Stimulation Effects in SSVEP-Based BCIs

Master Thesis

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Abstract: Brain-Computer Interfaces (BCIs) enable people to control appliances without involving the normal output pathways of peripheral nerves and muscles. A particularly promising type of BCI is based on the Steady-State Visual Evoked Potential (SSVEP). Users can select commands by focusing their attention on repetitive visual stimuli (RVSi) that change one of their properties (e.g. color or pattern) with a certain frequency. These properties as well as the device the RVSi are rendered on, can greatly affect the performance, applicability, comfort and safety of the BCI.

Despite this fact, stimulation properties have received fairly little attention in the BCI literature to this date. Furthermore, a heavy emphasis is placed on BCI performance to the detriment of other important factors such as comfort and safety. The research reported in this document aims at studying the effects of stimulation properties on performance as well as comfort of SSVEP-based BCIs. Research was performed in both offline and online settings, using a custom made high-performance BCI. Comfort was measured using a custom questionnaire.

A large variability across subjects was found, but the results confirm that stimulation properties have a considerable impact on performance and comfort of SSVEP-based BCIs. In general, a large difference between stimulation states is beneficial for BCI performance, but detrimental to user comfort. A couple of configurations were found that provide a good compromise between comfort and performance.

Conclusions: Both the performance and comfort of SSVEP-based BCIs depend significantly on the properties of the RVSi employed in them. In general, more pronounced differences between stimulus states result in better performance, but less comfort. Some property combinations were found that provide a good compromise between comfort and performance. Color stimulation on a dark background seems especially promising.

These findings suggest that the choice of stimulation properties should be made with great care when designing an SSVEP-based BCI. More research is necessary to determine what settings of properties and combinations thereof generally provide the best results. Stimulation property optimization for individual users can also yield great advantages for the usefulness of a BCI.

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Chapter 1

Introduction

Controlling the environment with the sheer power of one's mind is something you used to only find in science-fiction and fantasy stories. Brain-Machine Interfaces or Brain-Computer Interfaces (BCIs) allow us to do just that. The field is still in its infancy, so it might still be some time before we can Force Pull a cup of coffee from across the room, but systems for controlling wheelchairs [1], prostheses [2], cursors [3], communication [4, 5, 6, 7] and even games [8, 9] already exist.

It is not yet possible to read someone's mind based on signals extracted from the brain. Most BCIs therefore 'listen' to these signals and determine if they match some predetermined template, associated with a command which depends on the specific application. Because of its high time resolution, noninvasiveness, ease of acquisition, and cost effectiveness, the electroencephalogram (EEG) is the preferred brain monitoring method in current BCIs [10]. An application specifies a number of commands that the user can execute by completing associated tasks (such as imagining the movement of a body part, focusing on a stimulus, or simply by relaxing or concentrating). Since these tasks involve little to no muscle activity, even users who are severely disabled may be able to control such an application [11].

Making sense of a person's brain signals is a complicated task. The signals depend on the person, the time of day, his/her state of mind, the task, the environment, the measuring equipment and many other factors [11, 10]. One type of response that is relatively easy to measure is the steady-state visual evoked potential (SSVEP) [12, 13, 14, 15]. This potential occurs when the user focuses on a visual stimulus that is oscillating at a fixed frequency. In SSVEP-based BCIs each command is associated with a repetitive visual stimulus (RVS) oscillating at a different frequency or phase and the user selects the command by focusing on the associated RVS. BCIs based on the SSVEP provide a relatively high speed of operation when compared to most other BCIs and are therefore very promising [16, 17]. Furthermore, SSVEP-based BCIs can be used by more than 90% of users without much training, in contrast to most current systems that use other brain activity [18, 3, 19]. It is for these reasons that the research in this thesis focuses on improving SSVEP-based BCIs.

Project motivation and objectives

Although using the SSVEP has many benefits, there are also some disadvantages. The first is that looking at a flickering stimulus causes fatigue and can be very annoying. The second is that it may even induce seizures in epileptic users [20, 21, 22, 23, 24]. The literature to this date has largely ignored these issues and instead focused on how to increase BCI performance, mainly by studying different signal processing techniques. However, properties of the stimuli such as size, color and contrast can also have a big impact on performance. Additionally, these properties also greatly affect how comfortable and safe a BCI is to use.

The main goal of this project is to help improve SSVEP-based BCIs in terms of performance as well as applicability, comfort and safety by studying the SSVEP phenomenon. It is likely that no combination of properties exists that optimizes all evaluation criteria and it is important to understand the tradeoffs that can be made. This is done primarily by researching the effects of several different stimulation properties in both online and offline settings. This research can also increase our knowledge of certain physiological aspects of the SSVEP and the part of the brain that it is elicited in.

Main contributions

The main contributions of this thesis can be summarized as follows:

- An overview of the most important properties of repetitive visual stimulation used in SSVEP-based BCIs, and how their values affect SSVEP strength, BCI performance and user comfort and safety.
- The development of a short questionnaire to measure how comfortable the stimulation in a BCI is.
- Suggestions on how to improve SSVEP-based BCIs for future applications, both in terms of comfort and performance.
- The development of a high-performance SSVEP-based BCI for experimentation and demonstration.

Outline

The rest of this thesis is organized as follows: Chapter 2 provides an overview of the technologies and neural phenomena that are relevant to SSVEP-based BCIs. Chapter 3 discusses the methods and experimental setups used for acquiring and analyzing the data. In Chapter 4 the most important stimulation properties are presented along with findings of how they affect performance and comfort of SSVEP-based BCIs. Introduction, experiments, results and discussions are interleaved here in order to keep all information about each property in one place. The conclusions about the found results are reported in Chapter 5.

Appendix A discusses how human-computer interfaces in general (and BCIs in specific) could be enhanced by tapping into the human error-detection system using EEG. Three articles were published based on work reported in this thesis and are included in Appendix B. Appendix B.1 contains a survey of which stimulation properties have been used in SSVEP-based BCIs to date. Appendix B.2 presents the most important results of the main research presented in this thesis. Appendix B.3 discusses how the human error-detection mechanism can be recognized by a computer system and is mostly related to Appendix A.

Chapter 2

Concepts

The systems discussed in this thesis are brain-computer interfaces that measure the brain's steady-state visual evoked potential response to the user's focus on a repetitive visual stimulus and convert it into commands that are useful to the user. This chapter provides an introduction for the most important notions that are relevant to these systems. First, methods of brain activity measurement are introduced (Section 2.1), followed by a discussion of visual evoked potentials (Section 2.2) and repetitive visual stimulation (Section 2.3). Finally, an introduction is given to brain-computer interfaces (Section 2.4).

2.1 Brain activity measurement

There are a number of neuroimaging techniques which can measure the brain activity required for brain-computer interfacing. Brain activity is characterized by the firing of neurons. When an area in the brain is active, the firing pattern changes and it is the goal of neuroimaging methods to detect this. When a neuron fires, it uses energy to send an ionic current with a negative charge along its axon (tail) to connected neurons, which in turn alters their probability of firing. This firing costs energy, which needs to be replenished (a little later) through the bloodstream. Hemodynamic techniques measure the amount of oxygen, or a tracer compound, in the blood, at each location in the brain. This allows for high spatial resolution, but temporal resolution is usually low, because the blood flow to an active part of the brain comes after the activity. Hemodynamic methods include *functional magnetic resonance imaging (fMRI)*, *positron emission tomography (PET)* and *near infrared spectroscopy (NIRS)*. The electrical activity that can be measured from the firing of neurons directly corresponds to the brain activity, and therefore allows a very high temporal resolution, but generally lower spatial resolution, because the electrical activity is distorted by brain, skull and skin tissue. It is the basis for *electroencephalography (EEG)*, *electrocorticography (ECoG)* and *magnetoencephalography (MEG)*. It can therefore be said that hemodynamic techniques are particularly useful for visualizing *where* neural activity occurs and electrophysiological methods are better at determining *when* activity occurs.

Depending on the specific application and the target demographic of a BCI, the characteristics of neuroimaging techniques have different priorities. In casual applications the emphasis may be on speed and robustness, whereas safety critical applications need to focus on robustness. For severely disabled people a properly working BCI can increase their value of life so significantly, that it warrants brain surgery and makes invasive methods such as ECoG feasible. For most people, however, the addition of an extra (relatively low-bandwidth) communication channel does not nearly outweigh the cost and risk of such surgery.

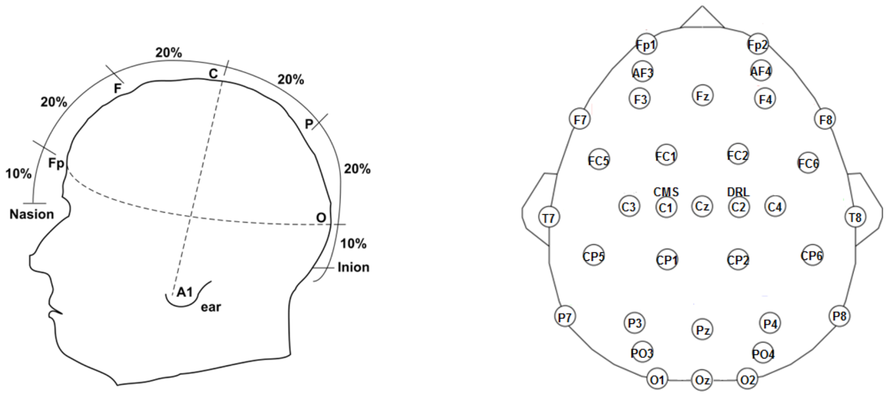
BCIs need a way to distinguish between commands based on associated brain activity. If different commands are associated with different brain areas, brain monitoring methods with a high spatial resolution, like MEG or fMRI, could be used. However, these methods require large and expensive equipment and need a magnetically shielded environment. Different commands can also be recognized by detection of brain signals in time. To measure the onset time or waveform shape of such brain waves (e.g. the SSVEP) a high temporal resolution is needed, as provided by EEG, ECoG and MEG methods. Because of its high time resolution, noninvasiveness, ease of acquisition, and cost effectiveness, the electroencephalogram (EEG) is the preferred brain monitoring method in current BCIs [10]. Therefore, EEG is the only neuroimaging technique considered in this thesis.

EEG

When a neuron fires, it causes post-synaptic currents in the post-synaptic neurons it is connected to, from the receiving dendrite to the cell body. EEG cannot measure these intercellular currents, but instead measures the opposite extracellular current that occurs in response. The electrical potentials generated by single neurons are far too small to be measured with EEG, but when thousands or millions of neurons with the same spatial orientation, radial to the scalp, become active it is detectable [25, 26]. Because voltage fields fall off with the fourth power of the radius, activity from deep sources is more difficult to detect than currents near the skull [27].

EEG measurements are done by applying electrodes to the user's scalp, often combined with the use of conductive gel or water in order to reduce the impedance. Although nowadays it is possible to do without these conductive products, "dry" alternatives do not provide nearly the same signal-to-noise ratio (SNR). Standard electrode locations are specified by the international 10-20 system, which is based on easily identified skull landmarks (see Figure 2.1). Electrodes and electrode locations are also often referred to as *"channels"*. At each electrode location, the voltage difference between the electrode at that location and a ground electrode is measured. The ground electrode can be placed anywhere on the body where no brain activity is measured.

The subject's body can pick up electromagnetic interference, specially 50 Hz noise from electrical power lines (60 Hz in some countries). Interference that appears in both ground and measuring circuit is



(a) (b)

Figure 2.1: *The international 10-20 system of electrode placement owes its name to the 10% and 20% location differences between electrodes. a) Side view of the head showing the distance between groups of electrodes. b) The electrode locations at which an EEG signal was measured in this thesis. A Common Mode Sense (CMS) active electrode is connected to C1 and a Driven Right Leg (DRL) passive electrode is connected to C2.*

called *"common-mode interference"*. Although this noise should theoretically be canceled out because voltages are measured relative to the ground, they are not in practice. Common-mode interference can be mitigated by a *"driven right leg (DRL)"* circuit, which actively cancels some of the interference by sensing the noise and negatively feeding it back into the circuit. By introducing a feedback loop between a *"common mode sense (CMS)"* active electrode and DRL passive electrode, the common mode rejection ratio can be greatly increased while the subject is protected from excessive flow of currents due to amplifier and/or electrode defects [28].

Because the ground (or DRL) electrode can be anywhere on the body, it might introduce broad body movement artifacts into the measurement. It is therefore useful to make use of a reference that is subtracted from the measured signal. This reference can be one other electrode (e.g. the center one; C_z), or a linear combination of a group of electrodes (e.g. the mean signal over the entire scalp). If one measurement electrode E_m and one reference electrode E_r are used, this will be referred to as "$E_m - E_r$". An ideal reference would pick up all of the noise that the measurement electrodes pick up and nothing else. If it picks up (part of) the desired signal, this is also subtracted out of the result, and if it picks up another signal that is neither desired nor picked up by the measurement electrodes, this is "subtracted in".

Electrodes can be *active* or *passive*. Passive electrodes are metal discs with a connecting wire to the electronic circuitry that amplifies the signal. This means that any interference occurring between the measurement at the electrode and the signal's arrival at the amplifier is amplified. Active electrodes have amplifiers on them, which ensures that as little noise as possible is amplified along with the signal. Using active electrodes increases the SNR and decreases interference and the influence of impedance, so skin preparation is not necessary.

2.2 Visual Evoked Potentials

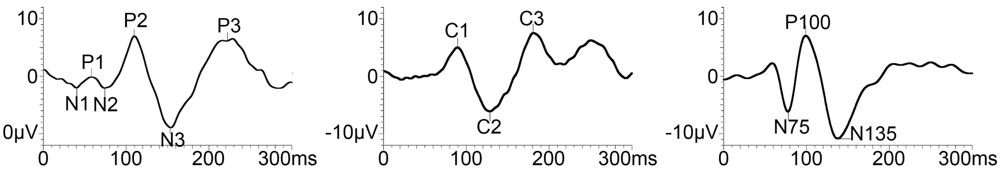
An evoked potential, contrary to spontaneous potentials, is an electrical potential recorded from the brain following presentation of a stimulus. Evoked potentials are time-locked to the stimulus and can be either transient (one time) or steady-state (repetitive). A *"visual evoked potential (VEP)"* is simply an evoked potential that is elicited by a visual stimulus.

Visually evoked responses are substantially enhanced if the visual stimulus falls within the area of spatial attention [29]. This effect is more prominent in the right frontal hemisphere than in the left one; however, this hemispheric asymmetry disappears after long repetition of the stimuli [30].

When light hits the human retina, it is absorbed by two types of photoreceptors: *rods* and *cones*. The rods are more numerous and sensitive, but are incapable of perceiving color. Furthermore, there are very few rods in the center of the eye, (i.e. the fovea). There are three different kinds of cones that are sensitive to light of different wavelengths (colors). The red and green cones are mostly concentrated around the fovea. Approximately 64% are sensitive to green, 32% to red and only 2% to blue light. However, the blue cones are relatively more sensitive.

Activation from each visual field is then sent contralaterally to the lateral geniculate nucleus (LGN) along three different pathways [12]. The M-pathway (named after the magnocellular neurons it is connected to) goes through brain areas V1, V3, V4 and IT, and represents the "where" part of visual information. It is involved in the detection of coarse and dynamic shapes, motion and depth, and is primarily associated with the rods in the retina. The P-pathway (after "parvocellular") is mostly connected to the red and green cones and is involved in the detection of high spatial contrasts, color information (specifically red and green) and details. Moving through the V1, V2, MT and STS/PP areas of the brain, it is slower than the M-pathway and represents the "what" part of visual information [31]. Fairly recently, a third K-pathway (after "koniocellular") was discovered that has properties that are roughly in between those of the M- and P-pathways in terms of speed and contrast perception. Originating mainly from the blue cones, the K-pathway also carries blue and yellow color information.

2.2.1 Transient Visual Evoked Potentials



(a) Flash VEP. (b) Pattern onset/offset VEP. (c) Pattern reversal VEP.

Figure 2.2: *Transient visual evoked potentials (tVEPs) elicited by different stimulation methods. These tVEPs can be elicited by any change in the visual field (figure from [32]). The most frequently used techniques are flashing a light (a), letting a pattern appear on a screen (b), or reversing the phase of a pattern (c). The evoked responses differ based on the stimulus used to elicit them. Characteristic peaks and valleys are given names for convenience.*

Transient visual evoked potentials (tVEPs) can be elicited by any change in the visual field. The most often used techniques are flashing a light (flash VEP), letting a pattern appear on a screen (pattern onset/offset VEP), or reversing the phase of a pattern (pattern reversal VEP). The evoked responses differ based on the stimulus used to elicit them [32] (see Figure 2.2). Flash VEPs consist of a series of negative and positive waves, most prominently are the N2 (90 ms) and P2 (120 ms) peaks. Pattern onset/offset VEPs have three main peaks: C1 (positive, 75 ms), C2 (negative, 125 ms) and C3 (positive, 150 ms). Pattern reversal VEPs consist of the N75, P100, and N135 components. Peaks in an evoked potential are often numbered (C1, C2, C3, ...) or named after the time at which they occur and the sign of the voltage (e.g. the N75 is a negative peak occurring 75 ms after stimulus onset). Transient VEPs can have many diagnostic uses for both cognitive and vision disorders [12].

The most well-known transient evoked potential is the P300 oddball response. It is elicited by infrequent (unexpected), task-relevant stimuli. Although the EEG signal is most strongly acquired around the parietal electrodes (contrary to most VEPs, which are most active over the visual/occipital cortex), interactions involving the frontal and temporal regions as well as several deep brain loci have been suggested [33]. The P300 can be used to aid in some forms of lie detection. In a proposed ”guilty knowledge test [34]” a subject is interrogated via the oddball paradigm much as they would be in a typical lie-detector situation. This practice has recently enjoyed increased legal permissibility while conventional polygraphy has seen its use diminish, in part owing to the unconscious and uncontrollable aspects of the P300. Since the response is greatly modulated by attention, the P300 can also be used in brain-computer interfacing, where the system can detect what stimulus the user is attending to.

Detecting and evaluating transient VEPs is complicated because there may be significant inter and intra subject variation in responses to the same stimulation. Because of this, it is often necessary to average data from multiple trials in order to get the characteristic waveform. This can be problematic in applications where a one-time event is signalled by the stimulus, and in applications where this is possible, it can make detection and evaluation of tVEPs slow and complex.

2.2.2 Steady-State Visual Evoked Potentials

About 40 years ago, Regan [35] started experimenting with long stimulus trains, consisting of sinusoidally modulated monochromatic light. These stimuli produced a stable VEP of small amplitude, which could be extracted by averaging over multiple trials. These EEG waves were termed as “steady-state” visually evoked potentials of the human visual system.

Focusing on a repetitive visual stimulus that oscillates at a frequency between 1 and 100 Hz [36], a *“steady-state visual evoked potential (SSVEP)”* is elicited in the brain at the frequency of the stimulus and its harmonics. If the stimulus is not flashing, but rather reversing a pattern, the SSVEP occurs at the reversal rate and harmonics. SSVEPs can be distinguished from tVEPs because their constituent discrete frequency components remain closely constant in amplitude and phase over a long time period [37].

The SSVEP starts approximately 300 ms after stimulus onset and is preceded by a tVEP of that length. The nature and source of this response is a matter of debate. Some research has suggested that this phenomenon is nothing more than a sequence of VEPs elicited by each of the state changes in the RVS [20]. However, a lot of research is operating under the assumption that it is safer to assume a less linear relationship between the stimulation and the SSVEP response.

On the other hand, the SSVEP, much like tVEPs, can also be used for diagnostic goals [12]. Its amplitude is also greatly modulated by attention, which makes it suitable for use in BCIs. Because of their nature, it is possible to evaluate the presence or absence of an SSVEP response in the frequency domain, rather than or in addition to in the time domain. This makes detection of the signal much more robust than simply detecting single trial tVEPs and faster than detecting tVEPs averaged over multiple trials. SSVEPs are less susceptible to artifacts produced by blink and eye movements [13] and to electromyographic noise contamination [14]. SSVEPs can be relatively easily quantified and reproduced; in contrast, it is hard to describe, quantify, and reproduce transient VEPs [15].

Medium- and high-frequency components in SSVEPs have been attributed to two different but potentially overlapping visual cortex sources, located primarily in V1 [38]. Conversely, low-frequency components of SSVEPs may be generated not only by cortical regions [39]. On the ground of topographical distribution, several authors have suggested that low-frequency SSVEPs originate in subcortical structures, at the retinal level or in fiber tracts. Recently, an early low-frequency SSVEP response was observed in the LGN, recorded by implanted electrodes in a human patient [40]. This confirms that low-frequency SSVEPs originate prior to cortical areas.

Different parts of the cortex besides the occipital area may play an important role in the generation of SSVEPs: a recent fMRI study reported 3-5 Hz SSVEPs in the medial frontal cortex as well (Brodmann areas 11 and 10, just above the eyes). Therefore, SSVEPs seem to occur in a large-scale functional occipitofrontal cortical network, which may be functionally connected to certain extracortical structures [41].

The strongest local source of SSVEPs is located in the striate cortex (V1), but this source does not seem to be entirely responsible for SSVEP generation [42, 41]. Figure 2.3 shows the propagation of the SSVEP response throughout the head [12].

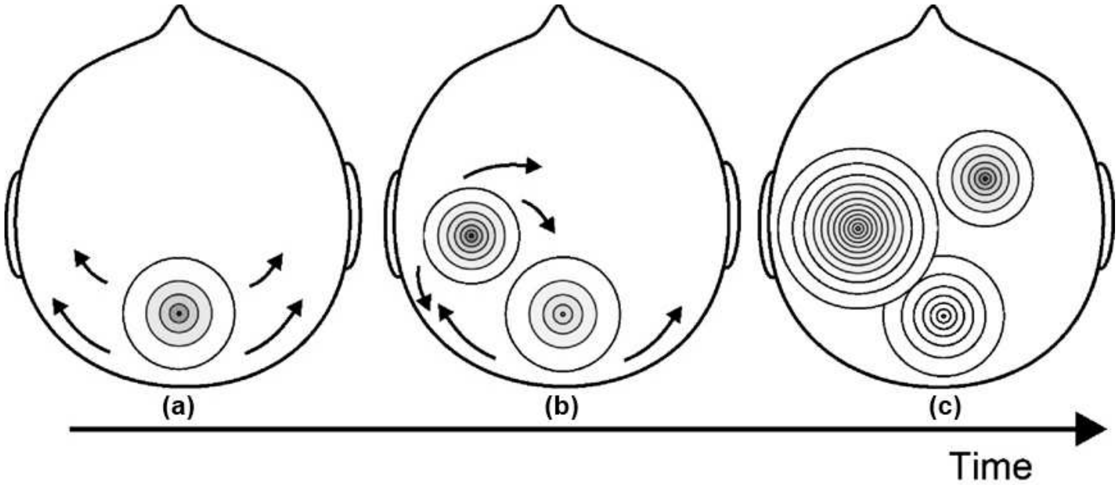


Figure 2.3: *SSVEP propagation by the combination of locally and broadly distributed sources. The concentric circles with red colors represent dipoles, and the arrows their propagation. a) Preliminary local activities in primary visual areas, observable with PET/fMRI, start propagating. b) The activity propagation, in turn, activates secondary broad sources (observable with EEG). c) The VEP reaches its steady-state with a succession of local and broad dipoles. These dipoles depend on stimuli characteristics, which explains the complex patterns observed in EEG topography. Figure adapted from [12].*

2.3 Repetitive visual stimulation

A *"repetitive visual stimulus (RVS; plural: RVSi)"* (also known as "intermittent photic stimulus") repeatedly cycles through a number of extreme states (e.g. light on and off). The number of states is almost always 2. The transition between these states is defined by the waveform of the stimulus (see Section 4.5). For instance, a square wave is used for instant transitions, whereas a sine wave or triangle wave can be used for smoother transitions. Smoother transitions require that the stimulation device can render intermediate states. The time spent in each state does not necessarily need to be the same. The *"duty cycle"* of an RVS denotes the percentage of time spent at (or near) one of the states.

The frequency that is most often reported is the *"cycle frequency"* and denotes the number of times that the entire set of states is repeated per second. The *"change frequency"* or *"alternation frequency"* denotes the number of state changes per second. In this thesis "10 Hz stimulation frequency" always refers to the situation where both states are shown 10 times in one second, in which time 20 state changes occurred. When one of the states is a simple unpatterned stimulus and the other closely resembles the background, the stimulus in a sense elicits a series of flash VEPs (see Figure 2.2(a)) at the (cycle) frequency. When pattern reversal is used (e.g. a checkerboard changing phase) the SSVEP is evoked primarily at the change/alternation frequency (i.e. the cycle frequency's second harmonic).

RVSi can elicit epileptic seizures with luminance or chromatic stimuli in about 0.01% of the population [43]. The most famous case happened in Japan during the Pokémon TV show in 1997, where flashing red-blue images induced massive photoepilepsy and photosensible migraines [21, 22]. Epileptic responses were reported from 3 Hz and up to 84 Hz but with predominance between 10 and 20 Hz. The chromaticity of the stimulus also has a strong impact on the response effect, and especially low luminance chromatic stimuli using red colors can induce epileptic responses [23]. A large size or bright stimulus is also more likely to evoke seizures [43]. Furthermore, repetitive visual stimuli can be very annoying and tiring to look at, making it less likely that someone would want to use the BCI in the first place.

Brainwave entrainment

By evoking an SSVEP response, RVSi introduce activity in the brain at a certain frequency. When brain rhythms form of their own accord, they have been associated with certain mental states (see Table 2.1). It is currently not definitively known if introducing a certain frequency of activity in the brain – by means of repetitive stimuli – actually elicits these mental states, but this is being actively researched [44].

Rhythm	**Frequencies**	**Mental states**
delta δ	0-4 Hz	slow wave sleep, continuous attention
theta θ	4-7 Hz	drowsiness, arousal, idling
alpha α	8-12 Hz	relaxation
beta β	12-30 Hz	alertness, working, concentration
gamma γ	30-100 Hz	meditation, memory matching, cross-modal sensory processing

Table 2.1: *Examples of different brain rhythms and the mental states with which they are commonly associated.*

"Brainwave entrainment" is the process of purposely inducing a certain brain rhythm by means of repetitive stimulation. Simply put, the assumption of the therapeutic application of brainwave entrainment is that if a certain brain rhythm becomes more prominent in a certain mental state, eliciting that brain rhythm (e.g. an SSVEP with the right frequency) will cause the user to slip into that mental state. If this assumption is true, it has tremendous implications for all sources of rhythmic stimulation like CRT monitors, lighting and sound-making machinery.

If used purposefully, brainwave entrainment can produce very useful results enhancing mood, performance, memory and attention or decreasing stress, pain and behavioral problems [44]. These results are all very promising, but they also imply that great care should be taken with rhythmic stimulation, because otherwise there might be a risk of inducing the wrong brain states. Long term effects on the brain and cognition should be researched.

2.4 Brain-Computer Interfaces

A brain-computer interface (BCI) or brain-machine interface detects the presence of specific patterns in a person's ongoing brain activity that relates to the person's intention to initiate control and translates these activity into meaningful commands. It gives users communication and control channels that can be used instead of or in addition to the normal output channels of peripheral nerves and muscles [11, 45]. Applications range from enhancing the experience of playing a video game, to driving a wheelchair, to writing messages. BCIs are currently mostly used to enhance the quality of life for nearly locked-in patients to allow them to communicate and to control devices that would normally require the muscle control that they have lost.

Because it is currently not yet feasible to determine what a user is thinking about by analyzing his brain signals, BCIs have a number N of predefined commands that the user must choose from. The manner in which this choice is made depends on the type of BCI. For instance, a user could concentrate on a stimulus or imagine moving a body part associated with the desired command. The BCI system needs to detect that a command was issued and determine which command it was.

Applications and target demographics

Applications of SSVEP-based BCIs are generally focused on disabled people [45]. These people have often lost control over most of their muscles and struggle with basic tasks such as driving their wheelchair, controlling home appliances and sometimes even communicating with health care professionals and loved ones.

In order to expand the target demographic, researchers are now also investigating the application of SSVEP-based and other BCIs into more mainstream areas like video gaming [9]. Although BCIs are currently not nearly fast enough to compete with more traditional input devices such as the keyboard, the mouse and the controller, having an additional channel can be beneficial. In some games proficient players perform over 200 actions per minute, and it is suggested that the bottleneck in speed might very well be physical, suggesting that additional use of a BCI can be beneficial. It might also be more fun due to the novelty or even because of increased immersion. Situations where the user literally or figuratively has their hands full are called *"induced disability"* and can be improved by BCI use [45]. This means that military personnel, surgeons, astronauts and many others might benefit [46, 47].

Another possible application could be to provide additional information to a user based on what he is looking at. People in a museum could for instance be provided with auditory information about the painting they're looking at.

SSVEP can also potentially be used in passive BCIs. These system make use of the information extracted from the brain in order to make the interaction with them smoother. Links have been found between the SSVEP and alertness and emotion [48, 49] and research is currently being done in how to incorporate this knowledge in BCIs. It is also easy to imagine using the SSVEP to set things such as screen brightness and contrast automatically.

Before thinking of who might *want* to use BCIs, it is important to consider who *can* use them effectively. Inter-subject variability often leads to the well-documented "BCI illiteracy" phenomenon; across different BCI approaches (SSVEP, P300, motor imagery), about 10-25% of users are unable to attain effective control [50, 51, 52, 53, 54, 7, 55]. SSVEP-based BCIs can be used by more than 90% of users without much training, in contrast to most current systems that use other brain activity [18, 3, 19]. Being young, female and having a gaming background correlates positively with SSVEP-based BCI performance [56]. Older subjects often have smaller evoked potentials in visual attention tasks.

BCI aspects

There are several dimensions along which a BCI can be qualified. For instance, they can be endogenous/active or exogenous/reactive [11, 10]. *"Endogenous"*/active BCIs utilize the brain activity corresponding to intended actions as electrophysiological source of control. This category comprises BCIs using sensorimotor activity, slow cortical potentials, and mental tasks. Endogenous BCIs provide a better fit to a control model because the trained user exercises direct control over the environment. On the other hand, these systems often require extensive training. These BCIs are necessarily *"asynchronous"*, which means that the system has no way of knowing a priori when a command might be issued. *"Exogenous"*/reactive operation refers to the utilization of brain responses to external stimuli as electrophysiological source of control. SSVEP and P300 based BCIs are in this category. Exogenous BCI's may not require extensive training, but do require a somewhat structured environment (e.g. stereotyped visual input). These systems can be *"synchronous"*, because they control the stimulation that the brain is reacting to.

Applications relying on the use of brain activity as an additional input, allowing the real time adaptation of the application according to the user's mental state are categorized as *"passive"* BCIs [57]. In contrast to more conventional (controlled) systems, the user is not consciously controlling a passive BCI. Instead, the system is 'eavesdropping' on the user's brain activity so that it can, for instance, make use of the user's finely tuned error detection capabilities (see Appendix A), notify the user of a lapse in alertness, or make adjustments to the application in reaction to a change in the user's mood [10].

A BCI is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain's normal output pathways of peripheral nerves and muscles [11]. A *"dependent"* BCI does not use the brain's normal output pathways to carry the message, but activity in these pathways is needed to generate the brain activity (e.g. EEG) that does carry it. Most VEP-based BCIs are typical examples of dependent BCIs, because they require the user to shift his gaze to the visual target associated with the desired command, which makes them dependent on the muscles required to move the eyes. Since the primary target audience of BCIs consists of severely disabled people, it is useful to try and make them *"independent"* of muscle activity.

2.4.1 Functional model

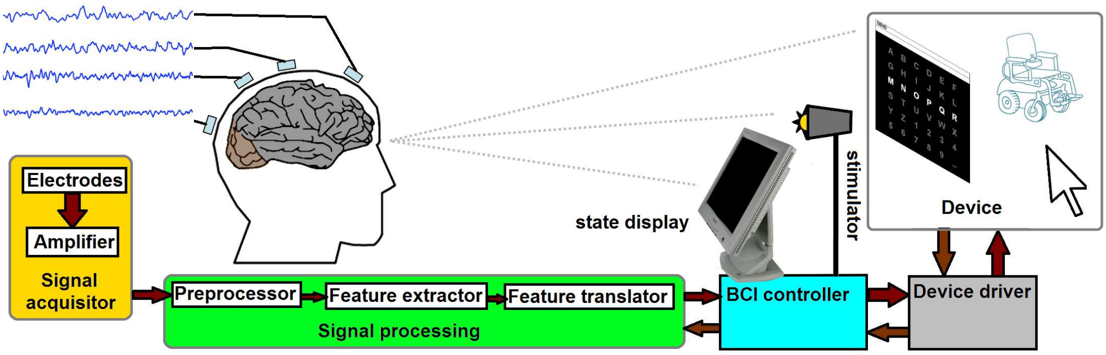


Figure 2.4: *Functional model of a BCI system (adapted from [58]).*

Figure 2.4 depicts the functional model of a BCI system that uses visual stimulation (adapted from [58]). The *"user"* modifies his or her brain state in order to generate the control signals that operate the BCI system. The *"signal acquisitor"* converts the user's brain state into electrical signals. The acquisitor usually amplifies the electrical signal measured with electrodes on the user's scalp in order to increase the quality of the signal. Active electrodes contain an amplifier themselves, whereas passive electrodes rely on an external amplifier, which might then also amplify some of the noise that was introduced on the way from the electrodes to the amplifier.

The *"signal processing"* component is responsible for converting the signals from the brain into logical (device-independent) control signals. Three distinct components can be identified. The goal of the *"preprocessor"* is to increase the signal-to-noise ratio of the signal. This can be accomplished by filtering out power line interference and/or by detecting and handling artifacts (e.g. caused by movement). The *"feature extractor"* then transforms the cleaned up signals into feature values that correspond to the underlying neurological mechanism used for controlling the BCI. The *"feature translator"* finally translates the feature vector into logical (device-independent) control signals.

The *"BCI controller"* translates the logical control signals from the classifier into semantic control signals that are appropriate for a particular type of device. This mapping may be instantaneous (i.e. its output is calculated directly from the current logical control signal input) or by integrating inputs over time (e.g. if a letter is typed by selecting its X and Y coordinates in a letter matrix of a speller program). The controller is the central unit in the BCI as it is connected to most other components. It can receive input signals from the user, their brain and the device so that it knows exactly what is going on. Using this information, it can display the system state to the user to give them feedback. In addition, it also has control over the stimulator and the signal processing component. Imagine a primarily SSVEP-based BCI that has a command to turn it partially off. If this command is issued, the controller could turn off the control display, stimulator and device and swap the SSVEP signal processing unit out for a signal processing component that detects imagined movement, so the user can turn the whole system back on.

All of these components can be device-independent to a degree. In order to finally control an actual device, a *"device driver"* is needed to map the commands from the system onto inputs that the specific device accepts. If the device has outputs, it is also the device driver's task to translate those back so that the controller may know about the state of the device. The device or application finally executes the commands and the user observes the behavior so he can decide what to do next.

Although these units can be viewed as separate components in a functional model. It is common for several units to be integrated. For instance, the device can often be an application that runs on the same computer as the rest of the system. Stimulation can be rendered by an external device, but can also be displayed on the same computer screen that is used for displaying the system and the device state. It is however useful to distinguish between these components, because it allows us to evaluate them separately. Ideally, it should be possible to use the same system with, for instance, different feature translators in order to determine which one works the best. This thesis focuses on properties of the stimulation and evaluates them in the context of a BCI where all the other components remain constant.

2.4.2 Signal processing

The signal processing in a BCI consists of three steps: preprocessing, feature extraction and feature translation. During the preprocessing step artifacts and noise can be removed from the signal. Next, features are extracted from the data and translated into commands. In SSVEP-based BCIs the features often consist of the energies of all the stimulation frequencies in the most recent part of the signal. Feature translation could then be accomplished by determining thresholds for each frequency and selecting the one where the energy exceeds this threshold.

Preprocessing

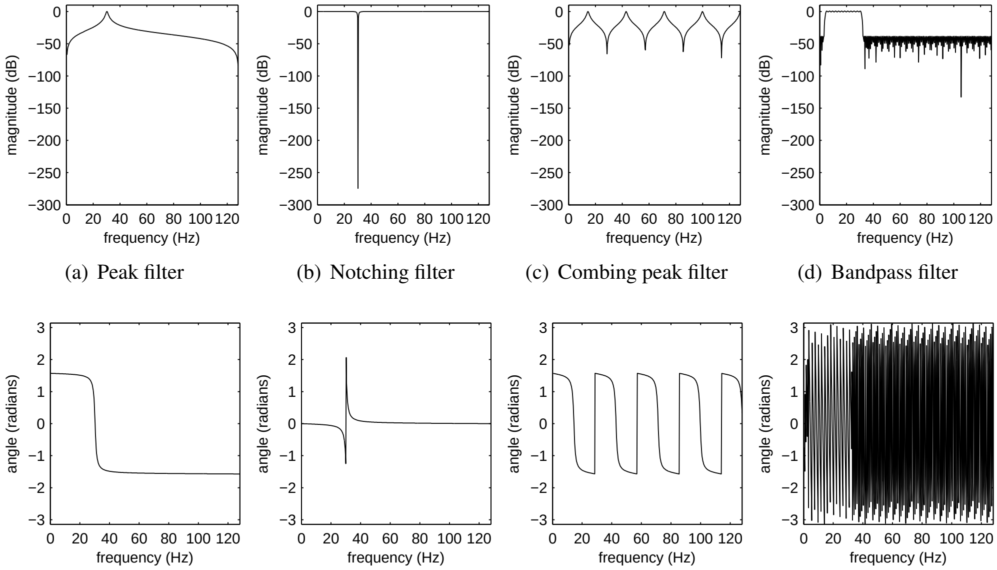
The goal of the preprocessing step is to enhance the signal-to-noise ratio (SNR) of the brain measurements. The idea is to remove, reject, or repair parts of the signal that contain noise and artifacts that may interfere with the later signal processing stages. These can be caused by muscle movements (e.g. eye blinks), electrode movement, power line interference (50 Hz in Europe) and spontaneous brain activity (e.g. alpha rhythms).

The preprocessing stage is somewhat dependent on the other signal processing stages. The feature extraction stage determines what should be considered as signal and what should be considered as noise, and the classification stage's accuracy places a certain demand on the quality of the input it requires in order to operate sufficiently well.

Power line interference can often have an amplitude that dwarfs that of the relevant signal, which complicates analysis. It can be dealt with by applying a notching filter with the power line frequency. By using a comb filter, all harmonics of the power line frequency are dealt with as well.

If the relevant parts of the signal are all in a known frequency range, it is possible to use a bandpass filter to exclude frequencies outside that range in order to remove all of the noise that occurs outside that range. Similarly, high pass and low pass filters can also be used. Filtering out low frequencies can exclude some movement artifacts, and filtering higher frequencies can remove power line interference and some muscle artifacts (such as teeth clenching). Sometimes it is also desirable to exclude a range of frequencies (e.g. the alpha range), in which case a bandstop filter can be used.

Figure 2.5 shows how some of these filters transform the signal. They attenuate the (hopefully undesired) frequency components while leaving others intact. Unfortunately, it is impossible to only filter the desired frequencies. Components with similar frequencies will always be affected. Furthermore, the



(a) Peak filter (b) Notching filter (c) Combing peak filter (d) Bandpass filter

(e) Peak filter (f) Notching filter (g) Combing peak filter (h) Bandpass filter

Figure 2.5: *Effects of different IIR filters on a signal. Top: effect on magnitude for each frequency, bottom: effect on phase. The first three filters are centered around 30 Hz, the last is a bandpass filter between 5 and 30 Hz.*

bottom row shows that these filters can also alter the phase of the signal in some frequency bands. Finally, in order to determine the new value of a point in the signal, these filters use the values of preceding points. Since in the beginning there are no preceding points, the effect is that the first values of the filtered signal are not accurate. This effect diminishes gradually and the anomalous part is sometimes referred to as the transient of the filter. This part should not be used in analysis.

Another way of dealing with spontaneous brain activity is to do baseline substraction in the frequency domain [59, 60, 61, 62]. This baseline activity should contain (some of) the spontaneous brain activity that will also occur during BCI operation. Baselines are often recorded during a period in which the user is asked to do nothing (and sometimes even close their eyes). A disadvantage of this is that the task might affect the spontaneous brain activity, which would render the substraction less useful. Another approach is to take the baseline during execution of the task. Such an activity baseline contains more relevant spontaneous activity, but also the relevant signal. This can be remedied by taking baselines for all conditions of a task (e.g. focusing on all of the targets in an SSVEP-based BCI) and averaging the spectra to get the activity baseline. This baseline still contains the relevant signal(s), but to a much smaller degree than the actual signal should have.

The noise discussed up to now has been distributed over the entire (relevant) signal measured from the brain. Artifacts are more local in time. Some will have already been filtered using previous means. For instance, teeth clenching causes a fairly high frequency muscle artifact, which might already have been dealt with by a lowpass filter, and low frequency head movements can be eliminated by highpass filters. Often though, these artifacts are not filtered and need to be detected. There are many different ways to do this that are beyond the scope of this thesis. A very simple approach is to simply see if the measured signal exceeds some predefined amplitude threshold (which might work for some artifacts). Another – more labor intensive – approach is to use visual inspection.

When an artifact is detected there are a number of possible actions. Ideally, only the artifact is removed and the rest of the signal is left intact. This is relatively hard and beyond the scope of this thesis. It is also possible to replace the segment containing the artifact by something else (e.g. the channel average) so that the segment is unremarkable, but can still be used for processing. The segment or channel with the artifact can also simply be rejected or ignored. In that case, it only makes the BCI slightly slower, but does not otherwise affect the processing.

Spatial filtering In many BCIs, the goal is to find some known evoked potential embedded in the EEG signal. It is likely that this potential is not distributed over the entire brain, but that it is primarily caused by one or more sources. Ideally, the system would get the signal from that source, and nothing else. However, multiple electrodes pick up information from the relevant source(s) as well as from other sources. The goal of a *"spatial filter"* is to convert the EEG signals obtained from each electrode location into source signals. This problem is called the *"inverse problem"* and is technically unsolvable [63]. However, using some assumptions, spatial filters can be constructed with sources that have significantly increased the signal-to-noise ratios compared to simply using a single electrode's measurements. A spatial filter takes the form of a weight matrix that determines how much each EEG signal contributes to each source.

The weight matrix can be determined using several different algorithms. Beamforming methods use information available a priori about signal sources, electrode locations and properties in the environment that might affect transmission of the signal from a source to a detector (e.g. density and composition of the head). Examples include linearly constrained minimum variance (LCMV) [64, 65], low resolution brain electromagnetic tomography (LORETA) [66] and Bayesian beamforming [67]. Independent component analysis (ICA) on the other hand makes no assumptions about the source locations in the brain and effects from the environment, but instead assumes that the sources are all statistically independent, which is not entirely correct [68]. The weight matrix is then estimated so that this assumption will hold. These methods are all independent of the extracted features and knowledge of the BCI task is not necessary.

Common spatial patterns (CSP) is a method that ensures that source power varies maximally between classes in the BCI [69]. In an SSVEP-based BCI with two targets for instance, the spatial filter would ensure that the difference in power between the two classes is as large as possible (or alternatively, a spatial filter could be constructed for each class, that maximizes the power difference between that class and "no class"). It works best in narrow frequency bands, relies on robust channel covariance matrix estimates and can be prone to overfitting. Furthermore, it requires a calibration phase in order to obtain a train set with labeled data.

Some spatial filters can also take into account the specific feature(s) that will be extracted in the feature extraction phase. In the case of SSVEP-based BCIs, the primary feature will most likely involve harmonics of each stimulation frequency. Constructing a spatial filter for each of the stimulation frequencies, can significantly increase the SNR for each target. Noise can be reduced simply by averaging the signal over a couple of electrode locations, but phase differences of the actual signal over multiple locations causes the signal to be severely diminished as well. The minimum energy combination (MEC) attempts to minimize the energy of the signals after having subtracted the relevant frequency components, thereby greatly diminishing the noise [70]. The maximum contrast combination (MCC) goes one step further and in addition also maximizes the energy of these relevant frequencies.

Feature extraction

In the feature extraction phase the elements that are used for classification are extracted from the pre-processed signal. Ideally, a feature is used that contains all relevant information and that maximizes the difference between classes. Often used examples include the energies of the frequency components for each of the targets in an SSVEP-based BCI, or the height of a peak 300 ms after the onset of a stimulus in a P300-based BCI. The feature extraction phase is the one that depends the most on the BCI paradigm used.

The feature used in the BCI used for experiments reported in this thesis (described in Section 3.4) is based on the energy of the (first four) harmonics of a target's frequency. For each harmonic, the signal is peak filtered and squared in order to get the energy. The energy is then summed over a certain time segment (1 second) and added to the summed energies of the other harmonics. This process results in a feature vector containing one energy value for each target. Another way to get a similar result is to sum the peaks of the harmonics in a Fourier spectrum.

Feature translation

In the feature translation phase, the feature vector from the previous phase is translated into something that the control interface can make sense of. The output of the translator can have discrete and continuous components. Imagine a wheelchair BCI that has a separate motor for each big wheel. The translation algorithm could have two purely continuous outputs, determining the speeds at which each wheel should turn (negative numbers mean backwards). The feature vector could also be translated into a discrete set, corresponding to commands for going backward or forward, or turning left or right. A hybrid could in addition have a continuous output value that determines the speed with which that happens.

Translations can be done using any number of algorithms. Continuous components are likely to be very application specific. For discrete components, the problem boils down to a general classification problem. Any classification algorithm can be used, from neural networks, to support vector machines, to simple comparison of feature strengths and thresholds.

Depending on the predictability of the feature vector and the specific translation algorithm used, calibration may be needed to determine appropriate parameters. The calibration period generally involves the subject performing a constrained version of the task where the data can be labeled. The length and amount of necessary repetitions of calibration should be kept to a minimum. Ideally, if the system allows for it, calibration could occur during the operation of the BCI. This allows the system to be adaptive, even during operation, which is a great advantage, because a user's brain signals may change over time due to factors like fatigue, habituation, motivation, training and distraction. The easiest way for the system to be adaptive is if it has a way of determining whether the actions it takes are correct. Another method could be to assume that it is correct most of the time and adjust parameters based on that assumption. For instance, if the second-last step of the classification algorithm calculates probabilities that each class is correct, the algorithm could be adjusted in such a way that the next time that it is presented with the same data, the difference between the highest probability and the lower ones has become larger.

2.4.3 Evaluation

BCIs can be evaluated on several different characteristics and measurements: performance, comfort, safety, usability (i.e. how many, and which, people can use it), ease of use, training time, robustness and cost. Most research focuses on improving the performance of BCIs. The performance can be represented in a number of ways. The simplest (and least informative), is to just report the accuracy of the system, which is defined as the probability P that the system correctly classifies the user's intent. What we actually want to know, however, is how much information can be communicated in a certain period of time.

A more informative performance measure is the *"bitrate "* B which measures the amount of information transmitted per symbol/target/choice/command/selection that the system makes.The calculation of the bitrate is based on Shannon's information theory and in the most general form can be reduced to the mutual information between the actual and expected classifications of the system. Nykopp's definition of the bitrate follows from this:

$$\begin{aligned}
B &= I(X;Y) = H(Y) - H(Y|X) \\
H(Y) &= -\sum_{j=1}^{M} p(y_j) \cdot \log_2 p(y_j) \\
p(y_j) &= \sum_{i=1}^{N} p(x_i) \cdot p(y_j|x_i) \\
H(Y|X) &= -\sum_{i=1}^{N} \sum_{j=1}^{M} p(x_i) \cdot p(y_j|x_i) \cdot \log_2 p(y_j|x_i)
\end{aligned} \tag{2.1}$$

, where X and Y represent the expected and actual outcomes, $p(x_i)$ gives the probability that the i^{th} symbol is expected (a priori probability), $p(y_j)$ gives the probability that any signal is classified as the j^{th} symbol and $p(y_j|x_i)$ gives the probability that the system classifies a signal as the j^{th} symbol, given that it is actually the i^{th}. I and H are the mutual information and the entropy.

Most research that reports a bitrate however, uses the simplifying assumptions first made by Wolpaw et al. [71]. First, it is assumed that all symbols have the same a priori probability (i.e. $p(x_i) = 1/N$). Second, that the classifier accuracy P is the same for all symbols (i.e. $p(y_j|x_i) = P$ for $i = j$). And third, that the classification error $1-P$ is equally distributed amongst all remaining symbols (i.e. $p(y_j|x_i) = \frac{1-P}{N-1}$ for $i \neq j$):

$$B = \log_2 N + P\log_2 P + (1-P)\log_2 \frac{1-P}{N-1} \tag{2.2}$$

These assumptions can be very reasonable. If the effects of all commands/symbols are equivalent, it should not matter which one can be classified more accurately (assumption 2). Similarly, if erroneous classifications are all equally bad, it should not matter which symbol is selected instead (assumption 3). Obviously, equal a priori probability of all symbols can be intended, or a useful estimate when the real probability distribution is unknowable (assumption 1). Furthermore, if these attributes are desired, using Wolpaw's definition will enforce them in the bitrate calculation, so that artifacts from a (bad) test run have a smaller effect (e.g. a run where the symbols were not all selected equally often by chance). Finally, it seems that using Wolpaw's calculation for the bitrate, multiplied by the average classification time, gives a better estimate of the information transfer rate in our experiments.

The *"information transfer rate (ITR)"* R represents the amount of information that can be communicated in one minute and can be estimated by dividing the bitrate by the average number of minutes it takes to make a classification. The notions of bitrate and ITR are often used interchangeably in the literature, but in this thesis "bitrate" will specifically refer to the amount of information communicated in one symbol, whereas "ITR" will refer to the information communicated in one minute.

The ITR can also be calculated more directly by multiplying the total number of correct symbols C with the number of bits needed to represent each symbol and dividing by the number of minutes T that were used:

$$R = C\log_2 N/T \tag{2.3}$$

This more accurately gives an estimate of how long it would take to complete certain tasks. However, many experiments are done offline in which the total running time of the task is not informative.

Almost every article about brain-computer interfacing mentions the performance of the considered system. Evaluation measures that represent subjective traits like user friendliness, comfort and safety are often overlooked. Most BCIs are exhausting to operate and the ones considered in this thesis can even induce epileptic seizures. Little attention is payed to these aspects, even though a user may perceive a user friendly and comfortable BCI as more valuable than a BCI with a higher ITR.

There are many other important aspects. It should be fast and simple to set the user up for BCI operation. Preferably, the user should require as little assistance as possible. The amount of training time needed to get the system working should be minimized. The measuring equipment should not be too big of a burden. Finally, and perhaps most importantly, the user needs to be able to use the BCI. This means that it is good to focus on systems that require as little muscle control as possible (independent BCIs) and that the measured feature should be easy to determine in most potential users. Ideally, the system should also be fun and rewarding to use.

2.4.4 VEP-based BCI

There are many different brain activity paradigms that can be used in brain-computer interfacing. Most BCIs provide the user with the ability to select one of a number of predefined commands by executing a task associated with the desired command. This task depends on the employed BCI paradigm. Users may be asked to imagine movement of a limb, remember a fond memory, or look at a visual stimulus.

VEP-based BCIs fall into the last category. In general, a number N of visual stimuli, called targets, are presented on the screen. Each is associated with a command and can be selected by focusing on it. Most VEP-based BCIs require that the user does this by actively gazing at the desired target, which makes these BCIs dependent on eye or neck muscles. However, because VEP amplitudes are enhanced by attention, it can also be sufficient to covertly focus on a target [72].

This is one of the main advantages VEP-based BCIs have over eye tracking systems, since these systems do require gaze shifting [55]. These systems can also not judge whether the person is actually interested in a target. Pupillary dilation and other measures available to eye tracking systems can sometimes tell if someone is zoning out, but this may require a more expensive system, significant calibration, or limited functional environments. If there are multiple targets at the same location or even gaze direction, only an VEP-based BCIs could determine which target is of interest. Finally, as BCIs are becoming more ubiquitous, some people might have access to a BCI, but not to an eye tracker.

VEP-based BCIs are reactive (exogenous). It can technically be argued that they are independent of muscle movement, since they work based on attention rather than gaze direction, but in practice many systems would not work without looking at the targets. VEP-based BCIs are mostly synchronous, since the system determines when the user can issue commands, although a perception of asynchrony can be achieved when these moments follow each other quickly and constantly. Since VEP responses occur in virtually everyone and happen involuntary, usually not a lot of training time is required and almost everyone can use them easily. Measuring VEPs usually only requires a couple of EEG electrodes, making such systems potentially relatively cheap and not extremely hard or costly to set up. Performance depends on the individual system and application, but tends to be good compared to BCIs based on other paradigms. VEP-based BCIs on the other hand are generally fairly uncomfortable to operate.

The following subsections focus on particular subparadigms of VEP-based BCIs.

P300

One of the first BCIs that was made was a system that allowed a user to spell a message by focusing on the individual letters [73]. Imagine a 5×6 matrix of greyed-out letters (and some punctuation) where one briefly lights up at a time. When the letter that the user was focusing on lights up, this causes a P300 response to be measured.

Especially in the early days, it was impossible to detect this response in a single trial [74]. Therefore the responses to multiple trials were averaged together until a P300 response could robustly be distinguished. Since there is some intra subject variability in P300 latency, the flashes of the letters have to be spaced sufficiently far apart in time. Even if we underestimate the inter-stimulus-interval (ISI) at 50 ms and the number of trials necessary for robust classification at 5, it would take at least 7.5 seconds to classify one character. In [74] the ISI was 100 ms and the number of trials necessary to get 80% classification accuracy was approximately 10.

There are a number of ways in which this process can be sped up. The letters can be rearranged and selected by moving a cursor in four directions and confirming the current selection [75]. Since there are only five targets (four arrows and a confirmation button), it would appear that one round of flashes would take only 250 ms ($5\cdot50$), so selection would take 1250 ms, and since at most 5 buttons have to be selected for one selection, this would lead to a total selection time that is likely to be lower. However, depending on the classification algorithm, a time of at least 400 ms should be between two flashes of the same target, because of the length of the P300 response. This means that the worst-case scenario would take 10 seconds, although the average letter selection time may still be lower than that of the original system. It appears however, that P300 systems lose some of their strength when the number of targets is smaller than the P300 response duration divided by the required inter stimulus duration.

Alternatively, it is possible to light up multiple letters at a time (e.g. an entire row or column in a matrix) [74]. If the flash sequence of each letter remains unique, the P300 should still be detectable, but since more than one letter is flashed at a time, the time it takes for a letter to flash the required number of times is decreased. A really simple design could sequentially flash all the 5 rows first, wait 400 ms, flash all the 6 rows, again wait 400 ms, and repeat. In the example, it would take 2.5 of these rounds to get 5 trials, so the selection of one letter should take at least 3.25 seconds.

SSVEP

In SSVEP-based BCIs all of the targets are repetitive visual stimuli that oscillate at a (usually) different frequency. When the user focuses his attention (overtly or covertly) on the desired target, the measured brain activity's frequency components for the target's frequency and harmonics increases. This allows the system to determine which target the user was focusing on. This method is called *"frequency tagging"*, since each target is tagged by a frequency. Since all targets are generally on all the time and simultaneously, there is no waiting time for a flash. Analysis of frequency components is easier and more robust than the analysis needed in tVEP-based BCIs and there is less inter- and intra subject variability in the

SSVEP response. Since averaging over multiple trials is generally not necessary, SSVEP-based BCIs can get higher performance than other BCIs.

Looking at RVSi can be annoying, tiring and epilepsy inducing. Furthermore, when a lot of targets are present in the BCI, a lot of different frequencies are needed. Consequently, some of these frequencies will be very close to each other, which means that classification errors become more likely and that the time segment needed for classification is large (because the frequency resolution of the Fourier transform is inversely correlated with the length of the data). The first problem is even worse on stimulation devices with low framerates, like computer monitors, since these can only generate a limited set of frequencies accurately (see Section 4.2).

There are a number of ways in which this can be remedied. Instead of, or in addition to, using frequency tagging, it is also possible to use *"phase tagging"*. Multiple targets with the same frequency, but phase difference φ, elicit SSVEP responses with the same phase difference φ. Phase analysis appears to be a little harder and less robust than frequency analysis, but it has great potential, because frequencies that the user responds to well can be used multiple times. Using phase information on low framerate devices is still problematic however, since only few different phases can be rendered for accurately displayable frequencies. Especially if the frequencies are high. Another possible remedy is to combine frequencies (see Section 4.3.2 for more information).

Noise tagging

"Noise tagging" [76] can be considered a mix of the previous two paradigms. Like in the tVEP-based BCIs (e.g. P300), each target's flash pattern is unique. However, in the noise tagging paradigm, the goal is not to extract a certain waveform. The flashes in this paradigm generally follow each other very quickly (like when eliciting an SSVEP) [77], which makes it impossible for a proper and characteristic P300 potential to form. Compared to the constant-frequency SSVEP eliciting stimuli, the seemingly random blinking sequences used in noise tagging stimuli look like noise. The sequences of the targets are however not random, but carefully selected to be unique and have the largest possible inter target distance. Since there is no constant frequency, and no time for a proper waveform to form, frequency and waveform analysis cannot be used. Instead, noise tagging approaches work by determining the correlation between the signals from the brain and the known sequences of the targets [77].

Noise tagging has some advantages compared to the other paradigms. It can more easily be used in systems with a lot of targets than SSVEP-based approaches, because the latter often have to choose from a certain number of suitable frequencies. Furthermore, it might be easier to design noise sequences that have a larger distance to each other than it is to select distant frequencies, making these systems more robust. Compared to P300 systems, it seems that noise tagging could potentially be faster, because the unique sequence of each target is presented more quickly.

The main disadvantage of this method is that fairly little is known about it, especially in the visual domain. It is not yet clear if correlation analysis can compete with frequency and waveform analysis methods that are available for SSVEP and P300 paradigms. Furthermore, it is unknown if these systems can be made independent, like P300 and SSVEP systems. Finally, it seems likely that noise tagging BCIs will not be able to compete with SSVEP-based BCIs in terms of speed.

Summary

Brain-computer interfaces are systems that give users the ability to communicate and control without using their muscles, by measuring activity from the brain. There are many different techniques for measuring brain activity. Because of its high time resolution, noninvasiveness, ease of acquisition, and cost effectiveness, the electroencephalogram (EEG) is the preferred brain monitoring method for SSVEP-based BCIs. When the eye detects a visual stimulus, a visual evoked potential can be measured. The strength of this response is modulated by attention as well as properties of the stimulus. Repetitive visual stimuli cycle between a number of states (usually 2) at a (usually) fixed frequency and thereby elicit an SSVEP response with the same frequency and harmonics. By analyzing the measured brain activity, the BCI can deduce which of several targets the user was focusing on. By executing a command associated with that target, the user is provided with an additional channel for control or communication.

This can be especially useful to patients who have lost control of some of their more conventional output pathways. However, healthy people can also benefit from having extra output channels. For instance when their conventional output channels are already fully occupied, or when system control using the brain is simply more convenient or fun. BCI performance (i.e. the speed and accuracy of the system) is very important to achieve this, and so are user comfort and safety.

BCIs based on the SSVEP have been shown to provide high performance, low training times, robustness and usability. On the other hand, the repetitive visual stimulation they require can be uncomfortable and even induce seizures in photosensitive epileptics. By carefully choosing the properties of stimulation, these disadvantages might be decreased, while the promising nature of this paradigm in brain-computer interfacing is preserved.

Chapter 3

Experimental setups and methods

This chapter outlines several experimental setups that were often used in the research for this thesis. Details of the actual experiments are not discussed here, but in the sections of Chapter 4 corresponding to the subject of these experiments. This chapter lists the hardware (Section 3.1), software (Section 3.2) and analysis methods (Section 3.3) used in the experiments. Furthermore, it gives a detailed description of the Experimentation BCI, which was used in many of the experiments (Section 3.4) as well as some general properties of the other, offline experiments that were carried out (Section 3.5).

3.1 Hardware

In order to carry out all experiments, a number of different stimulation devices were used in conjunction with either a signal generator or a computer. Additionally, a system for doing the EEG measurements is also necessary. This section describes the hardware used in the experiments that are reported in this thesis.

Stimulation devices For this research there were four stimulation devices available to us: an LCD, a CRT, a set of four green LED boxes (see Figure 3.1) and a white LED panel (see Figure 3.2). The white LED panel could be obscured so that only a 5×5 cm part of it was visible. The most important characteristics of the devices are summarized in Table 3.1. The refresh rates of the LEDs are determined by the Agilent signal generator used to drive them (see Section 3.1).

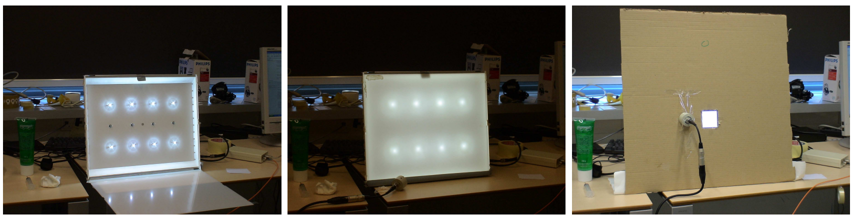
	LCD	**CRT**	**Green LEDs**	**White LED panel**
Brand	Philips	Philips	-	-
Type	$180P_2$	107P	-	-
Refresh rates	60/75 Hz	60/75/85 Hz	20 MHz	20 MHz
Size (cm)	36×28.8	32.4×24.7	8×8	50×30 / 5×5

Table 3.1: *Light stimulation devices*

(a) (b) (c)

Figure 3.1: *The green led box that was used.*

(a) (b) (c)



(d) (e) (f)

Figure 3.2: *The white led panel that was used.*

Agilent signal generator Whereas the computer screens can simply be driven by a computer, the LEDs receive their signal from a dedicated signal generator. The Agilent 33220a arbitrary waveform generator can generate sine, square, pulse, triangular and arbitrary custom-programmed waves. It has a TCP/IP interface that allows for automatic control.

BioSemi acquisition system A BioSemi ActiveTwo system was used to acquire all of the EEG signals from the brain. It has 32 active EEG electrodes in addition to a ground and a driven right-leg, which are connected to C1 and C2 on the 10-20 international system for electrode placement. The remaining electrodes are also placed according to the 10-20 system as shown in Figure 2.1.

In addition to acquiring EEG data, a light sensor could also be attached to the ActiveTwo system. This made it possible to exactly synchronize the EEG data with the stimulation.

3.2 Software

MATLAB Extensive use was made of The MathWorks' MATLAB development environment (version 7.8.0.347 (R2009a) [78]) for signal processing, data analysis, visualization and experiment design. The Filter Design toolbox was used for filtering the data, and the Statistics toolbox was used for statistical analysis, using especially the Student's t-test.

Psychtoolbox Psychtoolbox is an open source toolbox for MATLAB that, amongst other things, offers tools for fast and accurate visual stimulation [79]. It was not used for online experiments, because MATLAB lacks the threading support necessary for simultaneous (dynamic) stimulation and signal processing.

Neurostim Neurostim is an open source, OpenGL based, OS-independent C++ library for the presentation of visual stimuli in Neuroscience experiments [80]. It is used for the implementation of the Experimentation BCI (see Section 3.4), because it has good graphical and TCP support and allows for easy integration of stimulation and application modules.

BCI2000 BCI2000 is a general-purpose system for BCI research, written in C++ [81]. A BCI created with BCI2000 consists of four programs that communicate through the TCP protocol. There is a main controller, as well as separate programs for data acquisition, signal processing, and the application. In the Experimentation BCI, we used third-party modules for data acquisition using the BioSemi device and for delegating the signal processing task to MATLAB. The application module was left empty (a no-op), because a custom interaction with a Neurostim application was used directly from the signal processing module.

Java The Java programming language (version 6) was used to create a TCP networking module that could be called from the command line. This enabled easy use of TCP networking in MATLAB.

LabVIEW National Instruments' LabVIEW [82] was used by BioSemi to make the program ActiView to control their ActiveTwo acquisition system. Additionally, LabVIEW was used to run some of the earliest experiments that were done in this thesis.

3.3 Analysis methods

3.3.1 Fourier transform

Most signals are first considered in the time domain, because it is the way that the signals are gathered in the physical world: e.g. voltages at different time points. The time domain can be converted to the frequency domain, since frequency is simply "per amount of time". Where the time domain shows the amplitude of a function at each point in time, the frequency domain shows the amplitudes of sine and cosine waves modulated at each frequency. The (repeating) signal can be reconstructed in the time domain by adding all these sines and cosines back together. The Fourier spectrum shows for each frequency the sum of sine and cosine amplitudes (called the magnitude), or the square thereof (called the power).

Collections of neurons are continuously firing, often at fixed frequencies. This makes frequency analysis of the EEG signal very useful. The amplitudes of frequencies in different ranges, gives information about different states of mind, like idling (theta), relaxing (alpha) and working (beta and gamma). It is also extremely useful for SSVEP analysis since it directly shows the strength of the response for all harmonics over a certain period of time.

The range of frequencies that can be represented in the Fourier spectrum depends on the time resolution and duration of the source signal. The highest frequency in the spectrum is $\frac{1}{2 \cdot \text{time resolution}}$ and the frequency resolution is $\frac{1}{\text{duration}}$.

3.3.2 Energy calculation

Sometimes we want to know the "size" of a signal. We know for instance that movement causes the EEG signal to get much "bigger" and we might want to filter parts of the signal where that happens (see Section 2.4.2). The *"energy"* E of a signal x measures the sum of the squared amplitudes at each time point i in the signal of duration D seconds sampled at R samples a second (see Equation 3.1). The *"power"* P is defined as the amount of energy per time unit (see Equation 3.2).

$$E = \sum_{i=1}^{D \cdot R} x_i^2 \tag{3.1}$$

$$P = \frac{E}{D \cdot R} \tag{3.2}$$

Instead of doing a Fourier transformation to measure the SSVEP strength, it is also possible to apply a peak filter at the stimulation frequency, or a harmonic, to the signal and then calculate the energy of the remainder. One advantage of this approach is that it is faster than computing a Fourier transform, especially when it can be calculated continuously. If the system receives new data every 250 ms, but it uses a window of 1 second for analysis, the Fourier transform would have to be recomputed in its entirety, whereas the peak filter and energy calculation could just be applied to the new segment. Furthermore, if the BCI uses a targets oscillating at 7.5 and 8 Hz, a Fourier-based analysis would need 2 seconds worth of data in order to distinguish between these two, whereas the energies for those frequencies could be calculated with much less data. The main disadvantage of this approach is that the peak filter introduces a big transient in the signal. It is our experience that this does not affect the data by much after a couple of seconds, but it does imply that it is hard to analyze only a small piece of data in isolation.

3.3.3 Signal-to-noise ratio

The signal-to-noise ratio (SNR) can intuitively be obtained by dividing the energy of the relevant signal by the energy of everything else. In the case of the SSVEP, we first obtain the SSVEP energy, calculated as stated above using a peak filter. The SSVEP energy can consist of just the energy of the EEG signal at the stimulation frequency, or can be the sum of the energies at several harmonics. The SSVEP energy can then be divided by the energy of the entire signal, or by the energy of a notch filtered signal. If it is divided by the entire signal, we obtain a number resembling the percentage of the signal that is relevant to our goal. If the SSVEP energy is divided by the energy of the signal after removal of the SSVEP components, an actual SNR is obtained.

The SNR can be calculated in a similar way using the Fourier transform. Instead of comparing the SSVEP power to all of the (other) power in the spectrum, a commonly used approach is to only divide it by the power of surrounding frequencies (see Equation 3.3) [12].

$$SNR(f) = \frac{nF(f)}{\sum_{k=s}^{n/2} F(f + k\Delta f) + \sum_{k=s}^{n/2} F(f - k\Delta f)} \tag{3.3}$$

, where f is frequency, n is the number of surrounding frequencies to use, F is the Fourier power of the signal, and Δf is the Fourier transform precision ($\Delta f = 1/D$). In the case of SSVEP analysis f is generally the stimulation frequency or one of its harmonics.

3.3.4 Time-frequency analysis

The energy of each frequency can be expected to change over time. However, the above mentioned peak energy analysis only measures the energy of one (combination of) component(s) of the signal, and the Fourier transform only shows the power or magnitude of a frequency component in the entire signal. A time-frequency representation is a three dimensional plot that shows how strong each frequency component is at each point in time.

A couple of time-frequency analysis methods are used. In the *"Short-Time Fourier Transform (STFT)"* the signal is multiplied a window function and Fourier transformed for multiple points in time. The resulting Fourier spectra are associated with their center time points and juxtaposed to get the time-frequency spectrum. Since this method uses the Fourier transform it has the same tradeoffs with respect to resolution. A wide window results in a longer time sample for the Fourier transform and thus a higher frequency resolution, but a lower time resolution. In order to improve the time localization of the spectrum, the used window often has a bell shape (Gaussian, Hann, or Hamming).

These shortcomings are not shared by the *"Matching Pursuit (MP)"* technique [83]. This method chooses a subset of atoms from an extremely redundant, overcomplete dictionary to represent the signal in both the time and the frequency domain. These atoms are two-dimensional Gaussians with different values for the mean and variance in both dimensions. The MP algorithm greedily chooses the atom from the dictionary whose inner product with the rest of the signal is the largest, until the energy of the remaining signal falls below a predefined threshold. The main disadvantage of this method is that it executes slowly, because in each iteration it has to search a large dictionary.

3.3.5 ROC curve

At some point the BCI will need to make a classification. For the classification of one class (i.e. whether it is currently active or not), it is often possible to adjust the classifiers sensitivity. For instance, classification may depend on whether a certain value exceeds a certain threshold. By lowering the threshold (i.e. increasing the sensitivity), more instances are correctly classified as active (more true positives), but more instances are wrongfully classified as active as well (more false positives).

The *"receiver operating characteristic (ROC) curve"* plots the false positive rate on the X-axis and the true positive rate on the Y-axis for different threshold values. The optimal threshold will depend on the application. Some applications will simply try to strive for the highest accuracy, while others will want to minimize the number of false positives at all costs. The ROC curve can provide insight into the tradeoffs that are available. The area under the ROC curve (AUC) provides an objective measure of how well the classification algorithm works on the current data, as it is equal to the probability that a randomly chosen positive instance will be ranked higher than a randomly chosen negative one. In a training or calibration phase, this number can help in selecting the best settings for the experiment or the classification algorithm.

3.4 Experimentation BCI

Most experiments were done with a custom made BCI running on a computer, which will be referred to as the *"Experimentation BCI"* and is depicted in Figure 3.6. The goal is to move the red arrow to the blue square by concentrating on the targets in the corners (more details in Section 3.4.4). Since LCD monitors are more common than CRTs nowadays, an LCD monitor was used most of the time. Subjects were seated approximately 70 cm from the display. Because online and offline evaluation of BCIs can be very different, we wanted to do both in order to get a good understanding of stimulation properties in SSVEP-based BCIs. These experiments therefore featured both an online and an offline part.

3.4.1 Frequency selection

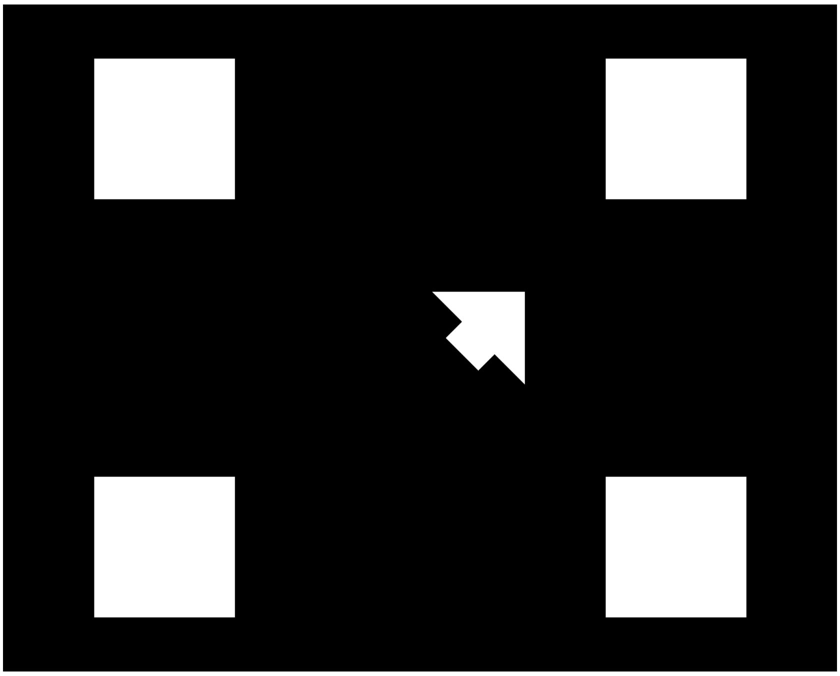


Figure 3.3: *During frequency selection the user was prompted to focus on the top right target with a white arrow and an auditory cue.*

Because the targets need to be distinguishable from each other, the system requires four different frequencies. Different people respond well to different frequencies so the performance of an SSVEP-based BCI system depends greatly on the used frequencies. In order to select the four that would work best, a frequency selection procedure was performed the first time the user participated in an experiment.

In the corners of the screen four 6×6 cm targets separated 16 cm horizontally and 12 cm vertically were flickered at a certain (equal) frequency. For conditions in which the stimulus was a square (and not a checkerboard) integer frequencies between 13 and 20 Hz were tested. These frequencies were chosen because preliminary experiments had shown that most people have little response in the lower frequency ranges, our monitor could not reliably display high frequencies and we wanted to avoid the alpha range. For checkerboard conditions we additionally tested 6.5-10 Hz with a 0.5 Hz step because the literature shows that they elicit responses at twice this frequency.

The frequency selection procedure started with 10 seconds of black screen where the user was allowed to rest. After 9 seconds an auditory cue was given to indicate that the user should start paying attention again. A second later the four stimuli would appear for 5 seconds and the user was asked to pay attention to the top right one (see Figure 3.3). This was repeated for each tested frequency in a randomized order.

Each frequency was analyzed by computing a spatial filter based on EEG signals obtained during the time that that frequency was displayed. After the spatial filter was applied, the whole signal was peak filtered at this frequency and the energy was computed with a sliding window of half a second. Then the area under the ROC curve (AUC) of the energy of the 5 seconds of stimulation and the 5 seconds before the cue was computed after which the experimenter picked out which 4 should be used in later phases of the experiment. Simply taking the 4 frequencies with the highest AUCs is not optimal because the distance between frequencies (the probability of confusing one with another) is also important and not properly reflected in this number. For instance, taking frequencies where one is the other's harmonic does not work and taking frequencies that are too close together is riskier than taking ones that are very different. The picked frequencies were then used in all experiments of the same kind (i.e. using flashes versus pattern reversal; see Section 4.8).

3.4.2 Questionnaire

Each experiment tested multiple related conditions in a random order. Each of the four corners of the screen displayed one stimulus. In the beginning of the experiment, the user was asked to fill out a questionnaire with questions about each of the conditions, in order to find out how comfortable they were. They had to give a score between 1 (not) and 7 (very) for each of the following four questions while watching each of the conditions in turn:

- How much do you like this stimulus?
- How much will this stimulus increase your tiredness?
- How long could you look at this stimulus?
- How annoying is this stimulus?

These questions were asked again after the experiment. Additionally, users had to score their level of tiredness on a seven point scale both before and after the experiment.

3.4.3 Calibration

The testing of each condition consisted of a calibration phase and an operation phase. The goal of the calibration phase is to determine how to set certain parameters during the operation phase. In the calibration phase the subject was asked to pay attention to one (or none) of each stimuli 4 times in a random order (see Figure 3.4). Each trial consisted of a rest period of 4-4.5 seconds after which an auditory cue was given and an arrow appeared on the screen indicating which target to focus on. After another 4 seconds the screen was flashed for 1 screen refresh period (i.e. 1/75 = 0.013 s when the refresh rate was 75 Hz) with a red or green color and another auditory cue was given (either low or high pitched). This indicated the end of the trial and was done for consistency with the operation phase (see Section 3.4.4). During the rest period the subject was allowed to do anything, so in order to get 'no stimulation' trials, the subject was also occasionally asked to focus on a diamond shape in the center of the screen that would appear instead of an arrow. Four repetitions for each of the five targets (4 stimuli + 1 no stimulation) of on average 8.25 seconds gives a total calibration time of 165 seconds or almost 3 minutes.

The goal of the calibration is to obtain good spatial filters and energy thresholds for each of the used frequencies. In order to determine a suitable spatial filter from the calibration data, we first calculate the energy based on the occipital channels ($\frac{O_1+O_z+O_2}{3} - C_z$). Then, for each of the 4 trials, we select the second where the energy was consistently the highest and use this interval to calculate the spatial filter for channels P_3, P_z, P_4, PO_3, PO_4, O_1, O_z and O_2. Then, we apply the filter to the signal and calculate the energy (see Figure 3.5(c) and (d)). A ROC curve is computed using windowed data from target intervals versus that from non-target intervals (see Figure 3.5(a) and (b)). Using the area under this curve is a good measure for how distinct the target class is from the others.

However, selecting a threshold from this curve that gives satisfying results with respect to the number of true and falsely positive classifications that the system will likely make, is not straightforward. Since misclassifications can be frustrating and in some applications hard to fix, we have focused on correctness rather than speed of operation. We took the maximum energy value from each of the 4 target trials and

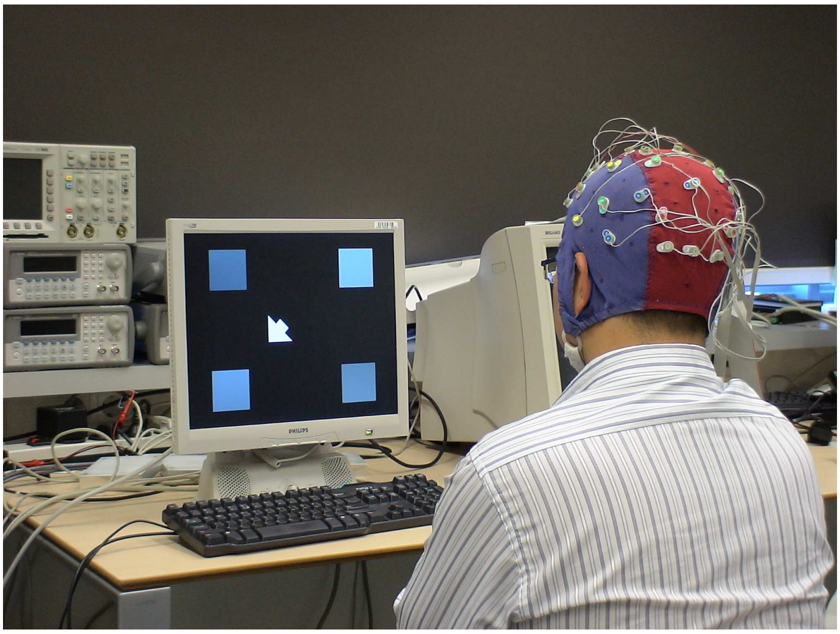


Figure 3.4: *During calibration the user was prompted to focus on a target with a white arrow and an auditory cue.*

computed the number of true and false positives taking these values as thresholds would generate. The threshold that could classify the largest number of targets while still exceeding a true-to-false positive ratio of 3 was selected. This was repeated for each of the spatial filters (that were computed for each trial) in order to find the one that would allow correct classification of the most target intervals while minimizing the number of false positives.

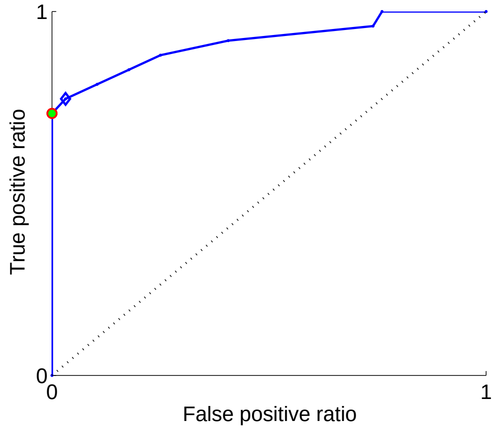
3.4.4 Operation

The goal for the operation task was to give the user a sense of freedom, autonomy and accomplishment in order to prevent boredom, while not imposing any difficult mental tasks on the user and still being able to judge if the BCI was making correct classifications or not. The result was a task where the user had to move an avatar (red arrow) along a curvy path or corridor to a goal (see Figure 3.6). There were no branches, so there really was only one way to go, which means that there was little mental effort required and it was easy to judge right decisions from wrong ones. Nevertheless, the task is a lot less boring than the calibration (although it is not exactly a thrill ride).

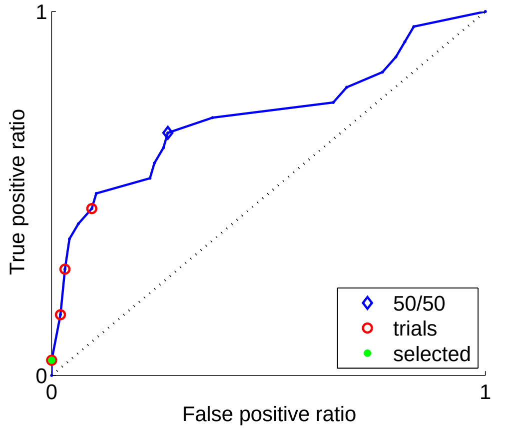
The user could move the avatar by focusing their attention on the target associated with the intended direction. If the energy for exactly one frequency would exceed the threshold, the avatar would turn towards the signified direction and try to move there. If the avatar bumps into a wall, he does not change position. Good moves are accompanied by a green screen flash and a high pitched tone and bad moves are identified by a red flash and a lower tone. After a move, no classification is made for at least one second in order to prevent making many subsequent classifications that can likely be incorrect after the first one. This gives the user some time to react to the move and the SSVEP response for the (previously) attended frequency to decrease.

Every corridor consists of 24 steps and it should be possible to complete it in under one minute. After this time, the subject gets a break of 20 seconds in which stimulation ceases and the subject can relax. After this, he/she is given another minute followed by a 20 second break. If in the minute after this the corridor can not be completed, the rest of the level is skipped.

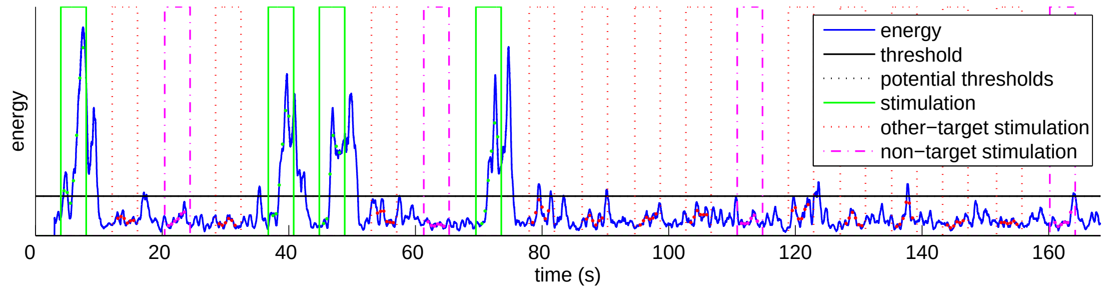
For each condition there are two levels of 24 steps. Each direction should in principle be taken 12 times. If moves in the wrong direction occur, this number changes. Furthermore, this only ensures that the number of true positives for each target is roughly the same. The a priori probabilities of each target



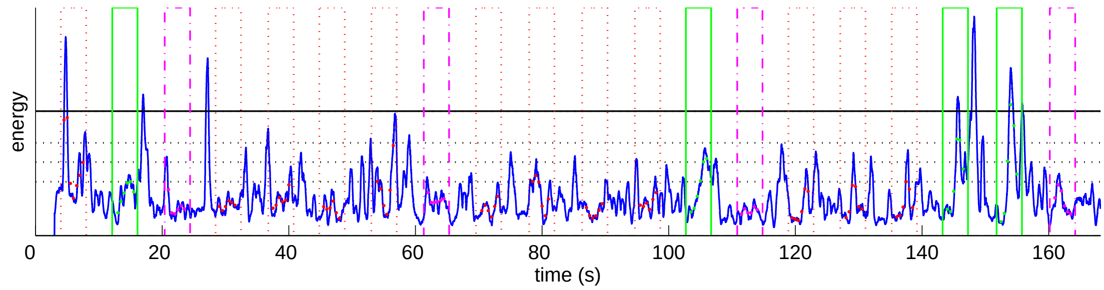
(a)



(b)



(c)



(d)

Figure 3.5: *ROC curves (a and b) and energy plots (c and d) obtained from the calibration data for two different targets. The left ROC curve (a) is associated with the first energy plot (c) and the right one (b) with the second (d). Each point on the ROC curves shows the true to false positive classification ratio that would be obtained based on the calibration data. The blue mark on the ROC curves mark the threshold at which the true and false positive rate is equal, the red marks show the thresholds at which a new correct interval can be distinguished and correspond to the black dotted horizontal lines in the energy plots. The boxes in the energy plots (c and d) mark the times where the user was asked to pay attention (green for when the user was attending to the currently classified target, red for when he was attending to another target and purple for when he was attending to the center of the screen). The dots show the times at which the system can actually measure and the black solid horizontal line shows where the classification threshold was set. The black dotted horizontal lines indicate where the thresholds would be if one more (or less) trial should be classified and clearly show that this would result in more false positive classifications as well.*

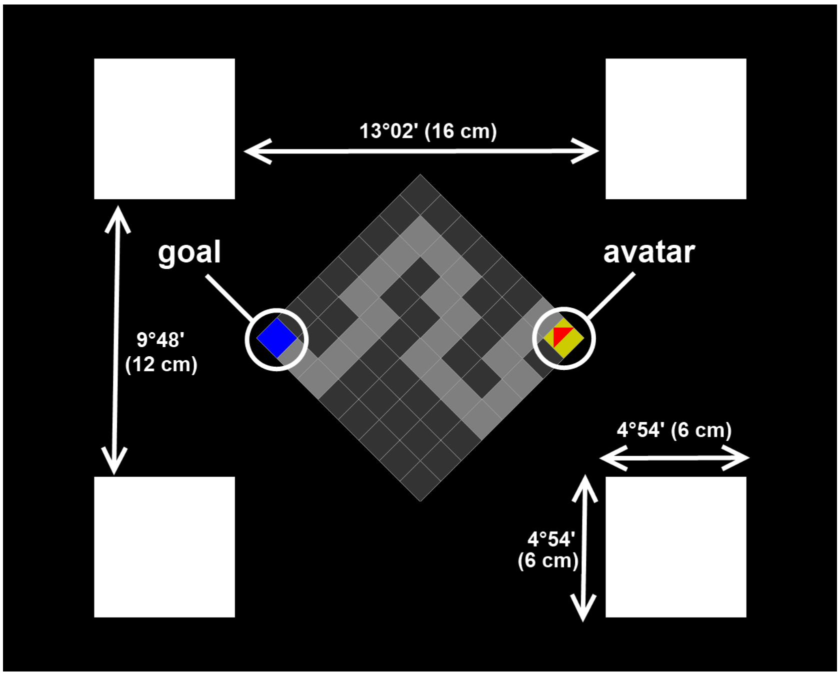


Figure 3.6: *The interface of the Experimentation BCI used for experimentation. The user can move the avatar to the goal by focusing on the white flickering targets associated with the desired directions. Distances are reported in terms of the visual angle that they stretch when the subject sits 70 cm from the screen.*

are however heavily biased towards targets that cannot be classified accurately, because upon a wrong classification, this target is asked again.

One of the problems of this setup is that every step has to be completed in order to get to the next. If for some reason the system cannot detect focus on one specific target, the avatar might be stuck forever. In order to counter this, after 10 seconds of no classification the system cheats and move the avatar in the right direction. Unfortunately, this measure is not completely sufficient, because the level design is such that multiple equal targets often occur in succession and false positives for the move in the opposite direction can sometimes still cause the subject to get stuck.

Signal processing Because the focus of the experiments was on finding differences between stimulation property values, a simple signal processing technique was used that is based on thresholding the energy of the SSVEP response for each target. Any increase in performance should come from the stimulation properties and not from sophisticated signal processing techniques. Although the performance of the Experimentation BCI is satisfactory when good stimuli are used, it can likely be enhanced by using better signal processing algorithms.

When the system first receives a new chunk of the signal (every 0.25 seconds) it is preprocessed using a 50 Hz IIR notching comb filter in order to remove the power line interference. Then an energy measure for each of the targets (frequencies) is calculated based on last second of the signal. The maximum contrast spatial filters [70] calculated after calibration are applied for the first 4 harmonics of the target frequency, based on coefficients obtained in the calibration phase. For each harmonic, the result is peak filtered, squared and averaged. The sum of these averages is roughly the energy in the first four harmonics of the stimulation frequency. It is compared to a threshold that was determined for each target in the calibration phase. If the energy for exactly one target exceeds the associated threshold, the system moves the avatar in the corresponding direction and the system does not make another classification for the next second in order to allow the user to respond to the changed system state. If the threshold for more than one target is exceeded, the system does not make a classification. This behavior can eliminate some sudden artifacts, because they can cause massive energy increases across most used frequencies simultaneously.

Implementation The Experimentation BCI was implemented using BCI2000, Neurostim, MATLAB and Java and ran on two different personal computers. The experimenter would start by executing a MATLAB function that would prepare Neurostim and BCI2000 configuration files and then start BCI2000. Third-party modules were used for BioSemi acquisition and for delegating the signal processing phase to an instance of MATLAB. The application module was left empty (a no-op), because a custom interaction with a Neurostim application was used directly from the signal processing module.

The Neurostim program contained all of the presentation logic and was run on a different computer. This has a number of advantages: first of all, the load of presenting the stimuli (and application) and doing the signal processing is divided over two computers. Secondly, it enabled the experimenter to have his own screen to operate the experiment and monitor the subject's brain signals from the subject. The Neurostim component has two separate modules that were simultaneously presented. One for the stimulation and a separate one for the application. This ensures that different applications can easily be plugged into the system. For instance, in the calibration and frequency selection phases, the application was replaced by the arrow indicating where to look.

Each part of the experiment was manually started by the experimenter after asking the subject if they were ready. In the calibration and frequency selection phases, the Neurostim component simply ran uninterrupted while the signal processing module only gathered the data (without doing anything with it) so that it could be analyzed shortly after. In the operation phase, the Neurostim program and the signal processing (and data acquisition) module ran simultaneously. Whenever the signal processing module was able to make a classification, a TCP message would be sent to the Neurostim program, which would deal with it by giving the user feedback about the classification (by changing the game state and presenting the cues that were discussed before).

3.5 Offline experiments

All other experiments were carried out offline and their goal was generally to see what would happen to strength of the SSVEP response under various conditions. These experiments were also carried out using the BioSemi ActiveTwo EEG acquisition system while the subject was seated approximately 70 cm from the stimulation device. All subjects had corrected-to-normal vision and did not suffer from epilepsy or migraines. The lighting in the room was generally on for these experiments.

These experiments were often carried out in order to test small hypotheses and were not done on the scale of the Experimentation BCI experiments. Each experiment was generally unique and is described in the sections where the results are also reported.

Chapter 4

Stimulation properties

In this chapter several properties of SSVEP stimuli are introduced, discussed and evaluated.

Property	**Description**	**Section**
Stimulation device	The choice of stimulation device (LED, LCD or CRT) has a great impact on the possibility to change other properties as well as the cost and flexibility of the whole system.	4.1
Framerate	A device's framerate specifies the number of changes it can render per second. When it is not an integer multiple of the stimulation frequency, errors will necessarily be made in the rendering of the stimulus.	4.2
Frequency	The speed at which the two states are cycled expressed in Hertz. This should be a number between 1 and 100 Hz in order to elicit an SSVEP.	4.3
Frequency change	The frequency of a single target can change during stimulation. This can potentially reduce the number of frequencies that have to be used in the entire system.	4.3.1
Frequency combination	Two different signals with different frequencies are combined. This can also decrease the total number of used frequencies.	4.3.2
Phase	It is possible to use targets with the same frequency but different phase. This limits the number of used frequencies.	4.4
Waveform	Specifies the way in which the transition between states happens over time. Examples include sine, square and triangle waves.	4.5
Contrast	In general, the contrast can be thought of as the difference between stimulus states as well as the background. However, brightness (expressed in cad/m^2) is often the measured feature.	4.6
Environment	The amount of noise, light and distractions in the environment can have an impact on SSVEP response.	4.7
Spatial frequency	On patterned stimuli (e.g. checkerboards) the spatial frequency is given by the size of each instance as expressed in degrees per alternation.	4.8
Blur	Blurring a stimulus makes the edges less sharp and thus easier to look at. Furthermore, it introduces (extra) noise to the interaction.	4.9
Size	The angle that a stimulus occupies in the visual field of the user, expressed in degrees. This number is calculated from the actual measurements of the stimulus and the distance between it and the user.	4.10
Color	Color can have an impact on emotion, comfort and SSVEP response strength.	4.11
Shape	Different shapes can include squares, circles and diamonds as well as semantically meaningful stimuli, such as an arrow pointing in the intended direction.	4.12
Texture	Stimuli can have checkerboards, lines, dots and other shapes on them in any orientation. Furthermore, the stimulus might be an image that either elicits a certain emotion or is meaningful to the associated command.	4.12
Number of targets	The number of targets that the BCI uses.	4.13.1
Target spacing	The spacing between targets as measured by the visual angle between the edges of the targets.	4.13.2
Target movement	Whether the targets in the BCI move during operation.	4.13.3
Target overlap	Overlapping targets saves screen space, but more importantly means that the subject only needs to look at one area. This makes the system independent of muscle movement.	4.13.4
State number	The number of states in the stimulus. The default is 2, but instead of cycling between (for instance) red and blue, it might as well cycle between red, green and blue.	4.14
State order	The order in which the states are presented can be either random, sequential (one state after the other in a fixed order and no repetitions) or in some other fixed order (e.g. 1 cycle could be red-blue-red-green).	4.14

4.1 Stimulation devices

In order to obtain an SSVEP, the user needs to focus on an RVS. Because visual stimulation is required, a device that can emit light is needed. Additionally, the stimulation device needs to be able to rapidly change a characteristic of this light (e.g. luminance or color). The most obvious choice for such a device is the Light Emitting Diode (LED), because it can be highly customized and is capable of adjusting to change very rapidly. Other lamps, like Xe-lights have also been used [84]. The advantage of lamps like these is that they can be highly customizable and accurate. However, big disadvantages are that they require specific and dedicated hardware, cannot be adjusted after production and require custom assembly for every BCI unit that is not mass produced (i.e. every BCI unit). Using computer monitors for stimulation solves these problems, but adds some new ones. This section describes and compares the most often used stimulation devices (LEDs, CRTs, and LCDs).

Light Emitting Diodes

Light emitting diodes (LEDs) are light sources based on electroluminescence, rather than incandescence (i.e. the light is a byproduct of electrical current rather than produced heat). When an LED is turned on, electrons move through a semiconducting material where they may recombine with electron holes, causing them to fall to a lower energy level. The extra energy is released in the form of photons (light) moving with a wavelength (color) depending on the energy gap in the semiconducting material.

LEDs present many advantages over incandescent light sources including lower energy consumption, smaller size, longer lifetime, improved robustness, and greater durability and reliability. However, they are relatively expensive and require more precise current and heat management than traditional light sources. Their main advantage with respect to eliciting SSVEP responses is that they can be switched on and off extremely fast without being worn down.

Computer displays

Because of the ubiquity of computers and the flexibility with which they can be programmed, computer displays are also often used as stimulation rendering devices. The most often used types of rendering devices are the cathode ray tube (CRT) monitor and the liquid crystal display (LCD).

Cathode Ray Tubes

A *"Cathode Ray Tube (CRT)"* is a vacuum tube with an electron gun that shoots electrodes at a fluorescent screen, causing it to light up. There are electron guns and phosphors for red, green and blue colors. Whenever a phosphor is hit by electrons from the right gun it lights up in the corresponding color for a brief moment. Due to the human vision's trichromatic nature the illusion of a continuous spectrum of hues is provided from small and closely packed the red, green and blue lights. The entire screen is rendered from the top right, going horizontally first, to the bottom left. The number of times that the entire screen is rendered in one second is called the *"refresh rate"*.

Liquid Crystal Displays

"Liquid Crystal Displays (LCDs)" are flat panel computer monitors that make use of the way that light passes through liquid crystals. To explain exactly how these monitors work is beyond the scope of this thesis, but a simplified explanation is given here in order to be able to discuss important characteristics of these displays. LCDs have a backlight (usually a cold cathode fluorescent lamp (CCFL) but nowadays LEDs are also used) that shines through layers of filters and liquid crystals. The way light passes through these crystals can be altered by passing an electrical current through these crystals. In a color LCD, each pixel has subpixels for red, green and blue that are created by placing colored filters over separate parts of the liquid crystals. The amount of current that goes through each subpixel and thereby the amount of light passed through the red, green or blue filter can be controlled separately.

Comparison

There are a number of important differences between LEDs, CRTs and LCDs. First of all, computer monitors are ubiquitous, especially LCDs. LCDs are cheaper, lighter, smaller and more friendly to the environment than CRTs. CRTs usually support higher refresh rates and contrast ratio's though, which can be beneficial to SSVEP response strength. However, CRTs flicker at their refresh rates, because the screen is redrawn every time, which may elicit an unwanted SSVEP response. LCDs do not need to redraw the screen, because the backlight is on constantly and the state of the screen is relatively persistent.

LEDs and the equipment required to operate them are not available in every home and are often custom made or selected. LEDs can often reach brightnesses far exceeding that of computer monitors and have framerates so high that they can almost be ignored. This means that it is often possible to accurately display any frequency relevant for eliciting SSVEPs using any desired waveform. For standard CRT displays operating at 85 Hz and standard LCDs with a 60 Hz refresh rate, there are only 9 respectively 6 frequencies higher than 8 Hz that can be displayed in this manner. To make matters worse, some of these frequencies are each other's harmonics, which is usually undesirable for SSVEP experiments. Because of this limited number of frequencies that can accurately be displayed, other frequencies are often used in practice as well (for more about the limitations imposed by framerates see Section 4.2).

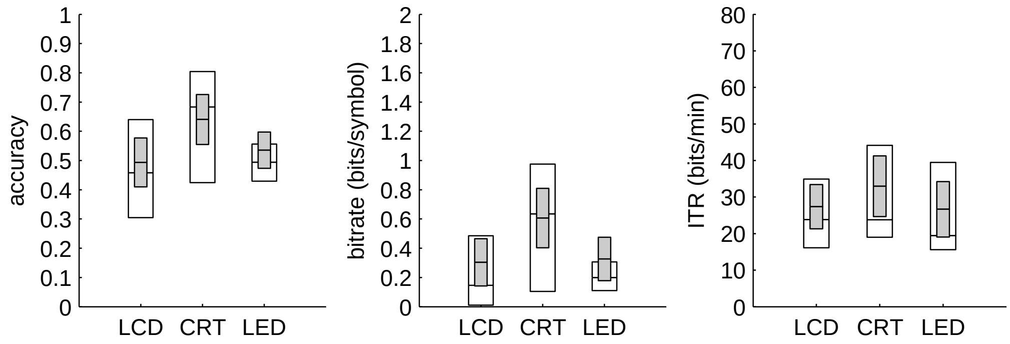
A computer monitor can be thought of as a huge collection of light sources, whereas an LED is just one. In that sense, we can say that monitors have good spatial resolution, whereas LEDs have good temporal resolution. However, research has shown that computer performance greatly affects how much stimuli can be on the screen at once [75].

Computer monitors have a number of practical advantages above LEDs, some of which have already been mentioned. Obviously, if the application is computer based, a monitor is already present and incorporating the stimulation into the same device makes for a simple setup. Furthermore, stimuli can more easily convey the semantics of the command that it is associated with (see Section 4.12). Although technically it would be possible to illuminate pictures with LEDs, it is much harder to create more complex stimuli, and virtually impossible to change them dynamically using LEDs. Dynamic change might be required when multiple pictures have to be alternated, or when the number, location or other properties of the stimulation depends on the application state. Also, during development, use of monitors is easier when an agile development method is used where the design of the system may evolve over time. If LEDs are used, their characteristics have to be decided at the start of the design cycle and are much harder to change afterwards.

(a) CRT (b) LED

Figure 4.1: *Experimental setup for conditions with LEDs and computer monitors. Setup with LCD monitor not pictured here.*

It was found that LEDs outperform computer monitors when it comes to eliciting SSVEPs and that CRTs are better than LCDs [85]. The effect of stimulation device on BCI performance was also tested in the Experimentation BCI, using the four green LEDs and both monitors described in Section 3.1 (see Figure 4.1(a)). In order to make the conditions as similar as possible, both computer monitors used green squares of the same size as the LEDs (10×10 cm). The luminance of the LCD monitor was 112.4 cd/m^2 for green and 0.86 cd/m^2 for black. The CRT was configured so that it would emit 0.024 cd/m^2 for black and 110.5 cd/m^2 for green. Due to our hardware, it was impossible to get the luminance of the LEDs much lower than 300 cd/m^2 because then it would turn completely off. In order to have a similar contrast, luminances of 300 and 400 cd/m^2 were used. For the condition with the LEDs, the LEDs were taped onto the CRT monitor over the positions where the stimuli would normally appear on the screen (see Figure 4.1(b)).



(a) Accuracy (b) Bitrate (c) ITR

Figure 4.2: *Accuracies, bitrates and ITRs of the Experimentation BCI obtained when using different stimulation devices. CRT stimulation significantly outperforms LCD stimulation at the* $p < 0.1$ *level.*

The results are summarized in Figure 4.2 and suggest that the stimulation device is not a major factor for BCI performance. The most obvious explanation for this is that it really does not matter what device is used. However, the result could also very well be due to our attempt to make the conditions as equal as possible. The fact remains that LEDs can have a far greater modulation depth and brightness than both monitors. On the other hand, the monitors would probably have done better with white stimuli rather than green ones. A third explanation is that benefits in SSVEP response do not always translate to BCI performance because of interference from non-target stimuli. Given these results it is hard to draw any definite conclusions. However, the experiment was set up in such a way as to avoid the strengths and weaknesses of each device, even though when selecting a device these strengths are what matters. It might have been better then, to compare the devices using settings that are optimal for them. However, this might have told us more about the settings than about the devices. The other sections discuss properties of stimulation that can make a difference on BCI performance. The flexibility of the devices with respect to these properties will likely determine which is the most suitable.

4.2 Framerate

Most SSVEP-based BCIs use stimuli that are alternating with just one frequency. These frequencies can either be *pure* or *polluted*. Signals of a pure frequency have a constant period of length $1/F$. Polluted signals do not have a constant period, either because of noise, or because the rendering device cannot display the desired frequency in a pure manner.

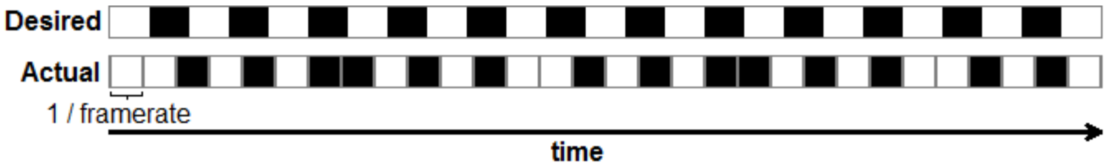


Figure 4.3: *The difference between which states (black and white) are desired at each point in time and which states can actually be rendered. The length of each rendering alternates between being too long or too short, but is never quite correct. The example shown was derived from a 60 Hz device trying to render 24 Hz stimulation over the course of a half second.*

Stimulation devices generally have a framerate or refresh rate that prevents them from accurately rendering most frequencies. This is not very important when the framerate is very high (as with the LEDs driven by the Agilent), but can have a significant effect when it is low, such as with computer monitors (see Figure 4.3). Rendering waveforms other than square waves requires an even higher framerate, because intermediate states need to be displayed as well. When rendering square wave stimulation, one whole stimulation period requires two state changes (back and forth). A device with framerate R can really only render frequencies of R/k Hz where $k \in \{\mathbb{N} \geq 2\}$ and the duty cycle is different than 50% for uneven k.

Only little research on this issue exists, although it appears that other researchers sometimes opt to only use frequencies that can accurately be generated [86, 17]. It has been shown that using frequencies that the monitor can accurately render, can greatly increase performance [87]. However, this research used two different sets of frequencies for the tested conditions. In order to test the effect of a low framerate on the SSVEP and BCI performance, two experiments were carried out. In the first, we compared the difference in SSVEP response to square waves generated using the signal generator's normal framerate of 20 MHz and an emulation of a 60 Hz refresh rate on the white LED board. There were 5 test subjects (all male, between 23 and 29 years old) who had (corrected to) normal vision. Subjects were seated 70 cm from the white LED board and were asked to pay attention to the 5×5 cm portion that was flickering at one of 5 different stimulation frequencies (14, 16, 18, 28 and 29 Hz). There were 20 trials per condition per frequency. Each trial started with a rest period during which the light was off of 5-7 seconds, followed by a brief flash to indicate the user should start paying attention again. After another 2 seconds, the stimulation would start and last for 3 seconds.

The results show that not using a proper square wave can significantly deteriorate the SSVEP response strength. Figure 4.4(a) shows how the energy of the SSVEP response in the first two harmonics evolves over time, averaged over all of the tested stimulation frequencies and test subjects. It is clear that the 20 MHz framerate is almost instantly elicits a significantly stronger SSVEP response. Figure 4.4(b) and (c) show the frequency spectra for both conditions when an 18 Hz stimulus was used, averaged over all subjects. The 60 Hz condition generally elicited a weaker SSVEP response, especially in the second harmonic. The power of the response in the first harmonic was on average 20% smaller ($p < 10^{-5}$) and the response for the second harmonic was 34% smaller ($p < 10^{-16}$) when a framerate of 60 Hz was used. In addition to this weaker response, there was also more noise in the spectra and extra peaks can be observed at other frequencies, which may confuse a BCI system. Frequency spectra for the other tested frequencies show similar results.

In a second experiment, we tested actual BCI performance using the Experimentation BCI. This was done by selecting two sets of frequencies, each optimized for a different refresh rate. The 60-Hz-set contained $\{15, 12, 10, 8\frac{4}{7}\}$ and the 75-Hz-set contained $\{18\frac{3}{4}, 15, 12\frac{1}{2}, 10\frac{5}{7}\}$. All combinations between these frequency sets and the refresh rates (60 and 75 Hz) were tested and grouped into two conditions to compare the situation where the frequencies were and were not optimized for the refresh rate. Figure 4.5

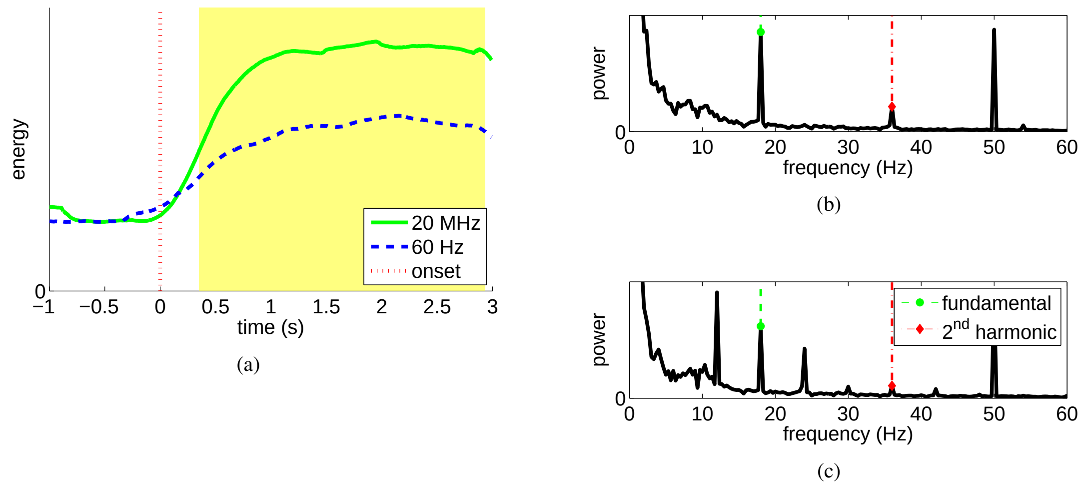


Figure 4.4: *Results obtained when comparing SSVEP responses elicited by accurate square waves (20 MHz) versus those elicited on a device with a low framerate (60 Hz) in $O_z - C_z$. a) Energy of the first two harmonics for both conditions averaged over all 5 subjects and 5 tested frequencies (14, 16, 18, 28 and 29 Hz). The background is colored when the difference is significant with Bonferroni corrections. b) and c) Average frequency response to 18 Hz stimulation for framerates of 20 MHz (b) and 60 Hz (c), averaged over all subjects. Both harmonics are generally larger when the framerate was high, and the spectrum contains several additional peaks when it is low.*

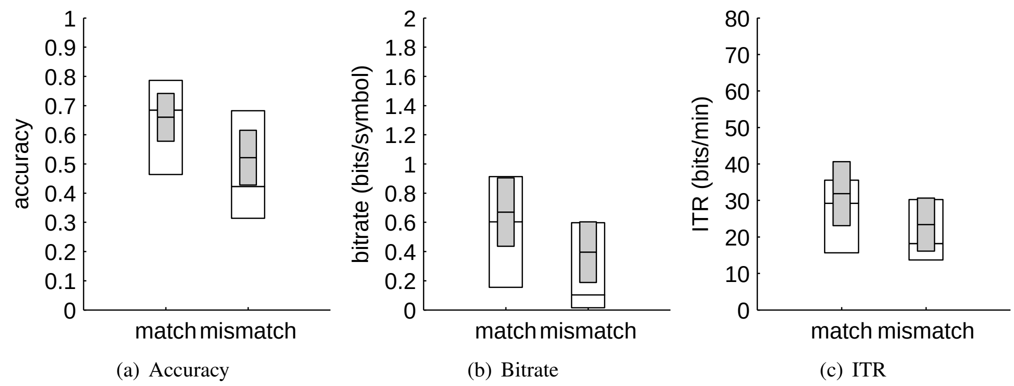


Figure 4.5: *Accuracies, bitrates and ITRs of the Experimentation BCI obtained when using frequencies that did or did not match the device's framerate. Using matching frequencies is significantly better ($p < 0.05$).*

clearly shows that having frequencies that are optimized for the refresh rate can be beneficial.

However, other experiments in this thesis have also shown that choosing frequencies that are optimal for the user may be even better. Compared to using manually selected frequencies determined in the frequency selection phase on a per-subject basis (see Section 3.4.1), the average ITR decreases with 19% when the frequencies are optimized for the refresh rate ($p < 0.1$). In many studies however, the monitor's refresh rate is not considered, so the used frequencies are not optimized for it. The frequencies used in this experiment resulted in a 40% drop in ITR ($p < 0.01$) compared to frequencies optimized for each individual user when they were displayed on a monitor with a mismatched refresh rate.

4.3 Frequency

The frequency of the stimulus is one of the most important characteristics, since it is used in the identification of the user's intention. Stimuli with frequencies between 1 and 100 Hz can elicit an SSVEP response [36], but the strength of this response varies across different frequencies and per subject. The existence of three distinct frequency bands was first reported by Regan [37], based on findings with one test subject (see Figure 4.6(a)). The strength of the SSVEP response is highest towards the centers of these bands and lowest towards the edges. Similar results were obtained by Pastor et al. [42] (16 subjects; Figure 4.6(b)) and Wang et al. [19] (1 subject; Figure 4.6(c)). Although the exact locations of the regions on the frequency axis seem to depend on the subject, it is custom to use Regan's division of the frequency space: *low* from 5-12 Hz, *medium* from 12-25 Hz and *high* for frequencies from 25-50 Hz.

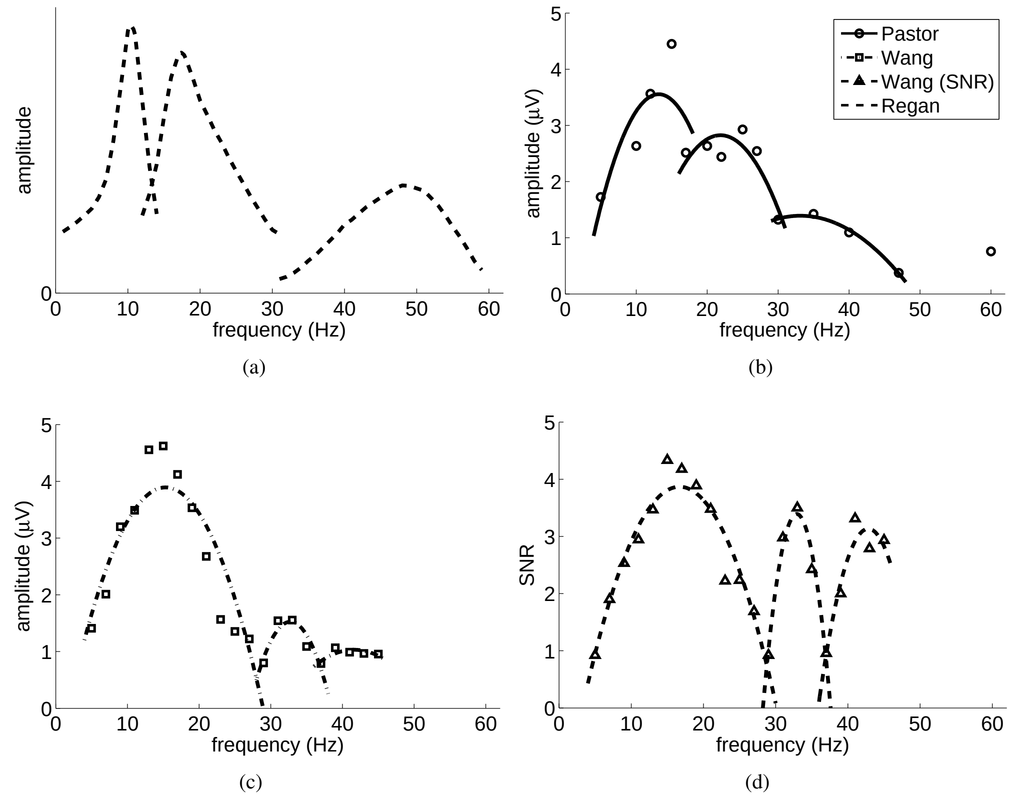


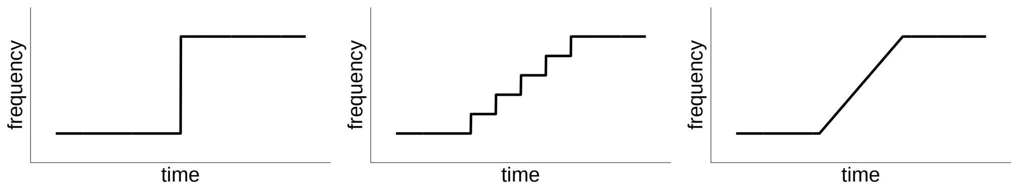
Figure 4.6: *SSVEP response strengths depending on frequency. The individual points show actual measurements, while the lines are second order polynomials fitted to the data for each of the three frequency regions. a) Data from Regan [37], the scale of the amplitude is unknown. b) Data from Pastor et al. [42] with less clear regions, possibly caused by the fact that data from 16 subjects was used. c) Data from Wang et al. [19]. d) SNRs reported by Wang et al. showing that while the amplitude in higher frequency regions is lower, the SNR is the same for each region.*

Although the amplitude obtained in the higher frequency band(s) is clearly lower, Wang et al. also found that the SNR is approximately the same for each frequency band, since there is little spontaneous activity at higher frequencies (see Figure 4.6(d)). In the literature the low and medium bands have received the most attention [88]. This is probably due to the fact that the SSVEP amplitude for these frequencies is higher. Since the SNR for the high frequency band is the same however, it should not be much harder to use and it has the added benefit of having a lower risk of inducing epileptic seizures [43] and being less fatiguing than slower stimuli. A big disadvantage of computer displays is that they have a lot of difficulty in displaying most high frequency stimuli (see Section 4.2).

The choice of which frequencies to use can obviously have a big impact on BCI performance as well. Choosing a frequency near the edge of a frequency range can severely impair the system's ability to recognize that the user is attending to it. Since the location of these regions is highly user-dependent, it is wise to use a frequency selection procedure like the one reported in Section 3.4.1.

Since a lot of research has already been done by others on the effect of frequency on SSVEP amplitude and SNR, and the result appears to be that it is highly subject-dependent, this thesis does not comment on it any further. Instead, it was investigated how the brain would respond to changes in frequency or combinations of multiple frequencies.

4.3.1 Changing frequencies



(a) Jump (b) Step (c) Chirp

Figure 4.7: *Ways to change frequency*

Experimenting with signals with changing frequencies can provide great insight into the workings of the SSVEP response. There are a number of ways to change between two frequencies: jump, step and chirp (see Figure 4.7). In addition, it should be possible to continuously change the signal's frequency.

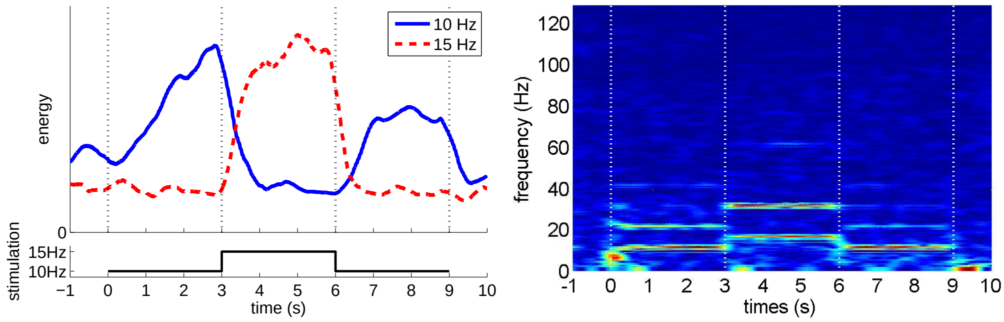
If the brain is able to quickly match the frequency of an RVS, this might make novel applications possible where one BCI target does not just have one frequency, but a unique sequence of frequencies that identifies it. This would decrease the number of required stimulating frequencies and potentially increase the difference between the identifying characteristics of the targets.

If a change in stimulation frequency can be detected quick enough, this might also be used to dynamically change the frequencies of the targets during BCI operation. If the system is for instance in doubt about which of two targets the user is focusing on, quickly changing the frequency of one or both and seeing what happens to the SSVEP might be a good way to quickly resolve such a conflict.

There are probably many more possible applications of a quickly adapting SSVEP response, but before these can be devised and tested, it is necessary to find out if the SSVEP response can indeed quickly follow the stimulation frequency.

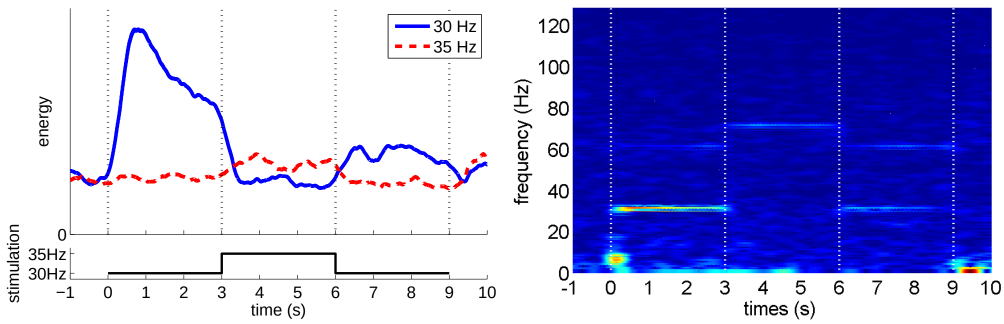
An experiment was carried out to see if the SSVEP response of one subject would follow a jump in frequency and if so, how quickly. The experiment used the 5×5 cm white LED configuration and consisted of 30 trials where there were 3 seconds of 10 Hz stimulation, 3 seconds of 15 Hz stimulation, again 3 seconds of 10 Hz stimulation, and a rest period of between 3 and 6 seconds. Figure 4.8 shows that the SSVEP indeed follows a jump in stimulation frequency. Figure 4.8(a) shows the average EEG signals from site O_z with reference C_z peak filtered at 10 and 15 Hz. The test subject had a strong response to the stimulation, as the amplitude of the signals increased significantly when stimulation started. It appears to take approximately 500 ms in order for the amplitude of the new frequency to overcome that of the old frequency. The STFT spectrum in Figure 4.8(b) shows that there were strong first and second harmonic responses and that the SSVEP frequency adaptation is very fast and accurate. After this, the subject requested that we used higher frequencies because they are more comfortable. The experiment was repeated with 30 and 35 Hz (see Figure 4.9). Although it might not be immediately clear from Figure 4.9(a), Figure 4.9(b) clearly shows that SSVEP frequency adaptation happened as quickly as before. But curiously, it appears that for this subject there is a large first harmonic response to 30 Hz and little to no second harmonic response, while this is the other way around for 35 Hz.

When the RVSi oscillate at a certain frequency for a fairly long time, the SSVEP appears to be able to follow the stimulation frequency. In order to see if this would also happen with more than two frequencies that were presented for shorter amounts of time, another experiment was carried out that tested SSVEP



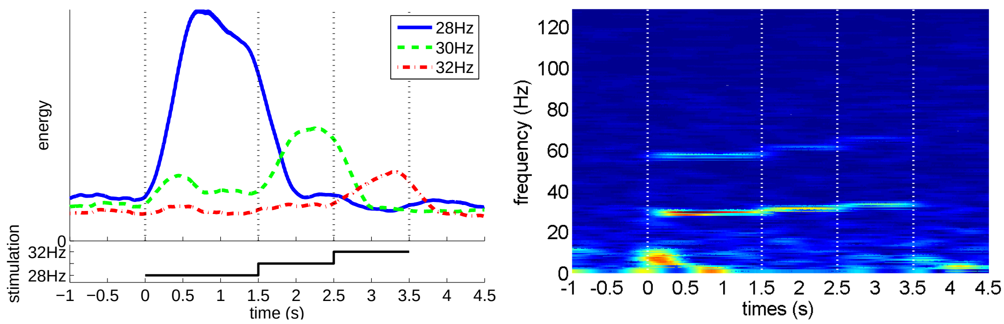
(a) (b)

Figure 4.8: *Response to stimulation containing jumps from 10 to 15 Hz and back in $O_z - C_z$. a) Mean energy for all constituent frequencies over time. b) Time-frequency (STFT) plot of the response to stimulation with a changing frequency.*



(a) (b)

Figure 4.9: *Response to stimulation containing jumps from 30 to 35 Hz and back in $O_z - C_z$. a) Mean energy for all constituent frequencies over time. b) Time-frequency (STFT) plot of the response to stimulation with a changing frequency.*



(a) (b)

Figure 4.10: *Response to stimulation stepping from 28, via 30 to 32 Hz. a) Mean energy for all constituent frequencies over time. b) Time-frequency (STFT) plot of the response to stimulation with a changing frequency.*

behavior with respect to step functions (see Figure 4.7(b)). First, 20 trials with 28, 30 and 32 Hz were carried out with stimulus presentation durations of 1.5, 1 and 1 second. The first period was longer in order to make sure that a proper SSVEP response would have the chance of forming and the initial transient VEP would have to be discarded. Figure 4.10 shows that in this case, the SSVEP quickly follows the stimulation as well.

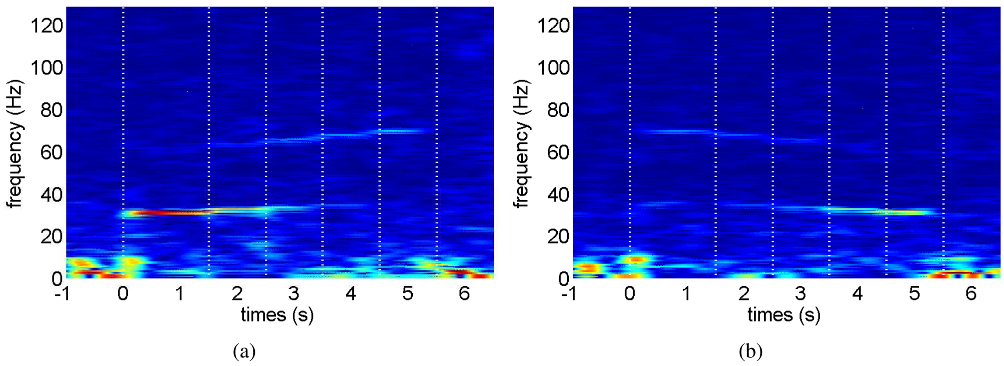


Figure 4.11: *Response to stimulation stepping from 30 to 34 Hz with 1 Hz steps (a) and back (b).*

To find out if this would also work for smaller steps and larger ranges, the same experiment was carried out with frequencies ranging from 30 to 34 Hz (and vice versa) with steps of 1 Hz per second. The results in Figure 4.11 show that the subject's response to the higher frequencies only manifested itself in the second harmonic. Furthermore, energy appears to leak between frequencies (i.e. energy increases for other frequencies than the stimulation frequency). Nevertheless, the SSVEP response follows the stimulation fairly well and fast.

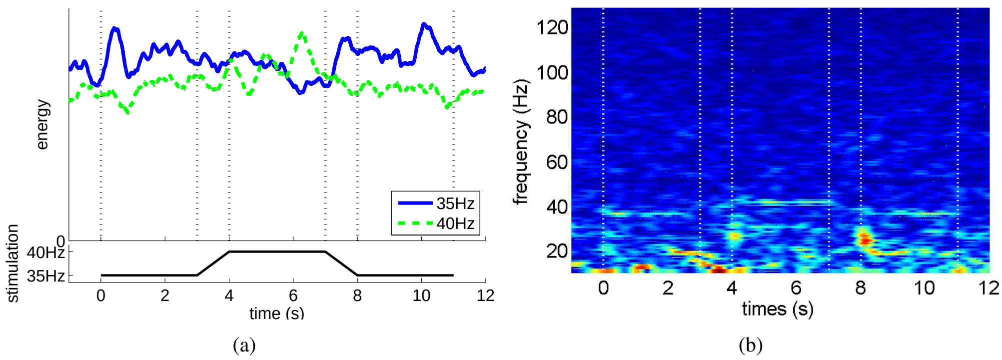


Figure 4.12: *Response to stimulation chirping from 35 to 40 Hz and back. a) Mean energy for all constituent frequencies over time. b) Time-frequency (STFT) plot of the response to stimulation with a changing frequency. Due to many low frequency noise, the range between 0 and 10 Hz is not plotted here.*

It was also tested if the brain would respond better to a chirp transition (see Figure 4.7(c)). Each of the 20 trials consisted of 3 seconds of 35 Hz stimulation, followed by 1 second in which a linear transition to 40 Hz was made, after which the stimulation remained at 40 Hz for another 3 seconds, took 1 second to decrease again and then oscillated at 35 Hz for 3 seconds again. Figure 4.12 (especially 4.12(b)) shows that while the stimulating frequency was constant, an SSVEP response was perceivable. During the periods that the frequency was changing, the result is too noisy to say with confidence whether the SSVEP is following. The low amplitude of the SSVEP and large amount of noise can probably be attributed to a weak response to higher frequencies and the fact that the subject was getting tired.

4.3.2 Combined frequencies

If a BCI requires a lot of targets, it has to distinguish between them. The classical way of doing this for SSVEP-based BCIs is to alternate these targets at different frequencies (i.e. frequency tagging from Section 2.4.4). More targets therefore require more frequencies, which means that frequencies must be used that are either less optimal in terms of SSVEP response, or closer together, making them less distinct and harder to separate during analysis.

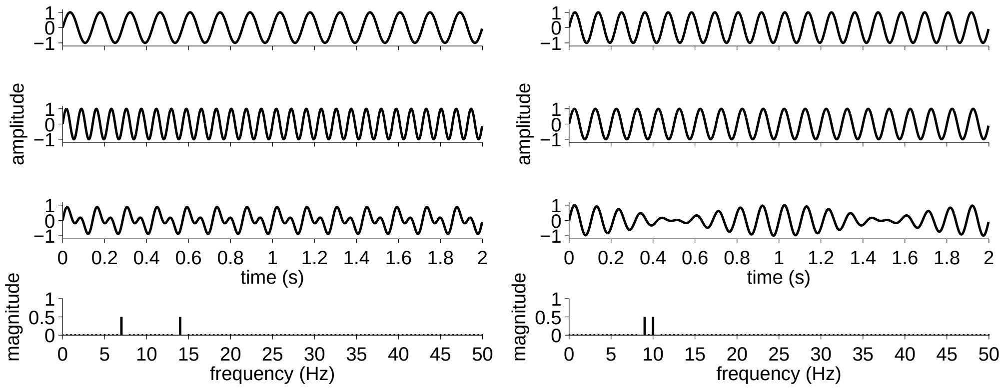
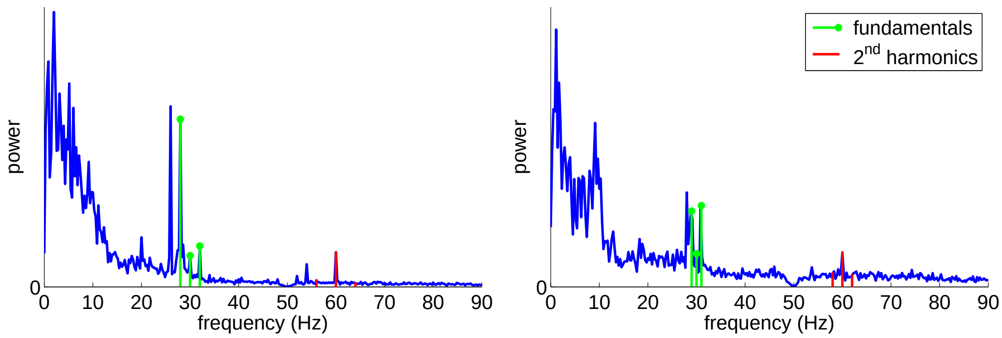


Figure 4.13: *Sine waves and how they can be combined into a new stimulation signal. The frequency plots on the bottom row shows that the resulting signal indeed only features the constituent components. a) Sine waves for 7 Hz, 14 Hz, and a combined stimulation of 7&14 Hz. b) Sine waves for 9 Hz, 10 Hz, and a combined stimulation of 9&10 Hz. Note that because these signals are not phase-locked, the amplitude varies significantly over time.*

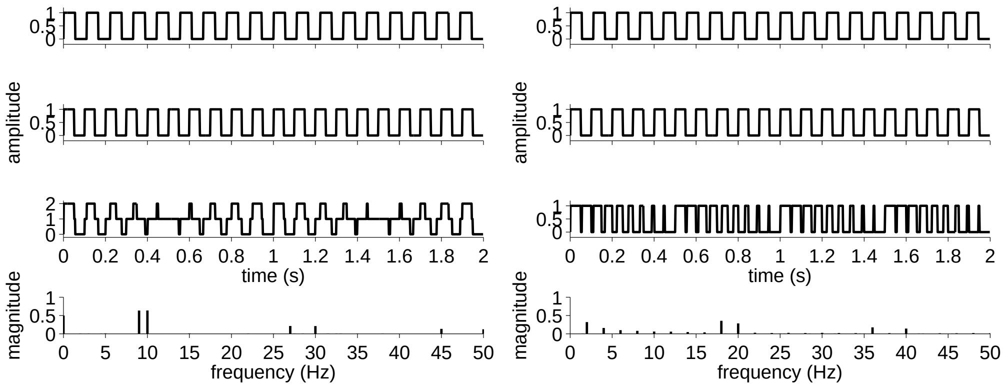
In some cases it may possible to combine certain frequencies by adding or averaging multiple pure frequency stimulations. Figure 4.13 shows how combined stimuli can be obtained from simple sine waves with a single frequency. Such a stimulation method supposedly elicits SSVEP responses at all constituent frequencies as well as linear combinations of those frequencies [37] (i.e. all frequencies $mF_1 \pm nF_2$, where m and n are integers). These extra peaks in the SSVEP frequency spectrum make it possible to distinguish between stimuli that use the same frequencies, but in different combinations. Using this principle only N frequencies are required to drive $N(N-1)/2$ stimuli, possibly in addition to using the N single frequencies for N other stimuli.



(a) 28-30-32 (b) 29-30-31

Figure 4.14: *Fourier spectra of the averaged responses to RVS modulated to oscillate at multiple frequencies. a) 28, 30 and 32 Hz. b) 29, 30 and 31 Hz.*

Figure 4.14 shows the Fourier spectra that were acquired from 20 trial averages where the user was presented with stimuli oscillating at 28&30&32 Hz and 29&30&31 Hz, for 3.5 seconds at a time on the white LED board. The spectra show peaks for each of the stimulating frequencies, as well as some linear combinations. It should therefore potentially be possible to distinguish between targets based on a specific combination of fixed frequencies. This might be interesting for systems with a large number of targets, since the number of constituent frequencies may be decreased.



(a) (b)

Figure 4.15: *Square waves of 9 and 10 Hz and how they can be combined into a new stimulation signal. a) Both signals are simply added together. The frequency response shows peaks at the odd harmonics of 9 and 10 Hz, but not at linear combinations, which is normal for square waves. b) The state of the combined signal changes whenever a state change occurs in one of the component signals. This results in a fairly noisy frequency response that appears to consist of linear combinations of the second harmonics of the constituent frequencies.*

While using combined frequency stimulation is fairly easy on a device that can generate sine waves (i.e. LEDs), it is not when devices are constrained to using square wave stimulation because they have low framerates (see Section 4.5 for more about waveforms and Section 4.2 for more about framerates).

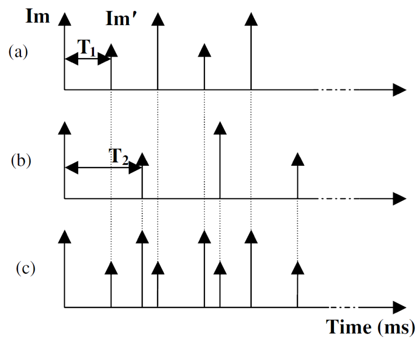


Figure 4.16: *Timing diagram from [89] for achieving stimulation at frequency F_1 and F_2 and dual stimulation F_1&F_2. Figure from [89].*

It is not as easy to combine square waves as it is to combine sine waves, because simply adding or averaging two signals introduces a third state that the device needs to display (see Figure 4.15(a). Since this may not be feasible, another method could be to simply look at the times of state change in the constituent signals and then use all of them in the combined signal [89] (see Figure 4.16 and Figure 4.15(b)). It was found that when two signals with frequencies F_1 and $F_2 = \frac{1}{2}F_1$ are combined, energy peaks occur at $mF_1 + nF_2$, where m and n are integers [89], which is consistent with [37].

It is suggested that this property holds for any F_1 and F_2 and does not depend on the fact that in the reported experiments F_2 was exactly half of F_1, however this is highly questionable. The way the combined signal turns out depends in part on the phases of the constituent signals as well as the framerate of the stimulation device. For instance, if there is a harmonic relation between F_1 and F_2 (i.e. $F_1 = nF_2$, where n is an integer, assuming $F_1 > F_2$), and both signals have a phase shift of 0, the combined signal simply has frequency F_1, since all state changes in F_2 occur at the exact same time as F_1's. If the state changes in the constituent signals are not simultaneous, there are theoretically exactly $F_1 + F_2$ state changes per second (with three different state display durations, instead of one for a normal signal of $F_1 + F_2$ Hz). However, some state display durations may be so short that they cannot be rendered on a device with a low refresh rate, which means that relative phase shifts can significantly alter the displayed stimulation. This problem can get even worse when F_1 and F_2 do not have a harmonic relationship.

4.4 Phase

The SSVEP is phase-locked to the visual stimulation. We verified this by doing an experiment where the subject was asked to focus 20 times for 3 seconds on a sinusoidal stimulus modulated at $12\frac{2}{3}$ Hz, each time with a different phase. When the SSVEP responses were added together, they canceled each other out and the average signal showed (virtually) no response at the stimulation frequency. When FFTs were computed for each trial separately, and then averaged, a clear peak was shown at the stimulation frequency, indicating that there had in fact been a strong SSVEP response.

Because the SSVEP response has a fixed phase lag, phase can be used as a discriminating property of a target [90, 91, 92]. Instead of using stimuli with different frequencies, it is also possible to use stimuli with different phases. This approach will be referred to as *"phase tagging"*. Using phase tagging, possibly in addition to the more common frequency tagging, requires the use of less different frequencies. This generally means that the best frequencies (for either performance or comfort) can be used [92].

In order to determine the phase of the SSVEP, the stimulation frequency component needs to be isolated. This thesis generally uses IIR filters, but since they destroy phase information, it is better to use a FIR filter, which only transforms the phase in a linear manner. The resulting signal should be almost perfectly sinusoidal and the phase can be extracted using a Hilbert transformation. Use of the maximum contrast spatial filter was shown to significantly improve performance compared to just using $O_z - C_z$ [92].

Use of phase tagging requires that the phase difference between the stimulus and the SSVEP response is known. This can probably best be obtained in a calibration period prior to BCI operation. The phase characteristics of the SSVEP can be affected by a number of factors [37], but it is unclear how stable they are over longer periods of time.

The phase lag can be obtained in a calibration period where the light from one of the targets is measured with a photodiode [92]. Then, when operation starts, the SSVEP phase can be compared to the phase measured by the photodiode to determine the phase of the RVS that the user is focusing on. Using a photodiode to measure the light signal prevents problems with phase drift of the stimulation, although a robust phase locking mechanism is always required between all the stimuli in a phase tagging paradigm.

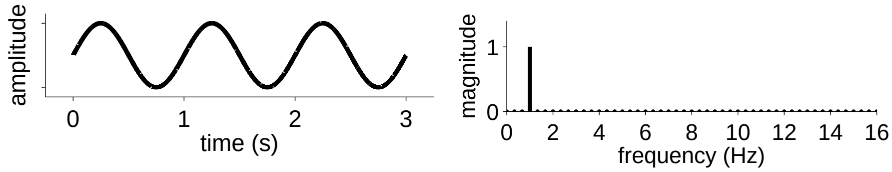
Use of a photodiode is technically not necessary, because the BCI can operate without exact knowledge of the stimulation phase. Instead of determining the phase lag with respect to one of the stimuli, it can also be determined with respect to a signal with a fixed but arbitrarily chosen phase φ. Since the "error" that is made using this approach is the same for each stimulus, it makes no difference. Not requiring a photodiode is an obvious advantage, but this approach only works if the stimulation phase does not change with regard to φ between calibration and operation. This means that, depending on the stimulation device, it might not be possible to turn the stimulation off between calibration and operation. Furthermore, if the phase of the stimulation drifts over time (as it does slightly on our hardware), the calibration data can slowly become invalid.

4.5 Waveform

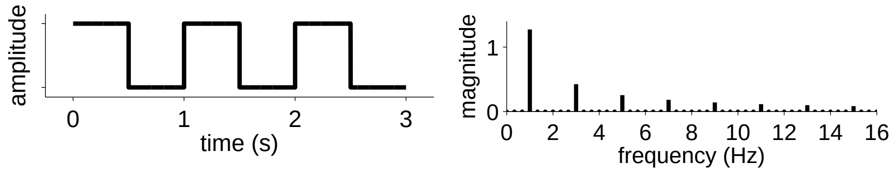
The waveform of a signal defines the transitions between states of the stimulus. Sine and square waves are used most often (see Figures 4.17(a) and 4.17(c)). Usually no reason is given, but both are logical choices. A signal of a certain frequency F is usually thought of as the sine wave described by $sin(2\pi Ft)$, where t is the represents the time in seconds. Such a signal has a sole peak at the stimulation frequency in the time-frequency spectrum. Using a sine wave means that the signal spends some of its time at or near the (extreme) states and some of the time in between, making the transitions fairly soft.

Because the brain often seems to react to change, a stronger SSVEP may be elicited by a square wave (see Figure 4.17(c)), although this is likely also less comfortable. When a square wave is used, transitions are instant. All of the time is spent in one of the extreme states of the stimulation (although in practice the transition may still take a small amount of time). When using stimulation devices with low framerates (like computer monitors), the square wave is the most logical choice. For lower frequencies it might be possible to try and approximate other waveforms, but this approach does not seem to be popular.

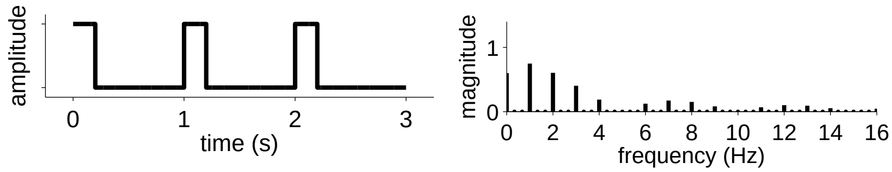
In order to better understand the relationship between waveform and SSVEP response, seven waveforms (see Figure 4.17) were presented to test subjects at frequencies from each frequency band: 8, 15 and 40 Hz (see Section 4.3). Figure 4.18 shows that the higher the stimulation frequency is, the smaller the SSVEP response is, especially in the higher harmonics. There appears to be little relation between the Fourier spectra of the brain response and those of the stimulation depicted in Figure 4.17, suggesting that the brain's transformation of the input signal is nonlinear. For instance, there are pronounced peaks at the harmonic frequencies of 8 Hz even when the stimulation was presented using a sine wave. The strength of the SSVEP response appears to be highly dependent on the frequency and waveform of the stimulation, as well as the interaction between those variables. Overall, it appears that a (non-narrow) square wave elicits the robust SSVEP response across the tested frequencies.



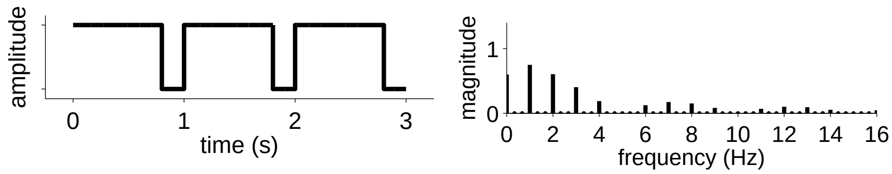
(a) Sine wave (b) Sine Fourier response



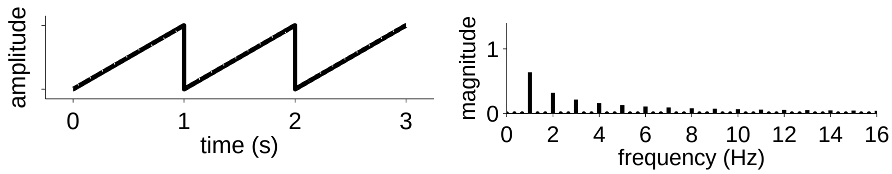
(c) Square wave (d) Square Fourier response



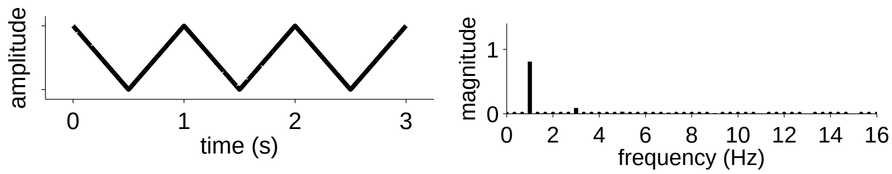
(e) Square wave with 20% duty cycle (f) Fourier response



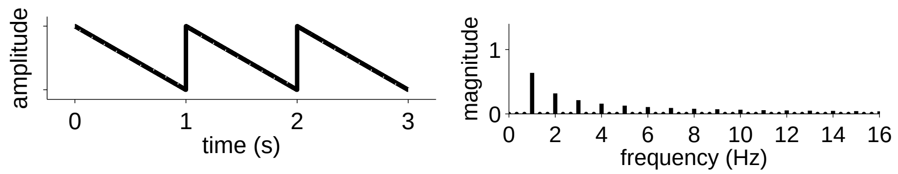
(g) Square wave with 80% duty cycle (h) Fourier response



(i) Sawtooth wave (j) Sawtooth Fourier response

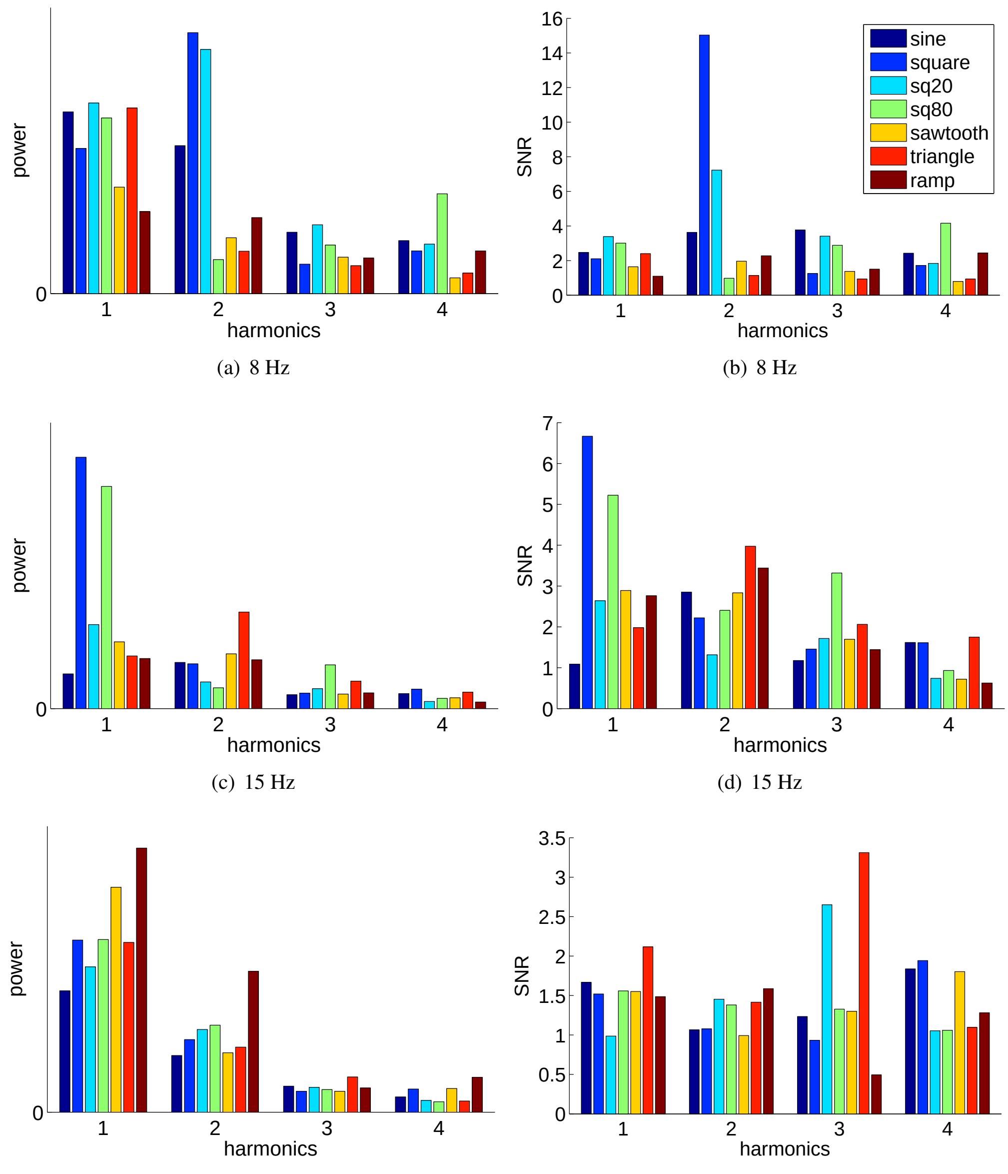


(k) Triangle wave (l) Triangle Fourier response



(m) Ramp wave (n) Ramp Fourier response

Figure 4.17: *Waveforms and their Fourier transforms*



(a) 8 Hz (b) 8 Hz

(c) 15 Hz (d) 15 Hz

(e) 40 Hz (f) 40 Hz

Figure 4.18: *Mean power (a, c and e; left) and SNR (b, d and f; right) of the SSVEP response at the first 4 harmonics of the stimulation frequency.*

4.6 Luminance and contrast

Conventional wisdom says that more pronounced differences between the states of a stimulus will result in a larger response in the brain. In most research, the difference in states is in luminance only. The luminance contrast or *"modulation depth"* is defined as $(l_{\max} - l_{\min})/(l_{\max} + l_{\min}) \times 100\%$, where $l_{\min}$, $l_{\max}$ are the minimum and maximum luminance, respectively [93].

The amplitude of the evoked potentials was found to be linearly increasing the logarithm of the contrast of a stimulus [94]. Brightness and modulation depth also tends to increase SSVEP amplitude [95]. Unfortunately, increasing the luminance or contrast of a stimulus is the easiest way to negatively affect more photosensitive subjects [96, 43].

Luminance contrast information is critical for perception of form, motion and depth [97, 98, 99, 100, 101]. Differences have been observed psychophysically in brightness and darkness perception and also in low and high-contrast perception [97, 102, 103, 104, 105]. Early neurophysiological studies demonstrated a functional dichotomy in the processing of positive- and negative-contrast [97, 106, 107, 108]. On-center (ON) and off-center (OFF) cells form this pair of parallel pathways, which remain independent up to primary visual cortex and which appear to mediate the separate perceptions of brightness and darkness [97, 102, 107, 109]. VEPs to bright and dark checks demonstrate differences in ON and OFF-cell activity [97]. The contrast sensitivity of cells in the M-pathway is nearly 10 times greater than that of cells in the P-pathway [97, 110, 111].

It was found that a raster of dark squares emerging from a neutral background elicited larger responses than did bright squares, especially when the spatial frequency was high [97]. The tested frequency was 10 Hz and a sine waveform was approximated on a computer monitor. Amplitude appeared to be a parabolic function of the spatial frequency of the stimulus (see Section 4.8).

It was tried to verify the research by Zemon & Gordon [97] with the Experimentation BCI. Eight conditions were tested, where both foreground and background luminance of the stimuli was varied:

Name	**Foreground color**	**Background color**	**Foreground luminance**	**Background luminance**	**Modulation depth**
w/k	white	black	175	0.86	99%
l/k	light gray	black	80.7	0.86	98%
n/k	neutral gray	black	31.8	0.86	95%
d/k	dark gray	black	8.6	0.86	82%
w/n	white	neutral gray	31.8	31.8	69%
k/n	black	neutral gray	0.86	31.8	-95%
n/w	neutral gray	white	31.8	175	-69%
k/w	black	white	0.86	175	-99%

Figure 4.19 shows the primary results in terms of comfort and performance. More details can be found in Figure 4.20. Two trends in performance are noticeable: 1) contrary to Zemon's work, it appears that bright stimuli work better than dark stimuli, and 2) there is a positive correlation between modulation depth and performance. Bright backgrounds are considered less comfortable, but neutral and black backgrounds are about equal. Brighter backgrounds are also more likely to invoke photosensitivity problems [43].

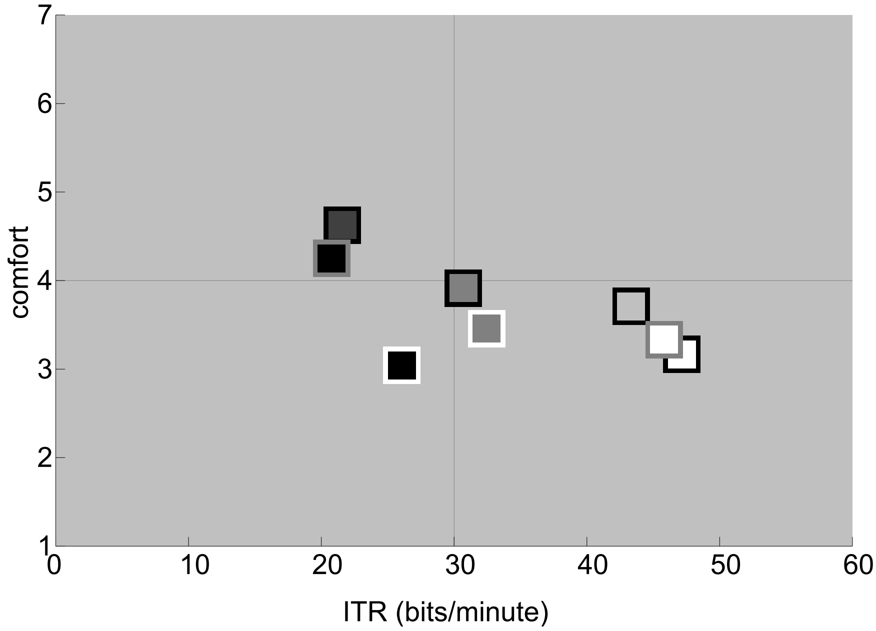
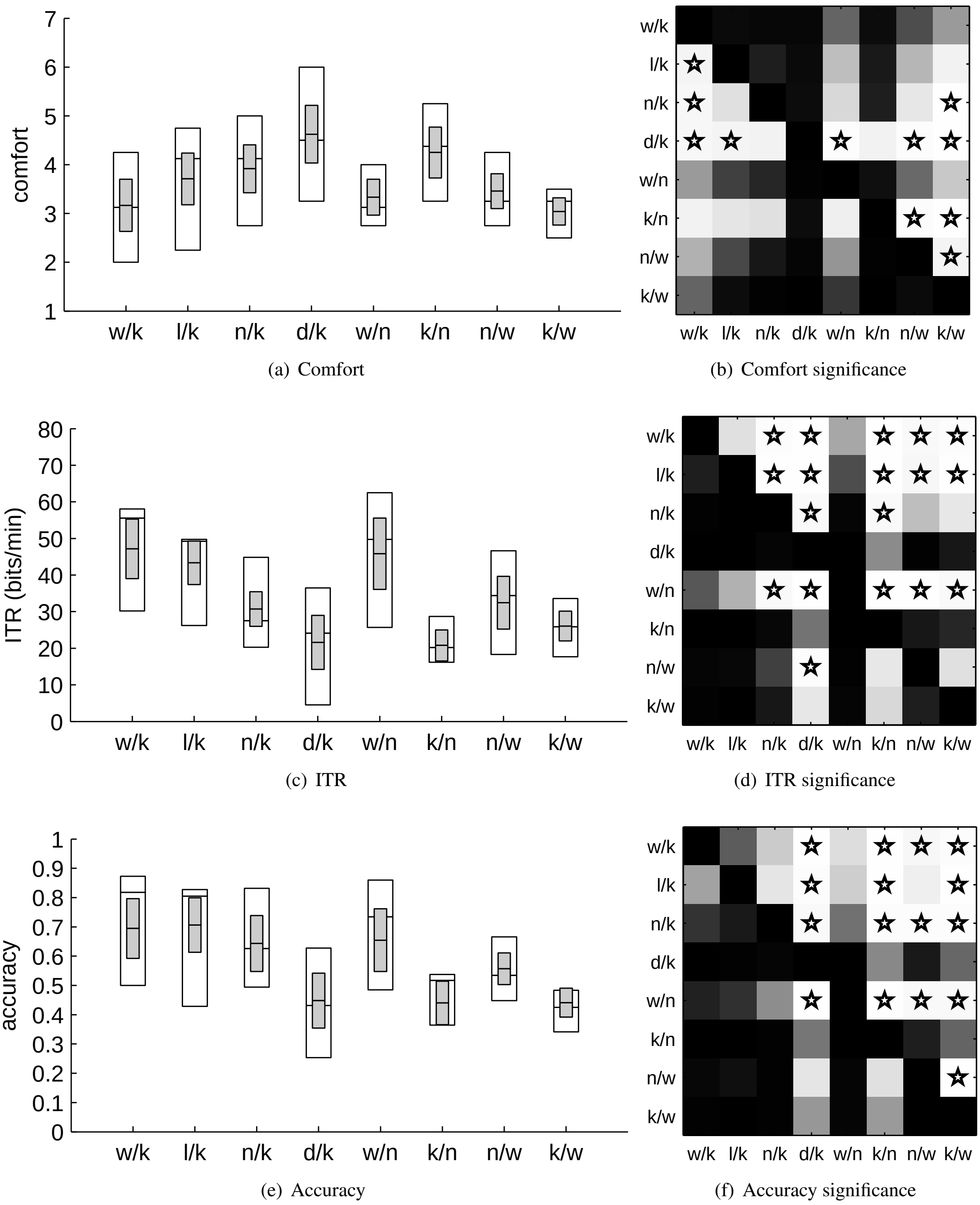


Figure 4.19: *Comfort and performance results for stimuli with different contrasts and achromatic configurations. The edge of the squares indicates the background color and the center depicts the stimulus color.*



(a) Comfort (b) Comfort significance

(c) ITR (d) ITR significance

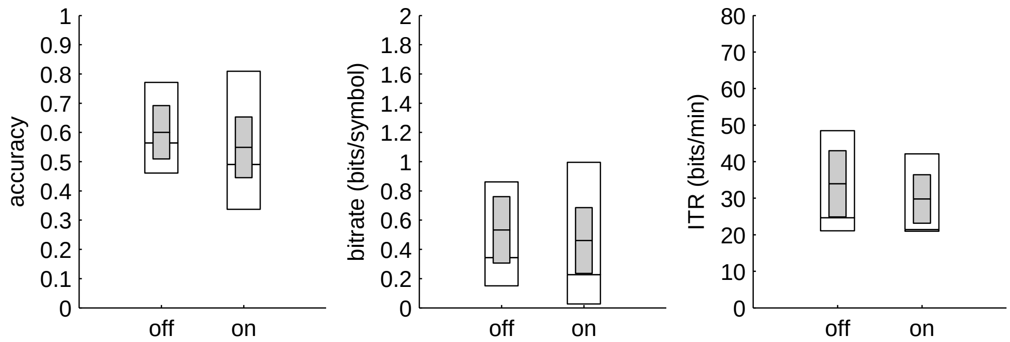
(e) Accuracy (f) Accuracy significance

Figure 4.20: *Comfort, performance and accuracy of the Experimentation BCI obtained stimuli with different luminance and contrast characteristics. Left: means with standard errors (gray boxes) and medians with first and third quartiles (white boxes). Right: significance p-values for the comparisons between conditions (white is low; black is high). A star on row α and column β means that the mean for condition α is significantly better than the mean of condition β.*

4.7 Environment

It is often observed that performance during demonstrations is worse than during carefully controlled experiments. This might be explained by bad luck or subject nervousness, but it might also have something to do with factors in the environment: lighting conditions, noise, and talking and moving people. Since the SSVEP response strength is modulated by the user's attention, distracting factors such as these are likely to deteriorate performance.

Illuminated environments are more natural and convenient than dark ones, but when it is dark, it is harder for the subject to perceive – and thus be distracted by – objects in the environment. In the dark a bright stimulus can also seem much more pronounced. The notion of environmental illumination is closely related to the contrast of the displayed RVSi (see Section 4.6). Pupil dilations caused by a dark environment might cause the eye to catch more of the stimuli's light. Furthermore, external light sources might also flicker a little, interfering with the SSVEP response. All of these observations suggest that BCI performance might be increased in dark environments [56].



(a) Accuracy (b) Bitrate (c) ITR

Figure 4.21: *Accuracies, bitrates and ITRs of the Experimentation BCI obtained when the lights in the room were turned either on or off. The increase in ITR when the light is turned off is significant at the* $p < 0.1$ *level.*

A dark environment is shown to be slightly more advantageous (significant at the $p < 0.1$ level), confirming the results from [56] (see Figure 4.21). Although no questionnaire was conducted, subjects did comment that they preferred the more natural condition where the lights were on. Effects of other environmental factors such as noise and movement should still be investigated.

4.8 Pattern reversal and spatial frequency

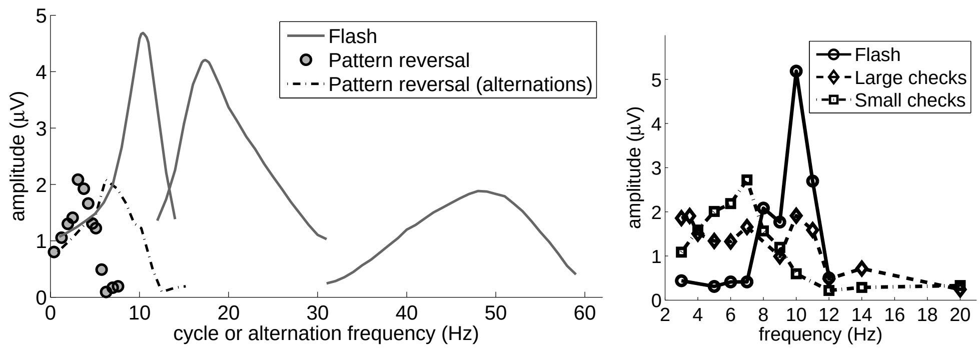
Patterned stimuli such as checkerboards or lineboxes are often used as an alternative to single graphic RVSi. The *"spatial frequency"* of such a stimulus defines how many changes there are within a certain space. More specifically, the spatial frequency is expressed in the number of changes per angle degree *"cpd"* of the visual field.

There are basically two ways in which patterned stimuli can be presented: by flickering them on and off, or by reversing the cells or checks of the pattern. No examples of BCIs were found that used flickering patterns, except those discussed in Section 4.13.4, so the remainder of this section focuses on pattern reversal.

Pattern reversal elicits an SSVEP response at twice the stimulating frequency. It is therefore suggested that pattern reversal stimuli work better at lower frequencies [112]. For this reason users of the Experimentation BCI go through a separate frequency selection procedure that uses additional lower frequencies. However, an interaction between frequency sensitivity and spatial frequency has also been found, where stimuli with high spatial frequencies elicit stronger SSVEP responses at lower temporal stimulation frequencies and vice versa [112].

The contrast of a pattern stimulus is defined between the luminance of the two kinds of cells it contains. However, decreasing the spatial frequency to a number below the size of the stimulus results in a simple square RVS and increasing it to infinity reduces it to a square with a constant color that is the combination of the cell colors. The fact that cells are smaller and tend to blur together at higher spatial frequencies, means that in any part of the visual field, changes between stimulus states are smaller than at low spatial frequencies. This suggests that increases in spatial frequency might be comparable to decreases in contrast [113]. There is however also evidence for a relationship between spatial frequency and contrast sensitivity that is not monotonically increasing [93, 114]. Results from [115] do confirm that there appears to be a continuum from small checks, to larger checks, to flicker stimuli in terms of frequency response strength. Figure 4.22 shows that SSVEP amplitudes for a checkerboard with high spatial frequency only exceed those of a simple flash stimulus at very low frequencies.

Zemon & Gordon [97] found that SSVEP amplitude appeared to be a parabolic function of the spatial frequency of the stimulus. This effect diminished when the contrast was smaller. It was also found that the phase lag of the SSVEP response with respect to the stimulation increased when spatial frequency and modulation depth decreased. Differences in phase lag between dark and bright stimuli were also the largest at low spatial frequencies. Possibly because low spatial frequency stimuli primarily use the faster M-pathway.



(a) (b)

Figure 4.22: *SSVEP response amplitude as a function of temporal and spatial frequency. a) Simple flash stimulation (solid line) and pattern reversal stimulation with checks smaller than* $20'$ *(markers). The dashed line also represents the pattern reversal condition, but is plotted with the alternation frequency on the x-axis rather than the cycle frequency. b) SSVEP amplitude for a simple flash and checkerboards with checks of* $40'$ *and* $12'$ *of the visual field. Both figures were taken from [37].*

Another salient observation is that if the pattern has an even (or large) number of cells, the entire stimulus remains (almost) equiluminant during the whole stimulation period, which might not be as fatigue inducing as stimuli with big luminance changes are.

Research suggests that the relation between spatial frequency and SSVEP response strength is non-linear and color-dependent. Results in [116] suggest that for black-white checkerboards the response strength at first slowly increases with the spatial frequency and then drops of fairly steeply. The response strength for red-green checkerboards started off higher at low spatial frequencies for the second harmonic, then remained roughly the same, until it started to deteriorate slightly earlier than black-white induced activity did (see also [37]). The response for the fourth harmonic was roughly the same for lower spatial frequencies but increased for black-white stimuli.

Although patterned stimuli take many forms, to the best of my knowledge only lineboxes and especially checkerboards have been used in SSVEP-based BCIs. In order to test the effects of spatial frequency on performance and comfort the Experimentation BCI experiment was conducted with 6×6 cm black and white checkerboards:

Check size (angle)	**Check size (mm)**	**Check number**
$2°27'$	30	2×2
$1°14'$	15	4×4
$0°37'$	7.5	8×8
$0°18'$	3.75	16×16
$0°09'$	1.875	32×32
$0°05'$	1.111	54×54

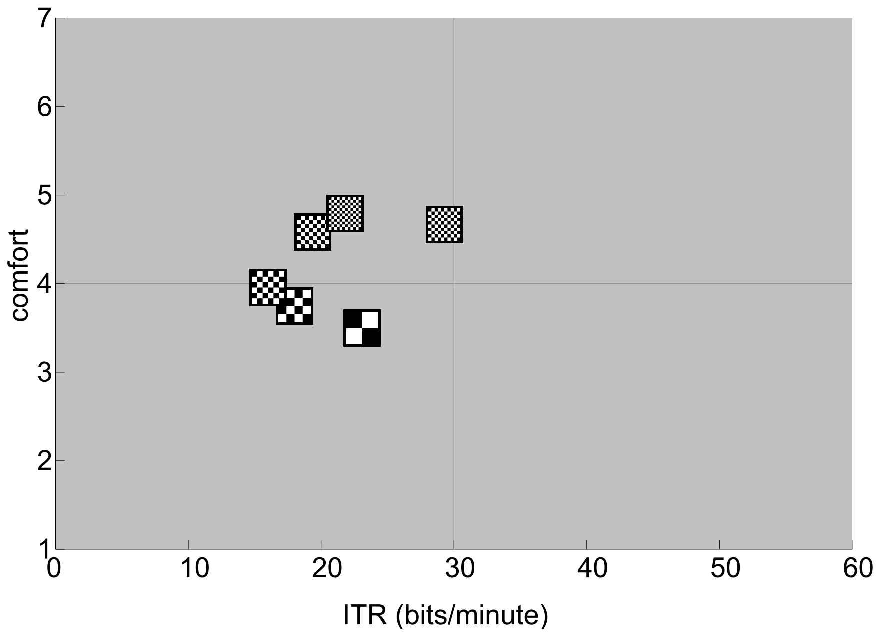
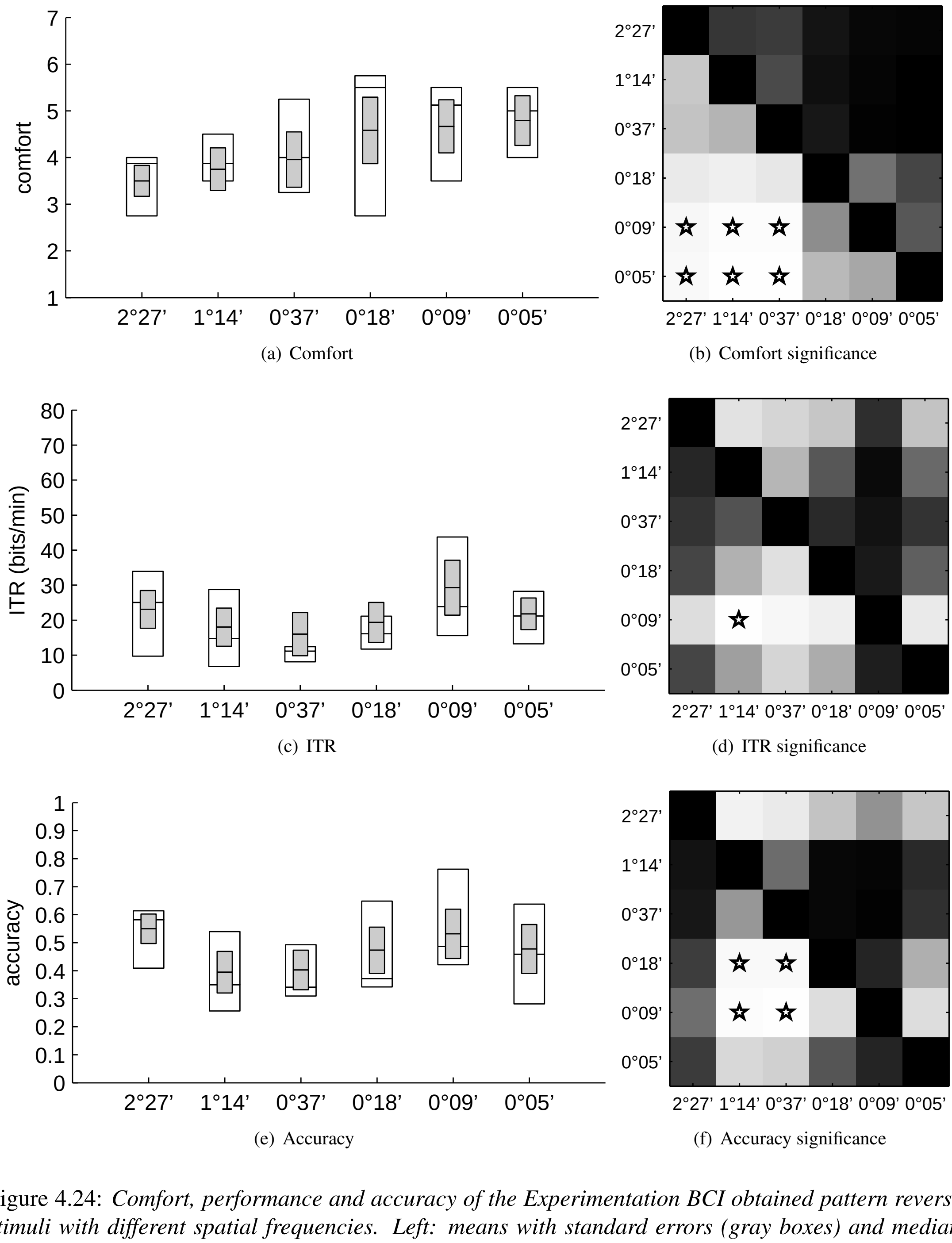


Figure 4.23: *Comfort and performance results for stimuli with different spatial frequencies. Since the figure is not large enough to show stimuli with the correct number of cells, the depicted number is smaller and can only be used to determine which stimulus has a relatively higher spatial frequency.*

It is hard to say anything definitive about the results, but it was found that using higher spatial frequencies (and thus smaller cells) can sometimes be beneficial (Figure 4.23). However, the relationship with performance appears to be nonlinear and strongly subject dependent. These findings contradict those of Zemon & Gordon [97], who found a parabolic function which suggested that low and high spatial frequencies were better than medium ones. User comfort is clearly positively related with the spatial frequency, which is likely due to the smaller cell sizes. Using a spatial frequency of 6.5 cpd appears to provide the best tradeoff. However, the performance is worse than that achieved in most of the single graphic conditions reported in Section 4.11 and Section 4.6.

Some studies have found that better brain responses are elicited by patterned stimuli [8, 12], while others have found the contrary [117]. The experiment carried out in order to determine the effects of RVS size on performance and comfort described more extensively in Section 4.10 also provides information about how pattern reversal stimulation compares to single graphic flicker. The results show that performance for single graphic flicker is vastly better than performance for pattern reversal.



(a) Comfort (b) Comfort significance

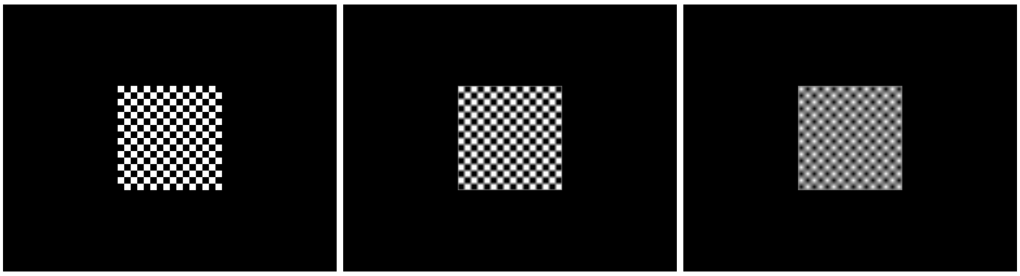
(c) ITR (d) ITR significance

(e) Accuracy (f) Accuracy significance

Figure 4.24: *Comfort, performance and accuracy of the Experimentation BCI obtained pattern reversal stimuli with different spatial frequencies. Left: means with standard errors (gray boxes) and medians with first and third quartiles (white boxes). Right: significance p-values for the comparisons between conditions (white is low; black is high). A star on row α and column β means that the mean for condition α is significantly better than the mean of condition β.*

4.9 Blur

It seems intuitive to assume that the abrupt state changes of RVSi as well as the hard edges of the stimuli are contributing to the fatigue inducing properties of these stimuli. Furthermore, they may also play an important role in photosensitivity problems because spatial contrast is such a big factor [43]. Making stimuli appear blurred can diminish these properties. Temporal blur is basically the same as using different waveforms than square-waves or pulses and was already described in Section 4.5. In a sense, the patterned stimuli described so far were described by square-waves in the spatial domain, i.e. all changes were sudden. By using bilinear filtering this "waveform" can be smoothened and the cell transitions are blurred spatially.



(a) No blur (b) Weak blur (c) Strong blur

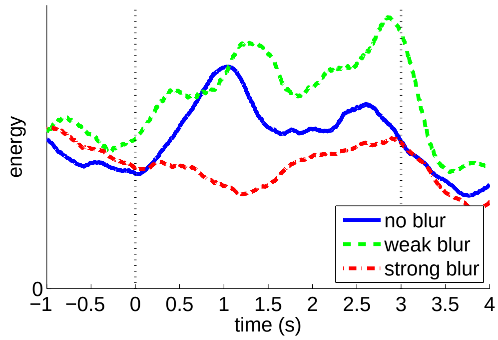
Figure 4.25: *Different levels of blur.*

Bilinear filtering is a texture filtering method used to smooth textures when displayed larger or smaller than they actually are. The texture in this case is the checkerboard and the most efficient way of representing it for rendering is to use one point, called a *texel*, per cell. If this texture is enlarged so that more than one pixel is rendered for each texel, each pixel is normally colored based solely on the texel that it is closest to (nearest neighbor principle). When bilinear filtering is used, each pixel's color is given by the average of the colors of the surrounding 4 texels, weighted by the distance to each texel, which causes a blurring effect. It is clear that on a checkerboard only the pixels between texels of separate cells are blurred and not the ones between texels within one cell. Assuming infinite resolution (i.e. no pixel is exactly on a texel) the amount of blurring can be measured by the proportion of blurred pixels to non-blurred pixels, which is given by $\frac{100\%}{T}$, where $T \times T$ texels are used per cell.

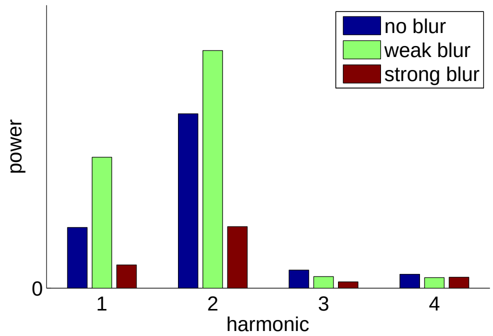
The effect of spatial blur was investigated with the CRT monitor using a refresh rate of 85 Hz. One test subject (right-handed male with corrected-to-normal vision) sat 70 cm away from the monitor that displayed a 10×10 cm 16×16 cell checkerboard alternating at 10 Hz. Three levels of blur were defined: no blur, weak blur (50%), and strong blur (100%) (see Figure 4.25). The subject reported that the weak blur condition was the most comfortable, followed by the strong blur condition. There were 20 randomly intermingled trials for each condition. Each trial started with a beep cueing the subject to pay attention. One second later, the RVS would appear for 3 seconds. Stimulus presentation was followed by a resting period of 3-5 seconds.

Figure 4.26 shows that blurring the stimulus can have a large impact on SSVEP response. The response for the first two harmonics was significantly weaker than for the other two conditions ($p < 0.05$). The fundamental frequency response was significantly larger for the weakly blurred stimulus than for the normal checkerboard without the blurring effect ($p < 0.05$). This means that the condition with 50% blur was the best in both performance and comfort.

Signals acquired during stimulus presentation for each condition were notch filtered to eliminate 50 Hz power line interference and then averaged. FFTs were computed for each condition and it was found that the SSVEP response for the weak blur condition was slightly higher than when there was no blur. Both conditions elicited significantly stronger SSVEPs than the strongly blurred stimulus did.



(a) Energy



(b) Powers

Figure 4.26: *Amplitudes of the SSVEP response to checkerboards with different levels of blur, oscillating at 10 Hz. a) The energy of the first 4 harmonics over time. The dotted vertical lines show when the stimulus turned on and off. b) Powers of the first 4 harmonics calculated over the entire interval using a Fourier transform.*

4.10 Size

The larger the stimulus, the easier it is to notice, but the harder it might be to ignore. Research has suggested that decreasing the area of a stimulus that must be attended to can decrease BCI performance [118]. Stimulus size can also affect the amount of light transmitted to the user and determines how large an application needs to be or how much surface area remains for other purposes.

To test the effects of both simple and patterned stimuli on BCI performance and comfort, the following eight conditions were tested:

Name	Size (angle)	Size (cm)	Check number	Check size (angle)	Check size (cm)
1cm	$0°49'$	1×1			
3cm	$2°27'$	3×3			
6cm	$4°54'$	6×6			
9cm	$7°21'$	9×9			
2@3	$2°27'$	3×3	2×2	$1°14'$	1.5
2@6	$4°54'$	6×6	2×2	$2°27'$	3
4@3	$2°27'$	3×3	4×4	$0°37'$	0.75
4@6	$4°54'$	6×6	4×4	$1°14'$	1.5

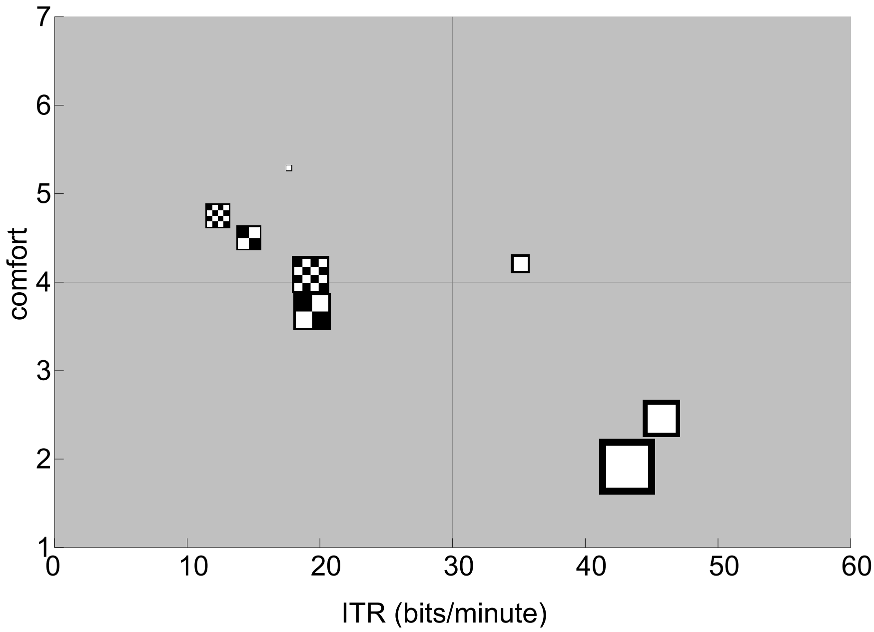
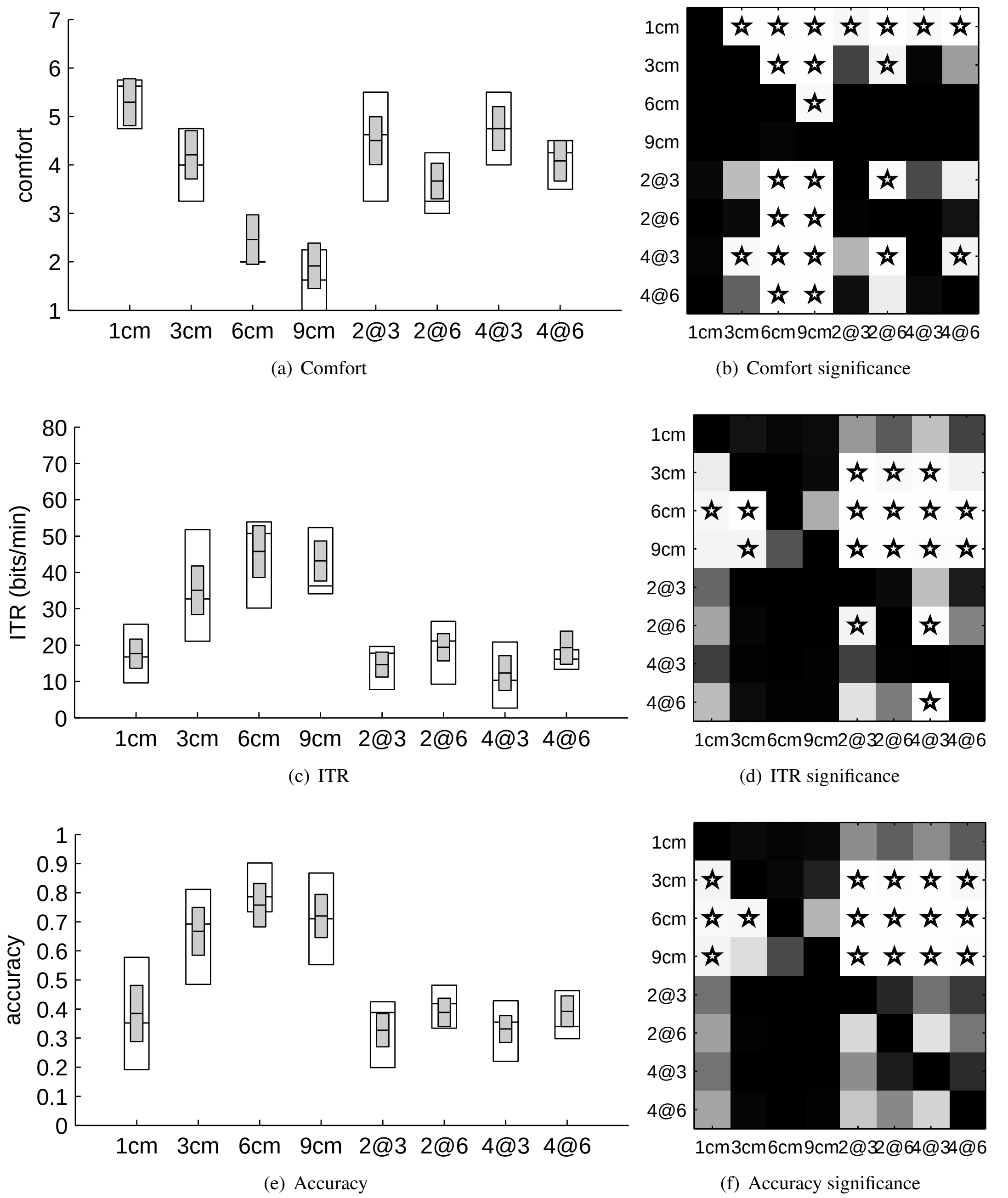


Figure 4.27: *Comfort and performance results for both single graphic and pattern reversal stimuli. The relative size of the stimuli is analogous to the size of the markers in this figure.*

The size of the stimulus seems to have a negative effect on user comfort for both checkerboards and flashing squares (see Figure 4.27). Furthermore, photosensitivity problems also occur more often as the stimulus size increases [43]. BCI performance was more positively impacted by an increase in stimulus size. However, when the BCI used the largest tested stimulus (9×9 cm; $7°21'23''$), performance was lower than when 6×6 cm ($4°54'29''$) were used.

The simplest explanation is that there is an optimal stimulus size that makes up a relatively small area of the visual field. A more likely explanation is that making the non-target stimuli larger and closer to the one the subject was attending to, had a detrimental effect on performance. This could be either due to increased interference in the eye, or increased difficulty to focus on the desired target. More experiments have to be carried out to investigate the cause of this anomaly.



(a) Comfort (b) Comfort significance

(c) ITR (d) ITR significance

(e) Accuracy (f) Accuracy significance

Figure 4.28: *Comfort, performance and accuracy of the Experimentation BCI obtained stimuli with different sizes. Left: means with standard errors (gray boxes) and medians with first and third quartiles (white boxes). Right: significance p-values for the comparisons between conditions (white is low; black is high). A star on row α and column β means that the mean for condition α is significantly better than the mean of condition β.*

4.11 Color

It is well known that color can affect mood as well as SSVEP response [119, 120]. Furthermore, different colors also have different luminance, so the choice of colors also affects the contrast. We tested different combinations of primary colors to see if hue and luminance would affect the performance and comfort of the system.

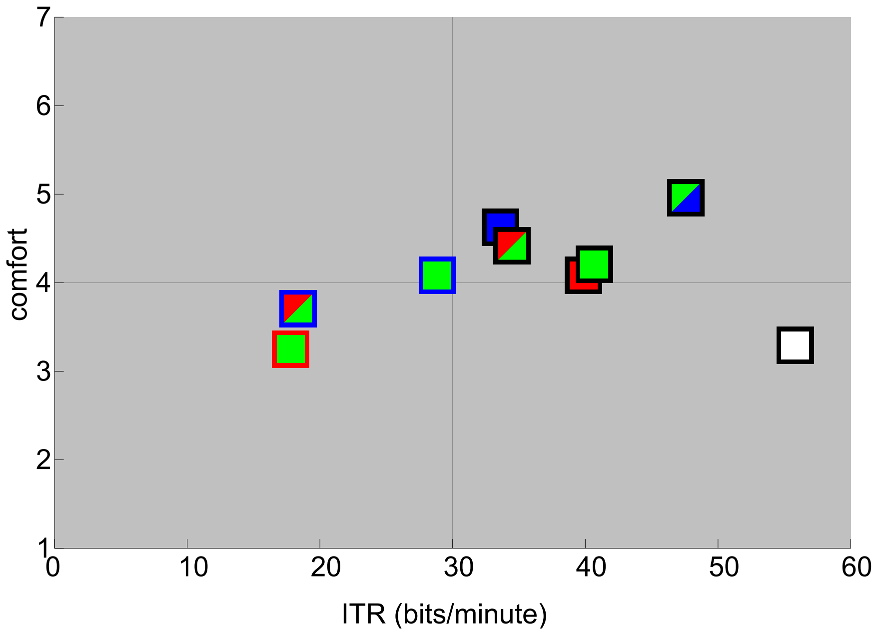


Figure 4.29: *Comfort and performance results for stimuli with different color configurations. The edge of the squares indicates the background color and the center depicts the stimulus color. When two colors are shown, the stimulus alternated between those colors and was otherwise still a square (not two triangles).*

In terms of color, the human eye is less sensitive to light in the red and blue parts of the light spectrum, while optimally sensitive in the green area at 510 nm (at 1700 lumen/m^2 of pupil area/Watt) and 555 nm (at 683 lumen/m^2 of pupil area/Watt) wavelengths for low light levels (below 0.003 cd/m^2) and high light levels (above 0.003 cd/m^2) respectively [37, 121]. The relation between SSVEP response strength and frequency is different for each color [119]. Furthermore, colors interact with the pattern (and spatial frequency) of the stimulus as well [37, 122].

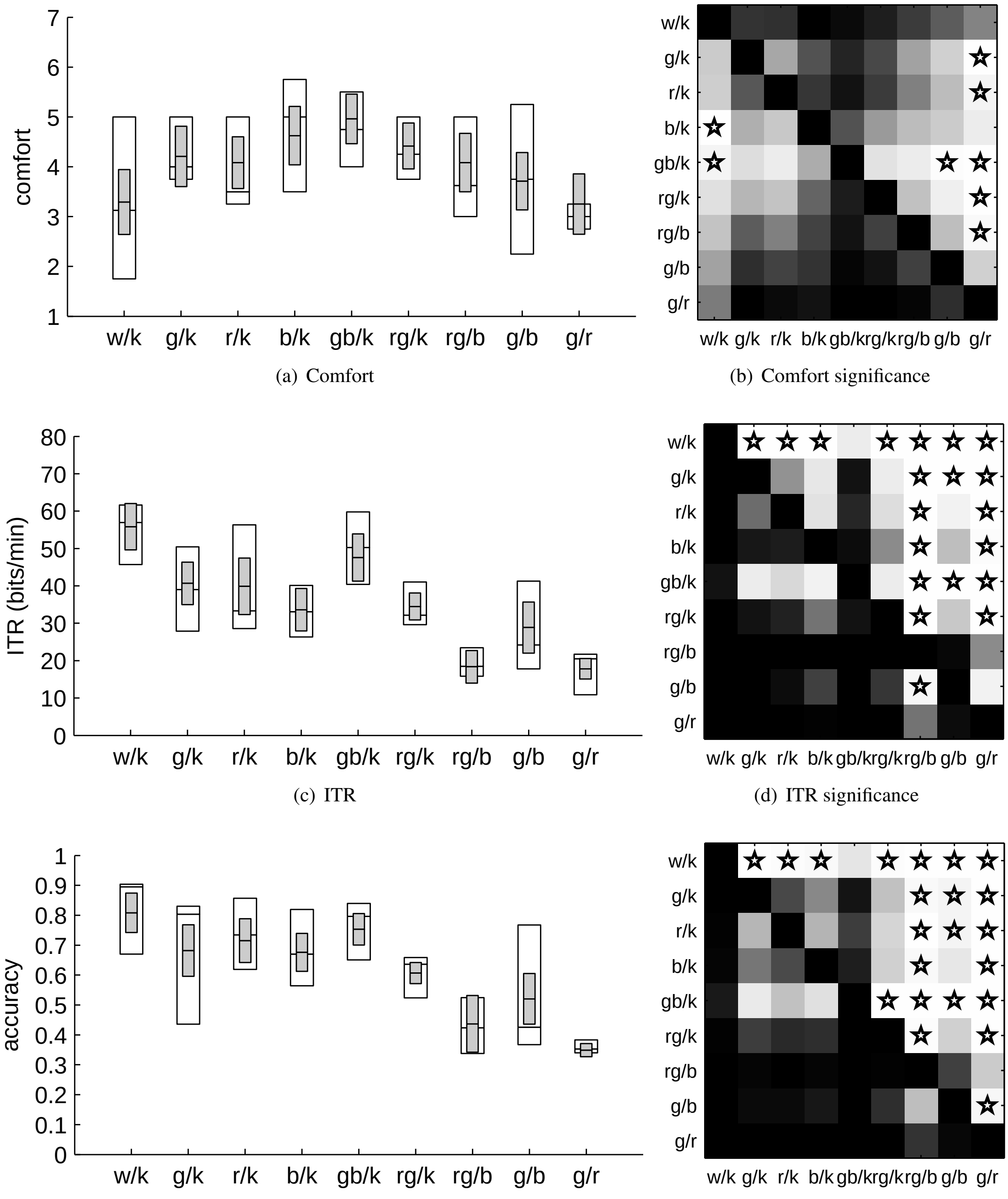
The role of color in photosensitivity problems sometimes caused by RVSi is debated [96]. Red and alternating between red and blue seem to be most often mentioned as the colors that have the largest response in patients [43]. Because our test subjects had declared that they were not photosensitive, we were able to carry out our experiments anyway.

In order to discover the effects of color on actual performance and comfort in a real BCI, nine conditions were tested with the Experimentation BCI:

Name	Color 1	Color 2	Background color	Luminance 1	Luminance 2	Background luminance	Modulation depth
w/k	white		black	175		0.86	99%
g/k	green		black	112		0.86	98%
r/k	red		black	49.4		0.86	97%
b/k	blue		black	15.2		0.86	89%
gb/k	green	blue	black	112	15.2	0.86	76%
rg/k	red	green	black	49.4	112	0.86	39%
rg/b	red	green	blue	49.4	112	175	39%
g/b	green		blue	112		15.2	76%
g/r	green		red	112		49.4	39%

The first observation that can be made from the results is that a black background appears to give better performance than a colored one does (see Figure 4.29 and Figure 4.30). This meshes well with the results of the contrast experiment (see Section 4.6), since colors are brighter than black. In fact, most of the other results can also be explained in the same manner, because green is brighter than red, which is brighter than blue. The fact that green was generally perceived as red might be caused by the same underlying mechanism that seems to cause red stimuli to elicit more photosensitivity problems [43]. Brighter backgrounds are also more likely to cause problems [96].

It has also been shown that stimuli alternating between two colors can get more pronounced responses than stimuli that appear from a background [37]. This can explain the success of the green/blue on black RVS. The lower performance of red/green stimulation might be explained by Hering's opposing-color theory, which states that red and green, as well as blue and yellow, cancel each other out, although that contradicts [37]. Another explanation could be that the luminance contrast between red and green is simply smaller than that between blue and green, although that would not explain why blue/green stimulation seems to work better than green on black. Finally, in a sense alternating between two colors on a different colored background may not work the same as the normal flash VEPs elicited when a stimulus continuously emerges from the background. It could be that like with pattern reversal stimuli, the brain primarily picks up the alternation frequency rather than the entire cycle frequency. This might suggest that these stimuli might work better when modulated at lower frequencies, which is also shown in [37].



(a) Comfort (b) Comfort significance

(c) ITR (d) ITR significance

(e) Accuracy (f) Accuracy significance

Figure 4.30: *Comfort, performance and accuracy of the Experimentation BCI obtained stimuli with different colors. Left: means with standard errors (gray boxes) and medians with first and third quartiles (white boxes). Right: significance p-values for the comparisons between conditions (white is low; black is high). A star on row α and column β means that the mean for condition α is significantly better than the mean of condition β.*

4.12 Shape, orientation and texture

In the early stages of visual processing, the brain has (arrays of) cells that respond particularly to certain low level properties of the visual signal in one part of the visual field [122]. For instance, some cells may fire when a line with a certain orientation is perceived, whereas others may respond primarily to corners. It stands to reason then that the different ways in which different stimulus shapes, orientations and textures are processed at the start of visual perception affect the strength of the SSVEP response.

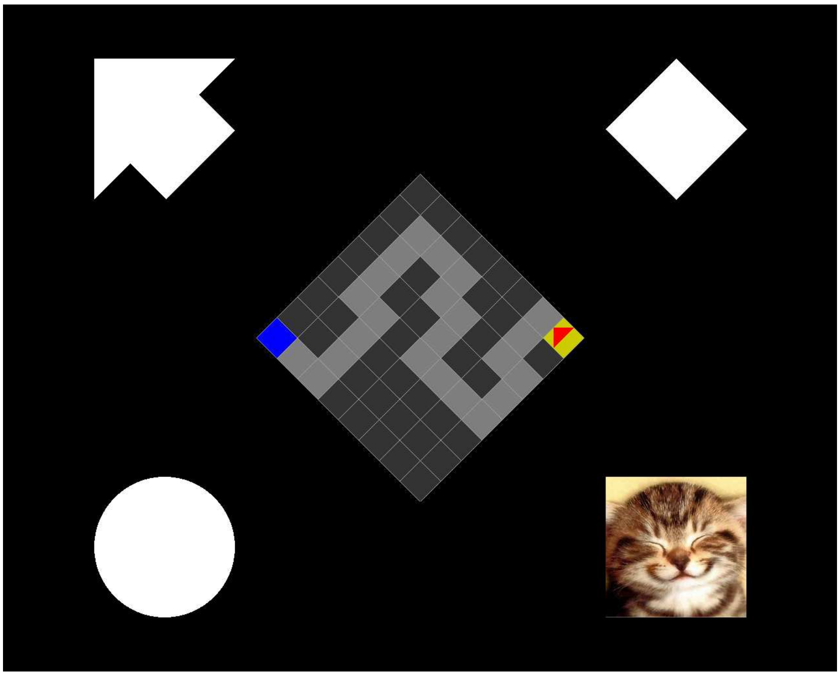


Figure 4.31: *The Experimentation BCI using differently shaped stimuli.*

Figure 4.31 shows the Experimentation BCI using differently shaped targets. Different shapes may also carry different semantic meaning. The arrow in the top left for instance signifies exactly what focusing on it will do, whereas a square is fairly neutral in terms of meaning. It would be interesting to see if semantic meaning can influence BCI performance.

Even if these stimulation properties do not directly increase SSVEP amplitude, using heterogenous stimuli might also enable a BCI to become more robust if these properties allow it to rely on more than just frequency tagging. If particular brain activity patterns can be associated with different colors, orientations or emotional valence of the stimuli [94], the BCI could incorporate this information into the decision making process.

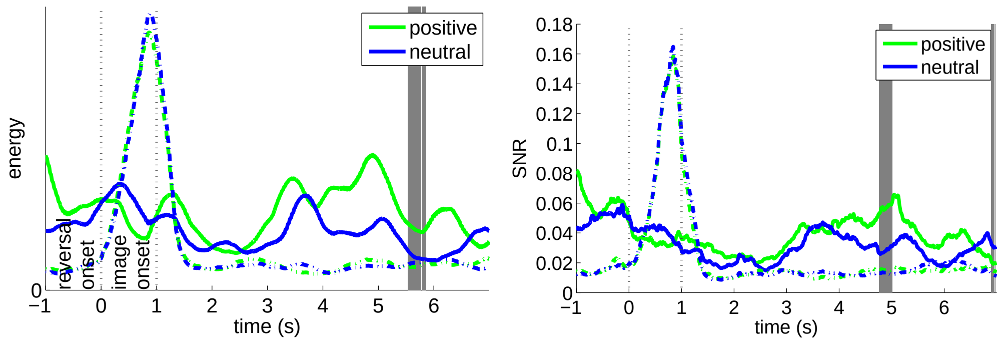
Stimuli might also be able to elicit emotional responses, which might in turn affect the SSVEP response. The performance, comfort and training time in a BCI are subject to numerous external factors like concentration, distraction, motivation, fatigue as well as emotional state (joy, frustration, etc.). It has been shown that stimuli containing an affective component do elicit differences in the latency and amplitude of the characteristic peaks of event related potentials [10]. Emotionally arousing pictures elicit higher SSVEP amplitudes in the parietal regions compared to neutral stimuli. This convenient finding could be utilized in a BCI where flickering affectively salient pictures are used as a stimulation. It was shown that images with positive emotional valence can elicit stronger SSVEPs than others, using 6 seconds long presentation of emotional pictures on a 13 Hz oscillating background [123].

Two experiments were carried out to see if this result could be reproduced and the SSVEP response could be used for the detection of emotion. In the experiments, the subjects were shown pictures with different valence values superimposed on a (weakly) 50% blurred (see Section 4.9) 16×16 checkerboard with a pattern reversal frequency of 13 Hz (26 alternations per second), resulting in a spatial frequency of

$1°37'44''$ per cell horizontally and $1°15'3''$ vertically. The stimulation was presented on a 32.4×24.7 cm CRT monitor with a refresh rate of 85 Hz. A small red cue square would be presented on a black background for 3 seconds, after which the stimulation started. One second into the checkerboard oscillation, a picture was superimposed on the center 49% of the screen (70% horizontally and vertically) for 6 seconds (see Figure 4.32), after which the picture was removed and the pattern reversal stopped for 3 to 5 seconds.

Figure 4.32: *A positively valenced picture superimposed on a 16×16 50% blurred checkerboard.*

The first experiment did not find any significant effect of image valence on SSVEP response, possibly due to low sensitivity to the 13 Hz stimulus of the test subject or the limited number of trials per condition. The second experiment used a different test subject (also male) and 20 neutral and 20 positive pictures.



(a) energy (b) SNR

Figure 4.33: *Energy and SNR evolving over time in position $O_z - C_z$ when positive and neutral images were superimposed on a blurred checkerboard RVS. The dashed lines correspond to the alternation frequency (second harmonic of the cycle frequency) and clearly show that the (initial) SSVEP for pattern reversal stimuli primarily responds to the alternation frequency. After a couple of seconds, the response to the cycle frequency (solid lines) becomes significantly stronger for positive images (gray background).*

Figure 4.33 shows how the energy and SNR of the SSVEP response evolve over time when a picture is superimposed on the RVS. After a couple of seconds, the response becomes stronger when a positive image was used. This result shows that the presence of emotional content can affect the SSVEP, which is important to consider when developing a BCI.

Furthermore, it shows that it is possible to detect some emotional content using EEG. Results from this experiment (not reported in this thesis) indicate that this seems to be possible without using the SSVEP as well, but since the BCI requires EEG anyway, this does not detract from the fact that having insight into the user's mental state can be tremendously useful in enhancing human-computer interaction.

Knowledge of the influence of emotional state on brain activity patterns can allow the BCI to adapt its recognition algorithms, so that the intention of the user is still correctly interpreted in spite of signal deviations induced by the subject's emotional state. BCI systems aware of the affective state of the user can adjust their settings to keep the user motivated and involved. For example, an educational computer system that adjusts the difficulty of the material based on the level of interest or irritation of the user [124]; or a computer game that adjusts its objectives to balance satisfaction and challenge.

4.13 Target configuration

The targets of the BCI are another aspect that might influence BCI performance and possibly comfort. The amount of targets, the way they are layed out and whether or not they move, can all have a great effect on performance.

4.13.1 Number of targets

The number of targets in a BCI places an upper limit on the attainable bitrate. The more targets, the more information is communicated by the selection of one. However, having a large number of targets places high demands on both the stimulation device and the signal processing computer (which might be the same machine) [125, 75].

Furthermore, it seems likely that having more targets will also result in lower accuracy or longer classification times when all other things are equal. Given a certain frequency resolution, there is only a finite set of frequencies that the stimulation device can render and that the user responds to well. When more targets are used, it may become necessary to use less optimal frequencies, or make the classification times longer in order to support a higher frequency resolution. Either way, the distance between the targets in feature space will necessarily become smaller when more targets need to be used, which might complicate distinguishing between them.

Finally, physical space should also be considered. An increase in the size of the BCI will likely be accompanied with greater cost and less portability and convenience. If the BCI size is chosen to be constant (e.g. it needs to fit on a computer display), then either the size of the stimuli or the amount of spacing between them would have to be decreased in systems with more targets. Section 4.10 already showed that a BCI with smaller stimuli generally has lower performance. The spacing of targets is discussed next.

4.13.2 Spacing

Research has shown that SSVEP response power is mainly directed by attention. It is therefore not strictly necessary for the user to change his gaze direction in order to select a target. Although covertly directing attention towards the desired target works, a performance boost can definitely be gained from also physically looking at that target [72]. Apparently, some part of the SSVEP response is not caused by attention. This begs the question of whether targets, other than the desired one, that are within the field of vision might still elicit small SSVEP responses. If this is the case, then BCIs can benefit by increasing the space between targets. Section 4.10 showed that the largest tested stimuli did not lead to the best performance, which may be caused by the fact that the stimuli in that condition were closer to each other. This, in addition to their larger size, may have caused a larger interference from non-target stimuli in the SSVEP response. Although this concern is shared in the literature, it appears that at least for good test subjects, a small spacing between targets may not prevent the system from working properly [126, 60].

4.13.3 Movement

Eye movements can significantly influence EEG signals, because the amplitude of muscle movements is usually far greater than that of brain activity. Many BCIs therefore use preprocessing algorithms to remove, reject or repair signal segments that contain these artifacts. Minimizing eye movements can therefore potentially increase the performance of a BCI. One way to help accomplish this, is to make the application state easily visible at all times, even when the user is focusing on an RVS.

In the Experimentation BCI, the application was visible from the periphery of the field of vision, but it was hard to determine which way the avatar should be sent while focusing on an RVS in a corner of the screen. This setup is similar to the ones used in some applications that controlled cursor movement [127, 3]. The extra feedback after each classification therefore played an important role. Whenever the avatar was moved in the correct direction, a high pitched beep was played and the screen flashed in green. If a wrong move was made, the beep had a lower pitch and the screen flashed in red. Since it was fairly easy to keep the next couple of moves in memory, the user could effectively switch focus to the next target when the system indicated that a correct classification was made. If a wrong classification was made, however, the user had to pay attention to the application state in order to see if the avatar had moved back, or was still in the same place. It was suggested that embedding the stimulus state in each stimulus might have worked better, since then the user would have been able to concentrate on the desired RVS while observing the application state (see Figure 4.34). There was no time to implement this idea.

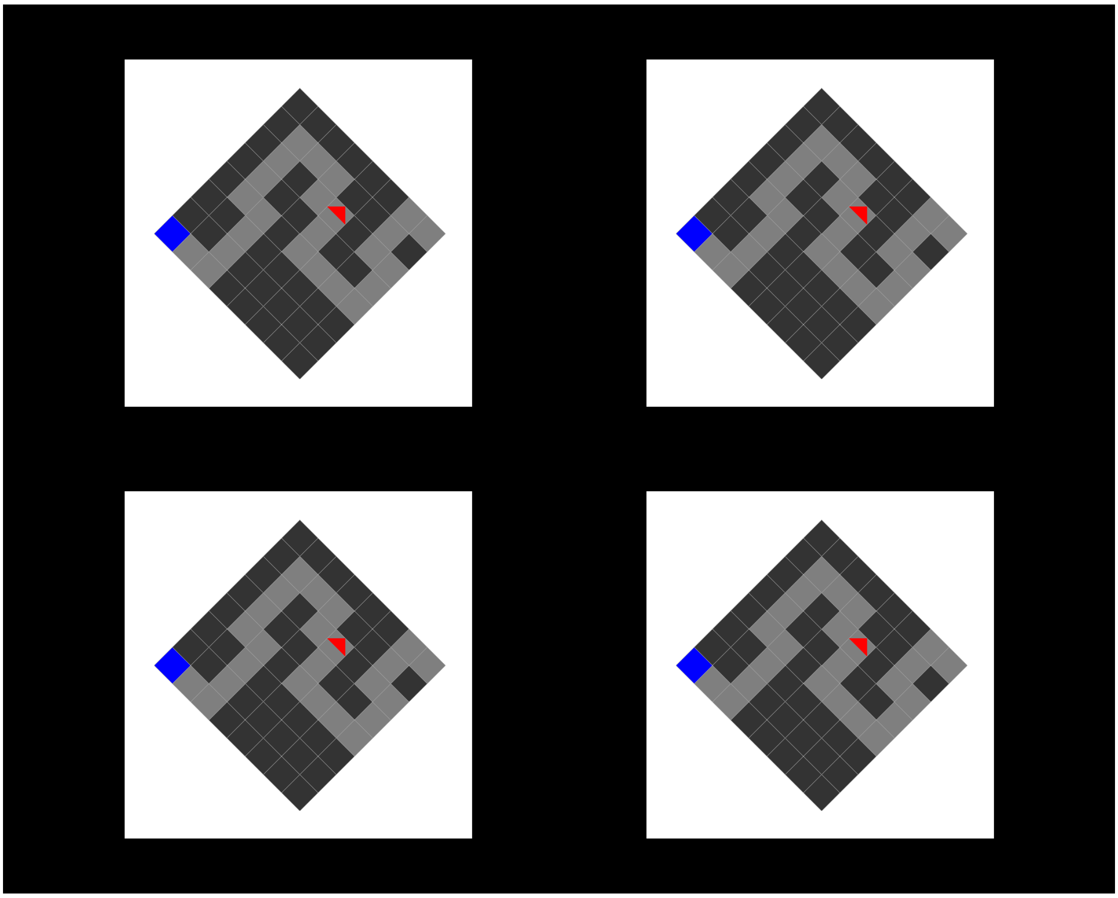


Figure 4.34: *The Experimentation BCI with the application state displayed on top of the RVSi so that the user can easily see it at all times.*

One downside of this solution is that it requires the application display to be much smaller. This may be somewhat feasible in the Experimentation BCI, but it is likely not so in cursor control applications. Another is that the application is obscuring the RVSi, although it would technically be possible to flicker the application rendering as well at the same frequency that it was superimposed on. However, this changes the appearance of the stimuli and it should be clear from the research presented in the rest of this thesis, that this can have significant effects on performance and comfort. In the figure, the size of each RVSi was increased in order to counter the fact that they are partially obscured, but Section 4.10 has shown that this may not always have the desired effects, possibly due to decreased spacing (see Section 4.13.2).

Another solution might have been to simply use the four fields adjacent to the avatar as stimuli. This would have made the RVSi far smaller than they were now, which Section 4.10 showed to be a big disadvantage. This could have been overcome by making them larger than one square on the grid, but in that case we would have to deal with the partial obscuration of the application. Furthermore, this would have moved the targets along with the avatar, encouraging users to move their eyes as well. Despite these disadvantages, this approach was successfully taken in applications for cursor movement [128] and for moving a car over a race track in a game [129, 130, 131, 60].

4.13.4 Overlap

In order to completely avoid eye movement artifacts caused by switching between targets, the targets can be superimposed on each other. In addition to avoiding artifacts, such a setup would also intuitively enable muscle-independent brain-computer interfacing. Note that in this case, the spacing between stimuli is 0.

When multiple targets overlap, they need a characteristic that distinguishes one from the other (e.g. color or pattern). Furthermore, a decision needs to be made about the interaction of each part of the stimuli. Often, at least part of the stimuli is defined as transparent. For instance, red and green stimuli where the alternate “off” state is transparent can be used [126]. If no stimulus is “on”, the background is shown. If one is on, the corresponding color is shown. Finally, if both are on the area could turn yellow (the sum of red and green).

Lineboxes have also been used where one stimulus has horizontal lines and the other vertical ones [118, 53]. In this case, one set of lines is transparent. The intersection of two non-transparent lines can then be the summation or average of those lines, or be turned transparent [53]. Of course, one stimulus' non-transparent parts can also simply be given priority over the other one's [132].

4.14 Multiple states

Repetitive visual stimuli oscillate between several visual states. Usually the number of states is two and the frequency of the RVS is described in terms of complete cycles (i.e. two state changes). The number of state changes per second is actually double the described frequency. For flash stimuli (i.e. simple stimuli that pop up out of the background) the main component of the SSVEP response is at the cycle frequency of the RVS. For pattern reversal stimuli however, the main SSVEP component is at alternation frequency, which is the second harmonic of the cycle frequency. It might be interesting to see if this SSVEP topology can also be elicited with other stimuli than checkerboards and lineboxes.

Results obtained from the experiments in Section 4.11 show that red/green and blue/green alternating stimuli primarily show a response on the fundamental frequency of the entire cycle. If another state were added, this could still be the case. It seems likely however, that such a large number of states could be used, that two occurrences of the same state are so far apart that the brain no longer responds to this. It would be interesting to see if at this point the SSVEP response would simply vanish, or if there would be an SSVEP response at the state change frequency.

When comparing the performance of BCIs with stimuli that elicit SSVEP responses at the cycle frequency to systems that elicit a response at the transition frequency, it is important to ask whether the cycle frequency of the first should be matched to the cycle frequency or the transition frequency of the second. It is well known that pattern reversal stimuli elicit stronger SSVEPs at lower frequencies and it has also been suggested that this is the case for stimuli changing between two colors [37].

, which means they can be modulated using a lower framerate, making them plausible on more stimulation devices. Section 4.8 and Section 4.10 indicate that

Perhaps they are perceived as having a higher frequency, and are therefore more comfortable to watch. Or perhaps the stimulation frequency should necessarily be kept low in order to still elicit significantly strong SSVEPs.

Adding more states to a stimulus likely has consequences for both the comfort of looking at it and the strength of the SSVEP response. There might also be interesting opportunities. For instance, it might be possible to encode multiple commands using one stimulus. When attending to a green-red-green-blue stimulus, it might be possible to ask the user to focus only on the red (or blue), only on the green or on all transitions. This could potentially elicit SSVEPs at 1, 2 and 4 times the rotation frequency.

No research on this subject was found, but it is an interesting avenue for future work.

Chapter 5

Conclusions

The goal of this study was to contribute to the improvement of SSVEP-based BCIs. Brain-computer interfaces can significantly improve the quality of life for severely disabled people, but can also be useful to the healthy. BCIs based on the SSVEP response are particularly promising, because they enable high information transfer rates compared to BCIs using different paradigms. However, operating an SSVEP-based BCI can be tiring, and looking at the required repetitive visual stimuli can be annoying and can even induce epileptic seizures in those susceptible.

The primary contribution of this thesis is the investigation of the effects of stimulation properties on the SSVEP response in the context of a BCI. Stimulation properties can have a significant impact on the performance and robustness of a BCI as well as the comfort and safety for the user. Operating the system in a dark and silent room can increase BCI performance. Stimulation contrast is positively correlated with performance, but negatively with comfort. High frequencies elicit smaller SSVEP responses, but are more comfortable to look at. The relationship between spatial frequency and performance is nonlinear, but higher spatial frequencies appear to be more comfortable. Having large stimuli can help increase the SSVEP response, but might also increase the interference coming from the targets in the BCI that the user is not focusing on and is obviously less comfortable and safe. The color of the stimulation also affects the comfort and performance. Colored or white backgrounds are perceived as uncomfortable and are associated with poor performance. White stimuli have the best performance, followed closely by green, and then red and blue. Comfort scores are roughly the other way around. Stimuli alternating between green and blue appear to provide an ideal tradeoff.

The choice of stimulation device has ramifications for performance, comfort, flexibility, cost and ease of development, as well as for the frequencies that can be used by the BCI, due to their framerate. LEDs allegedly elicit stronger SSVEP responses (although this study did not reproduce that result), but require additional hardware and are less flexible during development. Computers and their monitors are ubiquitous and cheap, but cannot properly render most frequencies. This, and computer performance limits the number of stimuli that can conveniently be used for SSVEP-based BCIs on monitors.

The effects of waveform, shape, texture, blur, target configurations and use of more than two stimulus states need to be investigated further as well as the interactions between all stimulation properties. Additionally, larger studies are required in order to get statistically significant results. The research reported in this thesis was generally done by varying the values of one stimulation property at a time. While this is perfect for isolating the effect of that stimulation property, it ignores the fact that many properties influence the response to each other. While it is impossible to test every possible combination of every stimulation property, it is important to find out more about the most important interactions, particularly how the stimulation frequency affects the response to other properties.

It would also greatly help if all researchers reporting studies with or for stimulus-driven BCIs would provide in depth descriptions of the used stimuli and a rationale for using them. Researchers should be aware of the great importance of the stimulation in these systems, and more insight into which stimuli work well can be very valuable in making BCIs more robust, comfortable, fast, easy and fun to use.

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Appendix A

Error related potentials

The human ability to detect these errors is extremely quick and precise. Different physiological studies have found *"error-related potentials (ErrPs)"* in the EEG signals of people detecting an error. ErrPs are associated with the anterior cingulate cortex (ACC) [133], which is also responsible for regulating emotional responses.

Three types of ErrPs are distinguished: response, feedback and interaction ErrPs. A response ErrP occurs shortly after the user himself has made an error, and is often referred to as the error-related negativity (ERN). Other studies have discovered a feedback ErrP that appears after the user is presented with feedback that indicates that he himself made an error. Both of these ErrPs are elicited when the user makes the error. As we all know though, machines can make errors as well. Perfect recognition of speech, handwriting, gestures and brain activity is not yet possible. When an error in these applications is made, the user often spots it instantly, causing an interaction ErrP.

Errors can slow the interaction with the system down and be frustrating and even dangerous. Having a robust error detection mechanism could make the system faster, safer, less frustrating and more user friendly. The rest of this section reports our investigation into the possibility of using the human error detection mechanism to notify the system of errors. Although detection of human errors can be useful, the focus here is on the detection of machine errors through the recognition of interaction ErrPs.

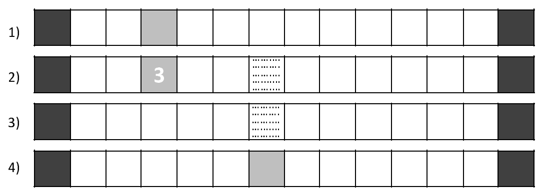


Figure A.1: *A correct trial in the experiment protocol: 1) The stimulus (gray square) appears on screen for 1700 ms. 2) A numerical and a visual (square with dots) indication of the expected next position are presented for up to 2000 ms. 3) The expected position of the stimulus (the square with dots) stays on screen for 1000 ms after a key is pressed. 4) The stimulus has moved to the new position.*

Six volunteers (3 men and 3 women), aged between 23 and 29 participated in the experiment. All were healthy, right-handed and had normal or corrected-to-normal vision. Subjects were asked to play a simple game, designed to elicit ErrPs. They had to move a square (the stimulus) from the left of the screen to the right. The subject was given 7 moves to move the square to the goal, 14 units to the right from the start. The game would continue until the subject finished it, but if more than 7 moves were used, the subject "lost". At the beginning of each trial the subject was presented with a random proposal to move either 1 or 3 squares to the right and the user could accept this proposal by pressing a button. If the proposal was not accepted (e.g. when the square was 2 steps from the goal and the proposal was to move 3, which would cause the square to move back to the beginning), nothing would happen and the next trial would start, possibly proposing to move a different number of steps. If the proposal was accepted, the stimulus would move to the designated space in 75% of the cases. In 25% of the cases, the system would make an error and the stimulus would move 1 or 2 steps back. In order to reduce the effect of habituation, no errors were made in the first two and every sixth game. The entire procedure is illustrated in Figure A.1. All subjects played the game for about 30 minutes, completing between 23 and 31 games (mean: 28).

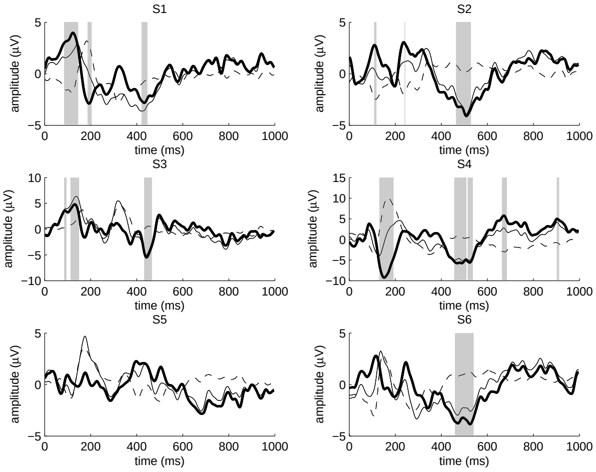


Figure A.2: *Difference (bold line) between potentials for error (solid line) and correct (dashed line) trials for all subjects (bipolar combination: $C_z - P_z$). Gray areas show the statistical significance* $(p < 0.0002)$.

The signals obtained using the usual EEG setup were subsampled to 256 Hz and then bandpass filtered in the 0.5-25 Hz band using a Butterworth filter. In 5 of the 6 subjects, an ErrP was found around the ACC area (near C_z, referenced to P_z) with a shape similar to previously reported results [134] (see Figure A.2). A paired t-test with Bonferroni correction was computed in order to check the significance of the difference between error and correct trials (the gray areas in Figure A.2). Clearly there is a lot of inter-subject variability, which suggests that a calibration period is required for each subject in order to get an acceptable error detection rate.

When the system knows that an error has been made, it can undo the erroneous action. This can make the system faster, safer and less frustrating. The consequences of making an error will differ between applications, but the constant factor is that it generally slows the interaction down. On the other hand, undoing correct actions also slows the interaction down. Whether using an error-detection mechanism is beneficial depends on a number of factors:

- The accuracy P of the original system without the mechanism
- The cost of an erroneous classification C without the mechanism, compared to a correct one. If the error simply needs to be undone by a good classification, this cost is roughly 2 (1 wrong + 1 right classification). If the user gets confused by the error, it might be 2.5. If the airplane the user was just flying crashes due to an error, the cost might be several magnitudes larger.
- The true positive error detection rate T
- The false negative error detection rate F
- The cost the undo operation C_u itself

Using some simplifying assumptions, we can say that a certain task simply requires N correct classifications. We define the cost of a correct classification as 1 (the cost is most easily thought of as an amount of time). The overhead O is defined as the extra cost per classification: $O = \frac{T-N}{N}$, where T is the total cost expended during the task. O can be easily calculated for a system without an error detection mechanism:

$$O = \frac{1-P}{P}(1+C) \tag{A.1}$$

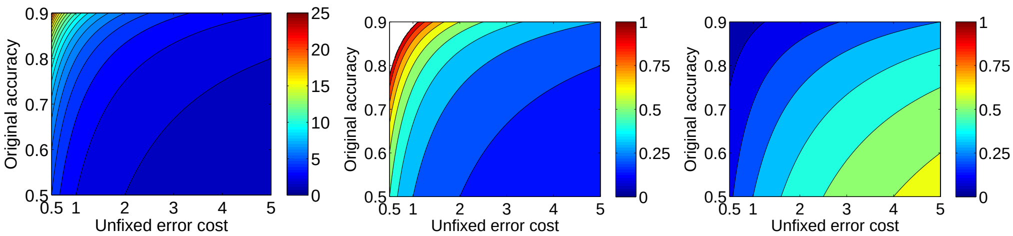
The overhead with an error-based undo mechanism O_e is given by the following equation:

$$O_e = \frac{F(C_u+1)+\frac{1-P}{P}(1+C-T(C-C_u))}{1-F} = \frac{F(C_u+1)+\frac{1-P}{P}(T(C_u-C))+O}{1-F} \tag{A.2}$$

Using these equations, we can calculate the minimum ratio of true to false positive rate R that the error detection algorithm needs to achieve in order to keep the system's performance the same:

$$T/F = R \geq \frac{(1-P)C+PC_u+1}{(1-P)C+PC_u-C_u} = 1+\frac{1+C_u}{(1-P)(C-C_u)} \tag{A.3}$$

If R is positive and the error detection algorithm's ROC curve has a point above the line defined by $T = RF$, error detection can be beneficial. When the cost of the manual correction of an error goes to infinity, R goes to 1, meaning that the true positive error detection rate should always be higher than the false positive rate. Figure A.3a plots the minimum required values for R for several different accuracies and manual correction costs, assuming that the undo cost C_u is 0.



(a) (b) (c)

Figure A.3: *Whether it is beneficial to use an error detection based undo mechanism depends on the performance of both the original and the error detection system, as well as the cost of an error and the cost of the undo operation. Assuming an undo cost of 0, and given a range of error costs and original accuracies, these figures show what is required of the error detection mechanism in order to be useful. a) The ratio of true to false positives. b) The minimum true positive rate, given a false positive rate of .1. The white area in the top left shows that given this false positive rate, low error cost and high original accuracy, it is impossible to justify using an error detection mechanism. c) The highest allowable false positive rate, given a true positive rate of .9.*

It is obvious that incorporating an error correction mechanism is only effective if the cost of making errors is high or the accuracy of the original system is low compared to the accuracy of error detection. It is therefore imperative to have a high error detection rate. Since inter-subject variability is large, finding the best parameters to use for each subject can significantly enhance classification accuracy.

The used classification algorithm used training examples to compute templates for correct and erroneous trials, as well as a vector of p-values (from the t-test) for the template differences at each point in time. The correct and error templates were computed by averaging the EEG response to each correct and erroneous trial for one bipolar combination. In order to classify one trial, the difference in distance measures to each template is thresholded (see Equation A.4).

$$\begin{aligned} d_c &= \sum_{i=1}^{N}(1-p_i)\cdot|t_{c,i}-x_i| \\ d_e &= \sum_{i=1}^{N}(1-p_i)\cdot|t_{e,i}-x_i| \\ C &= \tfrac{d_c}{d_c+d_e} < T \end{aligned} \tag{A.4}$$

Here N is the number of time samples in the template, d_c and d_e are the distance to the correct and error templates t_c and t_e, weighted by the vector of p-values p in order to emphasize parts of the signal where the difference between error and correct is significant. T is a threshold between 0 and 1 that determines the algorithms sensitivity and specificity. C is the classification result, “true” for a correct trial and “false” for an erroneous one.

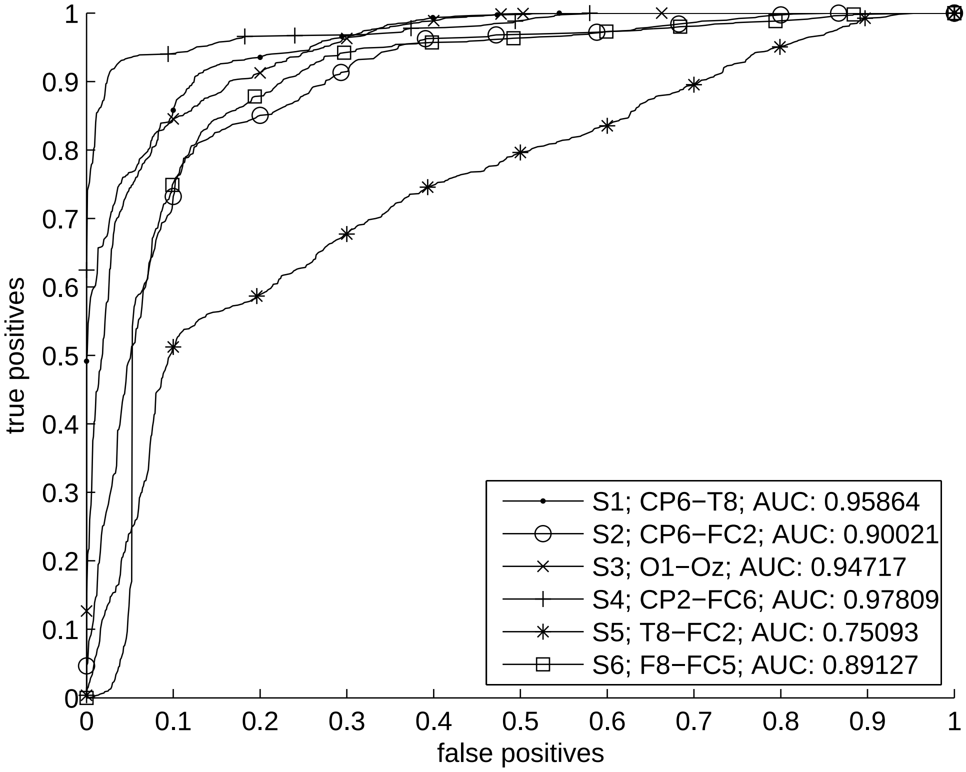


Figure A.4: *ROC curves for the BBC of each subject.*

For each subject, every combination of two electrodes (a bipolar combination) was evaluated and the best two electrodes were selected. Despite the fairly simple classification algorithm, this approach made fairly high performance possible (see Figure A.4).

In the game from the experiment, the goal was to reach the target square in as few moves as possible. If the system undid a move, the move did not count, which means that the cost of undoing in this system was technically -1. This means that it is impossible for the error system to detect too much errors. Therefore, it might be more useful to consider an example where the cost of undoing was 0 (in which case it would optimize the number of button presses).

Since the best strategy in the game is to move 3 steps at a time most of the time (but not always), and an erroneous trial moves the square back 1.5 steps on average, the cost c of an error in the game is a little over 0.5. Applying Equation A.3 leads to an R value of 9. For all subjects except S5 the error correction algorithm can be expected to increase system performance. The average percentage of saved button presses is 4.4% over all subjects.

Appendix B

Publications

This appendix contains all of the publications related to the work that was presented in this document:

Appendix B.1 Danhua Zhu, Jordi Bieger, Gary Garcia Molina, and Ronald M. Aarts. A Survey of Stimulation Methods Used in SSVEP-Based BCIs. In Computational Intelligence and Neuroscience, 2010. [88]

Appendix B.3 Tsvetomira Kirova Tsoneva, Jordi Bieger, and Gary Garcia Molina. Towards error-free interaction. In Proceedings of the 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2010. [135]

Appendix B.2 Jordi Bieger, Gary Garcia Molina, and Danhua Zhu. Effects of Stimulation Properties in Steady-State Visual Evoked Potential-Based Brain-Computer Interfaces. In Proceedings of the 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2010. [136]

B.1 A Survey of Stimulation Methods Used in SSVEP-Based BCIs

In this review article the authors perform a literature survey in order to find out what stimulation methods are used in SSVEP-based BCIs to date (June 2009). Many publications omit important details about the stimulation that is used in their experiments or BCIs. Even if the stimulation method is described in detail, reasons for the chosen configurations are rarely mentioned.

As of June 2009 use of the computer monitor (especially CRTs) is slightly more popular than use of LEDs. On these monitors flash stimuli (almost all rectangular) and pattern reversal stimuli (almost all checkerboards) were used about equally often. Most research focuses on using fairly low frequencies. When reported, the used colors were usually white, green or red for LEDs and black and white for computer monitors.

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Review Article

A Survey of Stimulation Methods Used in SSVEP-Based BCIs

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Brain-computer interface (BCI) systems based on the steady-state visual evoked potential (SSVEP) provide higher information throughput and require shorter training than BCI systems using other brain signals. To elicit an SSVEP, a repetitive visual stimulus (RVS) has to be presented to the user. The RVS can be rendered on a computer screen by alternating graphical patterns, or with external light sources able to emit modulated light. The properties of an RVS (e.g., frequency, color) depend on the rendering device and influence the SSVEP characteristics. This affects the BCI information throughput and the levels of user safety and comfort. Literature on SSVEP-based BCIs does not generally provide reasons for the selection of the used rendering devices or RVS properties. In this paper, we review the literature on SSVEP-based BCIs and comprehensively report on the different RVS choices in terms of rendering devices, properties, and their potential influence on BCI performance, user safety and comfort.

1. Introduction

A brain-computer interface (BCI) is a communication system in which the user's intention is conveyed to the external world without involving the normal output pathways of peripheral nerves and muscles [1]. BCIs are especially relevant for users with reduced motor abilities. Yet, applications for a wider range of users are emerging for entertainment, safety, and security.

In noninvasive BCIs, electroencephalography (EEG) is commonly employed because of its high time resolution, ease of acquisition, and cost effectiveness as compared to other brain activity monitoring modalities. Noninvasive electrophysiological sources for BCI control include event-related synchronization/desynchronization (ERS/ERD), visual evoked potentials (VEP), steady-state visual evoked potentials (SSVEP), slow cortical potentials (SCP), P300 evoked potentials and μ and β rhythms [2]. SSVEP-based BCIs have received increased attention because they can provide relatively higher bit rates of up to 70 bits/min while requiring little training [3].

An SSVEP-based BCI (see the functional model in Figure 1) enables the user to select among several commands that depend on the application, for example, moving a cursor on a computer screen. Each command is associated with a repetitive visual stimulus (RVS) that has distinctive properties (e.g., frequency or phase). The stimuli are simultaneously presented to the user who selects a command by focusing his/her attention on the corresponding stimulus. When the user focuses his/her attention on an RVS, an SSVEP is elicited which manifests as oscillatory components in the user's EEG, especially in the signals from the primary visual cortex, matching the frequency or harmonics of that RVS (see Figure 2). SSVEPs can be elicited by repetitive visual stimuli at frequencies in the 1 to 100 Hz range [4].

SSVEPs can be automatically detected through a series of signal processing steps including preprocessing (e.g., band-pass filtering), artifact detection/correction, feature extraction (e.g., spectral content at the stimulation frequencies), and feature classification. BCI performance is usually assessed in terms of classification accuracy, classification speed, and the number of available choices. These can be aggregated into a single indicator, namely the bit rate [1, 5]. In SSVEP-based BCIs, the classification accuracy is primarily influenced by the strength of the SSVEP response, the signal-to-noise ratio (SNR), and the differences in the properties of the stimuli. The classification speed depends on the time it takes for the SSVEP to be of sufficient strength. Increasing the number of targets offers a higher number of possible commands but can decrease classification accuracy and speed.

In addition to the bit rate, it is also important to consider the safety and comfort of SSVEP-based BCIs. Repetitive visual stimuli modulated at certain frequencies can provoke epileptic seizures [6] and flashes that are excessively bright may impair the user's vision. Furthermore, certain stimulation frequencies can induce fatigue.

The nature of the RVS in an SSVEP-based BCI influences the performance in terms of bit rate and can also have repercussions on user comfort and safety. In spite of being such an essential element of SSVEP-based BCIs, RVS selection is only superficially addressed in most SSVEP publications. Existing review papers focus on general VEP-based BCIs [7] and signal processing algorithms applied to BCIs [2]. This paper reviews the stimuli that have been used for SSVEP-based BCIs with the goals of: (1) categorizing the stimulation strategies reported in literature, and (2) providing a reference document to motivate the stimulus selection for BCI applications.

This paper is organized as follows. Section 2 describes the types of repetitive visual stimuli. Section 3 presents the methods used to conduct the literature survey as well as the inclusion criteria. A detailed categorization of currently used RVS is presented in Section 4. The results are discussed in Section 5 and the conclusions are presented in Section 6.

2. Repetitive Visual Stimuli

In SSVEP research, three main categories of repetitive visual stimuli exist.

Light stimuli are rendered using light sources such as LEDs, fluorescent lights, and Xe-lights, which are modulated at a specified frequency. These devices are generally driven by dedicated electronic circuitry which enables them to accurately render any illumination sequence or waveform. The intensity (time integrated luminance) of the light stimulus is measured in photopic candela seconds per square meter ($cd \cdot s \cdot m^{-2}$ or $nits \cdot s$) because the light luminance changes over time, whereas the background luminance is measured in candela per square meter ($cd \cdot m^{-2}$ or $nits$) [8]. An important parameter to quantify the stimulus strength is the modulation depth which is defined as $(l_{\max} - l_{\min})/(l_{\max} + l_{\min})$, where $l_{\min}$, $l_{\max}$ are the minimum and maximum luminance, respectively.

Single graphics stimuli (e.g., rectangle, square, or arrow) are rendered on a computer screen and appear from and disappear into the background at a specified rate (see Figure 3(a)). The stimulation rate is reported as the number of full cycles per second, normally simply referred to as the frequency of the stimulus.

Pattern reversal stimuli are rendered on a computer screen by oscillatory alternation of graphical patterns, for example, checkerboards. They consist of at least two patterns that are alternated at a specified number of alternations per second [8]. Frequently used patterns include checkerboards and lineboxes (see Figure 3(b)). Patterns are usually colored in black and white. A checkerboard stimulus is characterized by the subtended visual angle of each tile (spatial frequency), the number of reversals per second, the mean luminance, the field size, and the pattern contrast.

It is worth noting that single graphic stimuli could be viewed as a special case of pattern reversal stimuli where the graphic is the first pattern and the second pattern is the background. An important difference is that single graphic stimuli elicit an SSVEP response at the frequency of one full cycle (i.e. two alternations), whereas real pattern reversal stimuli elicit an SSVEP response at the frequency of one alternation.

All repetitive visual stimuli have various properties such as frequency, color, and contrast. Both the type and properties of stimuli affect the elicited SSVEP response.

3. Literature Search and Inclusion Criteria

To conduct the literature survey on the stimulation strategies in SSVEP-based BCIs, the following databases were consulted: INSPEC, COMPENDEX, PASCAL, MESCAL, MEDLINE, EMBASE, BIOSIS, BIOENG, HCAPLUS, LIFESCI, TEMA, and Google Scholar. Papers were selected for review if the following classes of terms are present in their title, abstract or keyword list: (1) *BCI*, *Brain-Computer Interfac?*, *BMI* and *Brain Machine Interfac?*; (2)*SSVEP*, *Steady State Visual Evoked Potential?*, *SSVER* and *Steady State Visual Evoked Respons?*; where the question mark "?" represents arbitrary letters (e.g., "e", "es" or "ing"). Figure 4 illustrates the search strategy as well as the number of papers retrieved at each step.

To be included in the review, papers had to distinctly mention the used stimulus. Papers that used SSVEP to research the visual pathway and attention as opposed to the goal of building BCI systems were excluded. Only papers written in English prior to June 2009 were considered.

4. State of the Art

Fifty-seven papers met the inclusion criteria. They are categorized into three classes according to the type of RVS they use: light, single graphic, and pattern reversal stimuli. Tables 1, 2, and 3 detail the specific properties of the RVS associated with the three classes.

In the remainder of this article we mainly consider the rendering devices, stimulation frequencies, and colors. The rendering device can significantly affect the strength of the SSVEP signal [9]. The stimulation frequency is an important property of the RVS. All the BCI systems reviewed in this paper use stimulation frequencies in the 4 to 50 Hz range. In [10] these frequencies were classified into three frequency

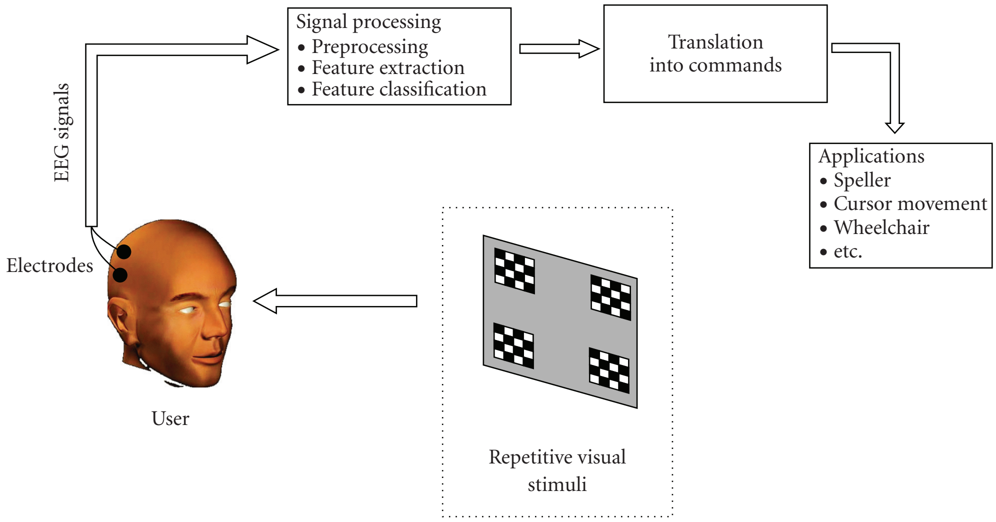


Figure 1: Functional model of an SSVEP-based BCI.

bands: low (1–12 Hz), medium (12–30 Hz), and high (30–60 Hz). In each table, these three bands are used to subcategorize the papers. Stimulus color also influences the SSVEP because the SSVEP responses are different for red, blue, and yellow light [11].

The history of the use of different stimuli in SSVEP-based BCIs is summarized in Tables 1, 2, and 3. The first known SSVEP-based BCI was presented in 1996 [12] and used a fluorescent light to render the stimulation. This system had only one stimulus and was based on the self-regulation of the SSVEP amplitude. Stimuli displayed on computer screens have been used since 1999. Single graphics were used to mimic light stimuli. The graphics included squares or rectangles [13] and arrows [14]. Since then, more than one stimulus were used and each stimulus corresponded to a different command. Although LEDs are popular in current SSVEP-based BCIs, they were not used as rendering devices until 2003 [15]. Pattern reversal is commonly used in transient VEP research and can elicit more prominent VEPs than other stimuli. It was first used in 2004 in an SSVEP-based BCI [16]. For some clinical applications the EEG recording equipment has its own visual stimulation (e.g., Xe-light). This type of stimulation was also tested in [17]. The color of the stimulus was first considered in 2001 [18].

Out of the 58 reviewed papers, 14 use checkerboards, 18 use rectangular stimuli on a computer screen, 1 uses arrows, 1 uses lineboxes, 24 use LEDs, 1 uses a fluorescent light and 1 uses an Xe-light. The sum exceeds the 58 reviewed papers because some employ more than one stimulation method.

The low and medium-frequency bands are both used in 49 of the reviewed articles, while the high-frequency band was only employed in 8. A combination of the low and medium frequency bands is used by 30 of the papers, while 1 uses a combination of the low and high frequency bands, 2 use a combination of the medium and high frequency bands, 1 uses all three frequency bands and 1 does not mention the frequency used.

Slightly more research has been conducted using computer screens than with light stimuli (33 versus 26 articles). More articles feature single graphic stimuli than pattern reversal (19 versus 14 articles). LEDs are almost always used for light stimuli, while plain rectangles and checkerboards are the basic choices for single graphic and pattern reversal stimuli. Other choices are rarely used [12, 14, 17, 62].

For stimulation on computer monitors, mostly black, and white colors are used. For light stimuli the colors red, white and green are frequently used. It is worth noticing that the two best-performing BCIs in this category used green lights [3, 15]. Further research on the influence of color on the SSVEP is necessary.

Direct comparison of the performance of different stimuli based on the performance of the BCIs that employed them is difficult due to the large number of variables that may influence a BCI's performance in addition to the stimulation properties. Furthermore, a large inter-subject variability of SSVEP response exists. However, such a comparison can still provide an indication on how suitable different stimuli are for BCI. We therefore list the best and median performance of SSVEP-based BCIs using LEDs, checkerboards, and squares here to give an indication: a system using LEDs achieved a bit rate of 68 bits/min with 48 choices [15], a pattern reversal system reached a bit rate of 45.5 bits/min with 8 choices [57], and a system using rectangle stimuli obtained a bit rate of 58 bits/min with 6 choices [45]. The median bit rate for systems using LED stimulation is 42 bits/min, while for single graphics it is 35.075 bits/min and pattern reversal systems achieve 26 bits/min. Unfortunately most articles either did an offline analysis or failed to mention the performance of the presented BCI systems in terms of bit rate.

In addition to the bitrate, user safety and comfort are important for the commercial applicability of SSVEP-based BCIs. However, these aspects are very rarely mentioned in the literature.

Table 1: Characteristics of light stimuli.

Frequency band	Study	Stimulus Device	Stimulus Frequency (Hz)	Stimulus Color	Bit rate (bits/min)
L	Maggi et al. 2006 [19]	LED	6, 7, 8, 10 Hz	Green	—
	Piccini et al. 2005 [20]	LED	6–10 Hz	—	—
M	Lüth et al. 2007 [21]	LED	13, 14, 15, 16, 17 Hz	Red	—
	Valbuena et al. 2007 [22]	LED	13, 14, 15, 16 Hz	—	—
	Leow et al. 2007 [23]	LED	14–29 Hz	Red	—
	Materka and Byczuk 2006 [24]	LED	25, 26.5625, 28.125, 29.6875 Hz	—	—
	Calhoun et al. 1996 [12]	Fluorescent light	13.25 Hz	—	—
H	Garcia Molina 2008 [25]	LED	40–50 Hz	White	—
	Huang et al. 2008 [17]	Xe-light	30–50 Hz	—	—
	Materka et al. 2007 [26]	LED	32–40 Hz	—	—
	Materka and Byczuk, 2006 [27]	LED	34–40 Hz	—	—
L+M	Parini et al. 2009 [3]	LED	6, 7, . . ., 17 Hz	Green	51.47
	Bin et al. 2008 [28]	LED	10, 11, 12, 13 Hz	—	—
	Wu and Yao 2008 [29]	LED	8.3, 10 Hz	White	—
	Wu et al. 2008 [9]	LED	4.6, 10.8, 16.1 Hz	White	—
	Müller-Putz et al. 2008 [30]	LED	6, 7, 8, 13 Hz	Red	—
	Müller-Putz and Pfurtschelle 2008 [31]	LED	6, 7, 8, 13 Hz	Red	—
	Scherer et al. 2007 [32]	LED	6.25, 7.25, 8.00, 13.00 Hz; 11.75, 13.00, 15.25, 17.25 Hz	Red	—
	Jia et al. 2007 [33]	LED	6, 6.5, 7, . . ., 19 Hz	—	46.1
	Friman et al. 2007 [34]	LED	5, 7, 9, 11, 13, 15 Hz	—	—
	Friman et al. 2007 [35]	LED	13, 14, 15, 16, 17 Hz	Red	27–30
	Müller-Putz et al. 2005 [36]	LED	6, 7, 8, 13 Hz	Red	31.5
	Wang et al. 2004 [37]	LED	9–17 Hz	—	42
	Gao et al. 2003 [15]	LED	6, 6.195, 6.390, . . ., 15	Green	68
M+H	Wang et al. 2005 [38]	LED	21, 23, . . . , 43 Hz	White	—
L+M+H	Ruen et al. 2007 [39]	LED	7–35 Hz	Red	—

5. Discussion

In this section we first discuss the effect of the repetitive visual stimuli that are regularly used in the reviewed literature on the SSVEP. We then present innovative stimulation designs that were designed to address some of the most relevant issues in BCI such as preventing loss of attention during operation, increasing the number of stimuli, SNR enhancement, and independent operation.

5.1. RVS Effect on SSVEP. Stimulation type, frequency, and color have all an effect on the SSVEP response they elicit.

5.1.1. Stimulation Type. The reviewed papers were categorized into three tables according to whether they used light, single graphic, or pattern reversal stimuli. The SSVEP response to these three types of stimuli is different. Pattern reversal stimuli can produce a more pronounced SSVEP than single graphic stimuli modulated at the same frequency [56]. In [9] light and single graphic stimuli were generated at 4.6, 10.8, and 16.1 Hz. It was found that the SSVEP response elicited by an LED was larger than that by a rectangle stimulus on a computer screen. Also it was stated that the SSVEP response for light stimuli was larger than that for pattern reversal in [10]. This might explain why we found that the bit rates of BCIs using LED stimuli appear

Table 2: Characteristics of single graphic stimuli.

Frequency band	Study	Stimulus				Bit rate (bits/min)
		Device	Shape	Frequency (Hz)	Color	
L	Wang et al. 2008 [7]	—	Square	10 Hz	—	—
	Ren et al. 2008 [40]	—	Square	10 Hz	White/black	—
	Touyama and Hirose, 2007 [41]	—	Cube	4.80, 6.86 Hz	—	—
	Touyama and Hirose, 2007 [42]	—	Cube	4.80, 6.86 Hz	—	—
	Beverina et al. 2003 [14]	—	Arrow	6, 10 Hz	Green	—
	Cheng and Gao, 1999 [13]	—	Block	6–9 Hz	—	—
M	Cecotti and Graeser, 2008 [43]	LCD	Box	15.5, 16, . . ., 17.5 Hz	—	—
	Kelly et al. 2005 [44]	CRT	Rectangle	14, 17 Hz	White/black	7.5
L+M	Bin et al. 2009 [45]	LCD	Square	6.5, 7.5, 8.6, 10, 12, 15 Hz	White/black	58
	Wu et al. 2008 [9]	LCD and CRT	Square	4.6, 10.8, 16.1 Hz	White/black	—
	Wang et al. 2006 [46]	CRT	Button	9–17 Hz	—	43
	Nielsen et al. 2006 [47]	CRT	Square	5.0, 7.08, 7.73, 8.5, 9.44, 10.63, 12.14, 14.16, 17.0 Hz	—	21
	Kelly et al. 2005 [48]	CRT	Rectangle	9.45, 10.63 Hz; 14.17, 17.01 Hz	White/black	—
	Kelly et al. 2005 [49]	CRT	Rectangle	10.03, 12.04 Hz	White/black	—
	Wahnoun et al. 2002 [50]	—	Block	5.000, 7.080, 7.727, 8.927, 11.087, 12.140, 12.750, 17.000, 21.250 Hz	White and a small light gray in the middle	—
	Cheng et al. 2002 [51]	CRT	Button	6–14 Hz	—	27.15
	Cheng et al. 2001 [18]	—	Block	6.45, 7.23, 8.01, 13.87 Hz	Red, green, and yellow	—
L+H	Sami and Nielsen, 2004 [52]	CRT	Rectangle	8.8, 35 Hz	—	—
M+H	Lin et al. 2007 [53]	CRT	Squares	27, 29, . . ., 43 Hz	—	—

to be higher compared to those of BCIs using computer screens. For each of these results, most variables were fixed (e.g., luminance, contrast, and color). At present, no general conclusions can be drawn because many conditions have not been tested and variables can interact with each other. For instance, the power of the SSVEP response is affected by both frequency and color of the stimuli [11].

From the viewpoint of implementation, it is in general easier to build a BCI that employs a computer screen as it mainly relies on software development and no hardware modification is necessary. Furthermore, BCI designers are

Table 3: Characteristics of pattern reversal stimuli.

Frequency band	Study	Stimulus				Bit rate (bits/min)
		Device	Shape	Frequency (Hz)	Color	
L	Kluge and Hartmann,2007 [54]	TFT	Checkerboard	10, 12 Hz	—	—
	Trejo et al. 2006 [55]	LCD	Checkerboard	5, 5.625, 6.4, 6.9 Hz	White/black	—
	Lalor et al. 2005 [56]	—	Checkerboard	8.5, 10 Hz	White/black	10.3
M	Kelly et al. 2004 [16]	—	Checkerboard	17, 20 Hz	White/black	—
L+M	Vasquez et al. 2008 [57]	CRT	Checkerboard	8.8, 9.4, 11.55, 12.5, 13.65, 15, 16.7, 18.8 Hz	White/black	45.5
	Oehler et al. 2008 [58]	—	Checkerboard	10–15 Hz	White/black	12.5
	Martinez et al. (2008 [59], 2007 [60])	CRT	Checkerboard	5, 6, 7, 8 Hz; 12, 13.3, 15, 17 Hz	White/black	26–30
	Krusienski and Allison, 2008 [61]	—	Checkerboard	6, 15 Hz	White/black	—
	Allison et al. 2008 [62]	CRT	Lineboxes and checker-board	6, 15 Hz	White/black; gray/white; red/gray; green/gray	—
	Bakardjian et al. 2007 [63]	—	Checkerboard	8, 12, 14, 28 Hz	White/black	—
	Mukesh et al. 2006 [64]	—	Checkerboard	6, 7, 12, 13, 14 Hz	White/black	—
	Jaganathan et al. 2005 [65]	—	Checkerboard	6–15 Hz	White/black	—
—	Lalor et al. 2004 [66]	—	Checkerboard	—	White/black	—

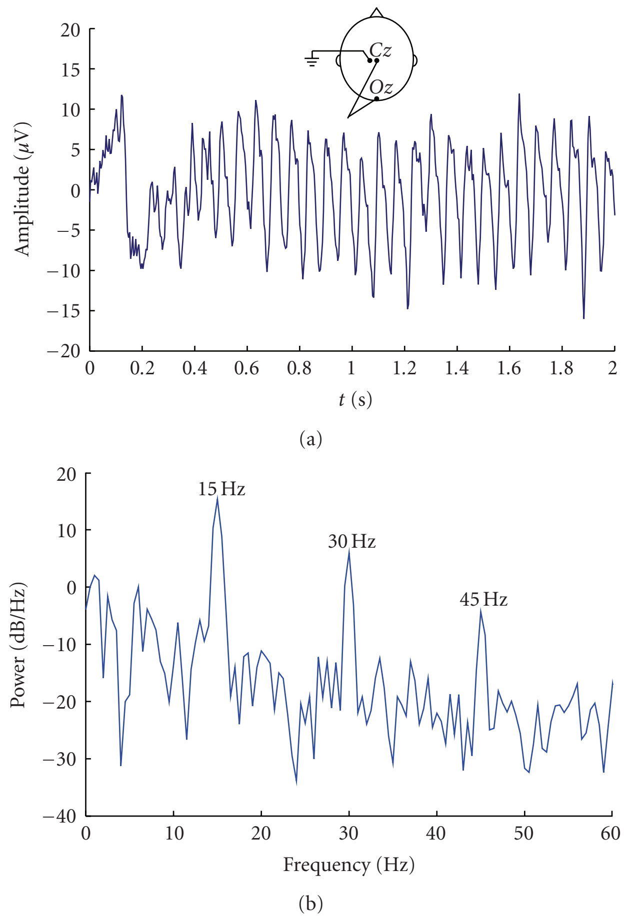
completely free in their choice of development platform for the implementation of this software. Use of computer monitors offers flexibility for combining BCI stimulation with the controlled application and makes it possible for the stimulation interface to easily be fine-tuned during BCI development or even for it to change during a BCI session.

BCIs using light stimuli on the other hand usually require the development of dedicated hardware in addition to software. Also, the used hardware often restricts the number of development platforms that can be used for software development. In return for this investment comes an extreme flexibility in the signals and frequencies that can be generated, because LEDs are usually controlled by waveform generators that are capable of generating many different frequencies. LEDs are said to be preferable in practical applications that require more than 20 choices, because monitors have difficulties to accurately display various stimuli at different frequencies [9].

Using a monitor severely limits the range of frequencies that can be used for stimulation. The refresh rate R of the monitor, that is, the number of times that the monitor redraws the screen per second, is usually lower than 100 Hz (for LCD monitors it is usually 60 Hz). Only frequencies that are lower than $R/2$ Hz can be used [67] and only the subharmonics of the screen refresh rate can be obtained [50]. Errors appear when rendering frequencies whose periods are not multiples of $2/R$. Such frequencies are either very low to elicit an SSVEP or are each others harmonics. This is often undesirable for SSVEP-based BCIs. Because of this, these BCIs often use frequencies that can be displayed less accurately. The rendering of the frequency can be further hindered by the task scheduling that most operating systems perform, which can cause unpredictable delays. Finally, if a large number of target stimuli have to be used, the computational load of generating or displaying them may cause inaccuracies in the displayed stimulations.

Computer screens with higher refresh rates exist (e.g., a screen refreshing at 120 Hz used in [59]), but are increasingly difficult to obtain commercially. Such screens can increase the available number of frequencies, but do not solve the above problem completely.

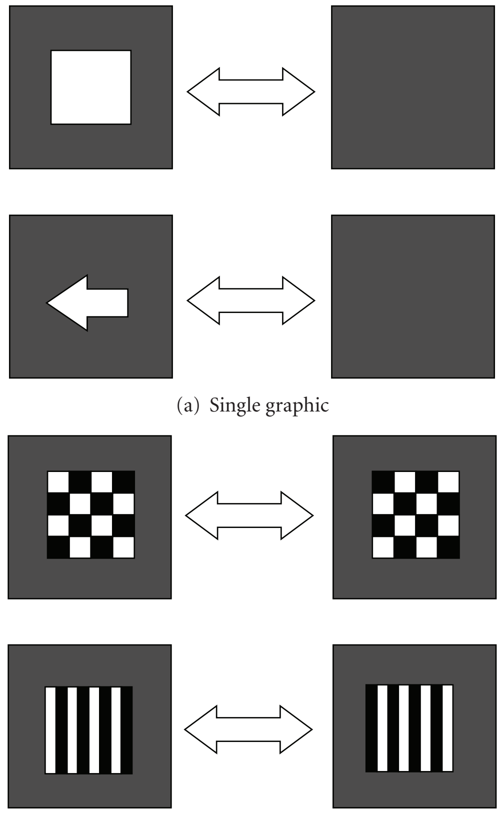
5.1.2. Stimulus Frequency. As mentioned in Section 4, the stimulus frequencies used in SSVEP research can be classified



(a)

(b)

Figure 2: Typical waveform of an EEG signal (Oz-Cz) acquired during visual light stimulation with a frequency of 15 Hz and its frequency spectrum. (a) SSVEP waveform resulting from the time-locked average of 10 realizations. A transient VEP can be observed at the moment where the stimulation began and a clear oscillation (the steady state VEP) can be seen afterwards; (b) Frequency content of the signal in (a). The SSVEP manifests itself in oscillations at 15 Hz and higher harmonics.



(a) Single graphic

(b) Pattern reversal

Figure 3: (a) In single graphic stimuli the graphical object alternately appears and disappears in the background. (b) In pattern reversal stimuli at least two patterns are alternated at a specified frequency.

into three frequency bands, that is, low (1–12 Hz), medium (12–30 Hz) and high (30–60 Hz). The largest SSVEP amplitudes were observed near 10 Hz followed by 16–18 Hz and the high frequency subsystem showed the smallest response [10]. As shown in Tables 1, 2, and 3, many SSVEP-based BCIs used the low and medium frequency bands, although the frequencies varied significantly. These two frequency bands, however, have some disadvantages. First, subjective evaluations showed that frequencies between 5 and 25 Hz are more annoying than higher ones; visual fatigue would easily occur. Second, flash and pattern reversal stimuli can provoke epileptic seizures especially in the 15–25 Hz range [6]. Third, the low frequency band covers the alpha band (8–13 Hz) which can cause a considerable amount of false positives. All of these disadvantages can be avoided by using the high frequency band.

The disadvantage of a weak SSVEP response is mitigated by the fact that there is less spontaneous brain activity in the high frequency band compared to lower ones [46]. Additionally, spatial filters that combine several lead signals into one channel [34] can be used to increase the SSVEP energy enough so it can effectively be used in a BCI. Furthermore, the SNR of the SSVEP response (calculated as the ratio of EEG power at the stimulation frequency to the mean power of the adjacent frequency bands) is similar in all frequency bands [46]. An offline analysis showed that utilizing the high frequency band can be very promising [38]. Therefore, the high frequency band can be expected to be applied in SSVEP-based BCIs in the future and should definitely be researched further.

5.1.3. Stimulus Color. It was reported in [11] that red, yellow, and blue light stimuli have different effects on the SSVEP in combination with the used frequency. Red light elicited the strongest response when modulated at 11 Hz, but SSVEP strength went downhill fast for surrounding frequencies. Blue light stimuli elicited a slightly weaker strongest response around 13 Hz, but were less sensitive to the used frequency. The SSVEP strength elicited by yellow light was lower and less dependent on the used frequency. Another study that focused on stimulus color showed that the second and fourth

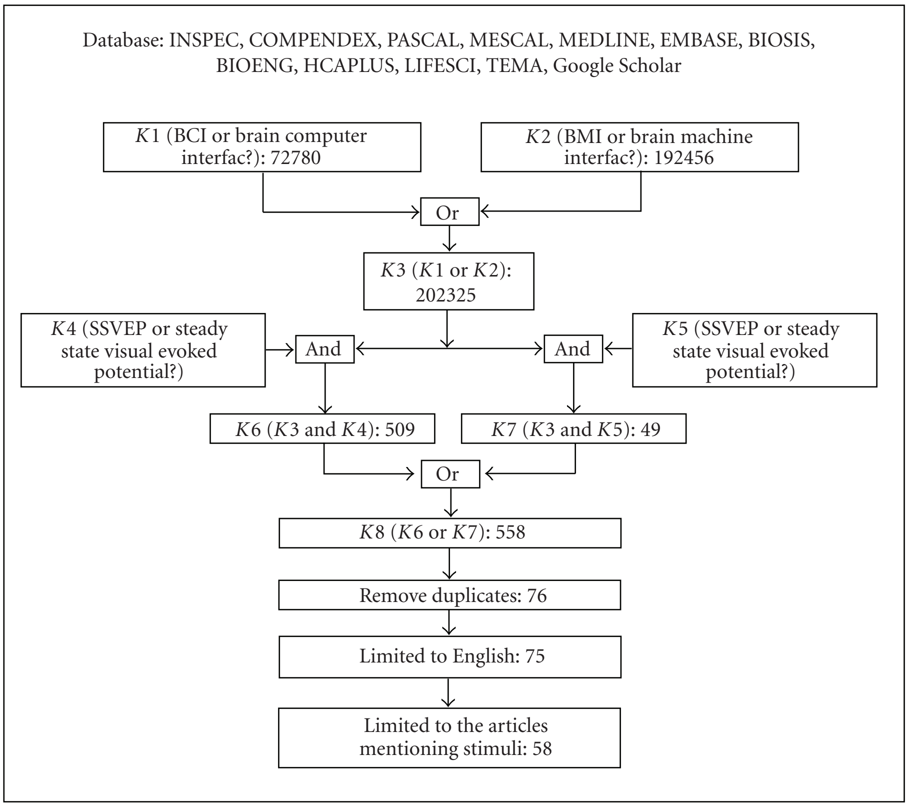


Figure 4: Literature search strategy and the number of papers retrieved at each step. “K” indicates “keyword” and “?” refers to arbitrary characters (e.g., e or es).

harmonic of the SSVEP are affected differently by chromatic and achromatic checkerboard stimuli [68].

At present, green, red, gray, black, and white stimuli have been used for SSVEP-based BCIs. It is difficult to decide which color is the best, because at present there is no comparison that shows how color influences the performance of SSVEP-based BCIs. A good solution for practical applications could be to use stimuli whose colors can be dynamically adjusted in order to take circumstances or the user’s characteristics into account.

5.2. Stimuli Improvements. Recent studies present some new stimulus designs based on more standard stimulation methods. Four important goals to be achieved with these enhancements are: (1) to maximize selective attention and to minimize the eye movements with respect to the controlled element; (2) to increase the number of available frequencies; (3) to enhance the SSVEP SNR; and (4) to change an SSVEP-based BCI from dependent to independent.

5.2.1. Maintaining Attention on the Stimuli. The position of the stimuli in current SSVEP-based BCIs is often fixed. However, the user needs feedback during BCI operation. While the user is moving an element (e.g., a cursor or a virtual car), his/her eyes can occasionally move away from the stimuli. Furthermore, the user can be distracted, which can deteriorate the signal because the SSVEP strength is strongly influenced by attention [69]. A possible solution for mitigating this problem is to make the stimuli move along with the controlled elements. In [57, 60], the stimulation unit was designed as a smart multiple choice table in the form of an array of small checkerboard images moving along with the controlled elements and was applied to a real-time BCI with a bit rate higher than 26 bits/min.

5.2.2. Increase the Number of Available Frequencies. Most current SSVEP-based BCIs use one frequency per target. Hence a large number of targets require a large number of frequencies. However, the frequency range with relatively high SSVEP responses is limited. Increasing the number of targets then decreases the frequency resolution which in turn makes classification more difficult. This is especially problematic on computer screens, since we have difficulty generating all but a select few frequencies accurately.

One solution is to differ the relative phases of the stimuli so that phase information can also be used to distinguish among targets. In [7, 54], all stimuli flickered at the same frequency and differed only in relative phase.

A second solution attempts to mitigate the problem by using dual-frequency stimulation: modulating a single stimulus with two frequencies. By adding together two frequencies F_1 and $F_2 = F_1/2$ a third stimulus $F_1 + F_2$ was obtained which would evoke peaks in the SSVEP signal at F_1, F_2, $F_1 + F_2$ and their harmonics [64]. Thus three options could be obtained using only two frequencies. In [64], the stimulus was a checkerboard rendered on a computer screen. This solution can also be applicable with light sources such as LEDs.

Unfortunately, these solutions have only been evaluated with two or three targets and were so far not tested thoroughly in online systems in which many targets exist.

5.2.3. Enhance the SSVEP SNR. High SSVEP SNR can simplify the feature extraction and improve the classification accuracy. In [27], a novel method based on half-field alternate stimulation was proposed to enhance the SSVEP SNR. The optic nerves from the retina's left and right halves cross at the so-called optic chiasm and finally reach the left and right part of the primary visual cortex. Based on this, a target stimulus consisting of two light sources that flashed with the same frequency but opposite in phase was proposed. Because the light sources flashed at different times and were located in different parts of the visual field the workload of the left and the right part of the primary visual cortex was alternated. Subtracting the signals obtained at the left and right occipital lobes from one another suppressed the noise from muscle-originated signals and spontaneous brain waves, and thereby enhanced the SSVEP SNR.

5.2.4. From Dependent to Independent. According to the definition of [1], BCIs can be either dependent or independent. A dependent BCI requires some activity from the brain's normal output pathways (e.g., muscles), while an independent BCI does not depend in any way on these output pathways. SSVEP-based BCIs are generally considered as dependent, because the user has to change his gaze direction to focus on the desired target. This might not work if the user is so severely disabled that he is unable to reliably control gaze. Consequently, it is very useful to make an independent SSVEP-based BCI. In order to make this improvement, one attractive option is to develop a stimulus which is able to evoke different SSVEP responses without the user's gaze.

The BCI in [49] utilized electrophysiological correlates of visual spatial attention mechanisms to make binary selection of left and right visual targets. Besides spatial attention, another solution is selectively paying attention to a certain stimulation of an overlapping stimulus. Two superimposed images consisting of vertical and horizontal parallel bars flickering at different frequencies were presented [62, 70]. A similar stimulus design was used in [18], where a red/black and green/black square alternating at different frequencies were superimposed on each other and yellow was used when both stimuli were in the "on" state. In another study spatially intermingled red and blue motion dots flickered at different frequencies while continuously shifting their positions at random [71]. All of these methods are based on the fact that selective attention to one stimulus while ignoring the other will enhance the amplitude of the SSVEP of the attended frequency [72].

6. Conclusion

SSVEP-based BCIs allow users to communicate with the external world by selectively paying attention to one out of a set of repetitive visual stimuli. In this review, we have highlighted important facts of these stimuli in BCIs: (1) checkerboard, rectangle, and LED-based stimulation are the most frequently used stimulation types, (2) stimulation frequencies in the low and medium frequency bands have been more often applied than those in the high frequency band even though the latter offer higher levels of comfort and safety.

From the reported bit rates it appears that SSVEP-based BCIs that use LEDs for stimulation have higher bit rates (median 42 bits/minute) than those using computer screens that render the stimuli through single graphic alternation (median 35.075 bits/minute) or pattern reversal (median 26 bits/minute). For a small number of RVS both computer screens and LEDs are plausible as rendering devices. For a large number of RVS (more than 20 according to [9]) or stimulation frequencies in the high frequency band, LEDs are preferable.

The choice of properties of the used stimuli can affect the performance, safety, and comfort of an SSVEP-based BCI. Improvements to stimuli can enhance the SSVEP SNR, simplify signal processing, enable the use of more targets, prevent loss of attention, and allow for BCI independent BCI operation.

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B.2 Effects of Stimulation Properties in SSVEP-Based BCIs

This article is essentially a very compressed version of the most important research reported in this thesis. It only describes the experiments done with the Experimentation BCI. As a result it only discusses the stimulation device, framerate, environmental illumination, contrast, color, spatial frequency and size.

It was accepted as a contributed paper at the *32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society "Merging Medical Humanism and Technology"* held from August 31 to September 4 of 2010 in Buenos Aires and will be presented at that conference on September 2.

Effects of Stimulation Properties in Steady-State Visual Evoked Potential Based Brain-Computer Interfaces

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***Abstract*— Brain-Computer Interfaces (BCIs) enable people to control appliances without involving the normal output pathways of peripheral nerves and muscles. A particularly promising type of BCI is based on the Steady-State Visual Evoked Potential (SSVEP). Users can select commands by focusing on visual stimuli that alternate appearance with a certain frequency. The properties of these stimuli, such as size and color, as well as the device they are rendered on, can significantly affect the performance, comfort and safety of the system. However, the choice of stimulation properties is often ad-hoc or copied. In this paper we report our findings about the effects of rendering device, refresh rate, environmental illumination, contrast, color, spatial frequency and size of visual stimuli. In order to investigate these effects online, a high-performance BCI was developed. User comfort was measured using a questionnaire. The results suggest that high contrast stimulation works the best, while also being the least comfortable. However, maximum black/white contrast is often not needed and other stimuli (e.g. blue/green stimulation) are shown to work almost as well, while being far more comfortable. Knowledge of these effects can help to improve SSVEP-based BCIs.**

I. INTRODUCTION

The steady state visual evoked potential (SSVEP) refers to the response of the cerebral cortex to repetitive visual stimuli (RVSi) oscillating at a constant frequency. The SSVEP manifests as an oscillatory component in the electroencephalogram (EEG) having the same frequency (and/or harmonics) as the RVS [1]. Because of their proximity to the visual cortex, the occipital sites exhibit a higher SSVEP response.

The SSVEP is an effective electrophysiological source that can be used as input for brain-computer interfaces (BCIs). An SSVEP-based presents the subject with a set of RVSi that in general oscillate at different frequencies from each other. The SSVEP corresponding to the RVS on which the subject focuses their attention is more prominent and can be detected in the ongoing EEG. Each RVS is associated with an action which is executed by the BCI system when the corresponding SSVEP is detected.

SSVEP-based BCIs offer two main advantages over BCIs based on other electrophysiological sources (e.g. P300, ERD/ERS): 1) they have higher information transfer rate, and 2) they require shorter calibration time. Unfortunately, the constant flicker can induce visual fatigue and even epileptic seizures in those that are susceptible.

The functional model of a BCI system is depicted in Fig. 1. The visual stimulation plays a key role in the system and has

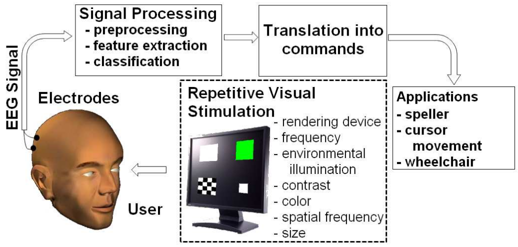

Fig. 1: Functional model of an SSVEP-based BCI.

many different properties. A BCI's performance is usually determined by the information transfer rate (ITR), which indicates how much information can be communicated in one minute. Since these systems are often used for extended periods of time, it is important to consider comfort and safety as well. In order to improve BCIs, research has generally focused on signal processing techniques [2], but these do not affect comfort and safety. Stimulation properties, like color and size of the stimulus, have received fairly little attention in the context of brain-computer interfacing even though they can have a great impact on the performance, comfort and safety of BCI systems.

In this paper we present a study investigating the effects on both comfort and performance of an SSVEP-based BCI of stimulation device and its refresh rate, environmental illumination, RVS contrast, color, spatial frequency and size. Section II introduces the most relevant stimulation properties and the conditions tested in our experiments. Section III describes our BCI implementation and the protocol that was used in our experiments. Section IV discusses each of the tested properties and the results we found in our experiments. The article is concluded in Section V.

II. STIMULATION PROPERTIES AND EXPERIMENTAL CONDITIONS

When designing an SSVEP-based BCI several choices need to be made about the properties of the RVSi that the system will use to elicit an SSVEP response. In this section, we introduce the RVS properties that are tested in this study (see Fig. 2 for examples).

a) Stimulation device: An important factor that influences both comfort and performance is the device that renders the RVS. The two obvious candidates are lights/lamps and computer monitors. Computer monitor stimulation has the advantage that monitors are ubiquitous and can be easily integrated in a computer-based system. In CRT monitors there is a constant flicker at the refresh rate that may elicit an unwanted SSVEP response [3]. LCD screens do not have this problem but often have lower contrast and refresh rates. It has

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been suggested that LEDs elicit stronger SSVEP responses than computer monitors do [3].

Specialized hardware can be used to accurately control lamps such as LEDs. This setup is less flexible and not as readily available, but the advantage is that LEDs can often be much brighter and can display frequencies accurately.

The differences between these devices are tested using green LEDs and LCD and CRT monitors with green squares of approximately the same size and brightness. This ensures that the conditions are comparable.

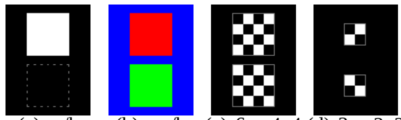
b) Frequency: SSVEP-Based BCIs generally use frequency as the discriminating characteristic for determining which target RVS receives the user's focus of attention. Therefore, a system with N targets needs to use N different frequencies that are sufficiently different, so that they can be distinguished from each other in the signal processing phase. The effects of frequency ranges on performance has already been studied repeatedly and will not be a part of our investigation. High frequencies are more comfortable and safer than low frequencies, but elicit a smaller response and may not be generated by some devices, specifically most computer monitors [4].

Computer monitors have refresh rates that determine which frequencies can be displayed accurately. A device with a refresh rate R can accurately render the set of frequencies R/k, where k is any integer larger than 2. Other frequencies can only be approximately rendered. It has been shown that using frequencies that the monitor can accurately render, can greatly increase performance [5]. However, this research used two different sets of frequencies for the tested conditions. In order to exclude the specific frequencies as the source of the difference, we took two sets of frequencies that were optimized for two different refresh rates: $\{18\frac{3}{4}, 15, 12\frac{1}{2}, 10\frac{5}{7}\}$ for 75 Hz and $\{15, 12, 10, 8\frac{4}{7}\}$ for 60 Hz. We then tested both sets with both refresh rates to evaluate the effect on system performance.

To optimally evaluate the effects of other properties a frequency selection procedure was used to determine the best stimulation frequencies for each subject.

c) Environmental illumination: Illuminated environments are more natural and convenient, but in the dark a bright stimulus can seem much more pronounced. The notion of environmental illumination is closely related to the contrast of the displayed RVSi (see the next paragraph). Pupil dilations caused by a dark environment might cause the eye to catch more of the stimuli's light. Furthermore, external light sources might also flicker a little, interfering with the SSVEP response. All of these observations suggest that BCI performance might be increased in dark environments [6].

d) Contrast: The contrast or "modulation depth" is defined as $(l_{\max} - l_{\min})/(l_{\max} + l_{\min}) \times 100\%$, where $l_{\min}$, $l_{\max}$ are the minimum and maximum luminance, respectively. It was shown that a higher contrast leads to stronger SSVEP responses, especially for dark-on-bright stimuli [7]. It seems intuitive however, that higher contrast also leads to lower comfort. We investigated this aspect by using different shades of gray in both the fore- and the background of our system.



(a) w/k (b) r-g/b (c) 6cm4x4 (d) 3cm2x2

Fig. 2: Examples of stimulation properties showing both states of a condition and the background color. (a) white-on-black stimulation and (b) red/green stimulation on a blue background. (c) and (d) checkerboard stimulation with the same spatial frequency of 0.8 alternations/degree, but different sizes.

e) Color: It is well known that color can affect mood as well as SSVEP response [1]. We tested combinations of the primary colors red, green and blue. In the more perceptually relevant color space that is described in terms of hue, saturation and lightness, these colors only differ in hue. However, device specificities might cause these values to be inaccurate.

f) Spatial frequency: Checkerboards are often used as an alternative to single graphic RVSi. Using checkerboards elicits an SSVEP at twice the stimulating frequency. Some studies have found that better brain responses are elicited this way [8], while others have found the contrary [9]. The spatial frequency is determined by the size and the number of cells of the stimulus. We tested powers of two for the number of cells in both dimensions as well as a checkerboard with cells consisting of 4x4 pixels (54x54 cells).

g) Size: The larger the stimulus, the easier it is to notice, but the harder it is to ignore. Stimulus size also affects the amount of light transmitted to the user and determines how large an application needs to be or how much surface area remains for other purposes.

III. EXPERIMENTAL SETUP

Seven experiments were conducted where the subject had to control a custom made BCI. We tested the effects of (1) rendering device, (2) stimulation frequency vs. refresh rate, (3) environmental illumination, (4) contrast, (5) color, (6) spatial frequency and (7) size. Ten people participated (7 men and 3 women) in several experiments in such a way that there were six different subjects for each experiment. The participants were aged between 24 and 32 and had normal or corrected to normal vision. They were seated comfortably at approximately 70 cm distance from the stimulation device and hooked up to the BioSemi ActiveTwo EEG acquisition system [10]. Electrodes were placed in 32 positions according to the international 10-20 system, but only 8 electrodes over the occipital region (visual cortex) were re-referenced to Cz and used by the system. Unless specified otherwise, the experiments were carried out using an LCD with a refresh rate of 75 Hz in a dark room and white flickering square stimuli of 6x6 cm on a black background. Each condition or experiment varied something about this default configuration.

Before the last four experiments the user was asked to complete an empirically designed questionnaire where they indicated how pleasant, tiring and annoying each condition was and how long they could look at it on 7-point scales. Their answers were averaged into one comfort score where 1 indicates low comfort and 7 indicates high comfort. The questionnaire was conducted before the experiment in order

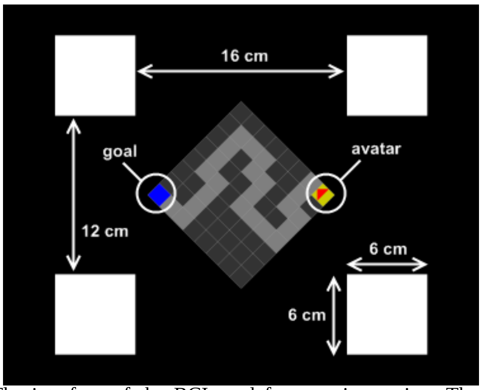
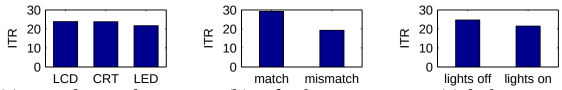


Fig. 3: The interface of the BCI used for experimentation. The user can move the avatar to the goal by focusing on the white flickering targets associated with the desired directions.


(a) stimulation devices (b) refresh rate (c) lighting
Fig. 4: ITRs for the stimulation devices, refresh rate optimization and illumination environment experiments.

to minimize the effect that performance might have on the answers. A 3 minute long frequency selection process was conducted in order to select the frequencies that worked best for each individual subject. For every condition, a 3 minute long calibration phase preceded operation of the BCI.

The user had to move an avatar (red triangle) along a curvy corridor to a goal (see Figure 3). There were no bifurcations, so there was only one way to move through the corridor.

The user could move the avatar by focusing on the target associated with the intended direction. When the system classifies the resulting brain signals, the avatar turns towards the signified direction and tries to move there. If the avatar is blocked by a wall, it will not change position. Correct moves are accompanied by a green screen flash and a high pitched tone and bad moves by a red flash and a low pitched tone. Each move was followed by a one second period of inactivity in order to provide the user with enough time to change his focus and for the SSVEP response to diminish.

For each condition there were two corridors of 24 steps. The subject could attempt to finish each corridor in three blocks of one minute separated by 20-second pauses, which were given in order to prevent fatigue and frustration.

The system estimates the power in the EEG signal of the frequencies (and harmonics) associated with the targets. The signal is first preprocessed using a 50 Hz IIR notching comb filter in order to remove the power line interference. The power for a target is then calculated by applying a maximum contrast spatial filter [11] for the first 4 harmonics of the target frequency. The result for each harmonic is peak filtered, squared and averaged over the last second. The sum of the powers of the harmonics is then used for classification. If the power for exactly one target exceeds the associated threshold, the system moves the avatar in the corresponding direction. After the calibration and frequency selection phases, suitable spatial filters, thresholds and frequencies are determined according to the procedure in [4].

IV. RESULTS AND DISCUSSION

BCI systems are usually evaluated in terms of information transfer rate (ITR) or bitrate, which is measured in bits/minute. This number can easily be calculated by dividing the number of communicated bits by the duration of the task in minutes. In addition to the bitrate, we also consider the comfort of the system on a 7-point scale ranging from low to high comfort, based on the subjective observations of the subjects before the experiments.

There was high inter subject variability in terms of overall performance. Different users may also respond differently to each of the conditions, but one pattern clearly emerges: more pronounced changes between stimulus states result in both better performance and lower comfort (Fig. 5). In addition to leading to low performance, bright backgrounds were judged as uncomfortable.

However, some compromises can be made to make the system more comfortable without significantly sacrificing performance. The tradeoff is visualized in Fig. 6. We have defined four quadrants where the comfort and ITR axes were (arbitrarily) divided at their middle point. The top right quadrant corresponds to good comfort and high performance (ITRs above 30 bits/min can be considered as high for BCIs [4]). Using (light) gray, blue or green/blue stimulation can give high average ITRs. Green/blue alternating squares on a black background provide the best tradeoff between comfort and performance.

We tested whether the stimulation device itself has any effect on BCI performance. Results from the literature suggesting that LEDs elicit stronger responses than LCDs and CRTs were not confirmed and it was found that there was virtually no difference (Fig. 4a). The results also show that matching the chosen frequencies to the used refresh rate improves performance (Fig. 4b). However, optimizing the used frequencies for the user rather than the rendering device may give even better results. A dark environment is shown to be slightly more advantageous (Fig. 4c), confirming the results from [6]. Although no questionnaire was conducted, subjects did comment that they preferred the more natural condition where the lights were on.

We found that contrast is indeed positively correlated with performance, but only for bright-on-dark stimuli (Fig. 5a), contrary to the results form [7]. Bright backgrounds were also judged as uncomfortable.

Color can indeed have a big impact on both comfort and performance (Fig. 5b). Again, bright (colored) backgrounds do not seem like a viable option. Green stimuli appear to work the best, which can be explained either by the fact that the human eye is the most sensitive to that color, or that green's brightness is higher than that of red and blue. Alternating green/blue stimulation seems to work exceptionally well, suggesting that alternating between hues can indeed give better results, especially given that the comfort level of this stimulus was high. Alternating red/green stimulation does not work nearly as well, but this can be explained by Hering's color opponency theory which states that red and

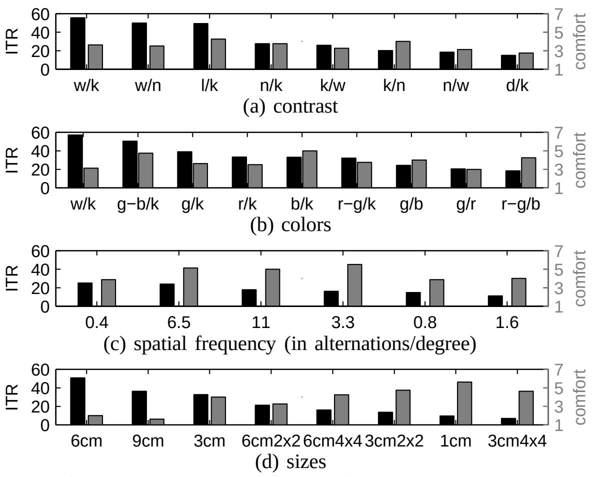


Fig. 5: Performance (dark bars) and comfort (light bars) scores. The conditions are listed in descending order of performance. Colors are referred to by these letters: **r**ed, **g**reen, **b**lue, blac**k**, **w**hite, and **l**ight, **d**ark and **n**eutral gray. The label 'r-g/k' means that the stimulus was alternating between red and green on a black background, 'w/n' means that a white stimulus was popping out of a neutral gray background.

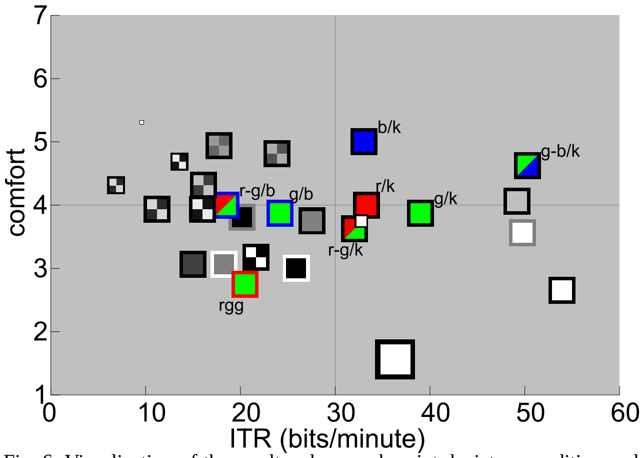


Fig. 6: Visualization of the results where each point depicts a condition and its position shows its ITR and comfort. The edge of each point shows the background color and the face shows the stimulus. If the stimulus alternated between two colors, both are depicted as triangles. For the checkerboards, a small checkerboard is shown where the contrast of the color is correlated with the spatial frequency. Colored RVSi are labeled because this paper is in black and white.

green (and yellow and blue) can cancel each other out.

Our results show that using higher spatial frequencies (and thus smaller cells) can sometimes be beneficial (Fig. 5c). However, the relationship with performance appears to be nonlinear and strongly subject dependent. User comfort is clearly positively related with the spatial frequency, which is likely due to the smaller cell sizes. Using a spatial frequency of 6.5 alternations/degree appears to provide the best tradeoff. However, the performance is worse than that achieved in most of the single graphic conditions. This observation that single graphics outperform checkerboards is confirmed by Fig. 5d.

The size of the stimulus seems to have a negative effect on user comfort for both checkerboards and single graphics (Fig. 5d). BCI performance was more positively impacted by an increase in stimulus size. However, when the BCI used the largest tested stimulus (9x9 cm; $7°21'23''$), performance was lower than when 6x6 cm ($4°54'29''$) were used.

The simplest explanation is that there is an optimal stimulus size that makes up a relatively small area of the visual field. A more likely explanation is that making the non-target stimuli larger and closer to the one the subject was attending to, had a detrimental effect on performance. This could be either due to increased interference in the eye, or increased difficulty to focus on the desired target. More experiments have to be carried out to investigate the cause of this anomaly.

V. CONCLUSION

Both performance and comfort vary in a broad range depending on the RVS properties. Our experiments show that comfortable conditions usually lead to low performance and that high performing conditions are often uncomfortable. Few settings combine high performance with relatively good comfort (top right quadrant in Fig. 6), but light gray, blue and green-blue stimulation provide a good tradeoff.

It is important to balance comfort and performance, especially if the system is used for extended periods of time. Our study shows that stimulation conditions exist that offer better comfort at the cost of minor decrease in performance.

Additional properties that are worth investigating are spatial and temporal blur, shape and general stimulus appearance. Furthermore, interactions between properties may not be linear, so different combinations need to be tested.

VI. ACKNOWLEDGMENTS

We gratefully acknowledge the contribution of reviewers and participants in our experiments.

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B.3 Towards Error-Free Interaction

This paper is very closely related to Appendix A and addresses some issues with the implementation of an EEG-based error-detection system in order to make human-machine interaction more error-free. The system should be fast, cheap, adaptable, easy to use and robust. To that end, a simple algorithm for error detection is discussed as well as a method for choosing only two electrode recording sites using a limited number of calibration trials. This also gives some insight into how the mechanism of the error potential works in the brain. Performance was measured using the area under the ROC curve (AUC) and was larger than 0.89 for five subjects while one subject lagged behind at 0.75.

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Towards error-free interaction

Tsvetomira Tsoneva[1] Jordi Bieger[1,2] Gary Garcia-Molina[1]

***Abstract*— Human-machine interaction (HMI) relies on pattern recognition algorithms that are not perfect. To improve the performance and usability of these systems we can utilize the neural mechanisms in the human brain dealing with error awareness. This study aims at designing a practical error detection algorithm using electroencephalogram signals that can be integrated in an HMI system. Thus, real-time operation, customization, and operation convenience are important. We address these requirements in an experimental framework simulating machine errors. Our results confirm the presence of brain potentials related to processing of machine errors. These are used to implement an error detection algorithm emphasizing the differences in error processing on a per subject basis. The proposed algorithm uses the individual best bipolar combination of electrode sites and requires short calibration. The single-trial error detection performance on six subjects, characterized by the area under the ROC curve ranges from 0.75 to 0.98.**

I. INTRODUCTION

Advanced human-machine interaction (HMI) relies on pattern recognition algorithms, which are not error free. Machine errors reduce the overall performance of the system and can be particularly annoying for the user. The human brain has developed complex neural and cognitive mechanisms that deals with error awareness. We can utilize these mechanisms to improve the performance and the usability of HMI systems like brain-computer interfaces (BCIs). Different neurophysiological studies have shown the presence of error-related responses in human electroencephalogram (EEG), called error-related potentials (ErrP). ErrPs are associated with the anterior cingulate cortex (ACC) [1], which is also responsible for regulating emotional responses.

Different studies have shown the presence of ErrP emerging shortly after an error made by the subject [2]. Usually they use a choice reaction task, which requires quick response to a stimulus. This type of ErrP is also known as error-related negativity (ERN) or response ErrP. Other studies have reported a different type of ErrP during a reinforcement learning task [3]. This type of ErrP appear after feedback indicating an erroneous response from the subject; hence it is known as feedback ErrP. Whereas these neural correlates of error awareness are manifested after errors committed by the subjects themselves, ErrPs are also present after an observation of an error, for example committed by the interface the subject is interacting with. These are known as interaction ErrP. ErrPs of this kind have been observed during simulated or actual brain-computer interaction [4][5].

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Our objective is to explore the brain mechanisms dealing with awareness of erroneous responses and to design a practical solution that can be integrated in any HMI system. That is why a number of requirements should be satisfied. Real-time operation is necessary prerequisite if we want to integrate such a solution in already real-time HMIs. Thus, we aim for computationally efficient signal processing and robust detection of erroneous responses. Individual specificities should be considered as different users might have different physiological responses. The solution must adapt to the user, ideally after a short calibration procedure. Convenience is also essential for a system working in a real-life environment, thus, we want to use only few measurement sites.

In this paper we report our approach for machine error detection following the above mentioned requirements. The paper is organized as follows. We first introduce our experimental setup in Section II. Then we report the results we have obtained in Section III. We address certain points of discussion in Section IV and conclude the paper in Section V.

II. EXPERIMENTAL SETUP

A. Participants

Six volunteers (3 females and 3 males) aged between 23 and 29, took part in the experiment. All participants were healthy, right-handed and had normal or corrected-to-normal vision. They signed an informed consent form before the start of the experiment.

B. Task

To minimize the influence of external factors and to isolate the response to errors made by the interface, we designed a relatively trivial experimental paradigm in the form of a game. The game was very simple, so that it was very unlikely that the subjects would make an error. The goal of the game was to move a square (the stimulus) horizontally from one side of the screen to the other by a single key press. The total length of the path was 14 squares, the last one being the target. The subject was given up to 7 moves to successfully complete the path. The stimulus could be moved with a step of one or three squares. The subject had to develop an efficient strategy in order to reach the target within the given number of moves.

Figure 1 illustrates one trial in the experimental protocol. At first the stimulus (a gray square) appears on screen. After 1700 ms a numerical and a visual indication of the suggested step size and the expected next position are presented. The step size can be either one or three (selected at random), therefore the expected next position is either one or three squares further from the current position of the stimulus. If

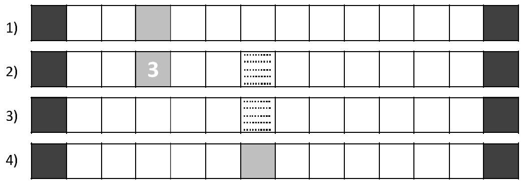

Fig. 1. A correct trial in the experiment protocol: 1) The stimulus (gray square) appears on screen for 1700 ms. 2) A numerical and a visual (square with dots) indication of the expected next position are presented for up to 2000 ms. 3) The expected position of the stimulus (the square with dots) stays on screen for 1000 ms after a key is pressed. 4) The stimulus has moved to the new position.

the subject likes the suggested step s/he is expected to press a key. If a key is not pressed in the next 2000 ms a new suggestion is given. After the key press, the visual indication of the expected position stays on screen for another 1000 ms, after which the stimulus moves to the new position. The new position of the stimulus may be the expected one (correct trial) or not (error trial). In an error trial the stimulus moves either one or two squares back from the current position. In order to finish the game, the last move should end exactly on the target. In case of selecting a step bigger than the remaining squares to the target, the stimulus jumps back to the beginning of the path. The game continues until the target is reached. The game is won if the subject reaches the target within the given number of moves, and is lost otherwise.

C. Experimental procedure

The subjects were told that they would play about 30 games and they were instructed to try to win as many as possible. All subjects played the game for about 30 minutes, completing between 23 and 31 games (mean: 28 games). There were two modes of the game: *correct mode* and *error mode*. In the correct mode the system did not commit errors. In the error mode, error moves appeared with a probability of 25%. The session started with two games in correct mode. Then a correct mode game was played every 6 games to reduce the effect of habituation. The rest of the games were played in error mode. The mean number of trials per game was 7, resulting in an average of 198 trials per subject. The mean number of error trials per subject was 40, and the mean number of correct trials was 158.

D. Signal acquisition

Continuous EEG from 32 scalp electrodes, digitized at 2048 Hz, was acquired using a BioSemi ActiveTwo system [6]. The electrodes were positioned according to the international 10/20 standard and were uniformly distributed over the scalp (see the axes of Fig. 3 for the electrode positions). The signals were subsampled to 256 Hz and then bandpass filtered in the 0.5-25 Hz band using a Butterworth filter. In order to minimize the effect of any background neuronal activity in the area of interest and to emphasize the differences in neural responses to error and correct trials we performed an exhaustive search for the best bipolar combination (BBC) of electrodes on a per subject basis. This procedure is explained in detail in Section III-C.

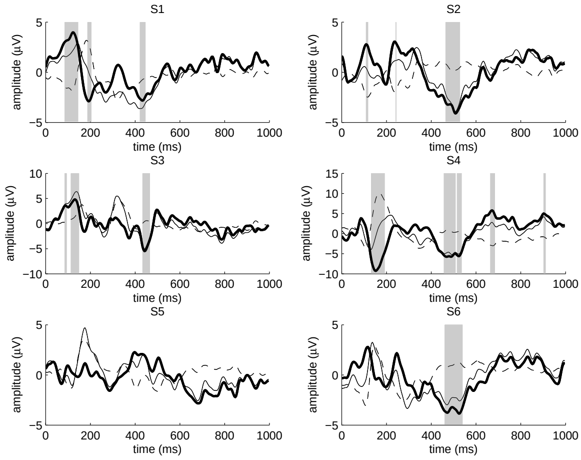

Fig. 2. Difference (bold line) between potentials for error (solid line) and correct (dashed line) trials for all subjects (bipolar combination: Cz-Pz). Gray areas show the statistical significance ($p < 0.0002$).

III. Experimental results

A. Error-related potentials

We first checked whether there were any differences in the brain responses to error and correct trials. Fig. 2 shows the brain potentials for error and correct trials as well as the difference (error-minus-correct) for the bipolar combination Cz-Pz. ErrPs are associated with the ACC located in the fronto-central sites of the brain and the choice of Cz is common in the literature (see Section I). For five of our subjects (S1, S2, S3, S4 and S6) a first positive peak is observable around 150 ms after the stimulus movement, followed by a negative peak around 200 ms and a positive peak around 300 ms. Finally, a broader negative peak occurs around 450 ms. This ErrP shape is similar to previously reported results [5]. Subject S5 did not exhibit this response. In order to check the significance of the difference between the responses to error and correct trials we performed a paired t-test with Bonferroni correction. The areas where the difference is significant are shaded in gray in Fig. 2. As it can be seen, the resulting error potentials differ between subjects, some of them exhibiting higher amplitudes than others. Furthermore, the statistical significance of the difference between error and correct trials is highly variable, as it could be expected from the low signal-to-noise ratio of EEG signals. If we want to use ErrP to improve HMI, we need to be careful as inappropriate adaptation of the interface could further frustrate the user. Emphasizing the individual differences in error processing could lead to a more robust solution.

To investigate the effect of frequency of error occurrence on error processing we invited two of our participants for a second experiment. We used the same experimental protocol but this time the probability of errors was 50%. The ErrPs from the second experiment were very similar (almost identical) to the ones from the first experiment, suggesting that frequency of errors does not affect the observed neural responses.

B. Error detection algorithm

Templates of the brain responses to erroneous and correct outcomes (*error template* and *correct template* respectively) for each subject can be obtained from a training set. In this experiment the training set was composed of a random selection of the recorded potentials. In practice the training sets results from a calibration procedure. The templates are one-second long averages, time-locked to the stimulus movement. The templates are univariate signals, which result from a bipolar EEG combination. To decide if a given trial is erroneous, a score is calculated as follows.

$$s = \sum_i (1 - p_i)(|x(i) - \tau_e(i)| - |x(i) - \tau_c(i)|), \qquad (1)$$

where x is the brain response to the current trial, τ_e and τ_c are the error and correct templates respectively, i is the sample index, and p_i is the significance level (determined by a paired t-test) of the difference between the templates at sample index i.

If the score is higher than a previously selected threshold (e.g. zero), then the trial is considered erroneous. The selection of the threshold depends on the application. Thus, a balance between the true positive and false positive error detection rates needs to be sought. A practical manner to assess the threshold selection impact on the system consists in drawing the ROC curve (see Fig. 5), which represents the true positive versus the false positive error detection rate for different threshold choices. The area under the ROC curve (AUC) provides an indication of the error detection performance.

C. Best bipolar combination

Given a set of M recorded EEG sites, $M(M-1)/2$ possible bipolar combinations exist. An exhaustive search for the BBC can be done by computing the average AUC (over 50 random selections of train/test sets) for all possible combinations. The result of this procedure is visualized in the colormap of Fig. 3, where the gray level of a cell is proportional to the AUC associated with the corresponding bipolar combination. For convenience of visualization, the AUC values of the diagonal elements has been artificially set to 0.5 (random level). By definition the colormap is symmetric with respect to the diagonal. Certain regions in the map, especially the ones representing fronto-parietal combinations, exhibit larger AUCs. Yet, these regions are not common to all subjects.

To better visualize the individual differences and to facilitate physiological interpretation, we represent in Fig. 4 the bipolar combinations corresponding to the largest twenty AUCs. The electrodes of each combination are connected through a line whose thickness is proportional to its AUC. For convenience of visualization the AUCs are quantized into three levels. For all subjects but S3, we observe strong connections between right and central sites. The electrode site F8 is of particular relevance for subjects S1, S4, and S6.

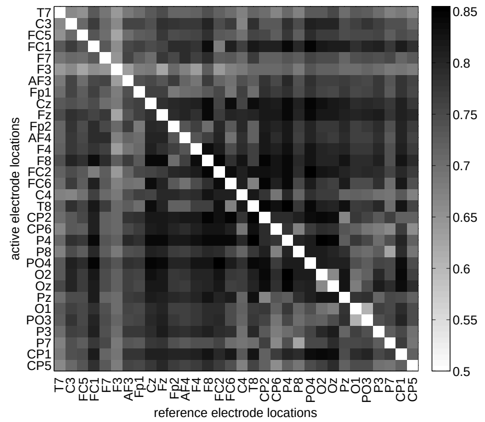

Fig. 3. Average AUC across all subjects for all possible bipolar combinations. The gray level of a cell is proportional to the AUC of the corresponding bipolar combination, darker cells indicating better performance.

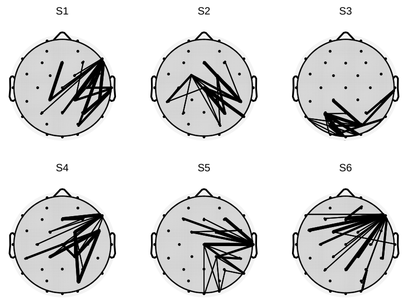

Fig. 4. Bipolar combinations for the largest twenty AUCs for each subject. The thickness of a line is proportional to its AUC value (quantized in three levels).

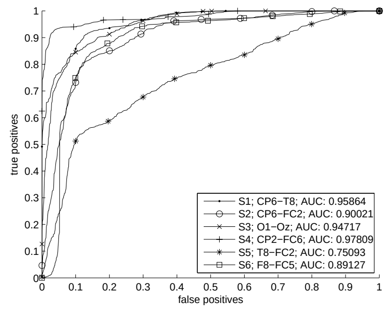

Fig. 5. ROC curves for the BBC of each subject.

The ROCs associated with the BBC for each subject are depicted in Fig. 5. All subjects but S5 have average AUCs above 0.89. The particularly low performance of subject S5 is expected given the lack of significant differences between responses to error and correct trials presented in Fig. 2.

D. Training set size

The number of elements in the training set needs to be sufficient to ensure a desired level of detection performance. It is generally true that a larger training set will result in better performance, yet we would like to limit the duration of the calibration procedure. To determine the influence of the training set size on performance, the following analysis was conducted. For each subject, the set of responses to error trials was randomly divided into a training and a testing set of equal sizes, along with an equal number of responses to correct trials. The detection algorithm was then run for the

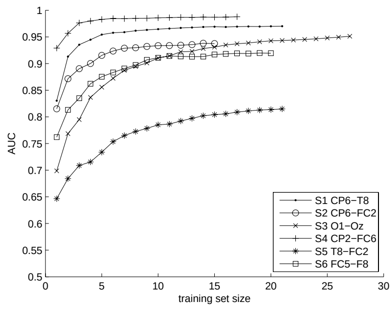

Fig. 6. Performance versus used number of training samples for the BBC of each subject.

subject's BBC with the first N elements (both erroneous and correct) of the training set, for N ranging from 1 to the size of the testing set for the particular subject. To estimate the average level of performance, this process was repeated 100 times with different random choices for the elements in the testing and training sets.

Fig. 6 shows how increasing the size of the training set improves the detection performance. The figure indicates that increasing the size of the training set beyond a certain size (about 10 responses for error and correct trials) leads to marginal gain in performance.

IV. Discussion

The suggested approach is suitable for real-time operation. This was tested in a demonstrator that used the paradigm explained in Section II-B. The signals were recorded between electrodes Fz and Cz (the BBC for the tested subject), analyzed real-time and whenever an error was detected the latest move was undone.

It is important to mention the time invariability of the reported potentials. The ErrPs of the second experiment examining the influence of frequency of error occurrence were very similar to the potentials from the original experiment, although the actual recordings were taken a few weeks apart. This was further confirmed by the fact that the real-time demonstrator functions with more than three months old data.

One could argue that the suggested experimental framework does not fully represent the spontaneity of machine errors in real-life. However, we did not find an effect of habituation when comparing the ErrP from the beginning of the experiment with the ones from the end of the experiment. Furthermore, considering the triviality of the task, the motivation of the participants could be to complete the whole session as fast as possible. So that, even if they do not care about winning or loosing after a certain point, every move backwards brings them a step further away from their goal, hence increasing their frustration. A few participants reported after the end of experiment that they found the task particularly annoying.

The effect of frequency of error occurrence was already addressed in the second experiment explained in Section III-A. Although we do not exclude the possibility that the element of surprise attendant to error trials might play a role in the error processing, the observed potentials do not seem to be due to the infrequency of the stimulus.

Hypothetically, the horizontal movement of the eyes could cause the differences between responses to error and correct trials. In that case one would expect the BBC to be defined by inter-hemispheric fronto-polar sites [7]. Yet, our results show involvement of right fronto-parietal sites, indicating that the reported differences are not caused by horizontal eye movement.

V. Conclusions and Future Work

In this paper we presented an approach for automatic detection of the neural correlates of error awareness in the human brain with the goal of improving the performance and usability of HMI systems. We have set a number of requirements for a practical solution that can be easily integrated in an existing HMI system. These requirements were real-time operation, accounting for individual specificities, and convenience of operation. Six subjects participated in an experiment, in which machine errors were simulated. Our results confirmed the presence of EEG potentials related to processing of machine error. We have implemented an error detection algorithm that achieves high error detection performance given by AUCs ranging from 0.75 to 0.98. The proposed solution sought the best individual bipolar combination of electrodes that emphasizes the differences in error processing. The impact of the training set size on the detection performance was investigated and it appears that only a few examples of brain responses to error and correct trials are sufficient for high performance. The feasibility of the proposed solution was tested using a real-time demonstrator.

More research is needed to evaluate the time invariability of the best bipolar combination for a given subject. In view of standard positioning of the measurement sites it is necessary to test for existence of a bipolar combination that guarantees reasonably high error detection rates for all users. To achieve this a larger group of subjects has to be involved.

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