate (ITR), a robust signal and the need for small amounts of training to operate the system. These properties have lead research groups to develop SSVEP-BCI systems to operate spelling devices [20, 37, 76, 89]. One such spelling device, developed by Cecotti [20], presents the user with a graphical user interface (GUI) depicting five boxes where each box is connected to a specific command (Fig. 7). The lower three boxes hold a set of letters, while the selection of the upper right hand box commands deletion of the last character and the last box controls cancelation of the last chosen command for rapid and easily correction. The initial configuration is shown in Fig. 7A, where each box flickers with a predefined frequency. By focusing his or her attention toward one of the boxes flickering at a constant frequency, an identical signal frequency can be observed in the EEG signal over primary visual cortex. When a command is chosen, an animation is produced by the system to tell the user which system command is produced. At the same time, the light flickering is halted for one second. Since letters are distributed in a treelike structure, box selection is needed at least three times to select the desired character. The amount of characters each box contains is reduced every time a box is chosen (Fig. 7B). This continues until only one character is left in each box (Fig. 7C) and choosing a box results in the typing of the character that the box contain. Disadvantages regarding SSVEP-BCI spelling devices are the need to have some intact muscle control and the ability to shift eye gaze between different stimulation points [20, 37]. This reduce the usefulness to the target group of LIS patients, who might have a hard time operating the device due to their limited muscle control (or none in the case of CLiS patients). Another, more general issue, is fatigue resulting from prolonged use.

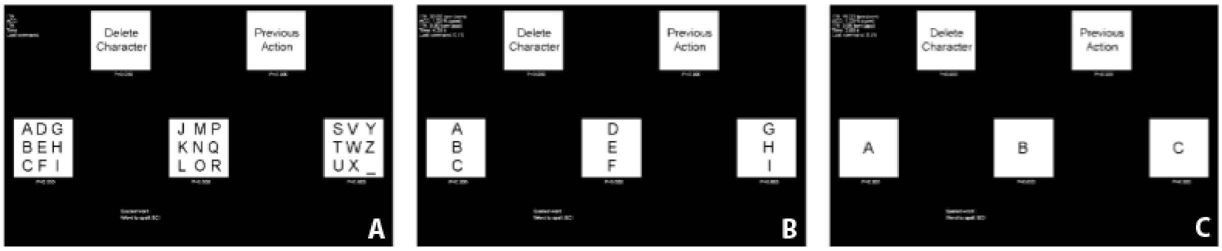

Figure 7: SSVEP GUI used by Cecotti et al. (2010) [20].

Spellers controlled by P300 event related potentials

Event-related signals, such as P300, are other options for communication through a BCI system. Farwell and Donchin where the first to introduce a speller based on the P300 event related potential, where they elicited the P300 response through the use of an oddball stimulation paradigm [33] (later assessed in [28]). They presented the user with a set of characters aligned in rows and columns (Fig. 8) from which the user chose a character by focusing his/hers attention on the desired character. By flashing row and columns one at a time in a random fashion, a P300 response was elicited every time the column or row containing the desired character flashed. Continuous alternating flashes and signal processing made it possible for the system to calculate which symbol the user intended to communicate. To complete a whole word or sentence, continuous repetition of the typing process was needed. When the desired word was spelled, the user would choose the ”TALK” command and a synthesized voice would give sound to the word.

MESSAGE

BRAIN

Choose one letter or command

A	G	M	S	Y	*
B	H	N	T	Z	*
C	I	O	U	*	TALK
D	J	P	V	FLN	SPAC
E	K	Q	W	*	BKSP
F	L	R	X	SPL	QUIT

Figure 8: P300 GUI used by Farwell and Donchin (1988)[33]

Recently Bernardo et al. (2010) developed a spelling device based on a hybrid BCI system which combined the P300 and error potentials (ErrP). They aimed to improve the overall performance of the system. While the use of P300 to choose and identify user intent was quite similar to what Donchin et al. used [28], the ErrP introduce a new aspect of functionality. When the user selects a symbol and the system presents this symbol to the user as a visual feedback (Fig. 9), the BCI system might have chosen a wrong symbol. This behavior is undesired to the user and hence an ErrP was produced 40 ms after feedback stimuli is given. When an ErrP is registered by the system, the selected symbol is cancelled [7].

Figure 9: SSVEP GUI used by Bernardo et al. (2010) [7].

Different spelling devices usable at home are just beginning to emerge from the laboratory BCI systems [89, 124, 136]. However, further work is needed to improve both accuracy and performance of different BCI systems, before widespread use is a possibility (reviewed in [74]).

1.3.2 Environmental control

Restoring environmental control is a very important step for restoring independence to patients with severe or total paralysis. Simple tasks, such as controlling television, telephone, lighting etc., might give paralyzed patients a whole new degree of independence and control over their own life, and consequently lighten the burden for the people closest to the patients.

Research has shown that restoration of environmental control is correlated with anticipated increase in the quality of life for severely paralyzed people [24]. Cincotti et al. (2008) reported that even seemingly minor abilities such as the ability to open the front door increases the users' feeling of autonomy. This gives users the ability to choose who were welcome to participate in their life environment and not. The control of the front door was picked as the favorite of all tested devices. All the devices were tested in three rooms at a hospital which was furnished as a normal house and necessary actuators were installed. In addition to the mentioned front door device, devices such as lighting, a TV, a stereo, a motorized bed, an acoustic alarm, a telephone, a robotic platform for moving around and a wireless camera to monitor other rooms, were tested. All mentioned devices were controlled by different instruments with the help of residual motor control when this was available. An EEG-based BCI system was offered as an alternative when the former control mechanism did not work. The BCI system was operated by the user through voluntary changes in SMR.

Other research groups have also been able to restore some environmental control to severely paralyzed patients. Hochberg et al. [49] tested a BCI system based on imagined motor movement. In their research, they were able to restore some simple environmental control such as control of channels and volume on a television and the ability to open emails. Kennedy et al. [58] used local field potentials measurements to control a light switch. An ALS patient was outfitted with skullscrew electrodes over part of the motor cortex representing the patient's foot. Through voluntary changes of sensorimotor rhythms, the patient was able to control the light switch. Gao et al. [38] used SSVEP based BCI as a basis for environmental control, giving users control of predefined electrical devices (e.g. television, video tape recorder and air condition) through the use of an infrared remote controller. Users selected a desired action through eye gaze, choosing the LED light on the controller corresponding to his desired action.

1.3.3 Mobility

Restoring mobility of paralyzed patients might lead to an increased independence for this patient group. Although much research has been conducted on animals [123], including primates, only research on human test subjects will be highlighted here.

Wheelchair

Patients with severely reduced mobility or no mobility at all could through a BCI-controlled wheelchair be given the ability to move around relatively freely on their own accord, restoring some independence. Several methods have been developed which tries to implement the necessary freedom and safety to meet the requirements needed for a day-to-day functional system.

A method developed by Rebsamen et al. [116] uses a P300 based BCI system which lets the user choose between predefined routes. Nine different routes are presented as buttons on a GUI. The wheelchair orientates and positions itself in the environment based on an extended Kalman filter (EKF) output which combines relative position information from glidewheels and global position information from barcodes. Barcodes are placed on certain crucial areas on the floor so they can be scanned by the system when the wheelchair passes by [143]. The wheelchair follows the chosen route and will not stop except if opposed by an obstacle, which is detected by sensors in the front of the wheelchair. The user is then presented with three choices, restoring movement or circumventing the obstacle on the left or right hand side. There are two methods for predefining a route, either with the help of a caretaker which pushes the wheelchair through the exact route or by offline alteration of the desired route.

Iturrate et al. [52] also used the P300 signal as the basis to control a wheelchair. In this case, the environment was virtually reconstructed in real time by a laser scanner. Different points were then generated in the reconstructed environments which the user could choose between. The user focused his/her attention on a point on the screen, selecting the desired destination and the wheelchair moved toward this point. The rest of the movement control is then managed by the system. If obstacles are detected by the laser scanner, the system automatically avoids these. The two presented P300-based BCI-systems are different in that the former method is not possible to use in an unknown place, while the latter method is.

While both of the former systems are based on P300-signal, other signals such as SSVEP can also be used for the purpose of wheelchair control [85]. It is worth mentioning that SSVEP might be difficult to use for severely or completely locked-in people because gaze fixation is necessary to operate this system.

Robotics

Restoring locomotion through the help of a wheelchair will let paralyzed patients move more freely, but it will not directly increase their interaction with their surroundings. Direct interaction with the surrounding is accomplished through environmental control and restoration of limb mobility (either through own limbs or robotic limbs). Restoring limb mobility is a central goal for BCI research. This would increase paralyzed patients' interaction with their surroundings, leading to further independence.

An approach used by Tavella et al. [133] has been to use functional electrical stimulation (FES) controlled by a EEG-based BCI system. User intentions were then conveyed to the system through voluntary changes in SMR to control grasp motion of a hand. When grasping was initiated by the user, FES stimulates the necessary muscles to close the hand (musculus flexor digitorum superficialis). In the case of opening of the hand, musculus extensor digitorum communis was stimulated. Users were instructed to pick up a pen, write a word and place the pen back in its holder before releasing it. Throughout the tests, users were participating in conversation parallel to the task of grasping the pen. This demonstrates the user's ability to choose when to interact with the system Müller-Putz et al. [84]. In a freehand system, electrodes are implanted in the forearm and hand of the user, giving the possibility to stimulate muscle fibers directly. The way of conveying user intentions to the system is by voluntary changes in SMR, which are measured with non-invasive EEG electrodes. Another approach demonstrated by Hochberg et al. [49] convey user intention much the same way as the two previous studies, namely through voluntary changes of SMR. The difference from the two other studies is that changes are registered with an 96-microelectrode array placed over the primary motor cortex. Through this setup, researchers were able to give a person with tetraplegia the ability to control a variety of devices. Among these devices were a prosthetic hand and a robotic arm, where the former device could grab and release an object (one-dimentional control) while the latter could grab and move an object before releasing it (two-dimentional control).

An interesting effect observed in monkeys and rats is that the long-term use of actuators controlled solely by the brain through a BCI system can lead to *remapping* of the cortical body map. Rats and monkeys, which were trained to use an artificial actuator, would over time stop moving their own limbs and only move the actuator. This lead to the belief that the brain is able to incorporate the actuator into the brain's cortical body map (cf. [65]).

1.3.4 Recreation

Recent years have brought to the market different programs and games controlled by BCI technology. Although BCI technology has a steadily improved in accuracy and ITR, further research is needed before BCI systems can replace traditional controllers in more general use [81].

Games

BCI can play both an active and a passive role in games. As a passive input modality, BCI can modulate game difficulty based on changes in emotional patterns, leading to an increased feeling of challenge and satisfaction for the player [105]. BCI can also be used in a more active role, as a game controller. Games with BCI as an interaction modality vary a great deal in their purpose, spanning from medical uses to research or purely recreational purposes [92].

As medical therapy, BCI games have been used to treat children with attention-deficit/hyperactivity disorder (ADHD). Children with ADHD have been trained to control their SCP through use of video games. After a training period, children were able to control their negative SCP. This was achieved through rewards of desired behavior and discouraging of undesired behavior [130]. This research showed that children with ADHD got ”better behavior”, attention levels and IQ scores.

Games have also played an important role in research settings by giving researchers ways to both experiment with and demonstrate their systems' functionality. Researchers have developed BCI both as an active modality, e.g. ”neural pong”, which is controlled by motor imaginary [49], and as a passive input modality, e.g. an affective Pacman game [118] which manipulates the game to induce user frustration. While ”neural pong” is primarily a way to demonstrate BCI system functionality, the affective Pacman game is primarily a way for researchers to manipulate participants for research purposes.

A growing number of companies are developing games which combine classic control system, such as mouse and keyboard, with BCI as a new interaction modality. EEG acquisition is primarily used to acquire necessary data and convey user intentions. Alternative parameters (e.g. physiological parameters and head/eye movement) are also used to increase ITR [92]. ”NeuroBoy” is a game that lets you take control of a boy in a virtual environment, with whom you are able to explore and interact with. Exploration is done by traditional methods, using a keyboard, while interaction with the environment is conducted through an EEG-based BCI-headset, based on changes in attention and meditative level. ”Brainwave Visualizer” is a simpler game, where changes in attention and meditative levels let you interact with a single object [86].

Creative expression

Creative expression is another way BCI technology tries to improve the quality of life of people incapable of expressing themselves in a traditional way. Methods of playing music and creating art are available and under continuous development [81].

1.4 Operating protocol - overall system control

Each functional BCI system has an *operating protocol* regulating essential parts of the system, with the main purpose regarding overall functionality and user safety [66].

1.4.1 System control

An essential feature of any operating protocol is the *system control*. The ability to turn the system on and off in any situation is a key to both system functionality and user safety. Further aspects of the system control includes deciding whether communication between a user and the system should be continuous or discontinuous and which device the user wants to control in a more complex BCI system coupled with several devices. Today all parts of the operation protocols are normally controlled by researchers. In the future, these functions will be needed to be user-controllable, thereby increasing both the general usability and safety of the BCI systems [74, 121].

1.4.2 BCI efficiency

Usability is strongly connected to the *information transfer rate* (ITR), or bit rate, which is directly affected by the operation protocol. ITR depends on the set threshold value relative to the SNR, a threshold set in the operation protocol. A low threshold combined with a low SNR gives a relatively poor ITR due to low accuracy, making it very hard to convey desired commands to the BCI system. The operation protocol will also affect the ITR based on the signal features and signal acquisition techniques chosen to convey the user intent to the BCI system. Different electrophysiological, metabolic and magnetic signals have different spatiotemporal resolutions which affects the overall ITR. Techniques with poorer spatiotemporal resolution will have a reduced bit rate, while the opposite is generally true for techniques with better spatiotemporal resolutions. Researchers have to balance between the optimal spatial and temporal resolution, since increasing one of them often leads to a reduction of the other.

1.4.3 Biofeedback

Biofeedback is crucial for the BCI system's overall functionality and in some cases user safety. Without any feedback the users would only have one-way communication with the system, making it increasingly harder, if even impossible, to use the system for its desired purposes. Biofeedback is also important in a BCI training situation, to optimize performance [67].

Visual feedback is most commonly used as biofeedback in current BCI research [22]. An alternative that is used to some extent is auditory feedback, either in combination with visual stimuli or as a single modality [88]. The reason for extended use of visual and auditory feedback is primarily due to the main target group being patients suffering from severe or total paralysis. This group generally still has intact vision and/or hearing, making this an effective and easy way to give necessary feedback.

The type of device being employed influences which kind of biofeedback that is useful. Spelling devices, environmental controls, gaming and wheelchairs for mobility can go a long way with only visual and auditory biofeedback. Other sensory modalities, such as touch and body position, should have a bigger part in a technology that restores limb mobility, especially hand dexterity. A body function where visual stimuli is often not enough and touch is a very important way to regulate the intensity of muscle contraction, is the gripping movement of a hand (cf. [22]).

Multiple artificial biofeedback signals (e.g. combining pressure and position sensors in addition to normal visual stimuli) might become an efficient way to assimilate a prosthetic limb into the cortical representation of the user's body. The brain might then be trained to incorporate stimuli from the prosthetic limbs in such a way that the prosthetic limb is maintained in the brains representation of the user's body. Research on monkeys has shown that cortical micro stimulation of the brain might become a good way of delivering such biofeedback from the prosthetic limb to the user [65].

1.5 Neuroethics - ethical challenges

A definition of the field of neuroethics is ”a discipline that aligns the exploration and discovery of neurobiological knowledge with human value systems” [51]. Neuroethics is a growing field of research and is developing in parallel with BCI research. Here I will only give a brief introduction to ethical challenges concerning BCI researched for patients suffering of CLiS and LiS. An extended presentation regarding neuroethics with references to key reviews on the topic can be found in [45].

Several ethical challenges are present in the BCI research today, one of them being the need for informed consent. Normally patients are able to interact with the research team, but in the case of patients suffering of LiS and especially CLiS, this is a major challenge. The question is how a person not able to communicate is able to give an informed consent. Another aspect is the fact that communication within a BCI team can be difficult due to the multidisciplinary nature of the research field. This is a challenge which can lead to unattainable expectations for both researchers and patients, where CLiS and LiS patients might feel they have nothing to loose and hence make decision solely on enthusiastic researchers who might or might not see the true potential of the BCI system.

In the future new ethical challenges (e.g. ownership of mind and performance modification) might become central topics in the field of BCI research [45, 60].

As a final remark, very few BCI systems have taken the step onto the global market. The few commercialized products that have made it, are primarily BCI system based on scalp EEG measurements [31, 86]. However, companies developing products utilizing invasive acquisition technique have got their BCI systems in clinical trials [18].

2 EEG signal features - P300 ERP and SSVEP

This section describes the theoretical background relevant to the following demonstration of two BCI systems based on P300 event related potential (P300-BCI) and steady state visual evoked potential (SSVEP-BCI). Both signal types are evoked potentials, meaning that they are responses to external stimuli. First a short summary presenting the electrophysiological origin of an EEG signal is given, followed by a presentation of the two EEG signal components (P300 and SSVEP).

2.1 Electroencephalography

The first to demonstrate how to measure human brain activity through EEG measurements was Hans Berger in 1929 [6]. Since then, the method has evolved to become an accepted and widespread technique for functional brain studies [87]. An EEG signal is primarily created by concerted electrical activity from populations of neurons, with minor contributions from glial cells. EEG signals can be measured by non-invasive recordings (e.g. scalp electrodes) and by invasive recordings (e.g. LFP and ECoG) [72].

2.1.1 Origin of an EEG signal

The basic unit responsible for the generation of an EEG signal is the neuron, which are numerous throughout the brain (total of $\sim 10^{11}$ in human brain). The neuron with its synaptic connections is central in storing and transmission of information, and interconnected neurons forms vast functional networks in the brain. Neural communication is mediated through movement of electrically charged ions (primarily by sodium, potassium, chloride and calcium) between the neurons' cytosol and extracellular matrix. Active neurons create electrical circuits, where an inflow of a positive current in one part of the neuron (sink) results in a corresponding outflow of a positive current in another part of the neuron (source) (Fig. 10). This flow of positive current results in a net movement of current through the extra cellular space, from the point of outflow along the cell to the point of inflow [87]. Action potentials and postsynaptic potentials are processes that drive the current flow, where the postsynaptic potentials generally depolarize a greater part of the cell membrane and hence has a greater effect on the EEG signal than the action potential. Another factor is the shorter duration of an action potential (≈1-2 ms) compared to a (graded) postsynaptic potential (≈10-250 ms), leading to a higher chance of overlapping action potentials than overlapping postsynaptic potentials [72, 87]. Postsynaptic potentials are either excitatory (EPSP) - depolarizing the postsynaptic cell membrane, or inhibitory (IPSP) - hyper-polarizing the postsynaptic cell membrane. Typically, a neuron will increase or decrease its activity (firing rate of action potentials) dependent on its input from other neurons, where IPSPs will reduce and EPSPs will increase the probability of firing. The created current flow can be measured with small electrodes placed in the vicinity of the cell membrane [94].

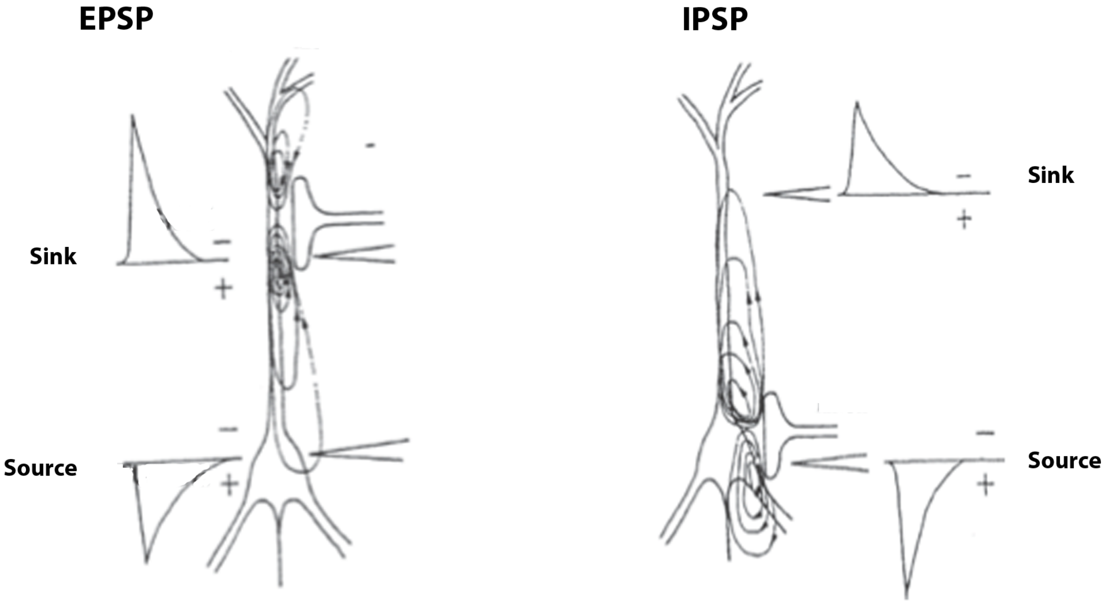

Figure 10: Synaptic activation of an idealized neuron and the following current flow patterns. On the left side an excitatory synapse is depicted, where inflow of positive ions at the level of the apical dendrite result in formation of an active sink. As a consequence a passive source is formed at the level of the soma, where positive ions flow out of the cell. The right side depict a inhibitory synapse at the level of the soma. This result in the formation of an active source at the synapse and hence passive sinks at distal dendrites (adapted from [72]).

A single active neuron is impossible to measure with scalp electrodes due to the distance from the electrodes, the small signal strength compared to the background noise and the ”blurring” effect of CSF and the meninges. Asynchronous active neuron assemblies also have problems producing EEG signal with high enough SNR due to the mentioned obstacles. The measured voltage changes will hence be slow and spread over a longer time interval, making it hard or even impossible to detect. Consequently, a concerted neuronal activity from a set of synchronous active neurons is necessary to produce a measurable EEG signal. This synchronous activity depends on the cortical micro- and macro organization. The neurons, form vertical and well defined columns spanning multiple cellular layers, called minicolumns. These minicolumns are part of an even bigger interconnected unit called cortical columns, which are connected through horizontal connections (each neuron forming up to 10^5 synapses with other neurons) [72]. The different cortical columns form a series of functional networks needed to conduct necessary neural processes to complete specific tasks.

Neuronal networks contributing to the total EEG signal do so by generating most of their electrical signal along a specific axis perpendicular to the scalp. Active neuronal networks producing electrical currents along other axes, will only produce a locally visible signal and have very small, if any, effect on the gross EEG signal (Fig. 11C). The same is true for neurons orientated in different directions relative to the brain surface. In addition to the orientation of the neuron, the morphology of the neuron will also affect its contribution to overall EEG signal. For instance, although symmetrical neurons extend in essentially every direction, their activity only contribute to a locally electrical current [87]. This is due to the fact that electrical currents produced by such active neurons will cancel each other and form a closed field (Fig. 11B). The primary contributor to an EEG signal is therefore cell assemblies with synchronous active neurons which are aligned parallel to each other producing electrical currents moving in the same direction, denoted open fields (Fig. 11A). Another aspect is increasing deterioration of the electrical signal with increasing distance between the origin of the electrical signal and the electrodes. Consequently, neurons in higher cortical layers will generally have a greater affect on the EEG signal than neurons in deeper parts of the brain.

Despite a general contribution of all types of neurons to the total EEG signal, the primary contributors are populations of pyramidal cells and neurons with apical dendrites orientated perpendicularly to the cortical surface (Fig. 11A) [72]. As all neurons will affect the concerted EEG signal to a varying degree, so will different pyramidal cells based on their geometric

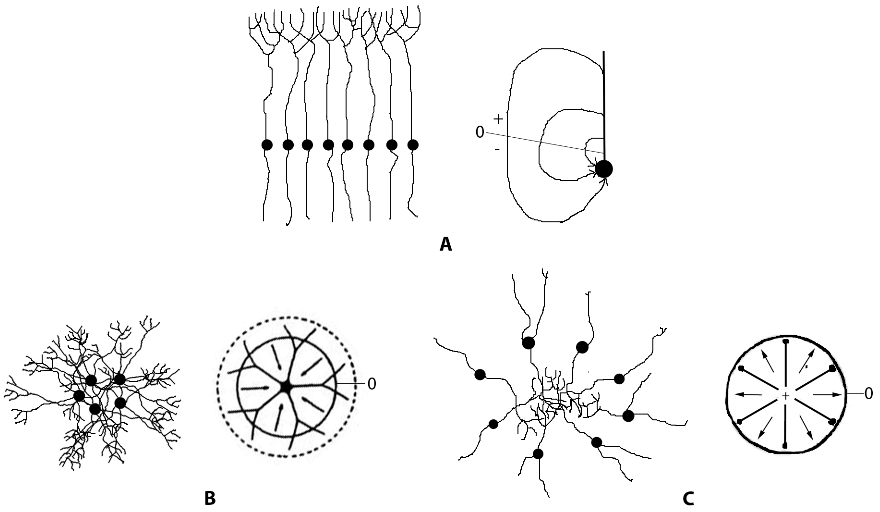

Figure 11: Each figure contains on the left side a depiction of the neuron populations and on the right side the current lines for a neuron representing the same neuron populations. The solid lines mark the zero isopotential. *A:* Synchronous active neuron populations parallel orientated with respect to each other, consequently forming an open field which can spread in the volume of the brain. *B:* Active symmetric neurons. In this case neurons with dendrites radially orientated outwards, result in formation of closed fields. The current will therefore only be measurable in the proximity of the neuron or neuron population. *C:* A neuron population where each neuron only has a single dendrite orientated toward the center of the population, giving rise to a closed field. (Adapted from [87]).

orientation. A pyramidal cell in the sulcus wall will have tangential orientation in relation to scalp electrodes, while pyramidal cells in gyrus will have a perpendicular orientation. As a result, pyramidal cells in the gyrus have a greater effect on the concerted EEG signal than pyramidal cells in the sulcus wall.

The EEG signal is affected by several other factors, both intrinsic and extrinsic, such as cognitive state. It is pivotal for the performance of an EEG-based BCI system to have knowledge of these factors and how they affect the chosen control signal(s). This must then be taken into account when designing the BCI system and deciding electrode placement.

2.1.2 Electrode placement

As EEG activity varies across the brain, electrode placement will affect the measured EEG signal. This fact has led to a need for a *standardized method of electrode placement*, such that intra- and inter-subject measurement variations could be compared [87]. The international *10-20 sys-*

tem (Fig. 12 B), which was proposed (in 1957) by the committee of the International federation of societies for electroencephalography and clinical neurophysiology [53], gave standardized electrode positions for up to 21 electrode based on landmarks of the skull. Development of equipment and the need of increasing spatial resolution later led to an extension of the 10-20 system, namely the 10-10 system and 10-5 system, consequently increasing the number of standardized electrode positions [97]. All three systems used the same skull landmarks as the basis for the electrode placement. These were the nasion (Nz), the inion (Iz), and the right and left pre-auricular points (RPA and LPA [T9 and T10]) (Fig. 12A), which are placed first following certain criteria. The next step is to mount Cz before the remaining electrodes are placed with a percentage distance from the mounted electrodes (for further details see [56] and [97]).

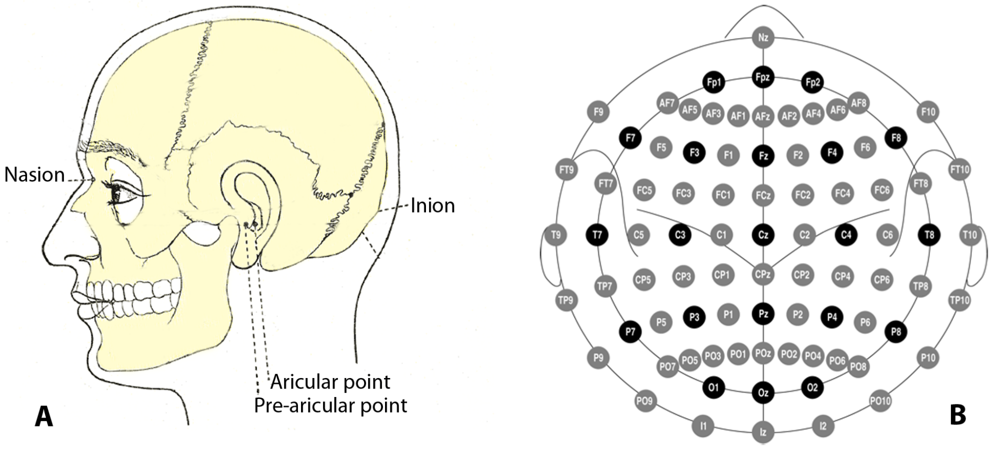

Figure 12: *A:* Anatomical landmarks of interest regarding electrode placement (adapted from [43]) *B:* The international 10-20 system (black) and the 10-10 extension (black + grey) (from [97]).

Most BCI systems based on EEG measurements rely on gel electrodes to reduce spatial blurring, improve electrical conductivity, and increase the electrical signal from the brain. Gel-based electrodes have been dominating in BCI, but is hampered with a time-consuming setup and the need for applying conductive (sticky) gels between the user's head and the electrodes. Over time, the conductive gel dries out and the measured signal degrades. An alternative to gel-based electrodes are dry electrodes, which reduces setup time and eliminates the limiting recording duration, increasing the overall user-friendliness, and the ability to be applied on a day-to-day basis [91, 111]. The use of dry electrodes has generally been associated with loss of signal strength, rendering it useless to BCI application. New generations of dry electrodes have brought necessary improvements, resulting in the development of an EEG-based BCI system for home use which acquires data with dry electrodes [69, 91].

Referencing

The recorded electrical signals of the brain are the measured signal differences between a registration electrode and a reference electrode, hence the minimum number of electrodes needed to measure an EEG-signal is two. Different techniques are applied with regards to referencing: monopolar, bipolar and the average reference. Monopolar recording references the active electrode to a common or fixed reference electrode(s) which is typically placed at the mastoids or earlobes (either single reference electrode or physically/matemathically-linked reference electrodes). These commonly used reference sites are chosen based on the influence of brain activity. Even if all EEG recordings are theoretically bipolar recordings, this term often refers to the situation where one electrode is referenced to an adjacent electrode. Another method, the common average reference, uses the average of all electrodes as a reference for each electrode [95].

2.2 Steady state visual evoked potential based BCI

Materka and Byczuk based their proposed BCI system on SSVEP [75, 76], a signal feature in the EEG signal which is the focus of this section. A brief description of processing of visual stimuli will first be given, followed by more details about the origin and function of the SSVEP signal.

2.2.1 SSVEP - signal origin and function

Visually evoked potentials (VEPs) are produced by making (sudden and typically periodic) changes in visual stimuli resulting in an increased neuronal activity over the primary visual cortex [131]. The same is true for steady state (SS) VEP, which contrary to transient VEP relies on a higher stimulus frequency. A sufficiently high stimulus frequency leads to overlapping EPs, resulting in the generation of a SSVEP [138]. The measured SSVEP over the visual cortex is a periodic response with a frequency corresponding to an exact multiple integer of the stimulus frequency [117]. Eliciting VEPs is possible with flickering lights at a frequency range from 1 to 100 Hz [46]. SSVEP is a time- and phase locked brain potential.

As is well know, the visual field is divided into the left and right visual field, where the left part of both eyes' retinas and the right part of both eyes' retinas make up the right and left visual fields, respectively (Fig. 13). Introduction of a visual stimuli into one or both parts of the visual fields excites pigments in the cones and rods in the retina. These signals are then sent from the cones and rods through the two optical nerves to the brain's two hemispheres. Before the signals reach the primary visual cortex in the two brain hemispheres, both optic nerves partially cross at the optic chiasm. Visual stimuli introduced in the left and right visual field lead to more synchronous firing neurons and hence a stronger response in the right and left hemisphere, respectively [117].

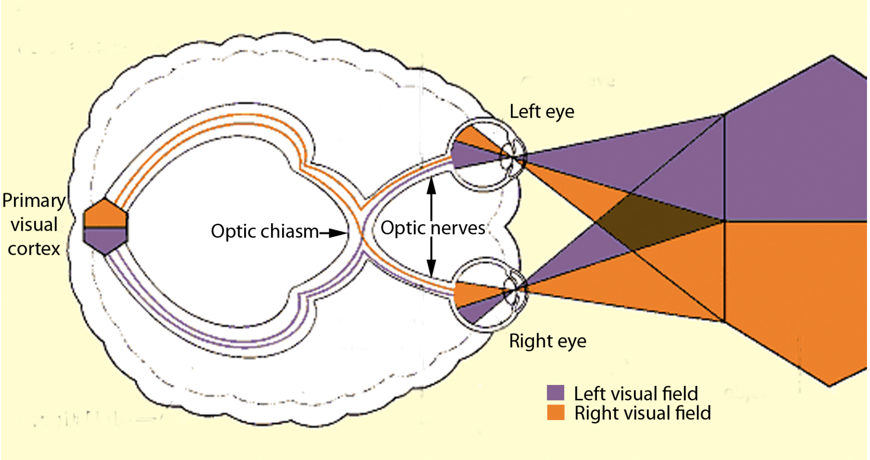

Figure 13: The visual pathways. Here, the different pathways of the left and right visual field are highlighted (adapted from [98]).

Functionally, VEP reflects the spatiotemporal processing of visual stimuli and attention allocation in the brain [82, 117]. Studies have shown that attended stimuli elicit SSVEP of a greater magnitude, due to the relatively large number of cones and rods which are excited in the central vision compared to peripheral vision [59, 131].

2.2.2 Stimulation paradigms

The types of visual stimuli used to elicit a SSVEP response are divided into three groups: (i) light stimuli, (ii) single graphics stimuli, and (iii) pattern reversal stimuli [144]. The first group, light stimuli, uses hardware such as LEDs, fluorescent lights, and Xe-lights to elicit SSVEP signals. This group of stimuli typically has more freedom regarding stimulation frequencies than the other two groups due to the way the light stimuli are generated. Signals are presented with hardware built specifically for the task (e.g. Fig. 14A), which typically have their own electrical circuitry. Single graphic stimuli and pattern reversal stimuli both rely on computer screens for stimulus presentation. Pattern reversal stimuli are presented as oscillatory alternations of graphical patterns (Fig. 14B) whereas single graphic stimuli are presented as a figure which appears and disappears (e.g. square, or arrow as in Fig. 14C). The use of a computer screen reduces the range of available frequencies due to the relatively poor refresh rates of computer displays (typically below 100 Hz). Computer screens also have an observed difficulty with accurately displaying many stimuli with different frequencies [20, 138, 141]. One advantage, however, is the relative ease of developing software to produce the stimuli patterns on a computer screen compared to the need to develop both software and hardware in the case of light stimuli [144].

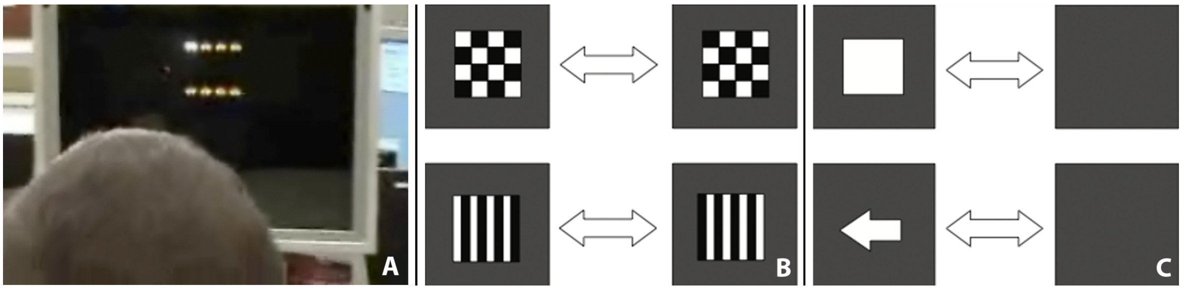

Figure 14: *A:* Light stimuli (e.g. LED lights). *B:* Pattern reversal - different patterns alternate at a given frequency. *C:* Single graphic - a graphical object is presented and disappear according to a pre-set frequency (modified from [144]).

2.2.3 SSVEP - control-signal in BCI

The performance of a SSVEP-BCI system can be assessed by its classification *accuracy*, classification *speed*, and *number of commands available* for the user - all contributing to the ITR, measured as a bit-rate [144]. ITR is related to both the software classification algorithms, and to the nature of the SSVEP, where several factors affecting SSVEP performance play a core role in the development of SSVEP-BCI. Important such factors are the signal features (e.g. stimulus color, type and frequency) and how they influence the SNR of the SSVEP and consequently the classification accuracy and classification speed.

A recent review by Zhu et al. [144] shows that light stimulation generally elicits a larger SSVEP response compared to computer screen stimulation. It should be emphasized that this result is not conclusive due to variation in stimuli conditions (e.g. frequency and color) between the different studies. Variations in SSVEP response have also been observed between single graphic and pattern reversal stimuli. The two other signal features, color and frequency, have been shown to influence the magnitude of SSVEP response, but no clear patterns have yet emerged [141, 144]. Stimulus frequencies used to elicit SSVEP responses typically generate SSVEP with the highest SNR when in the 5-20 Hz frequency range. Both within this frequency range and among other frequencies, an inter-subject variation can be observed [20, 99].

Various methods to improve the stimulus procedure and hence the SSVEP-BCI system's performance have been proposed (cf. [144]). Among them are: (i) different ways of maintaining attention to stimuli during both command selection and environmental orientation; (ii) increasing the frequency resolution of the system, consequently increasing the amount of available stimulation frequencies and hence the amount of available targets; (iii) improving the ITR by improving the SSVEP's SNR [76]; and (iv) extending the target groups for SSVEP-BCI systems by developing an independent SSVEP-BCI system, thereby eliminating the need of any kind of muscle control to operate the system.

SSVEP-BCI systems can also benefit from other changes than those of stimulus features, such as the use of several SSVEP harmonics generated by the stimuli. This might both give rise to an increase in the classification accuracy and classification speed [83]. Other factors affecting the SSVEP response are subject's sex and age, but further research is needed to obtain a clearer picture of all the influencing factors and their role [1].

2.3 P300 event related potential based BCI

The P300 ERP was the signal feature of choice when Hoffmann and coworkers [50] developed their BCI system. This signal feature of the EEG signal was initially described by Sutton et al. in 1965 [132] and was first used in a BCI system by Farwell and Donchin [33]. This section focuses on the neurophysiological background and function of the P300 ERP. For simplicity, the P300 ERP will hereafter be denoted P300.

2.3.1 P300 - origin and function

The P300 is a time- and phase-locked potential elicited in response to an external stimulus and characterized by the signal latency and peak amplitude, where basic information of both characteristics are given by the name of the potential. The same is true for many other ERP phenomena where a letter and a number give information on the sign of signal amplitude and its latency. The letters P and N refer to the general trend of the wave during the time window, whether it is a mostly positive wave or a mostly negative wave, respectively, in comparison to the mean pre-stimulus baseline voltage. The number indicates the time interval (in ms) between signal onset and the highest voltage peak in the time window. The P300 is therefore a positive voltage peak ($>10\ \mu$V) observed around 300 ms after signal onset.

Although the name indicates where to find the signal of interest in the gross signal, both latency and amplitude can vary based on intra- and inter-subject variation such as seasonal cycles and gender [27], exercise and fatigue [142], cognitive abilities [109], drugs [110], age [35], stimulus modality, task condition, etc. [29]. The P300 latency has been shown to vary from 200 to 700 ms [32] and a distinct scalp distribution has also been observed for the P300, where the magnitude of the signal decreases from the parietal lobe to the frontal lobe [54, 107].

The P300 can be divided into two subcomponents, P3a and P3b. Research has shown that the two signal components have two distinct scalp distributions, where P3a and P3b are thought to originate from the frontocentral area and the parietal area, respectively [17, 129]. Latency and amplitude differences are also evident, where P3a generally has a shorter latency (250-300 ms) compared to P3b which has a latency of 250-700ms, and the P3a amplitude habituates faster than P3b [107, 129]. No habituation of the P300 latency is observed [114].

Regarding neuropsychological function(s) of P300, the most dominant theory in the last decades has been the *context updating theory*. This theory is based on the idea that P300 plays a role in the cognitive processes of attention allocation to new or saline stimuli and the evaluation of incoming stimuli. If there are no changes in the stimuli attributes, only sensory-evoked potentials (N100, P200, N200) are observed in the EEG signal (cf. [107]). If changes in the stimuli are observed, a P300 can be observed in the EEG signal.

The different characteristics of P3a and P3b result in a belief that the two components play two distinct functions in stimuli evaluation. In a three stimulus paradigm, the largest magnitudes for P3a and P3b are elicited by a distractor stimulus and a target stimulus, respectively. These lead to the possible function discussed in a recent review [107], where Polich states that stimulus evaluation engages both focal attention (P3a) and the following context maintenance (P3b). In other words, P3a has a role in the process of allocating attention to new/salient stimuli, while P3b primarily plays a role in the process of evaluating a new stimuli with earlier stimuli represented in working memory.

Although P300 has been associated with distributed networks important for attention and memory operations, the exact neurophysiological origin (neurotransmitter systems, generator or a single unifying neurological explanation) of the P300 has not been found [70, 107]. One hypothesis trying to explain P300's role in these processes is the inhibition hypothesis, which states that P300 inhibit on-going neural activity to enhance the focal attention relative to the contents of working memory. The observed P300 scalp distribution is hence a consequence of facilitated transmission of stimulus or task information between frontal and temporo-parietal areas of the brain (for further details see [107]).

2.3.2 Stimulation paradigms

There are multiple ways to elicit a P300 response. The traditional and most frequently used method in a BCI system is the *two-stimulus oddball paradigm*, employed by e.g. Hoffmann et al. [50]. The two-stimulus oddball paradigm present to the user infrequent target stimuli interspersed in more frequent non-target stimuli to elicit the necessary response, enabling the user to convey his or her intent to the BCI-system. When the user is exposed to the infrequent target stimuli, a P300 is elicited (Fig. 15). Other methods are single-stimulus and three-stimulus paradigms, were the former method uses a single target stimuli with no other non-target stimuli interspersed, and the latter method usees one frequent non-target stimuli and two infrequent stimuli, one which is the target stimuli and one which is a non-target stimuli [107].

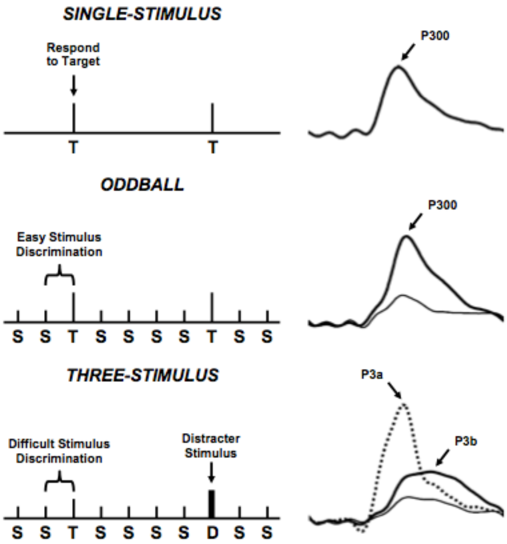

Figure 15: P300 stimulation paradigms (from [107]). The target stimuli results in the recording trace shown in bold, while the response to non-target stimuli and distractor stimuli corresponds to the thin-lined waveform and dotted waveform, respectively.

Another technique used to elicit P300 is the Posner paradigm [112], where subjects are asked to respond to a visual stimulus which appears in any of several locations. Subjects are cued to direct their attention to a certain spatial region before stimulus onset and the subsequent signal either appears in the area subjects are paying attention to (a valid trial) or not (an invalid trial) (Fig. 16). Trials without any cues to were the stimulus will appear are also used.

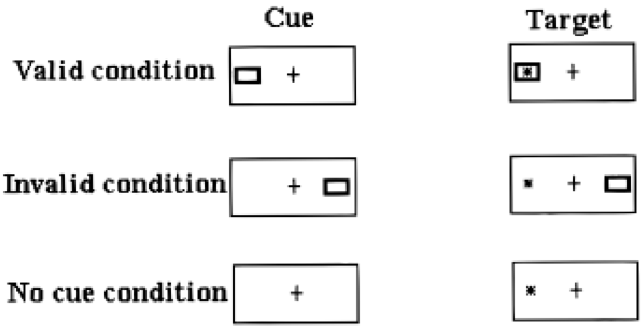

Figure 16: Posner stimulation paradigm (from [101]). Boxes are used to relocate participants attention to an area of the screen before the target stimuli is presented on the screen.

2.3.3 P300 - control-signal in BCI

As previously stated, a core aspect of any BCI system is the information transfer (user intent) from the user to the system. Several factors affect the information transfer in a P300-BCI, consequently changing the P300's latency, amplitude, or both. These changes could lead to a poor system performance or make it impossible for some users to operate the BCI system. Factors such as chronic changes in mental states (e.g. cognitive abilities, age, etc.), temporary changes in mental state (e.g. drugs, biorhythms, alertness, etc.) and task and stimuli related changes will all affect the P300 and hence the user's ability to control the BCI system (cf. [108]).

The P300 is also affected by factors which are out of reach for researchers to manipulate, such as temporary and chronic changes in the user's mental state. These changes in mental state must be taken into account by the researchers when designing the BCI systems. The P300 characteristics have been shown to vary with age, where a reduction of P300 amplitude and increase in latency are observed elderly subjects [35]. The same changes in P300 are also observed in people with reduced cognitive abilities due to different medical conditions [109, 107].

Studies have also shown gender specific P300 differences, with a P300 of larger magnitude for women compared to men [27]. The study by Deldin et al. (1994) also showed that the P300 varied with season. P300 latency and amplitude will also be affected during exercise, reducing both latency and amplitude. This is shown for both visual and auditory stimuli, indicating faster cognitive processing of information and reduced attention allocated to the stimuli [142]. Moreover, use of different drugs affecting the brain have been shown to affect both the P300's amplitude and latency [108].

Although the aforementioned factors are difficult to manipulate, researchers might use these factors as exclusion criteria for people not able to control a P300-BCI. Alternatively, these factors can be used to make BCI systems more robust and applicable to a wider user group through improved software which is able to account for users with ”unusual” P300.

Factors which researchers can manipulate more easily are those associated with the BCI design (e.g. stimuli and task). The nature of the stimuli used will affect the measured P300, thus making stimulus discriminability, target probability, time expectancy, and stimulus salience important variables available to experimental control by the researcher. Stimuli discriminability is most essential to elicit a P300 with a proper amplitude that is distinguishable from the background (high SNR). Too fast or too faint stimuli can lead to a reduced P300 amplitude and consequently reduced, or no ability to detect the stimuli [19, 120, 134].

Secondly, the P300 amplitude increases in magnitude by reduced target probability [30, 55], reduced target to target interval (TTI), the interval between successive target stimuli [41], and by increased interstimulus interval (ISI) - the time between the onset of the first stimulus to onset of the next consecutive stimulus [29]. These three factors interact with each other to determine the P300 amplitude. An increase in ISI will increase the P300 amplitude until ISI reaches approximately 6 s. Probability effects on the P300 amplitude will from this point on diminish until they are eliminated (between 6 - 8 s) [29]. The ISI should therefore be short enough to reduce the time needed to elicit necessary P300, and long enough for a clear and strong P300 amplitude to occur.

A non-target stimulus elicits a smaller P300 amplitude compared to a target stimuli with the same probability [30]. The salience of the target stimuli (i.e. affective value) reward and significance have also been proven to affect the P300 amplitude, where increased salience of the target stimuli is associated with an increased P300 amplitude [19, 29]. The last factor affecting the P300 is the amount of attention allocated to the stimuli resulting from the overall arousal level [57]. Difficult tasks are associated with an increased P300 latency and reduced amplitude, while simpler task needing less attention are associated with a relatively short P300 latency and a large peak amplitude [107].

In addition to affecting the amplitude of the P300, task condition might also affect latency of the P300 [41]. All factors mentioned here are important to consider when designing novel BCI systems in order to meet necessary requirements of targeted groups, as well as to serve as many prospective user groups as possible.

3 Experimental examples - ways to convey user intent

In this section, two experimental methods of operating an EEG-based BCI system are described. The first method introduces a novel stimulation paradigm that is incorporated in a BCI system based on the steady state visual evoked potential (SSVEP-BCI). The second BCI system, which employs the P300 signal feature (P300-BCI), has shown high classification accuracy and classification speed for both healthy subjects and disabled patients. A general positive feature of both these systems is the small amount of training needed to operated them, even though a little training might increase their performance.

My initial project plan was to conduct a pilot study with the SSVEP-BCI system developed by Dr. Byczuk and his coworkers. This led to a short research stay at the Technical University of Lodz (TUL), where a thorough demonstration and explanation of the system was presented and several test runs were conducted. The pilot study was cancelled due to unforeseen events that led to a shortage of time and lack of available equipment.

3.1 Steady state visual evoked potential based brain-computer interface (SSVEP-BCI)

This part of the project was conducted with help from Dr. Marcin Byczuk at TUL in Poland. Dr. Byczuk and his group have developed a new spelling system based on SSVEP and a stimulus paradigm with alternate light stimulation of each visual half-field [75, 76]. I will here report this new alternating half-field stimulation paradigm and experiments that I was introduced to (but not part of) at TUL. This BCI method, developed by Dr. Byczuk and Prof. Materka, represents a novel method of increasing the SNR in SSVEP-based BCI, and studies conducted with this method have shown much promise due to a significantly higher ITR value.

3.1.1 Subjects

Ten healthy volunteer subjects (students) from the Technical University of Lodz took part in the BCI experiment[2] .

3.1.2 Experimental procedure

Participants were placed in a chair, with extra head support, facing the BCI virtual keypad (Fig. 17B). The virtual keypad contained 8 visual stimulator units, each containing a set of three small light emitting diodes (LED) with an approximate surface area of 0.5 cm^2 (Figs. 17A and 17C). Each visual stimulator unit had a layout of a triangle with a fixating point (S_F) between and just above two stimulation LEDs (S_R and S_L) (Fig. 17C). This layout resulted in S_R and S_L stimulating right and left visual field, respectively, when the participant fixated at S_F (Fig. 13). Both parts of the visual field were stimulated by the same frequency (f_k), while S_R and S_L frequencies were in opposite phase. This resulted in a strong negative correlation between produced SSVEP signals in the two brain hemispheres, consequently increasing the SNR due to a larger increase in the SSVEP response compared to the background noise. Finally, a stimulation frequency higher than 15 Hz was used in this study to reduce eye fatigue of the user, as such higher frequencies were associated with less fatigue.

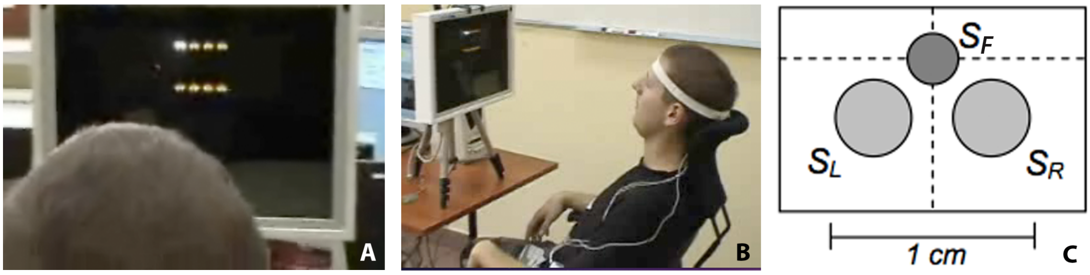

Figure 17: *A:* Virtual keypad *B:* Experimental setup *C:* Visual stimulator unit (from [76]).

User intent was communicated to the BCI system through two electrodes placed symmetrically over the primary visual cortex, one over each hemisphere (O_L and O_R, being O1 and O2 in Fig. 12). A third reference electrode was placed between them. Conductive gel was applied

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[2] The experimental procedure summarized in this section is described in more detail in Section 2 of [76].

between the scalp and the electrodes to increase the strength of the measured EEG signal. Due to the close distance between the two registration electrodes, the background noise components of the signal are very similar. As a consequence, the processed signal, being the signal from one electrode subtracted from the other, has an SNR inversely proportional to the distance between the two registration electrodes - and this was the basic idea and novelty of the method. Sampling frequency was set to 200 Hz with an amplitude range of $\pm 256\mu$V.

Decision making

Each decision process which led to the BCI system producing a character started with all visual stimulator units flashing at the same intensity. The user then chose characters by focusing attention on the S_F of the visual stimulator unit corresponding to the desired character. Each visual stimulator unit flashed at a different frequency, where S_R and S_L flashed in opposite phase. During the registration procedure, participants were given continuous visual and auditory feedback. As participants focused on S_F in a visual stimulator unit and the measured signal got stronger, the strength of the emitted light from S_F was reduced accordingly. This continued until S_F extinguished when the signal reached a set threshold value and the system registered a command. In addition to the visual feedback, registration of the command was also confirmed with an auditory feedback. The subjective experience was that by ”concentrating” on the target S_F you were able to extinguish its light emission.

Analysis

The difference between the two measured EEG signals was amplified, low pass filtered, sampled and sent to a computer for further analysis. A power spectral density of the EEG signal was then computed in sliding windows characterized by 1.28 s, 2.56 s and 5.12 s duration times. Use of three detectors increased accuracy and detection speed. Within each sliding window an SNR value was estimated and used to calculate an SNR coefficient. The SNR coefficient is here the ratio between the sum of frequency spectrum amplitudes in a symmetric window centered around the frequency f_k to the sum of amplitudes excluding the frequency f_k. The probability of SSVEP being present in the signal is then determined by comparing the SNR coefficient and a predefined threshold set by the researcher.

Stimulation frequencies were synthesized by a computer program controlled by the researcher. The sliding window of 1.28 s resulted in a frequency resolution of 0.78 Hz, meaning that the stimulation frequency of two visual stimulator units only needed to be separated by a frequency range of 0.78 Hz. Each stimulation frequency was associated with a specific letter in the alphabet, hence making participants able to type with the BCI system. Recently detected frequencies (producing a character) were removed from the decision process for a time equal to the spectral analysis window. This was done to eliminate detector ”memory effect” and potential SNR fluctuation around threshold value which could lead to several registrations of the same SSVEP signal. To further increase ITR, potential false registrations were reduced by the researcher through proper setting of threshold values.

3.1.3 Experimental Example - Results

Figures 18A and 18B show the EEG signal spectrums from O_L and O_R, respectively. In both signal spectrums the expected frequency bands are not observed, consequently no user intent is conveyed to the BCI system. The two figures show a registration interval of 180 s where the user focus on different stimulation units at different time intervals.

Figure 18C, where O_L has been subtracted from O_R clearly shows frequency bands in the expected frequency range. The BCI system's accuracy and ITR were enhanced by increased SNR. Conversely, Figs. 18A and 18B show no recognizable frequency bands. Figure 18C also clearly shows the frequency bands and how the user changed attention between different stimulation units at different time intervals.

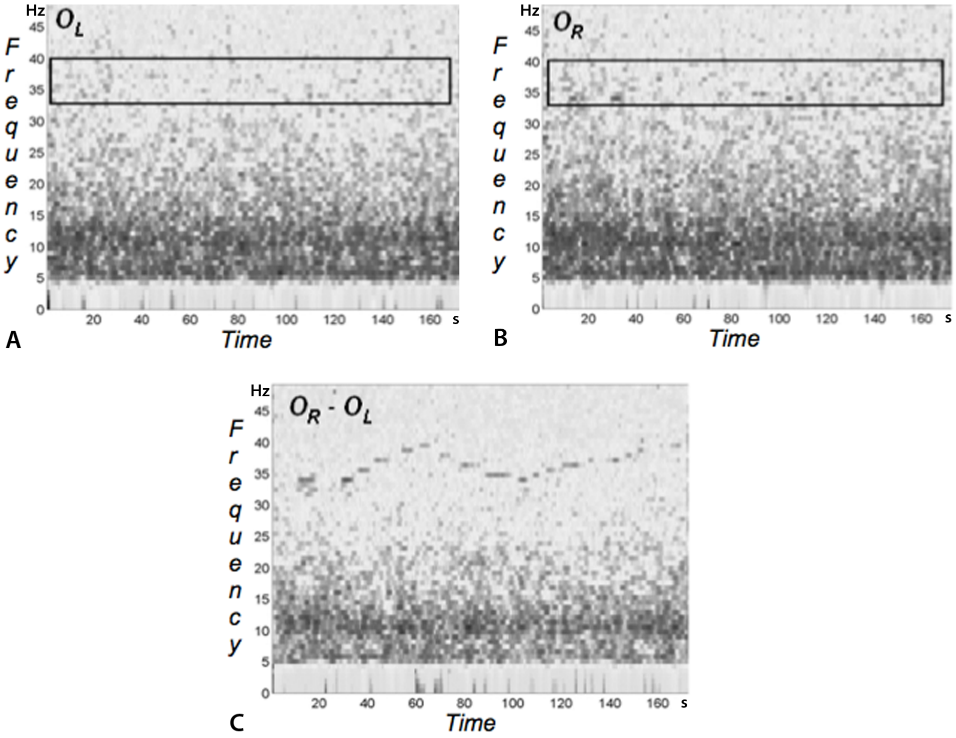

Figure 18: *A:* EEG signal spectrum registered by O_L *B:* EEG signal spectrum registered by O_R *C:* The difference between EEG signal spectrum registered at O_R and O_L (from [76]).

Table 1 shows the detection time for five of the participants, with a decrease in detection time between the first and the last recording session for each participant.

Table 1: Measured detection times for 5 different participants

Participant	Detection time (s)		
	max	min	average
AK2	2.24	8.64	4.15
AK2	2.00	8.08	3.10
AK2	1.84	7.52	3.24
LS1	2.72	43.38	13.38
LS1	4.88	25.12	8.67
MP2	1.52	10.56	3.49
WF1	3.52	32.96	11.63
MB1	1.36	4.24	2.66
MB1	1.04	1.92	1.62
MB1	0.40	2.32	1.51

3.1.4 Interim discussion

The primary strength of the method of Materka and Byczuk is the novel stimulation paradigm introduced. Alternating stimulation of each visual field and the subsequent use of the two SSVEP signals to improve the SNR, provides a higher ITR. This results in a BCI system with a higher performance, increasing both usability and the number of prospective areas of utilization (e.g. controlling movement of a wheelchair).

On the down side, BCI illiteracy was observed in the study, where several of the participants contributing to the study were unable to obtain a strong and clear SSVEP. Another issue, that was also observed during my studies at TUL, relates to instability. Even though the BCI system worked well when it was set up, too much movement or changing of users led to difficulties and sometimes a non-functioning system. Several components were probably not well enough insulated and consequently picked up noise from the environment.

During my stay at TUL I also experienced changes in the system performance on two consecutive days. While I had no problem communicating with the system the first day, the second day I was unable to operate it at all despite all my efforts. Another student accompanying me to TUL was on the other hand able to operate the system both days without any problem. None of us had any prior experience in operating this or any other BCI system from before this trip. I can only speculate as to why this happened, but the reason might be problems with the equipment. This instability is of concern, but it should be noted that some parts of the BCI system we used was among the first prototypes that were developed. Some of the newest parts were being repaired.

After my trip to TUL and the subsequent literature study, it is clear to me that several challenges are still to be overcome before SSVEP-BCI in general daily use is possible. One area of potential improvement is the system design, where an important and interesting topic is the effect stimuli features on the SSVEP response (cf. Section 2.2). Although there is a connection between SSVEP response and stimuli features, no clear and general pattern has been found so far [144]. Increased knowledge regarding intra- and inter-subject variation in terms of stimulus color, frequency, and type might therefore lead to improved system designs, consequently increasing the SSVEP-BCI performance. At the last day at TUL, Dr. Byczuk and his coworkers showed me a new stimulation device that was developed to investigate in more detail various stimulus features and how to stimulate different parts of the visual field and optimize electrode placement, illustrating that this type of SSVEP-BCI is work in progress.

3.2 P300 evoked potential brain-computer interface (P300-BCI)

This section describes experiments conducted by Hoffman et al. [50], designing a six choice P300 event-related BCI system paradigm for control of electrical devices. This method is highlighted primarily because of its excellent classification accuracy and ITR for both abled and disabled participants. Testing of both healthy volunteers and disabled subjects are highly relevant due to the expanding areas of BCI application. Hoffmann and coworkers have also made datasets and some algorithms from this research available to the BCI community through the website of the EPFL BCI group (`http://bci.epfl.ch/p300`).

3.2.1 Subjects

Two groups participated in the project consisting of five disabled and four able-bodied subjects, respectively. Four disabled males and one disabled female joined the experiments, all with varying degree of communication and limb muscle control abilities. A more detailed description of the disabled participants can be found in Table 1 in [50]. All able-bodied participants were male PhD-students with no known neurological deficits, recruited from the same laboratory as the experiments were conducted.

3.2.2 Experimental procedure

The experimental procedure summarized here is described in detail in Section 2 of [50]. All participants went through four sessions, each session included a set of six runs, one run for each of the displayed pictures (cf. Fig. 19). Each recording session started by asking participants to focus their attention on one picture and count how many times the picture flashed. Participants were then placed facing a laptop screen displaying six pictures of different devices found in most households. A warning tone followed and four seconds later a block-randomized sequence of flashes were produced. Each block contained one stimuli of each of the six pictures, consequently each picture flashed once before a picture could flash a second time and all pictures flashed a second time before one flashed for a third time, etc. The number of blocks was chosen randomly between 20 and 25. One run consisted on average of 22.5 × 1 target (P300) trials and 22.5 × 5 = 112.5 non-target (non-P300) trials. Each picture flashed for 100 ms with an ISI of 400 ms. In session 2-4 each participant were given visual feedback after each run based on the training of the classification algorithm with the data from the first session. Finally, each participant were asked to give their counting result, used to measure participants performance.

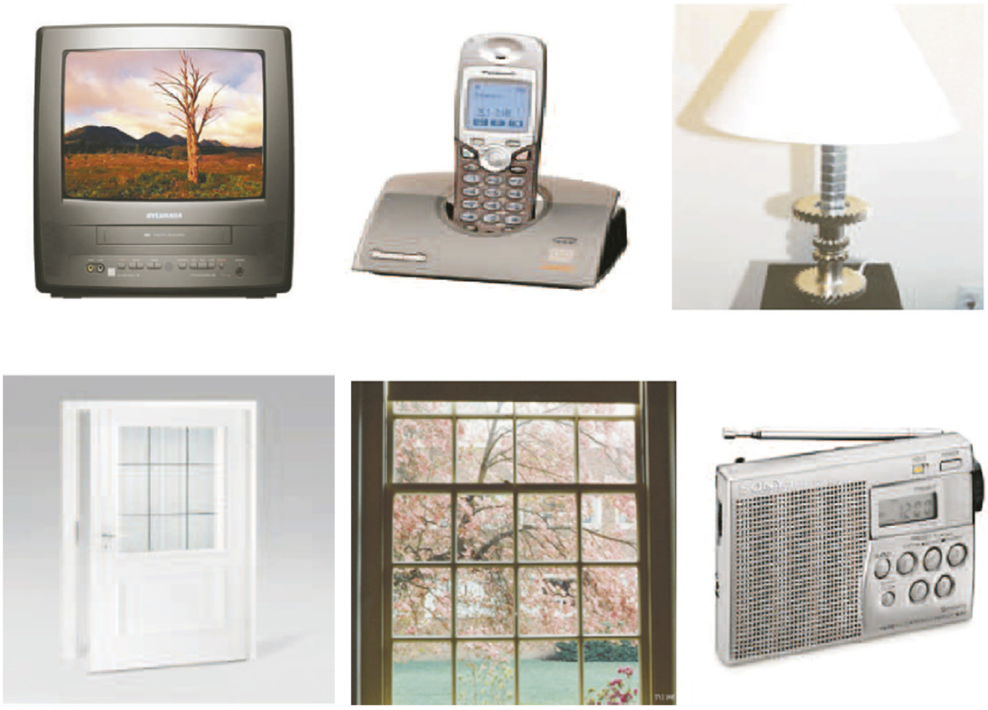

Figure 19: The six image stimuli (”tasks”) used in the environmental control system (adapted from Fig. 1 in [50]). For each run, the following protocol was used: (**i**) The subject was asked to count silently how often a prescribed image was flashed (for example: ”Now please count how often the image with the radio is flashed”). (**ii**) The six images were displayed on the screen and a warning tone was given. (**iii**) Four seconds after the warning tone, a random sequence of flashes was started and the EEG was recorded. See text for more details.

User intention were conveyed to the BCI system through scalp EEG electrodes. The EEG-signal were measured with 4 different electrode configurations, consisting 4, 8, 16, or 32 registration electrodes (cf. Fig. 20), all following the international 10-20 system and sampled at 2048 Hz. The average signal of two additional electrodes, placed over the mastoids, were used for referencing.

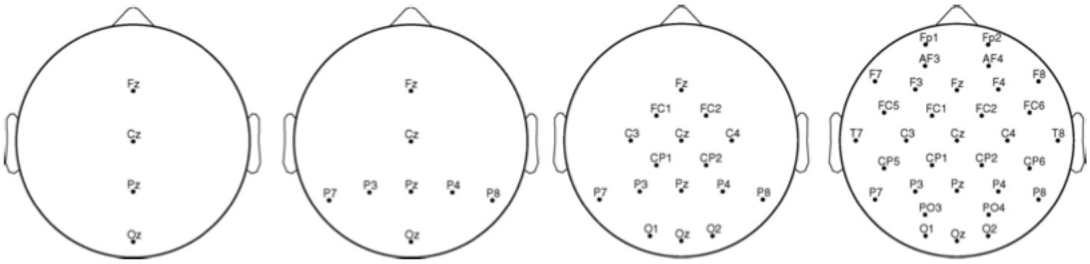

Figure 20: Electrode configurations used in Hoffmann et al. (2008) [50].

Decision making

Each run started with a warning tone followed four seconds later by a block-randomized sequence of flashes of the six pictures. Each run presented the participant with a random number of blocks (20-25). On average, 22.5 blocks were used in each run, each block containing 6 stimuli with an ISI of 400 ms, hence making an average decision process (run) last for 54 s. Only attended flashes produced robust P300 ERPs, which were used by the classifier algorithm to identify the picture of the user's attention and hence the user's intent. At the end of each run, the BCI system produced a visual feedback, in the form of five flashes of the chosen picture, based on output from the classifier.

Analysis - offline procedure

After registration of the EEG-signal, Hoffmann et al. used an offline analysis to calculate the impact of electrode configurations and machine learning algorithms on classification accuracy.

First, the acquired data was bandpass filtered using MATLAB, with cut-off frequencies of 1 and 12 Hz. Secondly, the dataset was downsampled from 2048 to 32 Hz by selecting every 64th sample from the filtered data set. Next, a single trial extraction of 1000 ms of data was done on the data set, starting from stimulus onset. Winsorizing of the data, limiting extreme values from each electrode, was then used to reduce effects of potential artifacts in the EEG signal (e.g. eye blinks, eye movement, muscle activity or participant movement). This was done by calculating the 10th percentile and the 90th percentile for each electrode and replacing all values below the 10th percentile and above the 90th percentile with the 10th percentile and 90th percentile, respectively. Following this step was scaling of the samples to the interval [-1,1] before desired electrode configuration was chosen. Finally, samples from selected electrodes were put into a feature vector construction with dimensions; N_e x N_t, where N_e denotes number of electrodes and N_t denotes number of temporal samples. The value of N_t was always 32 due to the trial duration of 1000 ms and downsampling to 32 Hz.

Bayesian linear discriminant analysis (BLDA) and Fisher's linear discriminant analysis (FLDA) were used to automatically train classifiers and percentiles were used for windsorizing. Three of four sessions from each participant were used to estimate classification accuracy, while the last session was used for validation. Each session served as validation once, hence four estimations of classification accuracy were calculated. Validation was conducted after classifier training, using single trials corresponding to the first twenty blocks. Single trials classification of every block resulted in six classifier outputs in each block, one for each picture. System decision regarding which picture the participant had focused on was decided based on the picture with the maximum summed classifier output over all blocks.

3.2.3 Experimental Example: Results

Table 2 shows the average bitrates of the participants, where generally higher bitrate was observed for able-bodied participants compared to disabled.

Differences in bitrates were also observed between the BLDA and FLDA classification algorithms, with generally higher bitrates for BLDA than FLDA given the same electrode configuration. This was especially true for electrode configurations containing 16 and 32 electrodes. While an increase in the number of electrodes gave a higher ITR for BLDA (Fig. 21B), the ITR

Table 2: Average maximum bitrates (bits/minute) for disabled (subjects S1-S4), able-bodied (subjects S6-S9) and all participants for all combinations of electrode configurations and classification algorithms

Subject	BLDA-4	BLDA-8	BLDA-16	BLDA-32	FLDA-4	FLDA-8	FLDA-16	FLDA-32
S1-S4	13.1 ± 6.8	15.9 ± 7.5	16.4 ± 8.2	19.0 ± 8.6	12.7 ± 8.6	16.3 ± 8.8	14.6 ± 11.0	11.7 ± 6.5
S6-S9	26.0 ± 9.2	29.3 ± 13.7	35.7 ± 15.2	38.6 ± 19.7	23.3 ± 15.0	27.6 ± 19.3	25.8 ± 16.0	21.0 ±12.1
All	19.5 ± 10.2	22.6 ± 12.5	26.1 ± 15.3	28.8 ± 17.6	18.0 ± 12.6	22.0 ± 15.2	20.2 ± 14.1	16.4 ± 10.3

increased for FLDA between 4 and 8 electrodes before its decreased from 16 to 32 electrodes (Fig. 21A). Differences between the two classification algorithms accuracy were strongest in the beginning of each run when only a few blocks were used.

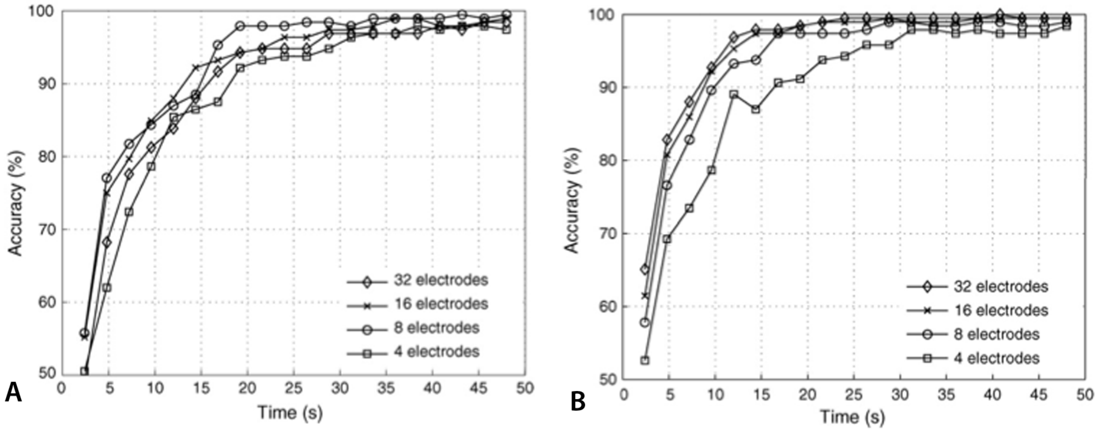

Figure 21: *A:* Averaged classification accuracy obtained with FLDA from all participants and sessions *B:* Averaged classification accuracy obtained with BLDA from all participants and sessions (from [50]).

3.2.4 Interim discussion

One strength of the study conducted by Hoffmann et al. is their investigation of several parameters that are important to simplify and meet requirements for a BCI system operating in a home environment. This was done by looking closer at the system's usability for different user groups, different classification algorithms and the effect of different electrode configurations. Their stimulation paradigm also resulted in a relatively efficient decision system which was able to convey user intent relatively fast compared to other developed BCI systems. Results also showed that the highest performances was observed with eight electrodes [50]. Finally the automatic training of the classifier algorithms made the BCI system fast regarding preparation time (within 1 minute) compared to other similar studies. Even though their results are promising, a study with more participants is necessary in order to obtain firm conclusions about performance and robustness of this P300 approach [50].

4 Closing remarks

A general introduction to the BCI research field has been given, followed by a detailed description of two specific BCI systems (SSVEP-BCI and P300 BCI) and their brain control signals.

This final section will address future aspects of BCI research and highlight some challenges that need to be overcome before the goals of broad clinical and home use are feasible.

General considerations

The vision of BCI research has been to introduce direct control of informational, electrical, and mechanical devices in our environment without the need of using the peripheral neural system or muscles. This has been partly driven by BCI research focussing on improvement of the daily life situation for motorically impaired patients, often with an initial goal of restoring communication for CLiS and LiS patients. These goals have evolved and expanded in parallel with the developments of equipment (e.g. sensors and computing devices), machine learning theory and algorithms, and now encompasses new areas of application, such as the gaming industry and the enhancement of healthy individuals' capabilities. A specific example regarding the evolution of the BCI research field is the goal of making prosthetic limbs with 360 degree of freedom, which might be achieved not too far in the future [65, 67, 123]. New goals and new technological advances have also led to a swell of economical and brain-power resources devoted to BCI research, consequently increasing the amount of research and commercial fields who seek to apply BCI technology in their areas of interest.

Visions and goals are important as both motivation and as future prospects - but what can BCI offer us today?

Regarding the initial goal of helping disabled people in a daily setting of a home environment, possibilities are scarce. Many studies have shown functional BCI system in a research setting, but few have made necessary efforts for transition into a system compatible for use in a home environment. Despite some promising result from clinical and real world trials [49, 125, 136], several landmarks need to be reached before a broader commercialization trend is possible. In other words, our general understanding of the brain has to be improved, followed by improved BCI systems to fulfill necessary usability requirements.

The first landmark needed to be accomplished in BCI research is development of compact and portable equipment. EEG-based BCI is often the researcher's choice when they develop portable systems, due to its manageble size, cost and the relative ease of operation [69]. The second landmark is the instability issues which need to be reduced to an absolute minimum, such that the BCI system perform well within the boundaries for what can be accepted in relation to system performance and the user safety. Extended recording intervals with SU is an example associated with a gradual deterioration of the signal strength. Stability issues also arise in other settings, such as changes in the user's physiological state, something which was observed in our test runs at TUL. On the first day, there were no problems in obtaining a strong and steady signal for two persons, while we only were able to obtain a strong enough signal from one person the following day. The same is true for other BCI systems such as BCI systems based on the P300 signal feature, where research has shown that the P300 response varies with several parameters such as age, gender, and seasonal and physiological cycles (cf. Section 2.3). One way to overcome these issues will be to improve existing classification algorithms so that they take into account variations in physiological states, including brain adaptation.

Areas of application also need to be comparable to the amount of available information which is transmitted between the user and BCI system. A BCI system which lets the user obtain some control over his/hers environment (e.g. heating devices, telephone apparatus, door openers, etc.) might be able to function with far less information transfer than a BCI system restoring movement of a prosthetic limb with high degrees of freedom. There are several ways of improving the ITR, where important issues are: (i) the acquisition techniques and equipment characteristics, including optimization of the recording sensor placement and stimulation paradigms (cf. Sections 1.1 and 2.1); (ii) the signal processing, where development of classification algorithms to increase accuracy and speed are pivotal (cf. Section 2.2.2); (iii) the overall system control, where an important factor to the ITR value is the aspect of continuous or discontinuous information transfer (Section 1.4.1). The user has to be able to control the stream of information transfer between himself and the system, or else both the usability and user safety will not be up to the expected standard required from such a BCI system.

When researchers design home based BCI systems the safety of the user is of utmost importance. Consequently, the control interface needs to be easy both to understand and to operate. In the future, users should be able to operate BCI systems independently or with limited amount of help from caretakers or other persons close to the user. In other words, researchers have to transfer the control of the operating protocol to the user (Section 1.4.1). This will lead to the need of training several persons to operate the system, and hence a functional support system needs to be in place before general home use arises. The support system will also play a role in case of a malfunctioning BCI system.

Additionally, the BCI system needs to be affordable, both in terms of acquisition and maintenance. Researchers and designers therefore need to streamline the BCI systems according to user group and remove unnecessary parts and functions. One example will be to reduce the number of electrodes in an EEG based BCI system to a bare minimum, while the system performance is kept sufficiently high (cf. the study by Hoffmann et al., 2008).

Another aspect is the general observation that around 15-30% of users are BCI illiterate, making them unable to use certain BCI systems successfully. Several ways of solving this problem have been proposed. Among them is the design of hybrid BCI (cf. Section 1.1.3). Improved classifier algorithms might also reduce the amount of users unable to convey their intent to the system.

The possibility of a future bringing high performing prosthetic limbs to disabled patients will require improvements in several areas. One is the ITR, which needs to be better than any BCI system can provide today. The probably best solution in this case, will be large ensembles of single unit recordings. This will require development of new technologies such as nano-detectors [135]. Following up on realistic representation and nature-like control of a person's limb, there will be a need to convey information from sensors in the limb to the brain, i.e. a computer brain interface (CBI). This is important for normal limb or hand use that we take for granted, such as holding a cup or a pen, where a too firm or rigid grip can be dysfunctional, or even destructive. In the future, this might be managed through micro stimulation of somatosensory areas of the brain [65].

Finally, in the view of Section 1.5, it is important to be critical and cautious regarding technology development and use and also in the design and assessment of BCI trials that one want to conduct. This is especially important in meeting with severely disabled patients who are placed in very sensitive and dependent psychological and social situations. Researchers should in such cases be very careful with respect to what they envisions for the patient and be both realistic and optimistic about the likely outcome of an enabling BCI system in the given case. As in other fields of medicine, the society's and the research communities' ethical norms have to be respected.

4.1 Conclusion

The brain computer interface technologies can be characterized as driven both by science and by fiction. BCI is still in its infancy, but important steps are being made for its clinical use by disabled (e.g. locked-in) patients, and also for enhancing the capabilities and experiences of normally functioning people. BCI has recently entered the gaming industry, and are being used in training and rehabilitation of patients with neurological or neuropsychiatric disease, and in neurocognitive research. BCI has thus a large potential in our society and can affect mankind in many ways, just like biotechnology and nuclear energy. It represents a great challenge both technologically, scientifically, and ethically, and we think it is time for its arrival into medical and neurobiological research environments also in Norway.

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