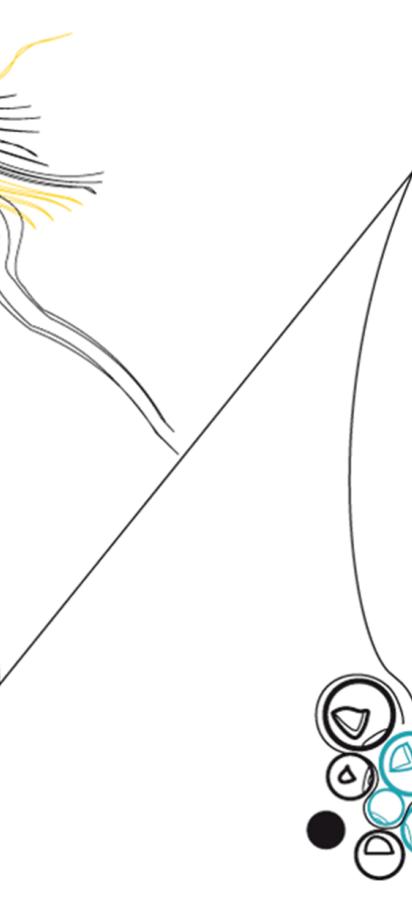




# UNIVERSITY OF TWENTE.

Faculty of Electrical Engineering,  
Mathematics & Computer Science

## Brain Computer Interfacing



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Portfolio  
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# 1 | Week 1

This chapter describes the progress of the first week and gives a general overview of the field of Brain Computer Interfacing (BCI), applications and challenges.

## 1.1 What is BCI

BCI is a method of measuring changes in brain activity to control an application, primarily for the benefit of severely disabled people by giving them a means of communication. The field of BCI is constantly growing since the 1990s due to high performance and low computation power as well as the electroencephalogram (EEG) enabling real time and closed-loop processing [4]. Related areas in science are signal processing, machine learning, computational intelligence, neuroscience, cognitive science, and electrical engineering. Problems in the field of BCI are similar to computer vision, speech recognition, pattern recognition, time series analysis, control systems & robotics.

## 1.2 Measuring Brain Activity

Brain signals that are typically used to control an application, are tonic states, phasic states and event related states. A tonic state describes the degree of relaxation or cognitive load, whereas the a phasic state is based on the switching of attention or type of imagined movement. Lastly, event related state: surprised / not surprised, committed error, event noticed / not noticed.

Brain signals can be measured by invasive, partially invasive and non invasive BCIs. Invasive BCIs have electrodes implanted directly into the gray matter to detect single-cell action potentials or local field potentials [4]. The electrodes used usually consist out of a microelectrode array, tetrodes or microwires. Invasive BCIs provide accurate measurements and a high spatial resolution of several micrometers, however this technique requires neurosurgery and thus limits the number of applications. In addition scar tissues can occur from the surgery which can diminish the brain signals and medical complications can arise if the body does not accept the implanted electrodes [5]. Partially invasive BCIs are not implanted in the gray matter but on the surface of the cortex and is referred to as electrocorticography (ECoG) [4]. This technique gives a spatial resolution of several millimeters but also requires neurosurgery and suffers of the same problems as invasive BCIs. Non-invasive BCIs have electrodes placed on the head of the subject according to the international 10/20 system, recording EEG mea-

surements [4]. This method provides a far lower spatial resolution of only a few centimeters but does not require neurosurgery and makes this technique far more accessible and widely used.

Since this portfolio is written in the context of interaction technology, a more detailed description of non-invasive BCIs are given, as they are by far more accessible than the other two types described above.

Non invasive BCIs can be either endogenous or exogenous. Endogenous BCIs are based on self-regulation of brain rhythms and potentials without external stimuli [6]. Users learn to generate specific brain patterns which can be 'decoded' by a BCI based on slow cortical potentials (SCP), sensorimotor rhythms (SMR). Early versions of the BCI were based on SCP, but this method requires months of training and is nowadays not commonly not used anymore. SMR BCIs are based on motor imagery strategies that generate event related desynchronization/synchronization (ERD/ERS) in the alpha and beta frequency ranges of the EEG. Gamma frequency ranges can also be used when a ECoG is used instead of an EEG [4]. Typically changes in SMR associated with imagined hand or feet movements are used for this kind of BCI. It is commonly applied for cursor control, navigation of wheelchairs or controlling virtual environments.

Exogenous BCIs are based on external stimuli that evoke a specific change in the brain activity [4]. Typical control signals used in exogenous BCIs are P300 response and steady-state visually evoked potentials (SSVEP). P300 responses require the user to focus on an external stimulus (e.g. visual or tactile), where the resulting brain signals differ for stimuli that the user notices and ignores. The resulting brain signal occurs around 300 ms after the event. Applications for this type of BCI is usually found in speller programs where letters are flashed briefly. The user selects a letter by counting the number of flashes for it, which can be then detected by the BCI. BCIs based on SSVEP utilize the fact that flickering light sources with frequencies between 5–20 Hz cause brain oscillations of the same frequency. In similar manner as P300 based BCIs, resulting brain signals differ between stimuli that the user either notices or ignores. This technique of BCI is used in robot control or mobile phone control.

On the one hand, exogenous BCIs require minimal training time, are easy to set up, have a high bit rate (60 bits/min) and only require one EEG channel, on the other hand users are permanently exposed to external stimuli which can cause fatigue and might interfere with daily life situations, additionally users are not free in their will but constrained to the choices presented to them [6]. Endogenous BCIs are on the one side independent of external stimuli, can be operated at free will and are useful for users with ALS or with sensory organs affected, on the other side, this approach requires weeks or months of training time, not all users are able to control this type of BCI, it requires multiple EEG channels for good performance and has a lower bit rate (20–30 bits/min) [6].

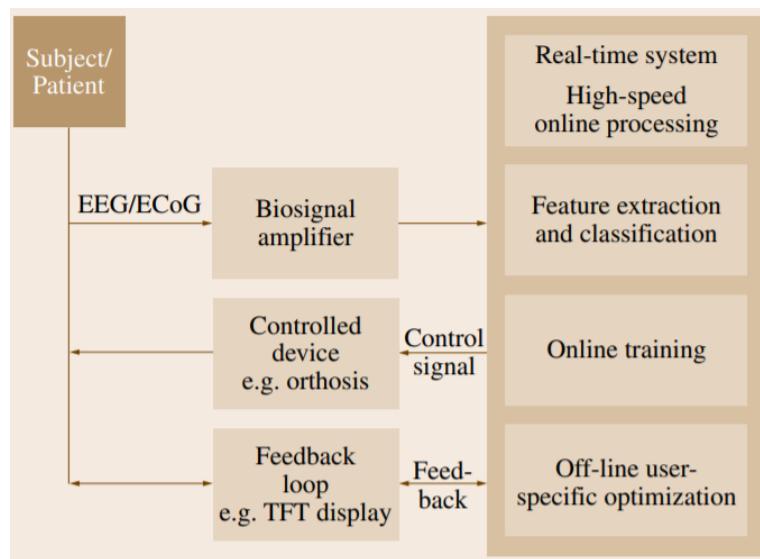
BCI subtypes to control application include active, reactive and passive BCIs [7], [8]. Active BCIs derive their outputs directly from the brain activity which is consciously controlled by the user (e.g. imagining to move your limbs), independent of external events. Reactive BCIs derive their outputs from brain activity arising in reaction to external stimuli, which

is indirectly modulated by the user. Passive BCIs derive their outputs from arbitrary brain activity without the purpose of voluntary control, for enriching Human Computer Interaction (HCI) applications with implicit information.

Finally, measuring techniques other than (partially) invasive and non-invasive BCIs include PET (positron emission tomography), fMRI (functional magnetic resonance imaging), functional NIRS (near-infrared spectroscopy), and MEG (magnetoencephalography) [4]. However, PET, fMRI, and MEG require highly bulky and spacious devices that are only available in special facilities or hospitals, making them relatively inaccessible and unpractical. Furthermore, PET, fMRI, and NIRS are based on the metabolic changes in the cerebral blood flow and thus longer time constants compared to the change of electrical brain signals, hence higher data transfer rates, possibly rendering them unusable for real time applications.

### 1.3 BCI System Structure

BCI systems are set up in a closed-loop setting and require real time feedback for optimal performance [4]. The complete system consists out of 4 components: Signal acquisition and signal conditioning, feature extraction and classification, controlling a device or application, and lastly a feedback loop, as depicted in figure 1.1.



**Figure 1.1:** Block diagram of a BCI structure [4].

The first component, signal acquisition and signal conditioning, is composed out of an amplifier including an analog to digital converter (ADC) to EEG/ECoG or neural spike signals. The system can record from one channel up to 512 channels depending on the experiment.

The second component, feature extraction and classification, converts stable and distinct signal features to control signals in order to manipulate an application. Features can be extracted both in the time domain and/or frequency domain. In addition, time series pre-processing algorithms like common spatial patterns can be used to enhance the signal to

noise ratio and to increase the differences between features. Next, supervised machine learning classifiers are then trained based on the individual features of the user. Subsequently, the features are then evaluated and optimized off-line in a testing phase where consequently the most reactive parameters are selected and used for the real-time application of the BCI system.

The third component, after the classifier has been trained based on the individual features of the user, an application can be controlled based on the control signals of the BCI.

Subsequently, in the fourth component, a feedback signal is sent back to the user. Feedback signals depend on the type of application and can range for example from audio feedback from a speller program to tactile or electrical signals.

## 1.4 Applications of BCI

Traditional applications of BCIs have been mainly designed to enhance communication and mobility systems for severely disabled people (E.g. Tetraplegia, locked-in syndrome, ALS) and include for example speller programs, mobility and prosthetic control systems as well as home automation systems [8]. Recently also commercial applications for healthy people have been designed such as BCIs that monitor the state (fatigue, workload, alertness) of an operator in various work scenarios such as long distance truck driving, navigation of aerial and nautical vehicles, or tele-manipulation in robotics [8]. Other applications include lie detection in law enforcement (experimental) and entertainment ... such as mood assessment, sleep recognition, neuro-rehabilitation, neuro-wear [8]. Finally, BCIs are also applied in neuro-science, multivariate pattern analysis, brain imaging and closed loop neuro-science experiments [8].

## 1.5 Challenges in BCI

The field of BCI has various challenges. The processing depends on unknown parameters which can be person or task specific. This means that every BCI session is dependent on the person and needs therefore calibrating. Reasons for variability include that the folding of cortex differs between any two persons, as well as relevant functional maps differing across individuals. In addition, sensor locations differ across recording sessions and brain dynamics are non stationary at all time scales [8].

In addition, sensitive measures are hard to obtain as the signal-to noise-ratio is challenging to deal with and relevant brain activity is small compared to interfering artifacts and background activity. Furthermore, specific measures are even harder to obtain as large collections of neurons are involved in many different activities.

Moreover, EEG signals are mathematically complicated to handle since all sensors record very similar signals with only very small differences. These signals need therefore to be computationally disentangled for optimum performance by various statistical methods.

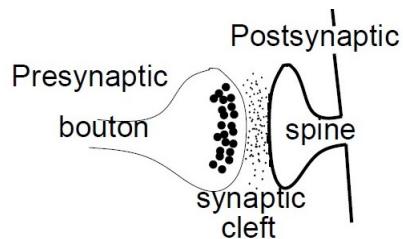
# 2 | Week 2

This chapter concerns week 2's process, including the first lab. It appears that there exist different opinions on the importance of biological knowledge of the brain for computational neuroscience [9]. As is assumed by some theorists, the basic principles upon which computational neuroscience is build are already known. In this case close attention to biological details of the brain may not be necessary. However, the author of the book chapter states that new concepts of computational neuroscience will for the main part emerge from study of the brain and therefore biological knowledge of the brain is useful and important.

## 2.1 Brain cells and information transfer

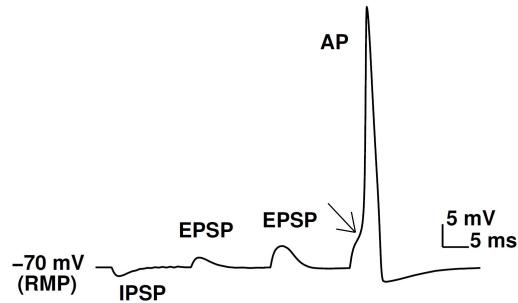
Cells in the human body are organized and specialized. Where liver cells concern the liver, brain cells concern the brain. The two major types of brain cells are neurons and glia. Glia are presumed to have a supporting function, but may also be involved in information processing. However, neurons are believed to be the principal elements of the brain's information processing and (although not all) have the ability to produce action potential.

A neuron consists of three parts. First the dendrites, where information enters the neuron. This information then travels to the second part of a neuron, the cell body (soma), which in turn activates the third part, the axon. The axon can then send a signal out of the neuron. Axons are thinner and longer than dendrites and can branch to connect with multiple target cells. Such a connection between an axon and a dendrite is called a synapse and is illustrated in figure 2.1. In this figure the terms Presynaptic and Postsynaptic indicate the direction of signal flow. The connection between two neurons is not direct, but communicate as follows: transmitter is released presynaptically, moves across the synaptic cleft, and then activates postsynaptic receptors.



**Figure 2.1:** Illustration of a synapse [9]

Neuron information is in the form of electric potential across its membrane. Information is conveyed via synapses through arrival of neurotransmitters on receptors, which trigger postsynaptic potentials (PSPs). This can be either excitatory (EPSPs) or inhibitory (IPSPs). An IPSP brings the membrane potential down to a value below the resting membrane potential (RMP), about  $-70$  mV, and further away from the neurons firing potential. Then a pair of EPSPs of increasing magnitude move the membrane potential towards the firing potential. A third and larger EPSP reaches firing threshold and causes the cell to fire its action potential (AP) spike. This is shown in figure 2.2. The AP is the signal that is sent through an axon to cause a PSP in another neuron.



**Figure 2.2:** Postsynaptic and action potentials. Arrow shows where 3rd EPSP triggers the AP. [9]

Next to chemical synapses where neurotransmitters are released and picked up creating an electrical signal in the receiving neuron, there exist also electrical synapses which allow current to flow directly from one neuron to another, and nonsynaptic interneuronal signaling, for instance volume transmission. In the latter transmitters are sent through extracellular space to many neurons in which glia as well as neurons may be involved. Lastly, there exists also transmission via a by a cell generated electric field which can influence other cells. This is called ephaptic transmission.

## 2.2 Central Nervous System

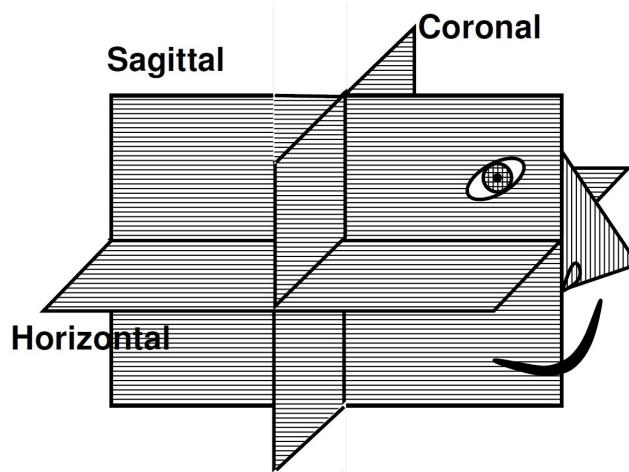
The central nervous system (CNS) consists of the forebrain, brainstem, and spinal cord. White matter within the CNS is made up of axons and gray matter is mainly made up of cell bodies and dendrites. The gray matter at the surface of the brain is called cortex and deeper in the brain it is called nuclei.

### 2.2.1 Slicing of the brain

Coordinates always refer to the subject's viewpoint in such a way that the subject is facing the viewer. This means when talking about a subject's left, it is the viewer's right. Slicing is done in three planes, as shown in figure 2.3. The coordinate system is placed on these slices as follows:

- Horizontal

- Anterior/posterior (towards/away from nose)
- Left/right
- Medial/lateral (towards middle/towards edge)
- Coronal
  - Dorsal/ventral (up/down)
  - Left/right
  - Medial/lateral (towards middle/towards edge)
- Sagittal
  - Anterior/posterior (towards/away from nose)
  - Dorsal/ventral (up/down)



**Figure 2.3:** Slicing overview [9]

### 2.2.2 Parts of the brain

As mentioned before in this section, the brain consists of the 'external' cortex and multiple internal nuclei. Both are made up of gray matter and the subcortical connections are made up of white matter. Answering questions about parts of the brain can be difficult, since for many parts the basic functions are still a mystery. The cortex can be subdivided into areas responsible for different functions. In the back the occipital cortex deals with vision, in the front the frontal cortex deals with socializing and judgement, the left temporal cortex (lateral & ventral) deals with speech recognition, the right parietal cortex (more dorsal) does spatial orientation, and in general the left brain is literate and numerate and the right brain is more focused on pictures.

Other more primitive cortical areas that are of interest for modeling are the piriform (olfactory) cortex and the hippocampus, responsible for smell, and episodic memory and certain types of epilepsy respectively. Furthermore, the thalamus is of interest for modelling. The

thalamus can be seen as the gateway to the cortex. Except for smell, all sensory information enters the brain via individual nuclei of the thalamus, of which the one for vision (lateral geniculate nucleus (LGN)) is the most studied. The basal ganglia is concerned with initiation and planning of movement and the cerebellum can be thought of as a motor area concerned with sensorimotor organization (limb & body position and movement/posture coordination).

Note that these are not all regions, but the ones considered most useful for the progress of the portfolio.

## 2.3 Learning about the brain

Important in discussing research methods is the distinction between anatomy and physiology. Anatomical methods concern structure and does not show activity, whereas physiological methods do show activity.

### 2.3.1 Anatomical techniques

Anatomical methods mostly involve the use of radiation in the form of visible light, infrared, radio, x-ray, and electrons. Tools used are for instance the microscope and the imaging device, including computer tomography (CT or CAT scan, using x-rays) and magnetic resonance imaging (MRI) which uses nuclear magnetic resonance (NMR). A problem with light microscopy is that it is not possible to clearly view anything much smaller than a micron. Somas (see section 2.1) can easily be seen under a microscope, but synapses can not. Also the raw brain doesn't show much contrast since it's mostly white on with some gray. Electron microscopy (EM) however provides a more detailed view, since it can show objects to about 10 nanometers, but the disadvantage is that zooming in and out is not possible. Imaging methods like CT & MRI can be used to look at macroscopic structures. These methods produce views of the brain that are extremely clear and sometimes even better than looking at a post mortem sliced brain. These methods are called *in vivo*, meaning that they can be used on living objects rather than looking at removed tissue (*in vitro*). Currently there exists a gap between the microscopic and imaging techniques, what one can see after and before death.

### 2.3.2 Physiological techniques

Physiological techniques provide a measure of activity rather than structure. Activity mainly in the form of change in electrical potential, but also flux of specific ions, uptake of nutrients, and binding of neurotransmitters. Examples of physiological techniques are Positive Emission Tomography (PET) and functional Magnetic Resonance Imaging (fMRI) (see section 2.4), which can be used to measure ions or metabolites in a living subject. Although neurophysiology ideally would be the study of function, it is often more concerned a description of dynamics than an explanation of meaning and intent.

Electrophysiology techniques involve the use of electrodes that measure voltage or current generated by the voltage across the cell membrane (see section 2.1). Cell membranes have a RMP and deviation from the RMP are electrical signals in the neuron. Hyperpolarizing signals are signals that further polarize the membrane's negative polarization (-70 mV). Signals making the membrane's potential more positive are called depolarizing. Measuring this potential can be done intracellular, where the inside potential is compared to the cells outside potential, or extracellular, where electrodes are placed near the cell. The latter method detects electrical fields closely reflecting the cell's potential rather than measuring the actual cell potential, but when placed close enough it is capable of measuring activity from a single cell (single-unit recording). Multiunit recording is also possible, moving the electrode further away to pick up signals from multiple cells. EEG is such a method, detecting very small potentials using electrodes attached to the subject's head which is possible because field potentials can be strong enough to be measured from outside the head.

### 2.3.3 Diseases

Brain diseases can be seen as natures experiments, of which much can be learned. Ablative diseases such as a stroke, brain tumor, or trauma knock out a piece of the brain. For example a stroke, caused by a blocked blood vessel, can starve and kill a part of the brain. A stroke of the left middle cerebral artery can cause a language disorder (aphasia), which have been widely studied in order to better understand how the brain processes language. Ablative diseases are not progressive, they do damage and then stop. Remarkable is that how well a brain can recover, certain lost functions can return although an MRI would still show a hole in the brain.

Intrinsic diseases, usually progressive, are caused by alterations in cellular organization, metabolism, neurotransmitters, or electrical conduction. Such diseases can provide important insights in the brains functioning as well, although often harder to study as compared to ablative diseases. An example of an intrinsic disease is Parkinson's disease, where the loss of a certain type of cell results in a decline in dopamine release which has effects on movement and thinking.

## 2.4 Imaging [1]

### 2.4.1 Structural imaging

Different types of tissue in the brain have different physical properties, which can be used to create detailed static maps of the brain's structure. Methods like CT and MRI are common used techniques. CT scans make use of differences in the amount of x-ray absorption of different types of tissue. CT cannot distinguish between white and gray matter and can't be adapted for functional imaging.

MRI has some advantages over CT, which are:

- It is completely safe, no ionizing radiation is used so people can be scanned multiple times.

- Better spatial resolution.
- Better distinction between white and gray matter.
- Can be adapted to be used in neural activity related blood oxygenation detection (fMRI).

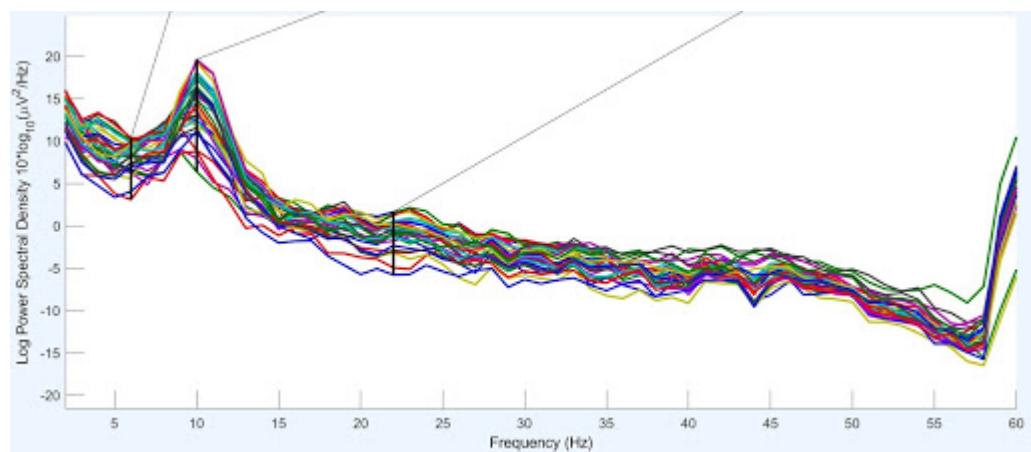
#### 2.4.2 Functional imaging

Neural activity causes local physiological changes in specific regions in the brain and this can be used to create dynamic maps of the brain, moment to moment variable characteristics which might be associated with cognitive processing. PET and fMRI are such techniques. The former measures change in blood flow to a certain region, the latter the concentration of oxygen in the blood.

All functional imaging has the requirement that physiological responses must be compared to a or multiple baseline responses. In contrast to EEG & MEG, PET and fMRI don't measure neurons directly. Rather they measure downstream consequences of neural activity.

### 2.5 Lab Session

In the first week we learned how to load, visualize and preprocess EEG data in EEGLab and Matlab, based on this tutorial [10]. The maximum frequency that can be observed in a FFT spectrum is half the sample frequency, also called Nyquist frequency. In this case the maximum observable frequency is 60Hz. The left peak in the frequency spectrum belongs to the  $\alpha$  frequency band (9-13Hz), which means that the subject was in a relaxed and calm state. The data set that has been used was recorded in America, as can be seen at the 60Hz peak in figure 2.4.



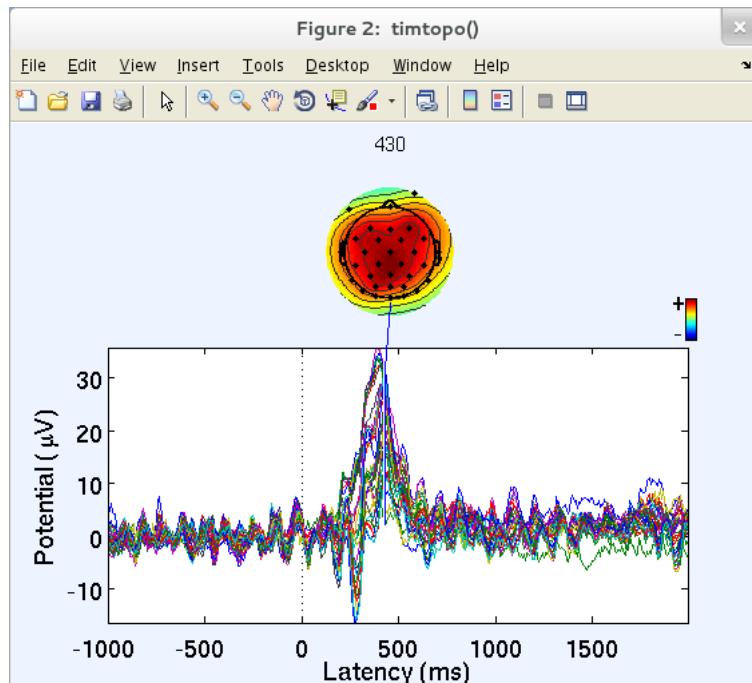
**Figure 2.4:** Power line peak of 60Hz.

The power line noise can be removed by using for example a linear finite impulse filter (FIR) setting the cut off frequency of the higher edge before 60Hz, in this case we set it to 50Hz.

The reference electrode used in EEG experiments is typically called the common reference if all channels use the same reference. Conventionally used references are one mastoid (TP10 in the 10-20 System), (digitally) linked mastoids, the vertex electrode (Cz), single or linked earlobes, or the nose tip. Some researchers use average references when the electrode montage covers nearly the whole head. The benefit of this is that sum of the electric field values on all electrodes is 0 as the outward positive and negative currents, added across an entire sphere, will sum to 0 due to Ohm's law. However, this technique requires the distribution of the electrodes to be even over the head which is rarely the case as researchers typically place electrodes only over certain scalp areas and seldom (if at all) on the lower half of the head surface. Therefore, experiments using average reference electrodes with one montage might not be necessarily comparable to experiments with other montages using average common electrodes.

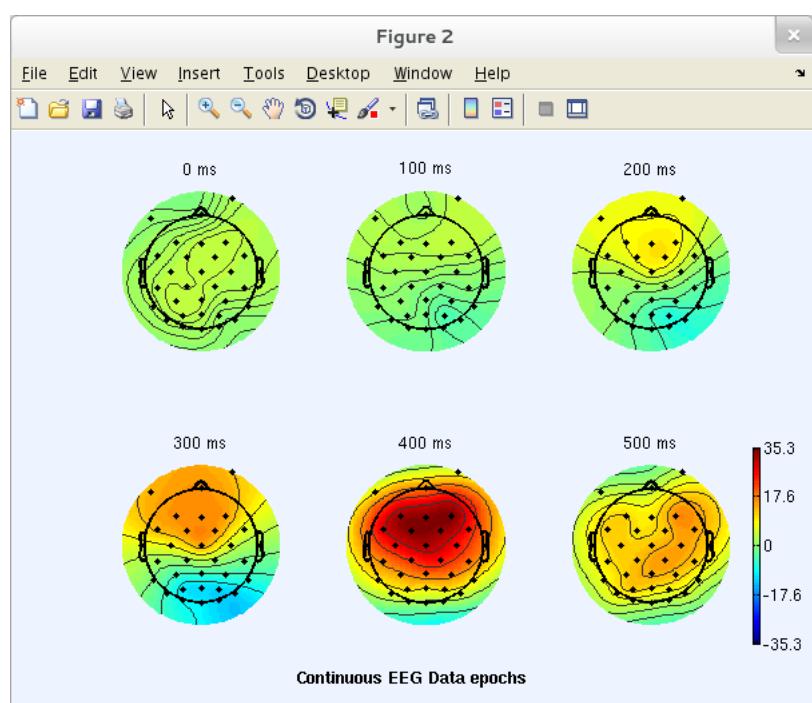
Baselining is comparing a data set to a historical metric, a baseline [11]. In this case an EEG signal is measured over a period of time and be used as a comparative baseline to monitor the performance and possible trends of the EEG signal. Removing the baseline before detecting event-related potentials (ERPs) will remove low frequency drifts or artifacts, if present.

Plotting the ERP data for all channels shows that the topographic distribution of the average potential is at 430 ms, as shown in figure 2.5.



**Figure 2.5:** Topographic distribution of average potential at 430 ms.

Plotting the ERP data for selected series of trial latencies shows that the highest activation at 0ms occurs at central and at 400ms at the frontal region of the brain, as depicted in figure 2.6.



**Figure 2.6:** ERP scalp maps at selected latencies.

# 3 | Week 3

In the third week we learned about basics of EEGs, physiological markers for controlling active and reactive BCIs, the electrophysiological brain, challenges in affective computing and ...

## 3.1 EEG Basics

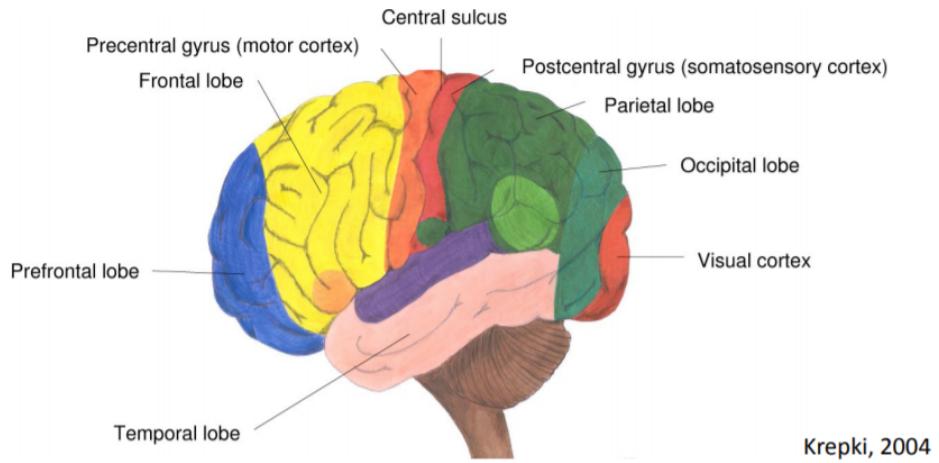
### 3.1.1 Underlying brain processes

BCIs need to operate on observable effects of the brain. Except for fMRI and fNIRs they function based on the effects of neural firing processes. Non-invasive BCI techniques such as EEG, MEG and ECoG are able to detect only large scale neural dynamics, for example 50000 neurons firing in at the same time. Large scale brain processes occur when an external event generates cascades of related neural process (e.g. perception), when an internal event triggers many related neural process (e.g. sudden "aha"!) or when neural populations enter a synchronized steady state firing pattern (e.g. idle oscillations). The root cause of the neural dynamics might not be directly observable but the change in electrical activity. For example, the cause for sudden realizations like the "aha" moment will not be visible in the electrical domain as they are modulated by chemical processes in deep structures of the brain. Widely scattered neural populations are unlikely to synchronize unless they are connected via fiber tracts. In contrast, spatially compact populations are more likely to have synchronized timing due to smaller propagation times. However, even large scale firing of very closely aligned fields of neurons might not be observable as electromagnetic fields can cancel each other out as for example in the Amygdala.

The two major BCI detectable EEG/MEG phenomena are event related potentials (ERPs) and oscillatory processes are. Furthermore, the primary contributors to the EEG measurements are the pyramidal cells which are orthogonal oriented in the cortex where the electromagnetic fields of co-aligned and co-activated neurons add up.

### 3.1.2 Spatial characteristics

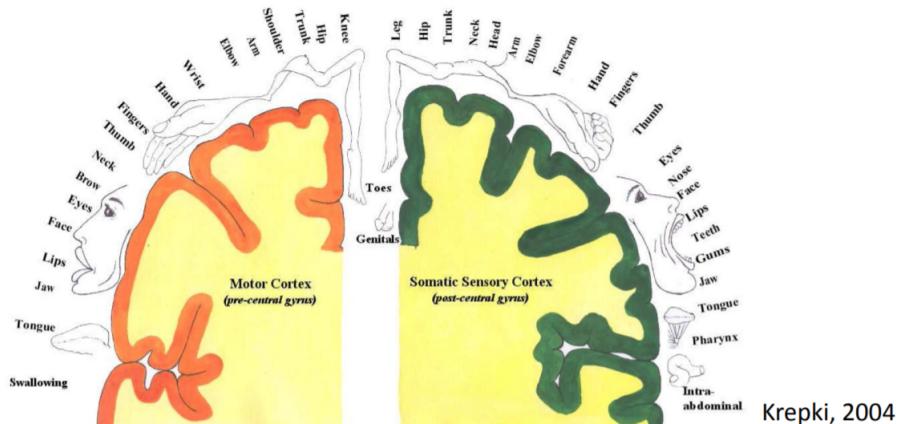
Many brain features can be associated to specific regions in the brain such as the hemispheres, lobes and gyri as depicted in figure 3.1. For example, motor processes such as moving your limbs will be triggered from the precentral gyrus while visual processes will be handled in the visual cortex.



Krepki, 2004

**Figure 3.1:** Anatomical regions of the brain

More detailed maps of the brain anatomy include for example the motor cortex, called the homunculus, as depicted in figure 3.2. It can be easily seen which motorary part of the body is controlled by which part of the homunculus.

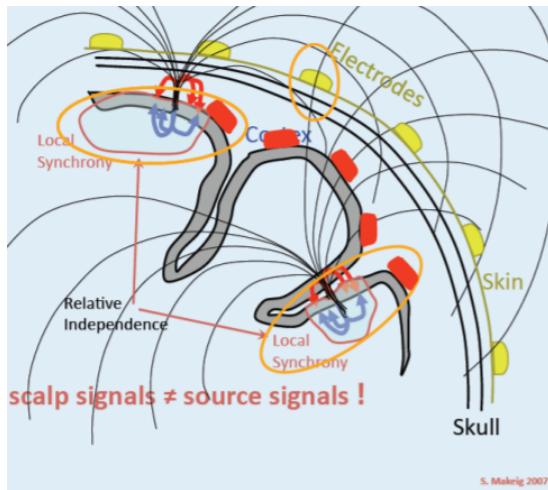


**Figure 3.2:** Caption

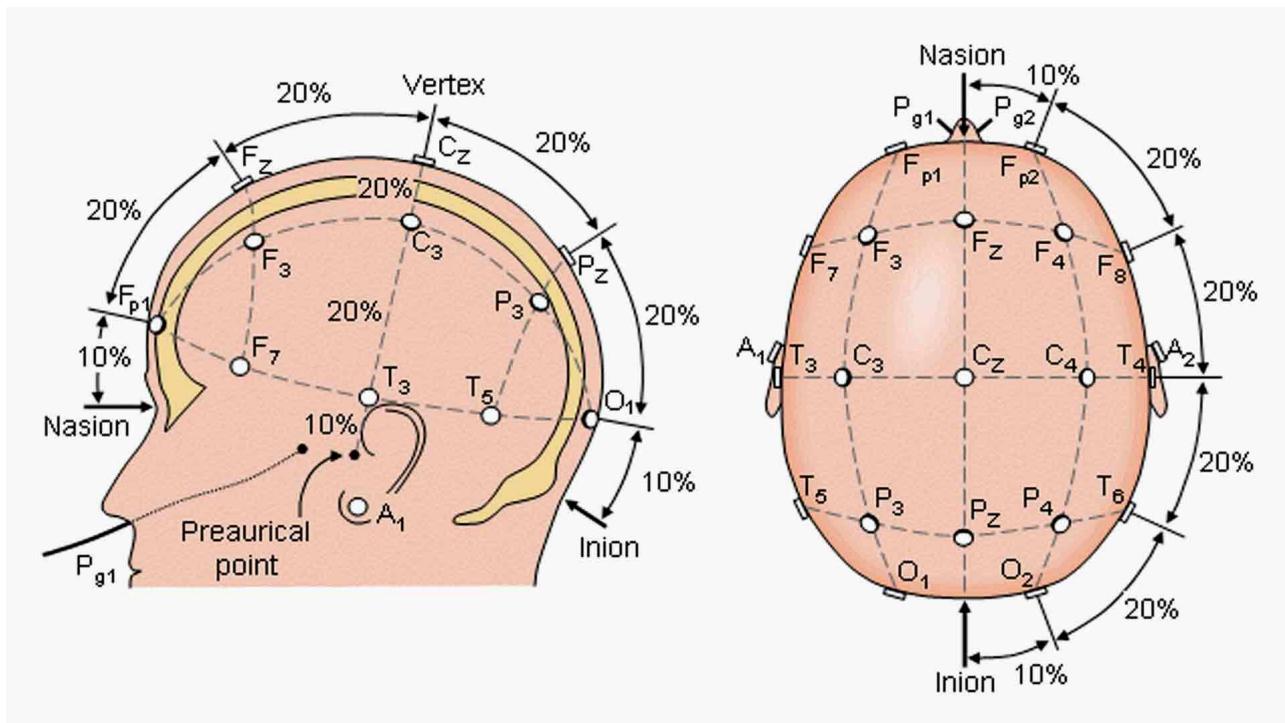
So far it has been discussed where changes in the cortex occur but not how signals get from there to the sensors of the body. Neural activity is conducted (linearly) through the brain volume to the scalp and sensors by volume conduction. Each sensor measures a weighted sum of each neuron's activity. Important to note is that neurons not necessarily relate to the closest sensors to them but to the ones they are oriented towards. This means that scalp signals are not necessarily source signals.

A standardized system that is widely used for brain measurement systems is the 10-20 system, as shown in figure 3.4. It is important to place the system correctly on the head for experiments that last over multiple sessions to get sufficient consistency between results.

Often scalp maps are used to plot the observed voltages to the corresponding locations of the brain by creating a model, called the dipole. Dipole modelling has various problems. High quality fits are hard to obtain because it requires precise knowledge of the sensor locations



**Figure 3.3:** Volume conduction in the brain.



**Figure 3.4:** Standardized 10-20 system.

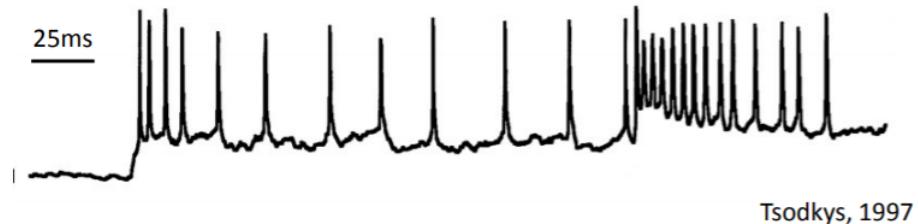
and also requires assumptions about conductivity of scalp, skull, cerebrospinal fluid (CSF) and brain tissue. In addition, knowledge of the folding of the cortex (candidate dipoles) is required unless simplistic spherical model is used. In addition scalp maps are usually not perfect due to data processing issues.

Other ways to fit a model for the brain include for example distributed source modelling that uses instead of a dipole a constellation of patches on the cortex, which allows to recover and image distributed cortical support of given scalp maps. There is a wide range of methodologies and underlying assumptions to this model (sLORETA, Beamforming, Sparse

Bayesian Learning,...) and it is prone to finding only locally optimal solutions.

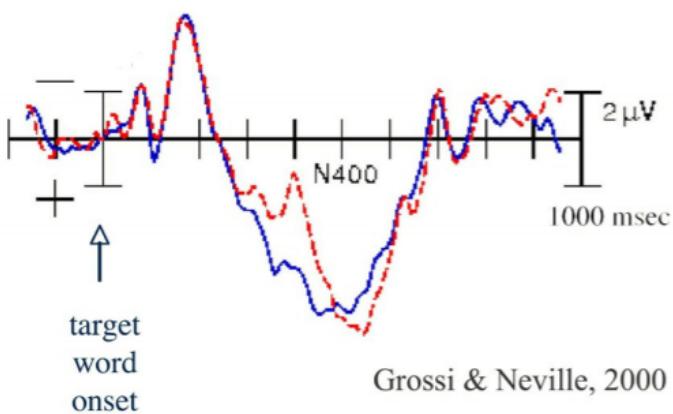
### 3.1.3 Temporal characteristics

Temporal characteristics of neurons include the so called spike train, time sequences of action potentials generated by the neuron a scan be seen in figure 3.5.



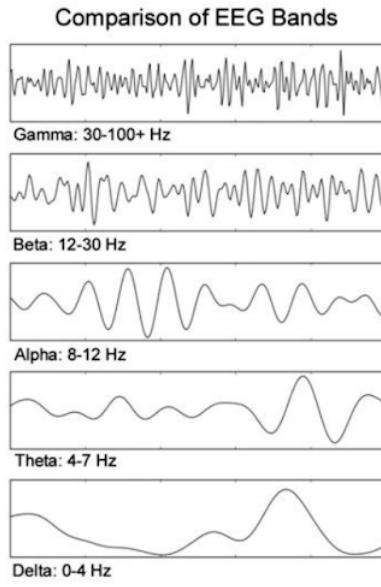
**Figure 3.5:** Spike train of a neuron.

Averaging these action potentials over many trials relative to an event results in primarily event-induced activity where the trial to trial variability as well as sensor and externally induced noise is averaged out, as shown in figure 3.6.



**Figure 3.6:** Averaged ERP.

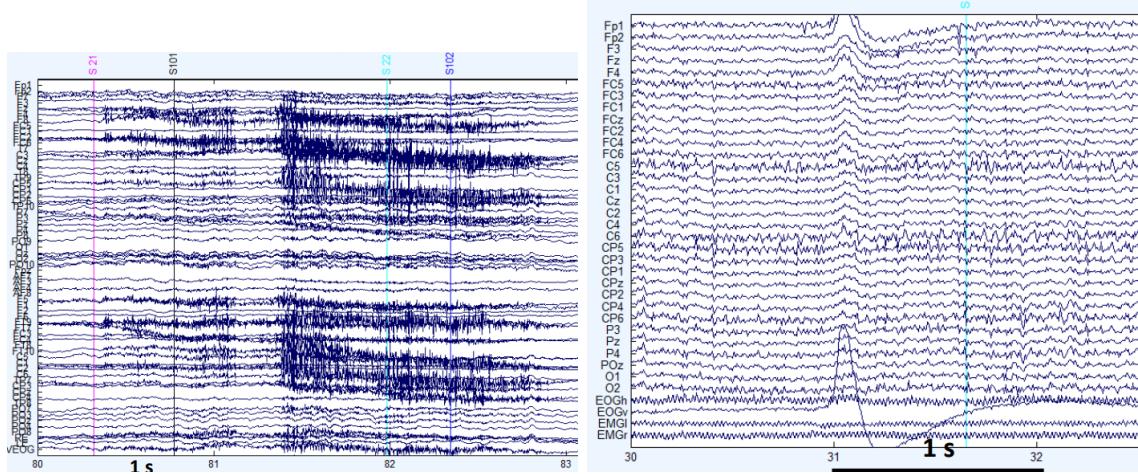
Oscillatory processes of the brain include the alpha, beta, gamma and theta bands, as depicted in figure 3.7. The delta band (1-3Hz) is related to deep and dreamless sleep, whereas the theta band (4-8Hz) is associated with deep relaxation and meditation, furthermore, the alpha (9-13Hz) is linked to relaxed and calm states and the beta band (14-30Hz) is related to awake and conscious states, finally, the gamma band is related (35-45Hz) is associated with learning and high alertness.



**Figure 3.7:** Oscillation bands.

### 3.1.4 Non-Brain Artifacts

Often non brain artifacts out scale the brain processes in magnitude by far. They can be internally generated by e.g. neck, eye, face muscles; eye dipoles and heart activity. Muscle artifacts for example tend to have very high frequencies and low amplitudes and are visible over all channels, as depicted in figure 3.8 on the left side. In contrast, eye blinks show large low frequency peaks with rebounds, and more dominant in the frontal electrodes, as shown in figure 3.8 on the right side.



**Figure 3.8:** Muscle (left) and eye (right) artifacts in EEG measurements.

Furthermore, non brain artifacts can also be caused externally by 50/60Hz power line noise, EM spikes from equipment and other sensors noise such as DC offset drift, cable sway, thermal noise or quantization noise.

### 3.1.5 Sensing and Acquisition

There are various types of EEG sensing methods used. Most EEGs are gel based and use active electrodes to amplify the signals instead of passive electrodes. There are also dry electrodes that have pins or bristles in order get through the hair and make contact with the skin; this are generally easier to set up than gel based EEGs.



**Figure 3.9:** Gel (left) and dry (right) EEG electrodes.

To digitize the signals, they first amplified and then low pass filtered using analog filters to prevent aliasing, afterwards it is digitally sampled at a fixed rate and is then band limited according to the Nyquist frequency.

## 3.2 Physiological Markers for Controlling Active and Reactive BCIs

This section will discuss the main physiological markers that being employed to control an active or reactive BCIs based on [12]. Despite the advancements in the recent years in the field of brain computer interfacing, it is still rather difficult to identify significant correlations between mental tasks and the physiological measurements of brain activities. It is impossible to record brain activity without the interference from other non-correlated brain signals, in addition, specific mental tasks generate non-stationary signals. Therefore, it is imperative to carefully select the mental tasks that the subject performs, as well as the methods being used to record brain activity.

Active BCIs derive their outputs directly from the brain activity which is consciously controlled by the user (e.g. imagining to move your limbs), independent of external events. Reactive BCIs derive their outputs from brain activity arising in reaction to external stimuli, which is indirectly modulated by the user. The choice between these two approaches and thus also the mental tasks, is mainly determined by the BCI application itself. For example, to enhance the communication of the user, both methods will work. However, for more specific tasks as for example the control of a prosthesis with several degrees of freedom, a reactive approach would not be suited.

Next to defining a specific mental task in order to create a marker of identifiable brain activity, it is also necessary to correlate the firing of large scale neuron assemblies with a specific event occurring in a given part of the brain and/or of time, when the subject is

carrying out a specific mental task. In addition, the brain activity needs to be converted into a measurable signal with sufficient spatial and temporal resolution. Good spatial resolution will allow to precisely locate the brain region in which the activity arises while good temporal resolution will allow to correlate variations of the brain activity with the subjects mental state.

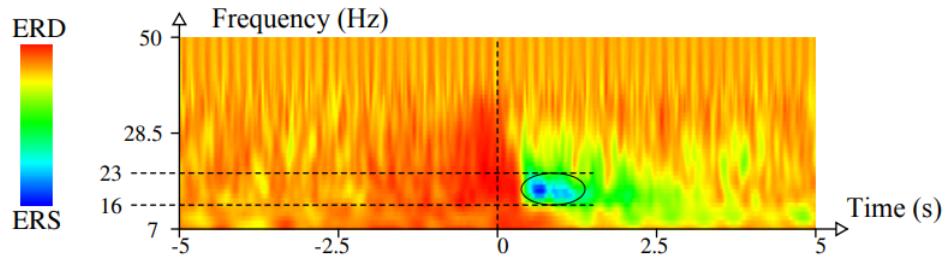
### 3.2.1 Markers for active BCI control

Markers for active BCI control include slow variations in average cortical potential and bereitschaftspotential (BP) or readiness potential, and synchronizations and desynchronizations related to the event (event-related synchronization (ERS), event-related desynchronization (ERD)). A slow evolution of average cortical potential (slow cortical potential [SCP]) corresponds to the dendrites' level of depolarization in the upper cortex and can be either positive or negative. Negative SCPs are caused by "very slow synchronized excitatory postsynaptic potentials emitted by the apical dendrites from the pyramidal neurons", while positive SCPs are caused by a "decrease in those same potentials, an inhibitive activity in the interneurons, or an excitatory influx coming from the cell bodies in layers IV and V" [12]. SCPs are useful markers for active BCI control because they are easy to detect by comparing average electrical potential at a given time to the baseline potential, in addition they caused naturally by changes in amplitude levels of cortical networks related to the preparation of a cognitive or motor tasks. Furthermore, a user is can learn to consciously modulate these variations in order to increase their signal strength by operant conditioning methods.

BP or readiness potential occurs in two successive phases through a reduction of cortical potential, which is first slow and then fast. It manifests itself between 1 second and 1.5 seconds before the execution of the conscious movement of the person itself, the (predicted) movements of other persons, and lastly, the imagining of performing a movement. The latter makes BP usable in active BCI systems and has been used in various applications involving the prediction of executing a movement, the direction of the movement and the limb that is concerned within that movement.

The most frequently used markers for active BCI applications concerning endogenous events are ERSs and ERDs, where the endogenous event starts with the subject executing a specific mental task. For an ERS, variations in activity can be observed in a temporal increase of the amplitude for specific frequency ranges, whereas for an ERD the opposite can be observed, the amplitude decreases. Tasks involving memory, an ERS in the gamma range ( $f > 25$  Hz) in the prefrontal dorsolateral cortex can be observed whereas for motor imaging tasks, ERDs/ERSs can be observed by the desynchronization of alpha (8 - 12 Hz) and beta (13 - 30 Hz) rhythms, followed by a resynchronization of the beta rhythm, as shown in figure 3.10. Other commonly used mental tasks include rotating objects, associating words, auditory imagination, mental navigation of a known space and imagining faces of known people.

Research has shown that short duration movement imagination generates directly desynchronizations in beta and alpha rhythms at the start of the task whereas when the subject imagines movements for a longer period of time, ERDs are less observable at the beginning of the task. For the latter, it is easier to capture the motor imaging task by the resynchronization



**Figure 3.10:** Spectrogram of desynchronization and synchronization of a motor imagery task.

of alpha and beta rhythms at the end of the task.

### 3.2.2 Markers for reactive BCI control

Markers for reactive BCI control entail repetitive stimuli whose spatial and/or temporal characteristics encode two or more options which the user must select from. The mental task lies here in the focusing, or not focusing, where the attention of the user is associated with the option he or she wants to select in the interface. The perception of the stimuli produces an exogenous potential, other potentials like P300 can also be generated if the perception generates a specific cognitive reaction in the subject. The most frequently used markers for reactive BCI applications concerning exogenous potentials are stationary sensory evoked potentials (SEPs), which are generated by a visual, auditory or tactile stimuli and are locked in phase with the stimuli; and P300, a cognitive evoked potential.

SEPs are easily extracted by repeating stimulations and averaging EEG recordings, but also allow with a single reading for good a priori knowledge of characteristic variations. One widely used form of SEPs are steady-state visually evoked potentials (SSVEPs), which can be generated by visual, repetitive stimuli with frequencies between 3 and 40Hz and are characterized by their amplitude and phase. SSVEPs are often used for reactive BCI applications because they are easy to extract with basic processing of EEG signals, their characteristics are relatively independent of the user and are generally less affected by muscular artifacts.

If a subject receives an unexpected sensory stimulus, the usual SEP is followed by one or several other, very specific evoked potentials that have greater latencies. If the user is attentive to the stimulus and generates a cognitive reaction in the user, a P3 or P3a potential occurs, which has a latency between 250 and 280 ms. The potential is located in the frontocentral region of the brain and the amplitude is correlated with the strength of the surprise effect caused by the unknown stimulus. A P3b is produced as response to an unexpected sensory stimulus, where the type of stimulus is already known by the user. P3b responses typically have a latency of between 250 and 500 ms and the spatial distribution is more posterior than the one of a P3a. A P300 is a P3b endogenous evoked potential and is used to determine the specific stimulus on which the subject focuses his attention. P300 are most commonly used in reactive BCIs as it requires very low training time, often possible to detect it in a single test and facilitate high-speed stimuli due to the high frequency of stimuli

to obtain adequate communication lags.

### 3.3 The Electrophysiological Brain

This section treats the electrophysiological brain and how single cell recordings and ERPs have been used to study it [13]. Cognitive and neural systems create representation of the world that include not only physical properties like sound and colour but also rather abstracts forms of knowledge such as beliefs or factual knowledge. It is important to distinguish between the mental representation and the neural representation as the outside world is not directly copied into your head but rather based on response properties of neurons and brain regions that correlate with real world features.

#### 3.3.1 Single Cell Recordings

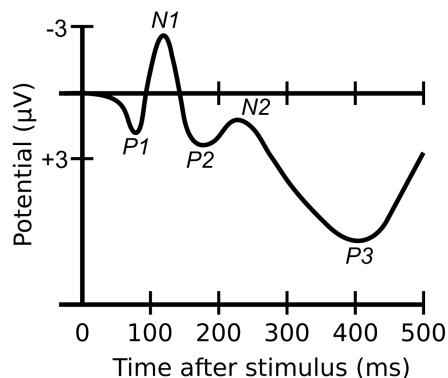
Single cell recordings measure the action potential directly by implanting an electrode either into the axon or outside the membrane and counting the number of spikes that are being generated in response to a stimulus. It is also possible to record 100 neurons simultaneously with multi electrode arrays, which is called multi cell recordings. These kind of recordings are due to their invasive nature typically used only on animals but have also been applied to humans that underwent brain surgery. It is not possible to execute single cell recordings with non invasive methods as the signal would be too weak and the noise from adjacent cells to high.

There are three different types of representations of neural levels that one can distinguish between: 1) Local representation, where all information about a stimulus or an event is contained in one neuron; 2) Full distributed representation, where all information about a stimulus or an event is contained in all neurons of a population; 3) Sparse distributed population where all information about a stimulus or an event is contained in a small group of neurons. Single/multi cell recordings may depend on sparse distributed groups of neurons in order to correlate a stimulus to a region in the brain. It is theorized that the sparseness of coding may allow the brain to have not only a high memory capacity but also be able to conserve energy. In addition, sparse distributed coding may protect the brain against memory loss if single neurons are lost.

Rate coding is the association between increased firing of neurons relating to external stimulus or event such as measuring responses to different gaze directions. Temporal coding is an alternative approach that relates greater synchronization of firing neuron groups to a given stimulus. For example, if two regions of the retinal image would be exposed with a single bar of light, both regions would fire in a synchronized manner, however if they would be exposed to two different bars, both regions would show an increased rate of firing, but not synchronized. Temporal coding could be used for combining information across spatially separated groups of neurons.

### 3.3.2 Event Related Potentials

Event related potentials (ERPs) are elicited by given stimuli and mental tasks and can be observed via EEG measurements which reflects neural activity from all regions of the brain. Some parts of the brain will relate to the particular task or stimulus, but most of the measurement will relate to spontaneous activity of the brain that is not correlated to the task or stimuli and will therefore create a very low signal-to-noise ratio in a single trial measurement which requires to run multiple trials (e.g. 50-100) and average the results to eliminate the noise. The results are then visually represented by plotting the time (milliseconds) on the x axis and the electrode potential (microvolts) on the y axis, as shown in figure 3.11. The positive and negative peaks are labelled "P" and "N" respectively, where P1 would stand for the first peak and P2 for the second, and so on. In addition, they can also be labelled based on the latency of the peak, e.g. P300 and N400 would refer to a positive peak at 300 ms and a negative peak at 400 ms, respectively. The polarity of the peaks is not significant cognitively or neurophysiologically, but the timing and amplitude of the signal is.



**Figure 3.11:** Waveform showing several ERP components.

Some practical issues concerning EEG research include that vocal responses cannot be recorded due to the movement of jaw muscles that will affect the EEG signal. In addition, movement from the eyes and eyelids will also disrupt the EEG signal, it is therefore necessary to either instruct the participant to not blink or blink at only specified times (which creates a secondary task to the participant and might effect the main task of interest); or filter out the effects of the eye on the EEG signals. In general, the subject should avoid to move his head and relating muscles as much as possible in order to obtain relevant measurements.

### 3.3.3 Mental Chronometry in Electrophysiology and Cognitive Psychology

Mental Chronometry is defined as "the study of the time course of information processing in the human nervous system" and states that changes in the nature or efficiency of information processing will be visible in the time it takes to complete a task. For example, it has been found that it takes humans longer to calculate  $4 + 3 = 7$  or  $4 + 4 = 8$  as in comparison to  $4 + 2 = 6$ . It suggests that mathematical tasks involve a stage in processing that relates numerical size with the assumption that larger sums place more limits on the efficiency of information

processing”, which can be visible in a slower verification time. Tasks like verification of sums are likely to involve multiple stages such visual recognition of the numbers, calculating the sum and generating a response, where the reaction time is the result of these stages.

The additive factor method is a general approach for dividing reaction times into different stages. It is theorized that stages can be influenced independently by different factors of a given task. If different factors have an effect on different stages of the processing, then the processing time of these stages will have an additive effect as in comparison to when they effect the same processing stage in which they will show an interactive effect. Thus, it can be determined whether an unknown factor (e.g. sleep deprivation) has an interactive effect on one stage or on multiple stages. However, it is important to note that the model is strictly sequential, which is not necessarily valid in all cases. How can we relate mental chronometry to the analysis and interpretation of ERP data? ERP signals consist out of various peaks that vary in time and are likely to correlate to the different cognitive stages of information processing. It is possible to compare the amplitude of the peaks in comparison to the element in the array of the processing, such as perceptual encoding. It could be also investigated whether a new variable will have an effect earlier or later peaks. However, it is not always possible to correlate ERP components and cognitive stages of a given task. It is possible for example that a single cognitive component correlates to several neuron populations or that various cognitive components appear at the same time and sum together or cancel each other out.

ERP components can be either exogenous or endogenous. Exogenous components are related to a presented stimulus while endogenous components are related to a give task that is executed by the subject and tend to occur later exogenous components. However, it should be noted that exogenous-endogenous classification should rather serve as a dimension than a categorical distinction.

The spatial resolution of ERP is relatively low due to the inverse problem which states that ”the electrical potential at the scalp is known but the number, location and magnitude of the electrical sources in the brain are unknown”. A typical way of solving these unknowns is called dipole modelling which requires the assumption of which regions in the brain are relevant for the observed pattern. For example, the response towards visual stimuli is mostly found in the back of the head.

### 3.3.4 Magnetoencephalography

A non invasive alternative to EEG is the magnetoencephalography (MEG) which is a device that measures the magnetic field in the brain as depicted in figure 3.12. As the size of this field relatively small in comparison to the ambient magnetic field of earth, it requires isolation via a completely, magnetically shielded room. In addition, it requires extreme cooling in order to function and is generally, significantly more expensive than an EEG and more limited in its availability. The reason for the usage of MEGs is that it allows for greater spatial resolution (2-3mm) as in comparison to the EEG. In addition, the signal is unaffected by the skull and meninges and is more sensitive to activity at the sulci. Lastly it is also important to know

that it is poorer at detecting deep dipoles as in comparison to the EEG.



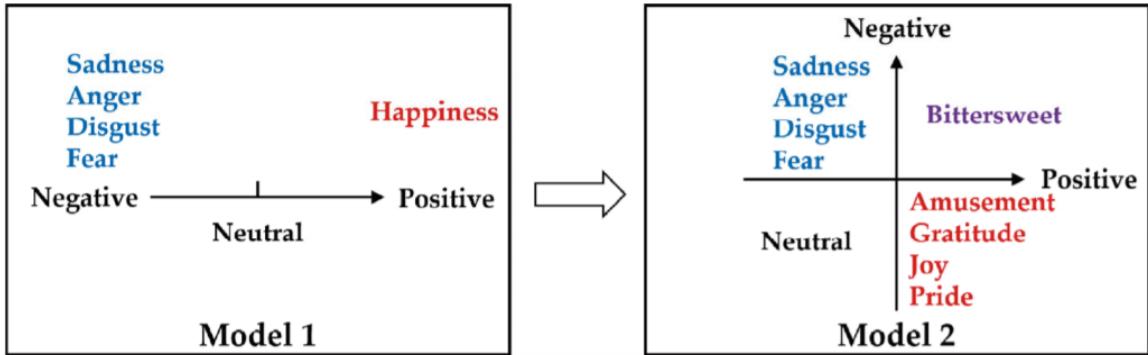
**Figure 3.12:** Magnetoencephalography (MEG).

## 3.4 Challenges in EEG based affective computing

Affective computing is a research field that is aimed at improving the understanding and responding of computers regarding the emotional state of humans in HCI applications by analyzing the behavioral and/or physiological response of a subject. EEGs are being used increasingly in affective computing due to the balance between mechanistic exploration and real-world practical application. The paper of Hu and et al. [14] reviews 10 challenges regarding affective computing in the light of information technology, psychology, and neuroscience.

### 3.4.1 Adoption of a proper theoretical framework of emotion

The first challenge is the adoption of a proper theoretical framework of emotion, which is a challenge for all affective computing studies. Two commonly used meta-theoretical frameworks for interpreting emotions are the categorical perspective and the dimensional perspective. The categorical perspective states that "emotions are categorically discrete, and complex emotions are the combinations of multiple basic emotions". As an example, contempt is based out of the basic emotions anger and disgust. In total there are at least 6 basic emotions according to the categorical perspective: anger, disgust, fear, sadness, surprise, and happiness. In contrast, the dimensional perspective states that emotions are governed by basic emotions and "every emotion can be mapped into a specific position in the multi-dimensional emotion space". The most used dimensional model for affective computing is



**Figure 3.13:** "Existing affective computing researches often took positive and negative emotions as polar opposites, and understated the diversity of positive emotions (Model 1), but recent advances have suggested the measurement of positive and negative emotions as bivariate, and the emphasis on the diversity of positive emotions (Model 2)", [14].

the Valence-Arousal model which assumes that valence (ranging from negative to positive) and arousal (ranging from calm to excited) are the two most important dimensions regarding human emotions. However, which one of these two primary frameworks should be used is still an ongoing debate. Recent studies have made some additions to these frameworks, especially regarding positive emotions. The field of positive psychology states that the difference within positive emotions is underrated in common emotional theories. For example, the categorical framework contains only positive emotion (happiness) while Fredrickson [15] proposes a new model that includes ten positive emotions (joy, gratitude, serenity, interest, hope, pride, amusement, inspiration, awe, and love) which seems to find support by other affective computing studies [16]–[18]. Hu and et al. argue that a better incorporation of positive emotions would be beneficial for HCI as it is aimed at creating positive experiences. Furthermore, it has been proposed that there are distinct functional roles of positive and negative emotions. While negative emotions relate to fight-or-flight responses, positive emotions are more related with broadening and building social resources. Thus, Hu and et al. suggest that it "might be oversimplified to have a single valence dimension to place negative and positive emotions at its two ends". In addition, they state that people can experience mixed emotions for example feeling happy and sad at the same time at a graduation ceremony. Hu and et al support the theory of having "positive and negative emotions as two separate unipolar dimensions, rather than taking them as the polar opposites" (see figure 3.13) and emphasize the need for a framework that includes recent findings from psychology and affective neuroscience.

### 3.4.2 Understanding the EEG representation of affective states

The second challenge is the understanding the EEG representation of affective states. In EEG-based affective computing it is assumed that emotions can be recorded with sufficient accuracy and sensitivity of the EEG signals. However, this assumption does not necessarily hold in all cases as the the relation between physiological signals and psychological states can

be rather complex. The paper cites that there are 4 kinds of relationships between physiological signals and psychological states: "(1) one-to-one (one psychological element is associated with one and only one physiological signal), (2) one-to-many (one psychological element is associated with several physiological signals), (3) many-to-one (several psychological elements are associated with the same physiological signal), and (4) many-to-many (several psychological elements are associated with several physiological signals)". A one to one relationship would be the most ideal kind for affective computing applications but this type of relation is hard to validate and has been rarely reported in existing studies. However, studies do tend to interpret results often in the fashion of one to one relationships. The paper gives the example of a study that related asymmetric frontal EEG activities to emotional valence, but later it has been found out that frontal EEG asymmetry "varied with motivational direction rather than emotional valence". In addition, existing studies rarely provide info on reliability of their experiments and it is often ambiguous "(1), whether they can be replicated consistently over time; (2), whether they can be applied to different populations; and (3), how far they can be generalized in varied situations".

The authors request that future studies should be more cautious of the validity of one to one relationships and the interpretation thereof as well as that future studies should present more evidence of reliability.

### **3.4.3 Bridging the gap between passive and active emotion elicitation methods**

In affective computing there are two categories of emotion elicitation techniques, passive (perception-based) elicitation, and active (expression-based) elicitation.

Passive methods let participants perceive emotional stimuli such as images, music and videos that are designed to elicit specific affective states. The advantage of this approach is that "stimuli can be highly standardized, and people's affective states can be well manipulated". Research suggests that videos might be the most effective passive emotion elicitation method, but there are also concerns about the ecological validity of this method as videos "require the willing suspension of disbelief and people's previous viewing experience/familiarity to the materials would also greatly impact the effectiveness of video stimuli".

Active methods let participants perform tasks that are designed to induce various affective states such as recalling personal achievements to induce pride, public speaking in events to induce anxiety, or being provided with negative feedback to induce anger. The advantage of this technique is that it is more naturalistic and closer to the emotional states occurring in the real world. In addition, it is also more efficient to induce emotions would be difficult to induce with passive methods, such as anger and guilt. However, active methods are more difficult to precisely manipulate due to the variability of individuals' emotional responses. In addition, these tasks will cause more artifacts in the EEG data which will make the analysis of the studies more difficult.

The authors state that in real life, people's emotional changes are caused by both the emotional stimuli they passively observed and the emotional interactions they actively par-

ticipated in. These kinds of emotion-inducing events are often occurring at the same time and interacting with each other. The authors furthermore state that "existing affective computing studies rarely include both of these two types and that transferability between the affective computing systems based on different emotion elicitation methods is still very limited". Therefore, it is appealed that future studies should be more cautious of difference between these active and passive emotion elicitation methods in order to create more naturalistic affective computing applications that are compatible for both the passively and actively induced emotions.

In addition, there is a "trade-off between the ecological validity and experimental control of the emotion elicitation methods: well-controlled experimental paradigm would facilitate data collection and analysis but possibly limit its generalizability whereas a high ecologically valid paradigm would better resemble real-life settings but bring more challenges to data analysis". The authors stress therefore the need to find the balance between specific research purposes: if the application scenario is very limited, having better experimental control should be preferred; otherwise, ecological validity should be given priority and more resources are expected to build the model.

#### **3.4.4 Collecting emotion data in a convenient and reliable way**

The fourth challenge is the collection of emotion data in a convenient and reliable way. For many years, gel based electrode caps have been used as they provide high-quality data. However, these kind of electrodes require long preparation times and are also very expensive, which makes it difficult to transfer them to real world applications. In recent years, other alternatives such as dry or water-based electrodes have been emerging, as described in earlier sections of this portfolio. These alternatives are cheaper, provide higher portability and a significantly less preparation time and overall more convenient and applicable for real life situations. However, these alternative devices also have a number of disadvantages: First, they have only a limited number of channels, thus providing less data quality, in addition, artifacts will be more present in real life applications, hence the quality will be even more poor. Secondly, the lasting time is only limited to roughly 2 hours, as pressure is needed to maintain rigid contact between the electrodes, causing discomfort.

Therefore, BCIs that are robust and comfortable while providing high quality data, are still lacking and need further research. The authors suggest to directly compare consumer-level devices and research-level devices in the same classical experimental paradigms before applying consumer level devices in the real world.

#### **3.4.5 Extracting robust features for affective computing**

The fifth challenge is extracting robust features for affective computing with sufficient discriminative powers. Features are commonly decomposed in temporal (entropy, the fractal dimension and higher order crossings), spectral (frequency bands, power spectral density, differential entropy, differential asymmetry, rational asymmetry and differential caudality) and spatial domains (relation of temporal and spectral features to regions of the brain).

The authors state that as most affective computing application using BCIs include continuous and complex audiovisual stimulations, inter-subject correlation (ISC) may provide a new perspective for feature extraction. ISC "describes the neural responses by calculating the inter-subject correlations rather than searching for single-subject activations compared to a certain baseline". As in comparison to the typically used features above, ISC could "effectively capture the neural dynamics to external stimuli while avoiding the challenging issue of defining discrete events from the complex and continuous stimulations". Furthermore, the authors state that the aforementioned features, including ISC, need further validation regarding their robustness. Careful experimental design with necessary control conditions considering confounding factors is needed to investigate the complicated relationship between the physiological responses and the psychological elements as described earlier in order to be able to correlate EEG signals and affective states more precisely. The authors request that researchers "psychologists for an improved experimental design for a more accurate affective definition of the elicited EEG responses. A better definition is expected to increase the robustness of the to-be-extracted features".

### **3.4.6 Decoding affective state accurately and continuously**

Once, proper features have been selected, machine learning classifiers to detect affective states need to build. Typically used algorithms include linear discriminant analysis, support vector machines, k-nearest neighbors, Naive Bayes classifiers but also neural network algorithms such as autoencoder, deep belief networks, deep recursive neural networks, and convolutional neural networks.

The authors state there is still gap between state-of-the-art research and real-world applications. Most algorithms were tested by assuming stationary affective states during a relatively long period time which may not always hold as emotions can easily change in the time span of one second. It is therefore "preferred to have affective labels that could accurately reflect the continuous, dynamic affective experience as the golden standard for training the algorithms". However, "obtaining such dynamic labels by subjective reports could be labor-intensive and time consuming and automatic tagging using internet-based crowdsourcing methods or information from other modalities (e.g. video content analysis, face expressions and peripheral physiological responses during video watching) could provide feasible alternative options". Furthermore, the lack of standardized large-scale data sets makes the performance evaluation across different algorithms difficult as the theoretical frameworks and the corresponding affective stimuli vary significantly between existing studies.

The authors stress the need for large-scale data set as benchmark for algorithms and appeal to their fellow researchers to collect it in a collaborative way with standardized stimuli and procedures shared across multiple research groups. In addition, they propose an alternative of collecting data from other modalities if possible during datasets acquisition. "Due to the richness of human emotional expressiveness, the fusion of information from other modalities (e.g., facial expression, peripheral physiological responses and eye movement) may

lead to better recognition performance, and the analysis of the relationship among modalities could perhaps shed light on the nature of emotions as well”.

### **3.4.7 Moving from offline to online affective computing**

Real world applications in affective computing using will require real time BCI systems. Until now, most studies have been conducted offline, while the performance of their online extensions remains to be investigated.

Transferring from offline to online applications is a critical and challenging step, as it imposes time constraints on the computation speed. While ”time-consuming and complex methods can be employed to achieve high classification accuracy in offline systems, the online affective computing pipeline, including pre-processing, feature extraction and classification, has to be carefully optimized toward the real-time need”. It is preferred to use simpler mathematical methods that reduce the computational cost while maintaining adequate accuracy. The authors therefore suggest to ”consider the computation time as a primary outcome besides the accuracy and report computation time”.

Furthermore, in order to maintain a continuous output of affective computing results, it is preferred to eliminate artifacts rather than to reject artifact-contaminated EEG segments which can be done via blind source separation techniques such as ICA or empirical mode decomposition. However, many of these algorithms are more suitable to be performed in a post-hoc manner as they requires large capacities of data. In addition, ”identification of the artifact like sources would require expert experience and it is still difficult to derive automatic yet powerful criterions.”

Another challenge in real time applications is the non-stationary nature of EEG signals, statistical differences of EEG measurements during offline and online may significantly lessen online classification performance of models trained with offline data, especially if the real time system is supposed to work for longer time periods. This problem could be solved by ”controlling the time information (e.g., used as covariate) during classifier model training to explore time-stable emotion-related EEG features. Alternatively instead of using a fixed classifier over a long time period, adaptive strategies could be employed to dynamically update the classifier parameters based on the statistical properties of incoming EEG data”.

### **3.4.8 Tackling individual difference to achieve model generalizability**

Emotional responses can highly vary between individuals. Most EEG based affective computing studies have been carried out in a subject-wise manner training individual-based computational models which is highly time-consuming and resource-demanding and also limits the scalability of such applications for real world scenarios. A model that can be applied to the general population would significantly advance the progress of affective BCI applications. To date, researchers have tried to identify robust EEG features across subjects and found that ”differential entropy, maximum power spectral frequency and Shannon entropy of gamma band shared similar patterns across subjects for EEG”; in addition, domain adaptation which maps features to subspaces to track invariant patterns between different subjects

also shows promising results.

The authors argue that due to the high individual differences in emotional experiences, similar patterns between subjects may not be enough to support an affective computing model towards real world applications as shown by the significant deterioration in performance when compared to their corresponding individual based models. Instead, a transfer learning approach is proposed to address the individual differences across subjects that adapts "a model for a new individual to the data or information from other subjects selectively so that the individual difference can be alleviated". Studies suggest that if a sufficiently large data set would be available, comparable performance to subject-dependent models could be achieved, again stressing the need for a standardized large scale data set.

However, the Hu et al. still suggest that "researchers should be aware that it is necessary to selectively use data in the dataset since the inter-subject variability might deteriorate the performance of models transferring." Moreover, they also propose to take the subject's dispositional traits into consideration as these can considerably influence peoples' perception of affective stimuli. Considering the dispositional-trait-based individual differences in the building of the classifiers may provide complementary information beyond the before mention feature based approaches towards a generalized affective computing answer.

### 3.4.9 Finding more application scenarios

Hu et al. suggest that researchers should be cautious of the terminologies being used for the concept of emotion as they might differ in different fields, when looking for new possible applications of BCIs in affective computing. One might use the words "mood", "affect" or "emotion" or other terms to describe similar psychological phenomena, with subtle differences in the definitions and experimental manipulations. Hu et al. stress the need to find a common ground between these differences as it would be valuable for launching new application scenarios in more fields as well as for "staying sensitive to the subtle differences and providing more targeted solutions for the differentiated needs could better integrated the affective computing into these new application scenarios". For example, the term "mood" is often more considered to be longerlasting and less intense than "emotion". The deliberate use of the term "mood" could "imply a special interest in the affective states over longer time scale, which might not be consistent with the current mainstream emotion recognition models, and requires more tailored experimental designs".

Furthermore, the authors state that researchers should take the hardware limiations of EEGs in consideration when designing for real world applications, such as low signal-to-noise ratio, poor signal stability, and short power supply time. In addition, to date the most applicable EEG-based affective computing systems are designed for closed environment where people do not execute sudden movements e.g., computer games, driver monitoring, and distant education.

### **3.4.10 Taking ethical issues into consideration**

Affective computing, aiming at decoding people's emotional states, has attracted a growing concern regarding ethical concerns in the recent years. Criteria to evaluate the implications of brain-reading techniques in general in terms of mental privacy have been proposed, including accuracy, reliability, informativity, concealability, and enforceability where concealability and enforceability are especially highlighted because of the potential threats to mental privacy and civil rights. At this point there are no universally recognized ethical rules for affective computing practice, the authors suggest that "ethical guideline or criterions from AI and BCI field could still be handy reference for affective computing researchers to evaluate their works". In addition, there is also a unique ethical challenge for affective computing as it is possible to not only recognizing but also influencing or even manipulating an individual's emotions and possibly influence choices by manipulating their emotions.

## **3.5 Introduction to Event-Related Potentials and Their Neural Origins**

This section describes the history of the ERP technique, basic concepts and examples, and finally some advantages and disadvantages of using ERP compared to other techniques.

### **3.5.1 Brief history of the ERP technique**

EEG proved to be very useful in clinical and scientific applications. However, raw EEG is a quite broad measure and its difficult to assess highly specific neural processes. Simple averaging techniques allow for extraction of neural responses associated with sensory, cognitive, and motor events from the EEG. These are called event-related potentials because they are electrical potentials associated with specific events.

The first cognitive ERP component was reported in 1964 by Grey Walter and his colleagues. Subjects were presented with a warning signal (click) followed by a target stimulus (series of flashes) 500 or 1000 ms later. In absence of a task both stimuli resulted in a sensory ERP response that was expected with these stimuli. If subjects were required to perform an action when detecting the target, for instance pressing a button, a large negative voltage was observed at frontal electrode sides during the period between the warning and target stimuli. This observed negative voltage was clearly not a sensory response, but was rather reflecting the subject's preparation for the upcoming target and task that had to be performed. This finding led to an increasing interest for researchers to explore cognitive ERP components.

The discovery of the P3 (or P300) component in 1965 by Sutton, Braren, Zubin, and John was the next major advancement. When subjects were unable to predict whether the next stimulus would be auditory or visual, a large positive P3 component was observed, which peaked around 300 ms post-stimulus but was much smaller than when the stimulus modality could be predicted perfectly. In the following 15 years a lot of research has been done on identifying cognitive ERP components and developing recording and analysis methods in cognitive experiments, of which most focused on discovering and understanding ERP

component rather than using them to address broad scientific questions. The author calls this ERPology, since it's simply the study of ERPs. ERPology is however of importance, since understanding specific ERP components is required in order to use them for a broader scientific context. Where researcher thought ERP research might die away when PET and fMRI techniques emerged, the opposite happened. Because of the high temporal resolution of ERPs, most cognitive scientist saw ERPs as an important complement to PET and fMRI.

Most cognitive neuroscience research uses the term ERP, but one could encounter other terms in for instance other fields. Since it might be useful to be able to recognize these, the alternative terms are listed here:

- Evoked response, which means the same as ERP.
- Brainstem evoked response (BER), also called auditory brainstem responses (ABRs) or brainstem auditory evoked responses (BAERs).  
Small ERPs elicited within the first 10 ms of stimulus onset by auditory stimuli such as clicks. This is frequently used in clinical audiology.
- Visual evoked potential (VEP) or visual evoked response (VER).  
Commonly used in clinical context to describe ERPs elicited by visual stimuli used to assess pathology in the visual system.
- Evoked response potential (ERP), which is an accidental miscombination of evoked response and event-related potential.

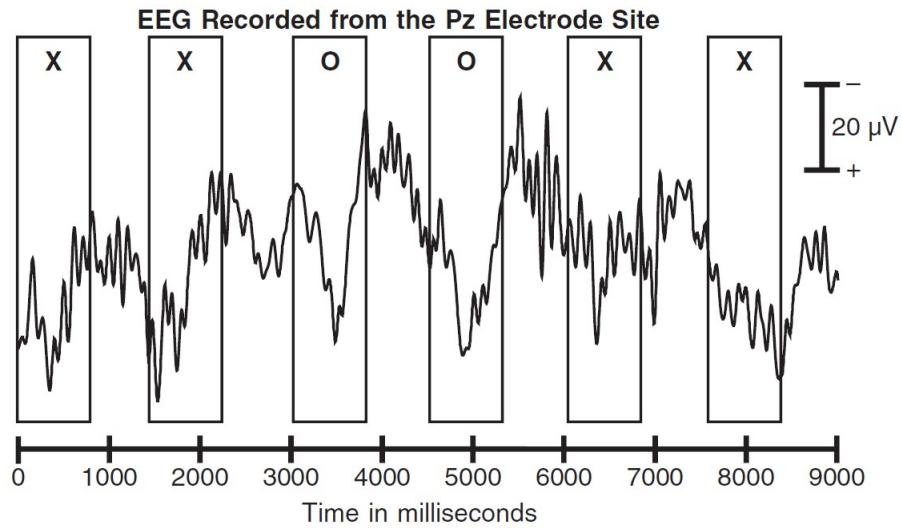
### 3.5.2 Basic concept of the ERP technique

#### Example experiment 1

This experiment was a variant on the oddball paradigm, which is widely used in psychopathology research. Subjects viewed 80 percent Xs and 20 percent Os on a monitor and had to press a button on seeing an X and another button on seeing an O. The letters were shown for 100 ms followed by a blank inter-stimulus interval of 1400 ms. Figure 3.14 shows the recorded EEG. Although when looking closely some consistency in the response to each stimulus can be observed, it is difficult to see what the responses exactly look like.

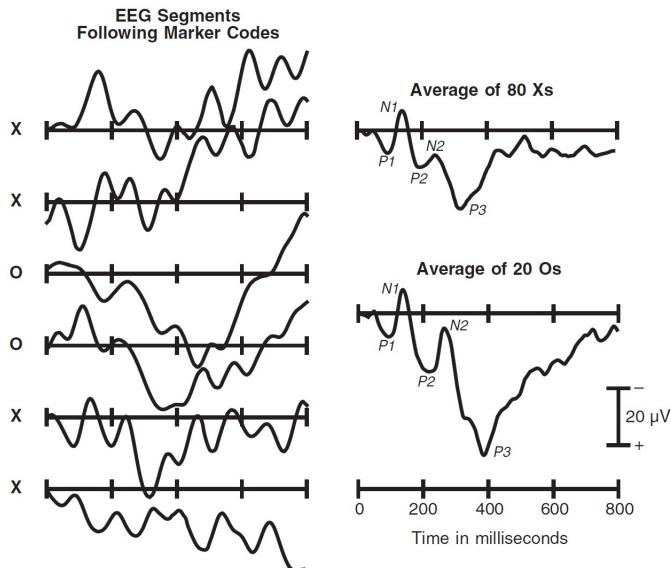
Averaging is applied in order to extract ERPs elicited by the X and O stimuli. Single trial waveforms were averaged for the X and O at each electrode site. The results are shown in figure 3.15. The resulting averaged ERP waveforms consist of a sequence of positive and negative voltage deflections, called peaks, waves, or components. These are then labeled with either P (for positive) or N (for negative) and a number (indicating the peak's position in the waveform).

The initial peak (P1) is elicited by visual stimuli no matter what the task is, but is influenced by stimulus parameters such as luminance. Specific tasks may however influence the amplitude of P1. Early sensory responses are called exogenous components, indicating dependence on external factors. The P3 wave in contrast depends on the task the subject performs, is not directly influenced by the stimulus' physical properties, and are therefore



**Figure 3.14:** EEG recorded from the Pz electrode site

called endogenous components (depending on internal factors). As can be seen in figure 3.15, the infrequent O elicited a much larger P3 wave than the X stimulus, showing exactly what thousands of previous oddball experiments have found.



**Figure 3.15:** Extracted X & O ERPs using signal averaging

Experiments like this one have several steps:

- Electrodes have to be attached to the subjects scalp
- EEG needs to be filtered and amplified in order to be stored as set of discrete voltage measurements on a computer
- Artifacts, if any, need to be addressed either by removing trials containing artifacts or subtracting an estimate of the artifactual activity

- Averaging to extract ERPs from the overall EEG
- Signal processing techniques (digital filtering) are applied to remove noise and isolate specific components.
- Measuring of size and timing of ERP components, which are then subjected to statistical analysis

### **Example experiment 2**

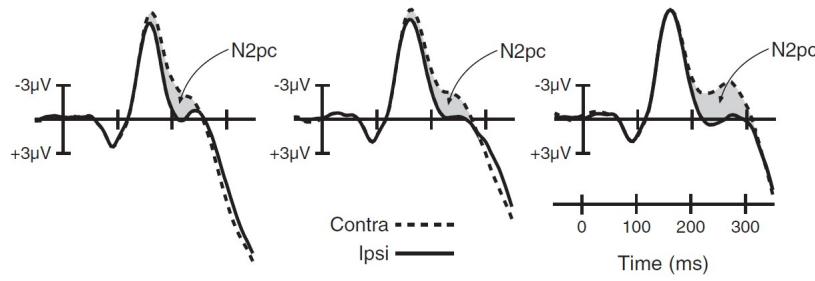
The goal of this experiment was to determine whether the same attention systems are used for detection of visual targets by color and by motion. Green bars where moving downwards across a screen. Now and then deviations (the targets) where shown, with either a different color, orientation, or direction of motion (pop-out stimuli). One of these three options would be the target with accompanied button and another button was used when one of the remaining two deviations occurred.

In order to determine whether a given attention system was used for a particular type of trial, the researchers focused on the attention related ERP component called the N2pc (N2-posterior-contralateral) wave. This N2pc wave can be isolated by examining the difference in amplitude between waveforms recorded from contralateral and ipsilateral electrode sites. This is shown in figure 3.16. Assumed was that if for all the 3 pop-out stimuli the same attention-related ERP component was present, the same attention system must be present. This was the case, but the N2pc component was larger with motion related pop-out stimuli which is consistent with earlier findings as well. This experiment illustrates three main points:

1. The N2pc effects shown in figure 3.16 are only about 2-3 micro Volts. Using appropriate methods to optimize signal-to-noise ratio these tiny effects can be seen very clearly.
2. This experiment uses ERP recordings as tool to address a fundamentally methodology independent question. An advantage, compared to if functional neuroimaging techniques such as PET and fMRI were used, is the temporal resolution, which is limited with PET and fMRI.
3. The use of ERPs to answer cognitive neuroscience questions usually depends on earlier ERPopology experiments (knowledge about the N2pc component for example).

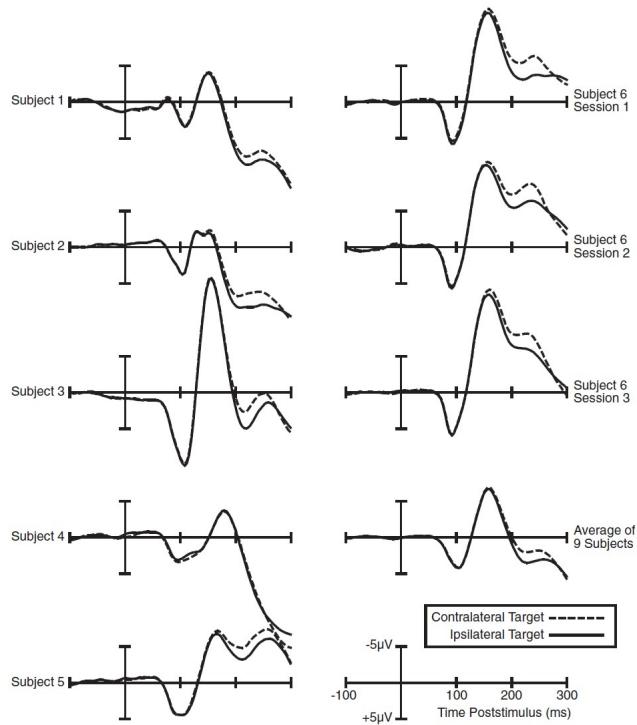
### **Reliability of the waveform**

The waveforms in figure 3.16 are called grand average ERP waveforms, the term used to refer to waveforms created by averaging the averaged waveforms of individual subjects. Individual waveforms are presented rarely. Grand averages mask the variability between individual subjects which can be a good thing since variability makes it difficult to see similarities, but the grand average may not reflect the pattern of individual results well. This is illustrated in figure 3.17, which contains individual averaged waveforms as well as the grand averaged waveform taken from the example experiment 2. As is clear from the image there is a lot of



**Figure 3.16:** Recorded waveforms

variability between subjects. Usually there is only little within subject variability (the upper 3 waveforms on the right side of the figure ??). Within subject variability can for example be influenced by the amount of sleep of a subject, changing task strategies, time since last meal, body temperature, and even time of year. Potential causes for between-subject variability include the idiosyncratic folding pattern of the cortex and to a lesser extend drugs, age, psychopathology, and even personality.



**Figure 3.17:** Individual averaged and grand average waveforms

### 3.5.3 (Dis)advantages of the ERP technique

#### Behavioural measures

There are two distinct advantages of ERPs in this context. First, variations in reaction time and accuracy are difficult to attribute to specific cognitive processes. ERPs however provide

a continuous measure of processing between stimulus and response, making it possible to determine which stage(s) are effected by specific experimental manipulation. Secondly, ERPs provide an online measure of processing stimuli, even when there is no behavioral response.

Disadvantages in the context of behavioral measures include unclarity of the functional significance of the ERP component as compared to the functional significance of a behavioral response. In most cases (consequences of) the specific biophysical events that produce a given ERP response are unknown. Events eliciting a ERP response are not always as clear as pressing a button. A second disadvantage is that ERPs are so small that it usually requires a large amount of trials to accurately measure them. To illustrate, most behavioral experiments regarding reaction time require about twenty to fifty trials per subject in each condition, whereas with ERP often requires fifty, hundred, or even a thousand trials per subject in each condition.

### Comparison with other physiological measures

Table 3.1 contains an overview of comparisons of ERPs with other techniques. Since the ERP technique has both significant advantages as well as disadvantages, choosing the right questions for which ERPs are well suited is very important. ERPs are very useful for questions regarding which neurocognitive process is influenced by a given stimulation. ERPs are not very suitable for answering questions requiring neuroanatomical specificity. Furthermore it is very helpful to ask questions that can be addressed with relatively easy to isolate components like the N2pc mentioned in the example experiments above.

	Microelectrode measures	Hemodynamic measures	Electromagnetic measures
Invasiveness	Poor	Good (PET) Excellent (fMRI)	Excellent
Spatial resolution	Excellent	Good	Undefined/poor (ERPs)
Temporal resolution	Excellent	Poor	Undefined/better (ERMFs) Excellent
Cost	Fairly expensive	Expensive	Inexpensive (ERPs) Expensive (ERMFs)

**Table 3.1:** Comparison of invasiveness, spatial resolution, temporal resolution, and costs for microelectrode measures (single-unit and local field-potential recordings), hemodynamic measures (PET and fMRI), and electromagnetic measures (ERPs and ERMFs)

### **3.5.4 Summary of major ERP components**

Before reading the remainder of this section, it should be noted that components with the same naming but different in modality are not related. Some late components like the P3 wave are largely modality independent, but even the P3 wave has modality specific sub-components.

#### **Visual Sensory Responses**

##### **C1**

The C1 component is largest at posterior midline electrode sites. This component is not labelled with a P or N, because its polarity can vary. The C1 wave is generated in area V1, the primary visual cortex, which in humans is folded into the calcarine fissure. The upper bank of the fissure codes the lower visual field and vice versa. The voltage recorded above the calcarine fissure is positive for lower visual field stimuli and vice versa. The C1 wave is small or positive on the horizontal midline which causes a single wave which is summed with the P1 wave, therefore the C1 wave is usually not observed unless upper visual field stimuli are used to generate a negative voltage potential for the C1 component. C1 is highly sensitive to stimulus parameters and onsets 40-60 ms post-stimulus and peaks 80-100 ms post-stimulus.

##### **P1**

The P1 wave follows the C1 wave and is largest at lateral occipital electrode sites. Although the onset time is difficult to assess due to overlap with the C1 wave, it onsets 60-90 ms post-stimulus with a peak between 100-130 ms. P1 latency will vary depending on stimulus contrast. The P1 wave is sensitive to variations in stimulus parameters, direction of spatial attention, and to the subject's state of arousal.

##### **N1**

N1 follows the P1 wave. There are several visual N1 components, of which the earliest peaks 100-150 ms post-stimulus at anterior electrode sites. There appear to be at least two posterior N1 components peaking 150-200 ms post-stimulus, from the parietal cortex and lateral occipital cortex. Spatial attention influences these components. The N1 sub-component that originates from the lateral occipital cortex appears to be larger when subjects are performing discrimination tasks rather than detection tasks.

##### **P2**

The P2 wave follows the N1 wave at anterior and central scalp sites. The P2 wave is larger for stimuli containing target features and even larger when the targets are infrequent. The P2 wave is similar to the P3 wave, but the anterior P2 effects only occur when the target is defined by simple stimulus features. Not much is known about the posterior P2 wave, since the overlapping with the N1, N2, and P3 waves.

## **N170 and Vertex Positive Potential**

There appears to be a difference (the Vertex Positive Potential) in response to faces and non-face stimuli between 150 and 200 ms at central midline sites. Recent studies have found that at lateral occipital electrode sites faces elicit a more negative potential than non-face stimuli, with peaks at around 170 ms (N170 wave). It is likely that the N170 wave and the Vertex Positive Potential are the opposite sides of the same dipole. The N170 is later and/or larger for inverted faces. An inversion effect is also observed for non-face stimuli when subjects have extensive experience viewing the stimuli in upright position.

## **Auditory Sensory Responses**

### **Very Early Components**

For an auditory stimulus under the right conditions, a sequence of ERP peaks can be observed within the first 10 ms of the stimulus onset. There is indication that these peaks arise from the brainstem auditory pathways and are therefore called brainstem evoked responses (BERs) or auditory brainstem responses (ABRs). BERs are very useful in assessing auditory pathology, especially in infants. BERs are followed by the midlatency components (10-50 ms), which probably arise (in part) from the medial geniculate nucleus and the primary auditory cortex. Midlatency components are followed by the auditory P1 wave (50 ms), typically largest at frontocentral electrode sites.

### **N1**

The auditory N1 wave has several sub-components as well: a frontocentral component generated in the auditory cortex on the dorsal surface of the temporal lobes that peaks around 75 ms, a vertex-maximum potential of unknown origin with peak around 100 ms, and a more laterally distributed component generated in the superior temporal gyrus with peak around 150 ms. The N1 wave is sensitive to attention.

### **Mismatch Negativity (MMN)**

MMN is observed when repetitive identical stimuli with occasional mismatching are used. This causes a negative-going wave, largest at central midline scalp sites and peaks 160-200 ms. MMN is observed even when subjects are not using the stimuli for a task. MMN likely reflects an automatic process that compares stimuli to a sensory memory trace of preceding stimuli.

## **Somatosensory, Olfactory, and Gustatory Responses**

Somatosensory responses begin with a rare ERP component, often called the N10. It arises from the peripheral nerves and reflects action potentials rather than postsynaptic potentials. Following the N10 about 10 to 20 ms is a set of short and medium latency cortical components (20 - 100 ms). At around 150 ms an N1 wave can be observed, followed by a P2 wave at

around 200 ms (these 2 are sometimes called the *vertexpotential*. Recording olfactory and gustatory responses is more difficult, since it is hard to precisely time sudden onset stimuli.

## N2 Family

A repetitive non-target stimulus will elicit an N2 deflection which is often seen as the basic N2, which contains several subcomponents. A larger amplitude can be observed if in a repetitive train other stimuli occasionally (deviants) occur. If these deviants are not task related the effect will consist of a mismatch negativity (N2a), if they are task-related a later N2 effect is observed as well, which is called N2b. This component is larger for less frequent targets and can be seen as a sign of a stimulus categorization process. For auditory task-relevant deviants this effect is largest over central sites and for visual deviants at posterior sites. In the visual domain deviance is often studied spatially. ERP waveforms elicited by a simultaneous array of homogeneous items can be compared to ERP waveforms elicited by a simultaneous array with several identical items plus 1 deviant. Three N2 components can be distinguished:

- Bilateral, anterior response. Present when the deviant item is not a target. It is however not as automatic as MNN, because it is not present unless subjects are looking for deviant targets.
- The N2 wave, which is bilateral and probability sensitive. Present only if the deviant item is a target.
- The N2pc (posterior contralateral). This means that the component is observed at posterior electrode sites contralateral to the location of the target. It is not probability sensitive and reflects the focus of spatial attention onto the target location.

## The P3 Family

In the time range of the P3 wave, there are several distinguishable ERP components, of which the first major distinction made was the frontally maximal P3a and the parietally maximal P3b. Both were elicited by unpredictable and infrequent shifts in tone pitch or intensity, but the P3b was only present when these shifts were task-relevant. When referring to the P3 component, almost always the P3b component is meant. It is not completely clear what neural or cognitive process is reflected by the P3 wave, so one should be careful in making assumptions about its meaning. Although the meaning is not exactly clear, it is known what factors influence its amplitude and latency.

The P3 wave is sensitive to target probability, the amplitude increases as the target probability increases. It is not just overall probability that matters, but also local probability. The P3 wave elicited by a target becomes larger when an increasing number of non-targets preceded the target. The P3 amplitude is larger when subjects put more effort to a task, but not when a subject is uncertain whether a stimulus was a target or a non-target. This means a more difficult task can increase amplitude by requiring more effort, but can decrease amplitude because of an increase in difficulty determining target/non-target.

## **Language-Related ERP Components**

The N400 is the most extensively studied language-related component, usually largest over central and parietal electrode sites with a slightly larger amplitude over the right hemisphere. The N400 can usually be observed in response to violations of semantic expectancies. An example is the sentence "While I was visiting my home town, I had lunch with several old shirts." The N400 can also be observed to the second of a pair of words, like "tire....sugar". "Flour...sugar" for example would elicit a small N400.

Another distinctive ERP component is the P600, caused by syntactic violations. An example is the word "to" in the sentence "The broker persuaded to sell the stock" where it elicits a larger P600 than in "The broker hoped to sell the stock". Syntactic violations can also elicit a left frontal negativity from around 300 - 500 ms.

Since there is a distinction between syntax and semantics, different ERP activity is elicited by these different types of words. Function words like to and with elicit a component called N280 at left anterior electrode sites, which is absent for content words like nouns and verbs. Content words elicit an N400, which is absent for function words.

## **Error Detection**

### **Response-Related ERP Components**

By comparing ERP waveforms of correct trials with error trials, something can be learned about the cause of an error and the brain's response following the detection of the error. An example is an experiment by Gehring et al. (1993) where subjects had to perform a speeded response task. They responded so fast that occasionally errors were made by for instance pressing the wrong button. By comparing ERPs of correct and error trials, they observed a negative-going reflection at frontal and central electrode sites just after the time of the response. They called this the error-related negativity (ERN). Independent of this example, Falkenstein et al. (1990) discovered this as well and called it the Ne component, often followed by a positive deflection called Pe. Most believe that the ERN reflects activity of a system that either monitors responses or is sensitive to conflict between intended and actual responses. The generator of the ERN is not yet known with certainty.

## **3.6 Lab session**

BioSemi makes use of active electrodes, which allows for reference free recording [10]. In this case a reference electrode must be chosen, since failing to do so will leave 40 dB of unnecessary noise in the data. For all datasets the Cz electrode was chosen as reference electrode. This is an electrode commonly used as reference electrode and some researchers claim that using non-scalp reference electrodes such as nose and ears introduce more noise.

For all datasets the channels analyzed are 13, 15, 16, and 17. This is because SSVEP stimulation is visual stimulation and the part of the brain that processes visual stimulation is in the back (the occipital cortex). The 3 main electrodes for analysis (15, 16, and 17) were

preferred over higher placed electrodes, since the response was expected to be stronger in lower placed electrodes. Electrode 13 was used as comparison for the previous statement.

In case channels 15, 16, and 17 are very similar, only figures for channel 13 and the channel with the clearest response are shown to prevent unnecessary large amounts of images. It seems that there is no direct relation with the 202 marker and the presence of the artifacts, since there were quite some epochs containing artifacts without the 202 marker. It should be noted however that markers are placed live by the researchers, who could be visually determining the possible causing of artifacts and therefore it would be possible that some live creation of artifacts could be missed. So still there is the possibility that the 202 marker is related to artifacts. These artifacts could be caused by for instance muscle activity (eye or head movement) or electrodes being slightly moved.

### 3.6.1 Part II

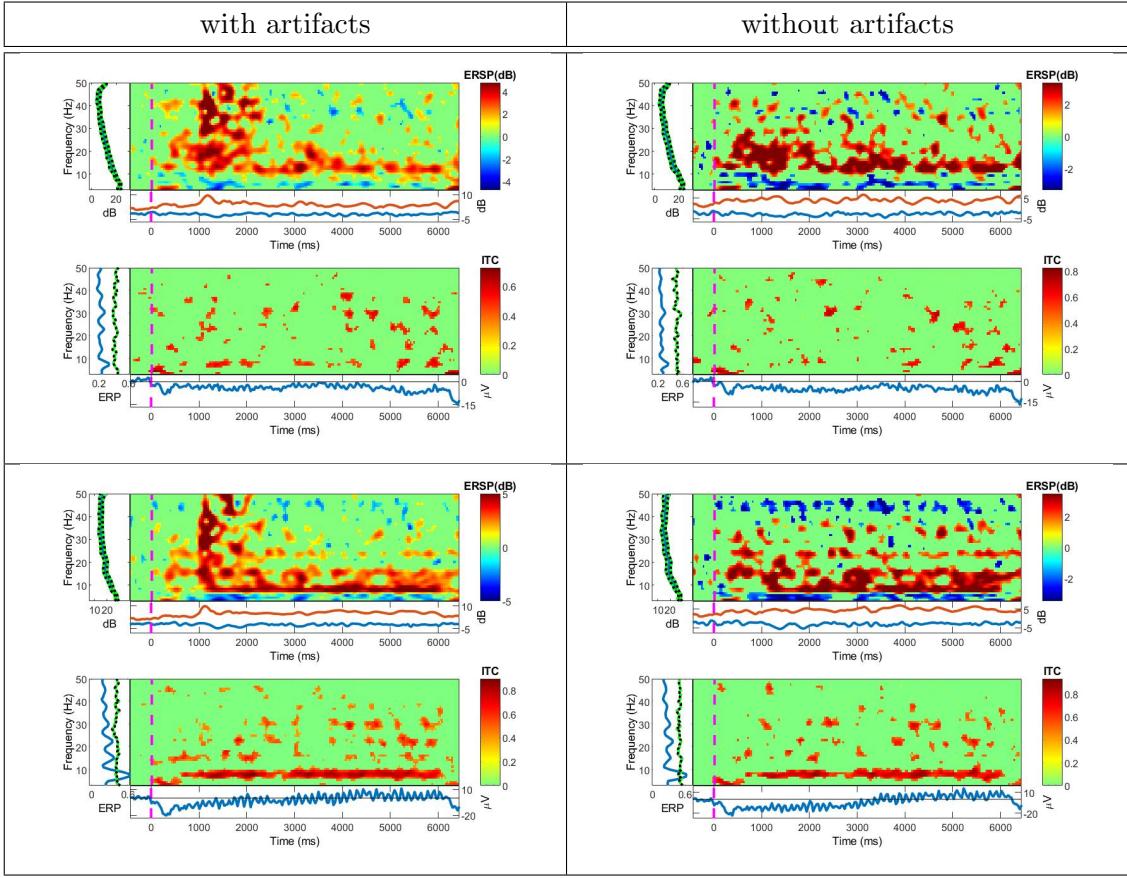
#### S02

For this dataset the baseline chosen was 1000ms. Inspecting the data by plot → channel data (scroll), we see that there is a minimum of approximately 1000ms between the stimulus stop marker and the next start marker. Epochs were extracted by Tools → Extract epochs, with marker 200 as time locking event type and Epoch limits -1 7. This means epochs are extracted with a time frame -1s prior to the start marker and 1s after start marker (stimulus duration of 6 seconds). 22 epochs were extracted, corresponding to the 6 seconds of stimulation -1 and +1 second. After manually rejecting epochs with artifacts, 15 epochs remained.

Table 3.2 contains the time frequency analysis plots of channel 13 and 16. By inspecting the plots it is clear that removing epochs with artifacts produces a clearer result in both cases. Also the expected difference between the higher placed electrode (13) and the lower one (16) is confirmed by inspecting the plots. There is a visible SSVEP response with stimulation frequency at approximately 7.5 Hz, indicated by the clear horizontal line in both the ERSP and ITC plots. There are some (sub)harmonics, although less clearly visible especially in the ITC plots. Removing epochs with artifacts does remove some noise which could be the cause of other non-harmonic responses which are more present in the plots with the artifacts.

#### S03

The baseline chosen was 500ms. Inspecting the differences between stop and start markers we found some with differences smaller than 1000ms, with a minimum of approximately 500ms. Using the start marker 23 epochs were extracted, again corresponding to the 6 seconds during stimulus with an extra -1 and +1 second. After manually rejecting epochs with artifacts, 16 epochs remained. Table 3.3 contains the time frequency analysis plots for channel 13 and channel 15. For this dataset visually determining epochs containing artifacts was less clear as compared to dataset S02. Comparing the plots with and without artifacts confirms this, since there is not that much improvement. The plot for channel 13 shows more

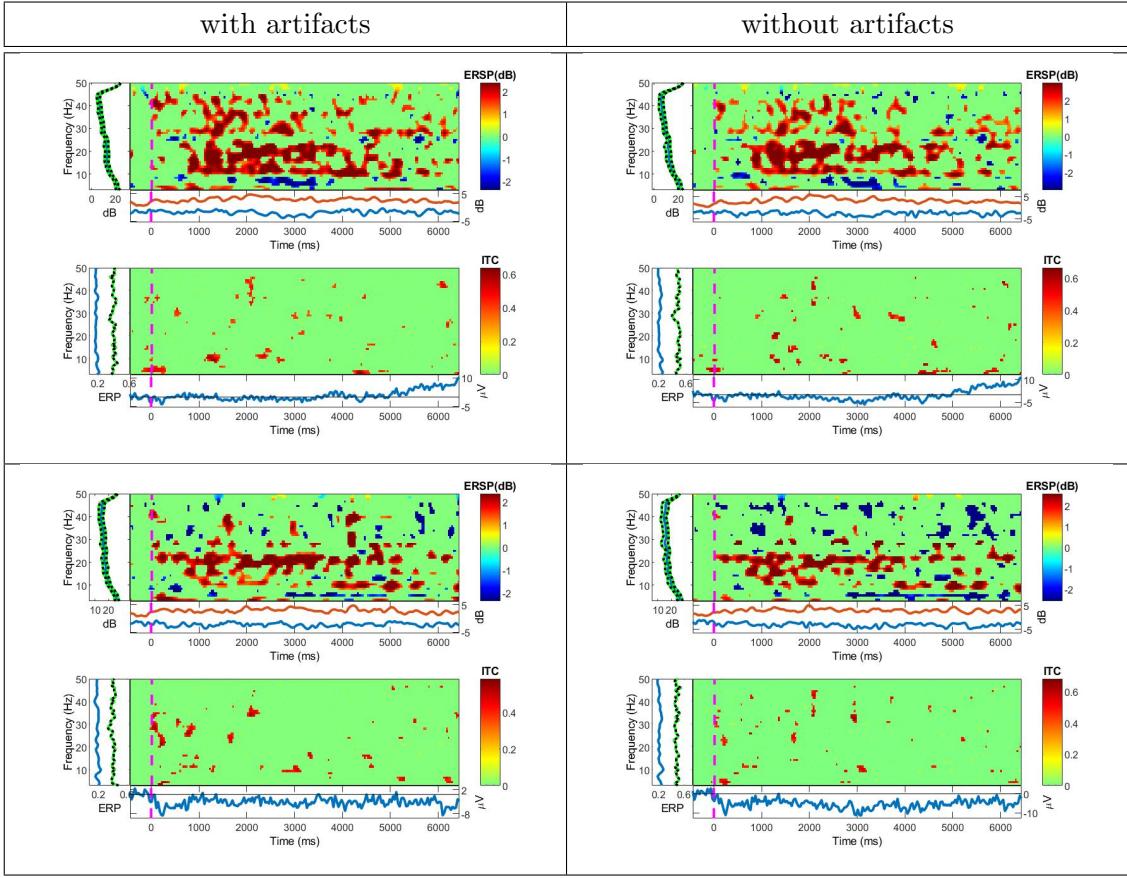


**Table 3.2:** Time frequency analysis S02, channel 13 (upper part) and channels 16 (lower part)

non-harmonic response, probably caused by more and/or remaining artifacts. Still there is a SSVEP response, with stimulation frequency at around 22 Hz. However this is not well reflected in the ITC plot, meaning that this is not as strong in all individual epochs as compared to the plots of dataset S02 in table 3.2 where the ITC plot shows a clear response at the stimulation frequency as well.

## S11

The baseline chosen was 900ms. For this dataset there were a lot of non-stimulation periods of above 1000ms, but a few below that. The minimum was approximately 900ms. Again using the 200 start marker, 23 epochs were extracted with -1 second and +1 second of the 6 seconds stimulation period. After manually rejecting epochs with artifacts, 16 epochs remained. Table 3.4 contains the time frequency analysis plots for channels 13 and 16. For this dataset determining epochs with artifacts was less clear as well as compared to dataset S02, possibly because there are simply less or less clear artifacts present in the dataset. The plots confirm this, since there is not much improvement after epoch rejection. Of all dataset this one show the clearest presence of harmonic responses in both the ERSP and ITC plots. Strongest present frequencies are approximately at 7, 21, 28, 38, and 44 Hz. Not all are reflected well in the ITC plot, such as the one at 21 and 28 Hz. Looking at these observations

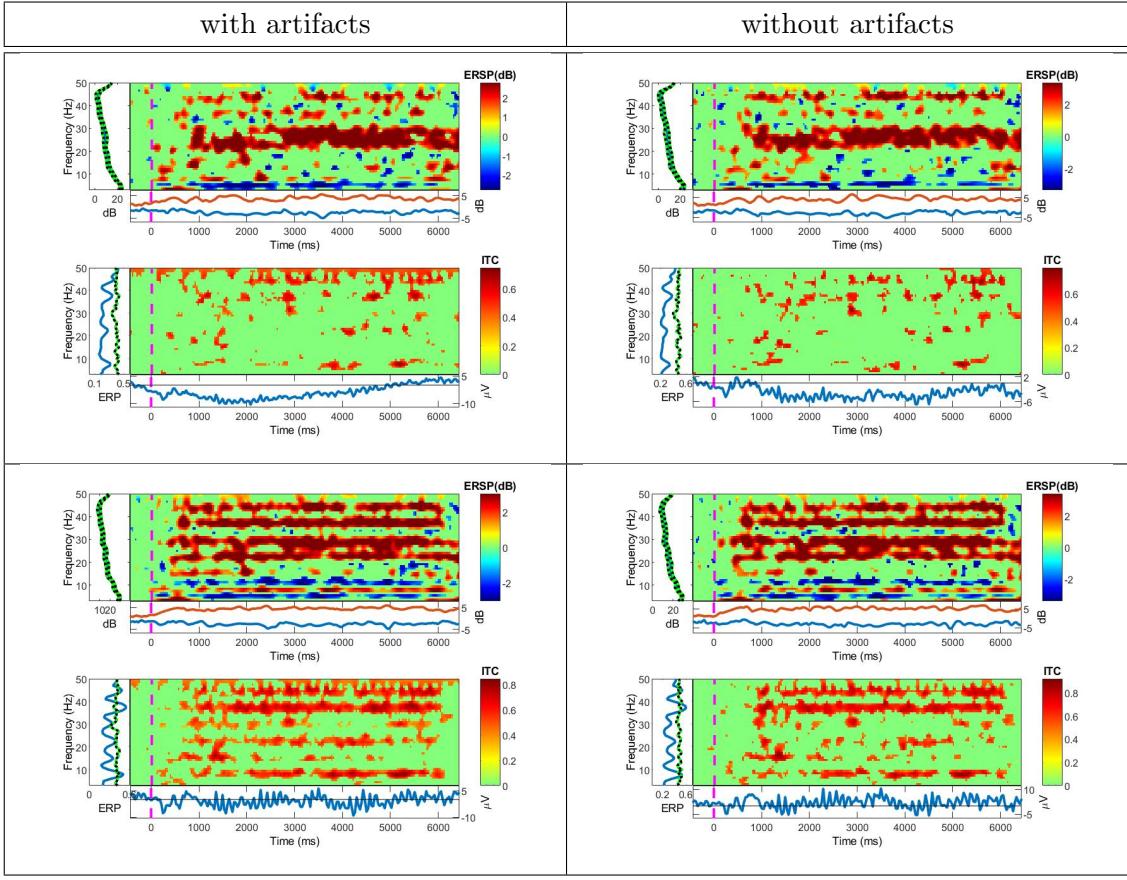


**Table 3.3:** Time frequency analysis S03, channel 13 (upper part) and channel 15 (lower part)

and regarding the fact that harmonics are multiples of the main response, we argue that the SSVEP stimulation frequency would be around 7Hz.

## S17

The baseline chosen was 1200ms. However this produced an error in EEGLAB, probably because there are no 1200ms prior to the first start marker, so a baseline period of 1000ms was chosen. Again using the 200 start marker, 21 epochs were extracted with -1 second and +1 second of the 6 seconds stimulation period. After manually rejecting epochs with artifacts, 13 epochs remained. Table 3.5 contains the time frequency analysis plots for channels 13 and 16. For this dataset the manual rejection of epochs with artifacts did not improve results shown in the plots that much, which could mean there aren't that strong present artifacts or we made mistakes in judgement. There is a quite clear response visible at the presumed SSVEP stimulation frequency at approximately 9Hz, with harmonic responses visible in the plots at 18Hz and 27Hz, and possible more higher harmonics but there are not well reflected by the ITC plots. There are some non-harmonic responses present, possibly due to presence of small artifacts and/or noise.



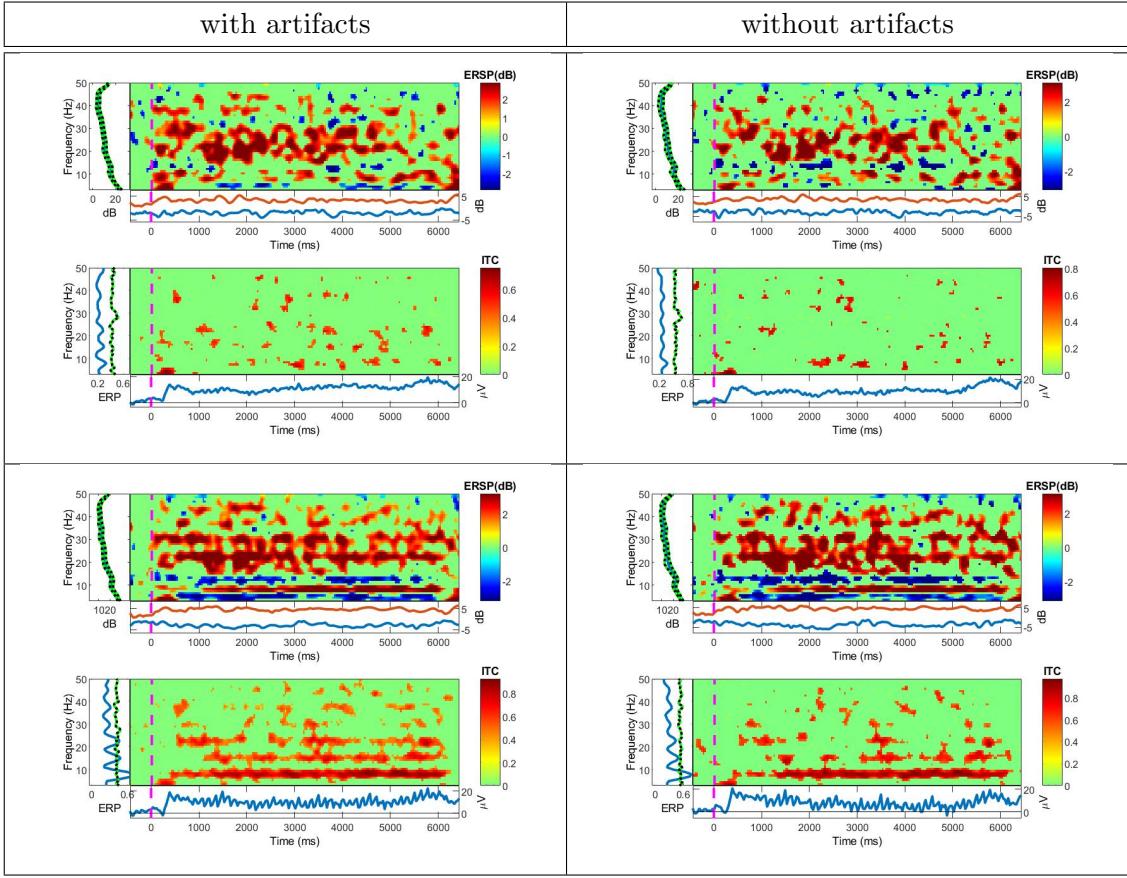
**Table 3.4:** Time frequency analysis S11, channel 13 (upper part) and channels 16 (lower part)

### 3.6.2 Part III

For this part the datasets used are the ones without the manually rejected epochs. The datasets chosen for this part were S02 because of the clear improvement by artifact removal and S11 because of the multiple strong visible response frequencies. The channel used for both datasets is 16, since this one produced the clearest plots of all analyzed channels (13, 15, 16, 17).

#### S02

Table 3.6 contains the ERSP and ITC time frequency analysis plots for 5, 10, 15, and 20 epochs for channel 16. The main changes in the ERSP plots are visible in the 20 epochs plot, which suggests that the majority of epochs with artifacts are in the last extracted epochs. The ITC plot doesn't show that many differences, however the stimulation frequency becomes more apparent. The artifacts mainly introduced in the 20 epochs plot are less visible in the ITC plot, since they are not reflected in every epoch.



**Table 3.5:** Time frequency analysis S17, channel 13 (upper part) and channels 16 (lower part)

## S11

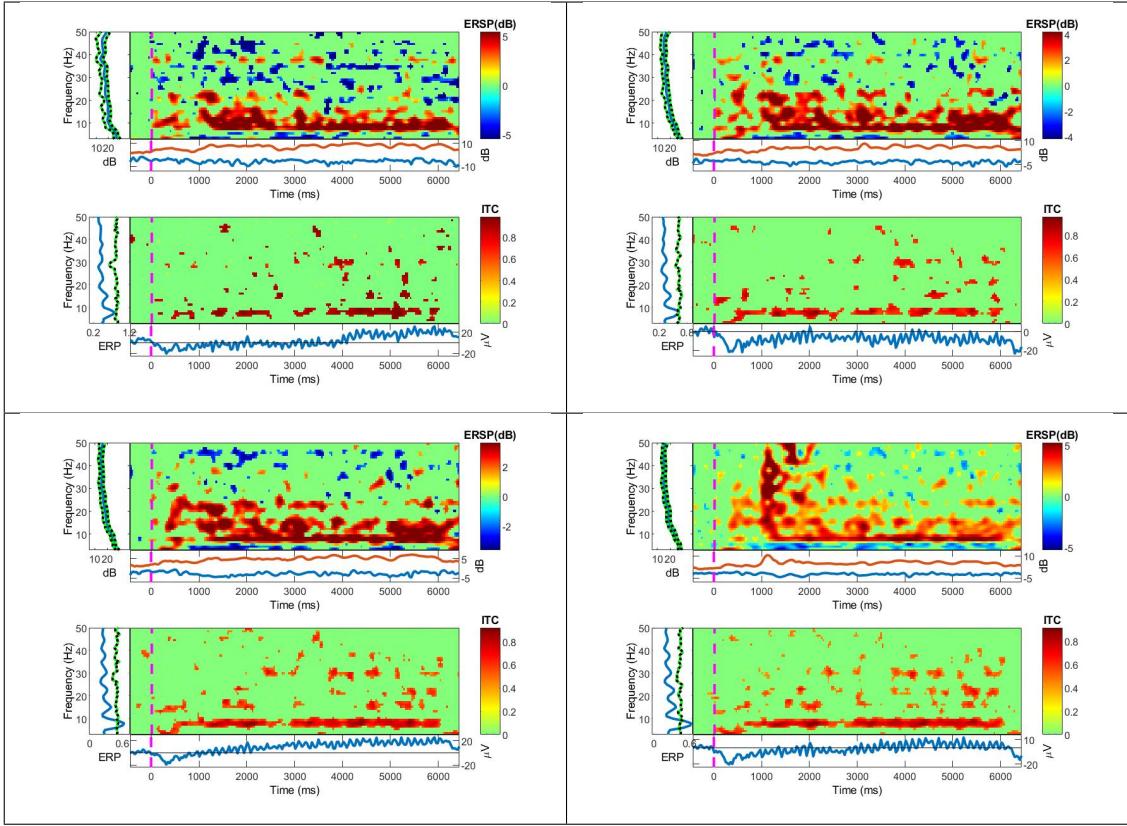
Table 3.7 contains the ERSP and ITC time frequency analysis plots for 5, 10, 15, and 20 epochs for channel 16. It seems there is a less clear presence of artifacts in this dataset as compared to S02 above. Since this method uses averaging of epochs, one would expect to see stronger responses when an increasing number of epochs is used and if these epochs show similar responses. This is clearly shown in the plots in table 3.7, where with an increase in number of epochs the responses are stronger depicted in both the ERSP and ITC plots.

### 3.6.3 Part IV

For this part of the lab the same datasets were used as in part III, namely S02 & S11. Instead of selecting a single epoch from the complete set, the single epochs were selected from the dataset without the manual rejected epochs with artifacts.

## S02

As mentioned in part II we approximated the SSVEP stimulation frequency at 7.5 Hz, based on the time frequency plots in table 3.2. Looking at the single channel single epoch spectrogram plots in table 3.8 we see a slightly less clear response. Still there is a peak at

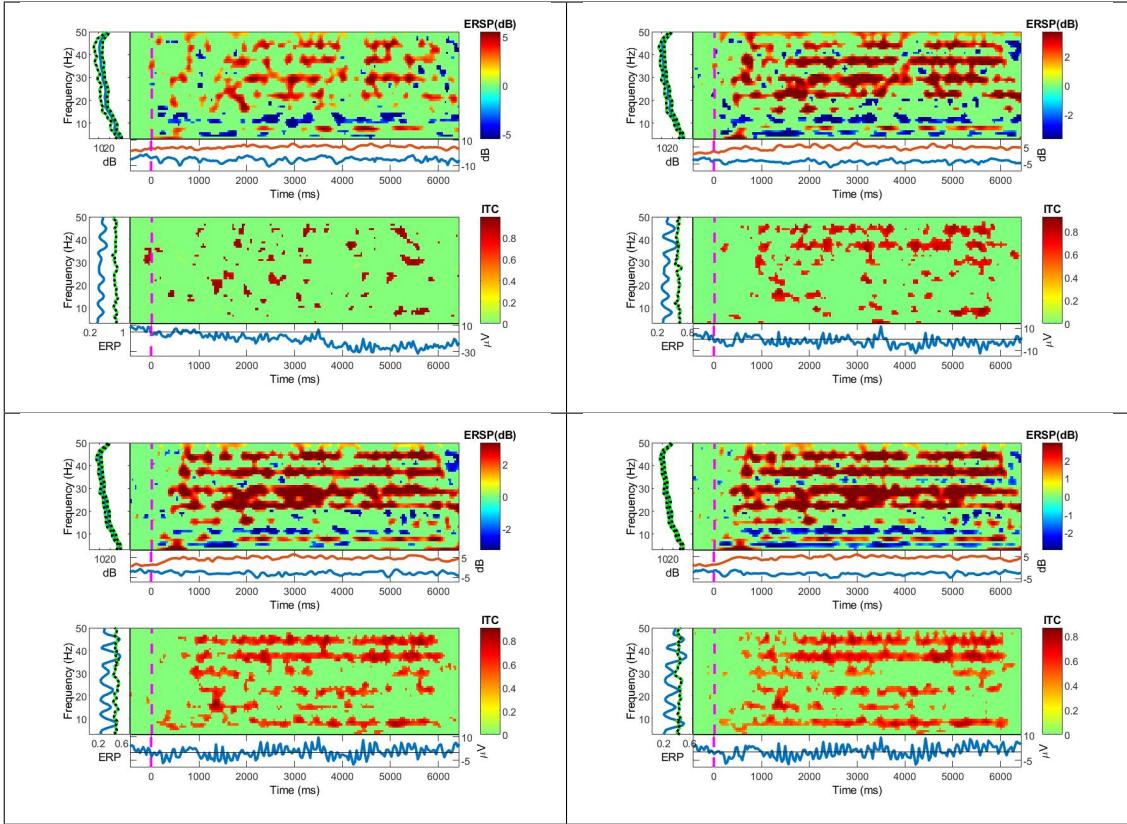


**Table 3.6:** Time frequency analysis S02, channel 16. 5 epochs (upper left), 10 epochs (upper right), 15 epochs (lower left), 20 epochs (lower right)

approximately 7.5 Hz for both channel 13 and 16, although this is not the strongest in all the plots. Ofcourse this is highly dependent on the selected epochs, since there are noticeable differences between epochs.

## S11

As mentioned in part II we approximated the SSVEP stimulation frequency at 7 Hz, based on the time frequency plots in table 3.4. Looking at the single channel single epoch spectrogram plots in table 3.9 we see a slightly less clear response. Still there is a peak at approximately 7 Hz for both channel 13 and 16, although this is not the strongest in all the plots. Ofcourse this is highly dependent on the selected epochs, since there are noticeable differences between epochs. Another observation comparing the spectrograms in table 3.9 and the time frequency plots in table 3.4 is that a lot of the plotted responses are more of a small frequency band than a clear single peak. In the time frequency plots this can be seen by the wider power areas and in the spectrogram plots, for instance channel 16 epoch 7, there is an area around 7 Hz with high power.

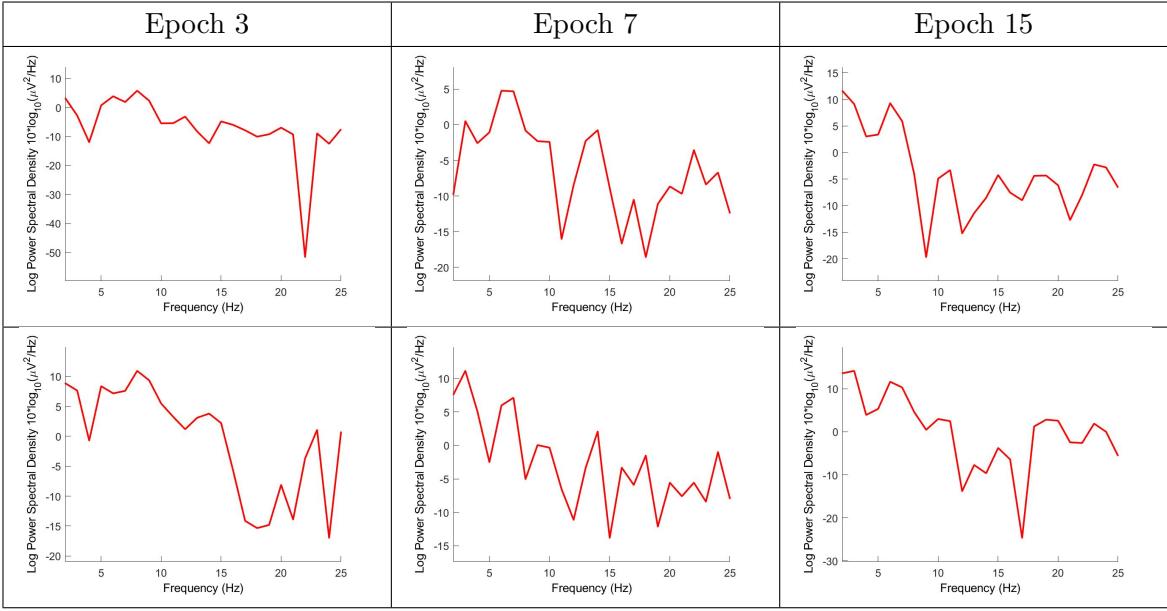


**Table 3.7:** Time frequency analysis S11, channel 16. 5 epochs (upper left), 10 epochs (upper right), 15 epochs (lower left), 20 epochs (lower right)

### 3.6.4 Conclusions

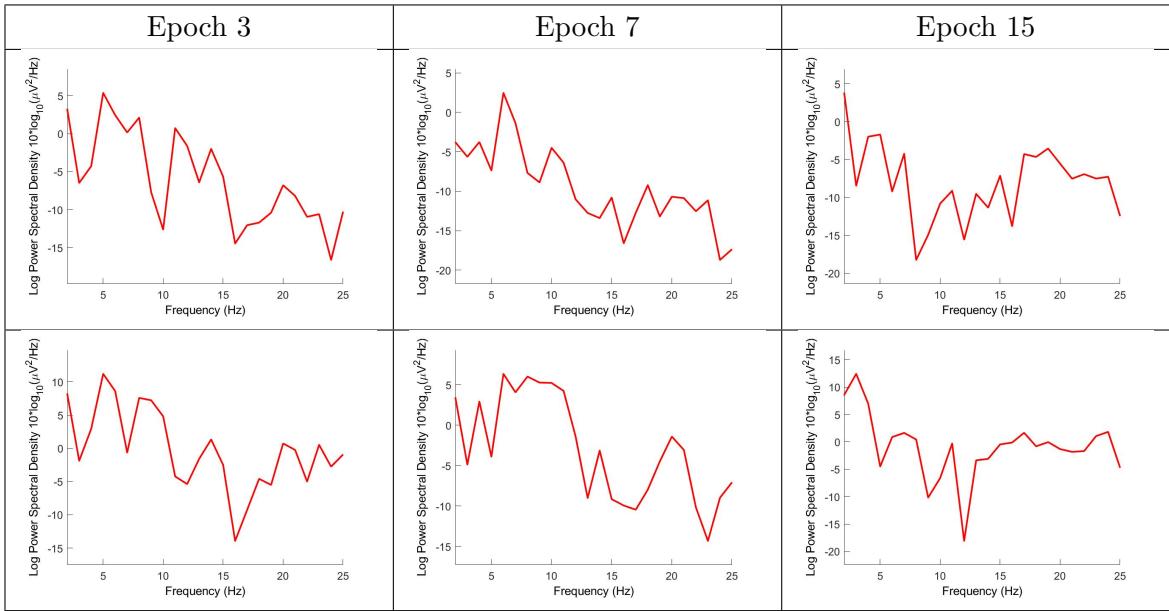
Regarding the first part of the lab we reported whether we could determine a SSVEP response and its stimulation frequency, whether there were (sub)harmonic and non-harmonic responses visible, and to what extend the ERSP and ITC plots match. Overall we could see a SSVEP response for all datasets, although not as clear in all datasets. In dataset S02 manual artifact containing epoch removal improved the plots. Regarding the remaining datasets we had more difficulties determining artifact containing epochs and this was reflected in the plots as well, since there was not much improvement after epoch removal. Except for dataset S03, the ERSP and ITC plots matched quite well, meaning that the frequencies present in the different trials occur quite consistent. In the case of S03, occurrence of certain frequencies were probably not as consistent over all trials.

Part III and IV of the lab were focused on the difference between averaged trials and single trial analysis. Regarding averaged trials it was observed that including more epochs produces a clearer overview of the present frequencies and a better match between the ERSP and ITC plots. Including more epochs in averaging could however also introduce more noise, which was clearly visible in the case of S02 moving from 15 epochs to 20 (see table 3.6). Looking at single channel single epoch plots of table 3.8 and table 3.9, we do see the earlier determined stimulation frequencies present, although not very clear in all cases. Single trial analysis is highly dependent on the selected epoch as well as channel. An example is the first



**Table 3.8:** S02, single channel & epoch spectrogram plots. Channel 13 (row 1) & 16 (row 2).

row in table 3.8, regarding the third epoch of channel 13, where there are less clear peaks visible and a rather straight line is shown. For automatically detecting SSVEP matching ERSP and ITC plots would be most useful, since just looking at single channel singe trial is quite dependent on the trial picked. Using averaging could emphasize frequencies that are recurring amongst trials, which could say a lot about the SSVEP stimulation.



**Table 3.9:** S11, single channel & epoch spectrogram plots. Channel 13 (row 1) & 16 (row 2).

# 4 | Week 4

In week 4 we explore ... as well as automatic detection of P300 and SSVEP (FFT vs CCA) in the lab.

## 4.1 N400

See also week 3, section 3.5, subsection on language-related ERP components. The N400 wave is an ERP, a negative going reflection peaking around 400 ms post-stimulus. It is typically maximum at central-parietal electrode sites and is a response to semantic context contradiction. It is not just a response to unexpected words, but rather related to semantic processing (see figure 4.1 below). The N400 can range from -5 to 5 microvolts and is not always negative, its just a more negative deflection as compared to other conditions.

### 4.1.1 Application

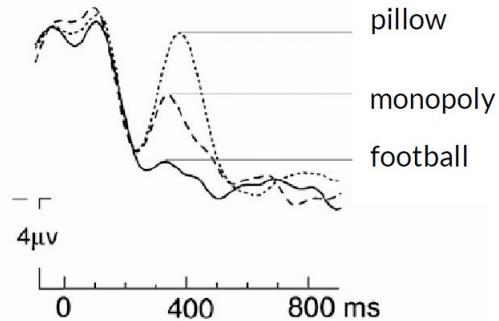
Applications include prediction of recovery from disorders of consciousness (Steppacher et al.), cognitive event-related potentials: biomarkers of synaptic dysfunction across the stages of Alzheimer's disease. (Olichney et al.), clinical applications of the Halifax consciousness scanner: tracking recovery in a severely brain injured patient. (Fleck-Prediger et al.), and a hierarchy of event-related potential markers of auditory processing in disorders of consciousness. (Beukema et al.). Overall mainly focused on recovery and diminishing of brain function. Limitations include the use of averaging, which can be unpractical since patients often lack the prolonged attention span, awareness, capability, and/or motivation. Figure 4.2 below shows an example of monitoring brain vital signs of concussion in hockey.

### 4.1.2 Experiment Protocol

Typically an experiment involves visual presentation of words in sentences or contexts. Electrodes are placed on the central-parietal electrode sites of the scalp and the subject is seated in front of a monitor on which words appear one by one in the center. Syntactically these are correct, but semantically the sentences are wrong.

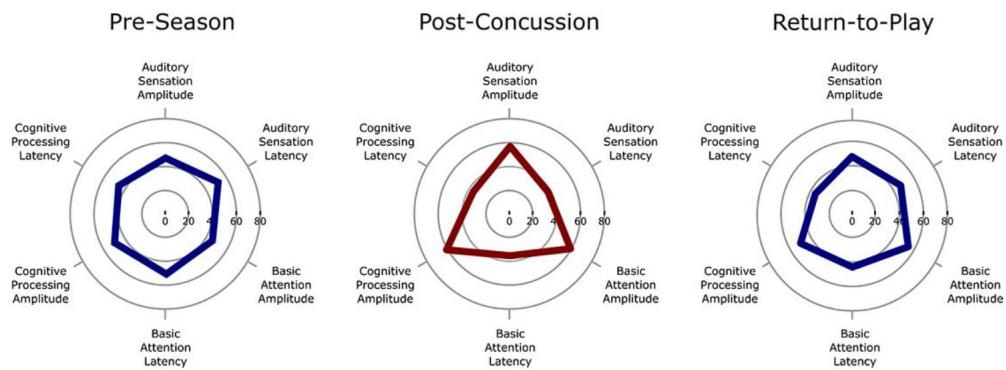
The N400 is not affected by negation. The N400 responds to the relationship between words, but is not necessarily sensitive to the sentence's truth value. An example of this non influential factor is: A pig a building versus a pig is not a building.

'He caught the pass and scored another touchdown.  
There was nothing he enjoyed more than a  
good game of ...'



**Figure 4.1:** Example N400 wave

## Brain vital sign monitoring of concussion in hockey



*Normal brain vital signs: Hexagon profile. Concussion brain vital signs: Triangle profile*

**Figure 4.2:** Example use of N400 [19]

There is a general invariance of the N400's latency, which can however be affected by aging and/or disease. Influential factors for amplitude are:

- The frequency of word usage, where a higher frequency causes for a higher amplitude.
- Word's orthographic neighborhood size, where an increase in neighborhood causes for an increase in amplitude.
- Priming, where the amplitude is reduced when a target word is preceded by a word that is semantically, morphologically, or orthographically related to it.
- Cloze probability, where an increase in cloze probability causes for an increase in amplitude.

## 4.2 P300

See also week 3 section 3.5, subsection on the P3 family. The P300 [20] is the largest component of the event-related potential (ERP) and can be generated using the oddball paradigm. This means subjects are presented with a sequence of events, categorized in two classes where one class is rarely presented. The occurrence of this rare event causes the P300 peak after about 300 ms after stimulus onset and is most visible in parietal lobe electrode sites. It has great potential in BCI applications. It is fast, easy to measure, non-invasive, requires almost no training since it depends on endogenous attention-based brain function, works with the majority of subjects including individuals with serious neurological disease, and gives goal oriented control especially suited for spelling or application control.

There are also some limitations in (real-time) P300 BCI. EEG patterns can change, caused by factors like motivation, level of attention, fatigue, mental state, learning, and other non-stationarities in the brain. Individual calibration is required, since individuals have unique EEG patterns. Also real-time detection of the P300 proves difficult, since for instance subjects attentional blinking, repetition blindness, and habituation can be causes for errors in P300 detection. As mentioned in section 3.5, when talking about the P300 almost always the P3b component is meant, see figure 4.5.

### 4.2.1 Visual P300 Paradigms

An important aspect of P300 BCI is eliciting large differences between target & non-target ERPs. Visual paradigms are typically displayed on a computer screen, where for a long time the most common paradigm for P300 BCI was using Row Column (RC), first introduced by Farwell and Donchin in 1988 [21]. This as well as some more recent attempts to improve on this paradigm will be explained in this section.

#### Row/Column paradigm

In the speller BCI system by Farwell and Donchin a  $6 \times 6$  matrix of all 26 letters plus digits from 0 to 9 are shown on a screen. Each row and column flashes in random order, the subject focuses on the desired letter and silently counts the number of flashes for this focused character. The flashing of (the row and column) of the desired character elicits a P300 response for the row & column, which does not happen for the other 10 rows and columns. By matching the detected P300 response to the flashed row and column the selected character can be determined. Several studies have since then been done showing for instance that more efficient operation is possible when targets symbols are fixated and overt attention is not necessary for highly accurate responses. In addition some new paradigms emerged, which will be explained in the following sections.

#### Single Character (SC)

The SC speller, as the name implies, randomly flashes only 1 character at a time, with a longer delay between flashed compared to the RC and fewer flashed per character required

for character classification. Due to longer flash & flash delay of SC, the RC is about twice as fast, however the SC (15 flashes) results in larger P300 amplitudes compared to RC (15 flashed per row & column). In the study mentioned subjects reached a mean accuracy of 85.3% and 77.9% for RC and SC spellers respectively with N = 19.

### Checkerboard (CB)

This paradigm was designed to overcome two specific problems with the standard RC: the CB eliminates subsequent flashing of the same character (also called double target item flash) and CB reduces distraction and/or inherent noise (non-targets receiving apparent target response). CB produces significant improvement on the SC paradigm explained above. Originally an 8 x 9 matrix was used. A virtual checkerboard is superimposed on the 8 x 9 matrix (see figure 4.4). Two 6 x 6 matrices are filled randomly, one with white items and one with black items and simultaneous adjacent flashes are prohibited by segregating adjacent items into separate flash groups while the subject visible matrix still appears to flash randomly. First (sequentially) all rows in the white matrix flash, then the rows in the black, columns in the white, and finally the columns in the black matrix resulting in 24 flashes for one complete sequence. Prior to the next sequence of flashes the character positions in the virtual matrices are randomized again.

Reaction time increases when nearby items belong to a class competing with the target class, the constraint of a minimum of 6 intervening flashes avoids overlapping target epochs, the larger matrix size (CB: 8 x 9 versus SC: 6 x 6) increases target item amplitude by reducing the probability of target occurrence. There exist already more improvements on the original design, such as the addition of a predictive spelling machine to increase effective information transfer rate, inclusion of mindfulness induction to improve classification accuracy by enhancing attentional resources, and suppression of items surrounding the attended item during calibration.

A	B	C	D	E	F	G	H
I	J	K	L	M	N	O	P
Q	R	S	T	U	V	W	X
Y	Z	Sp	1	2	3	4	5
6	7	8	9	0	.	Ret	Bs
?	,	;	\	/	+	-	Alt
Ctrl	=	Del	Home	UpAw	End	PgUp	Shift
Save	'	F2	LfAw	DnAw	RtAw	PgDn	Pause
Caps	F5	Tab	EC	Esc	email	!	Sleep

(a) Virtual checkerboard

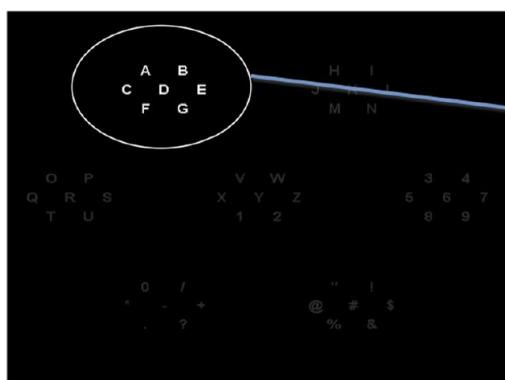
A	B	C	D	E	F	G	H
I	J	K	L	M	N	O	P
Q	R	S	T	U	V	W	X
Y	Z	sp	1	2	3	4	5
6	7	8	9	0	.	Ret	Bs
?	,	;	\	/	+	-	Alt
Ctrl	=	Del	Home	UpAw	End	PgUp	Shift
Save	'	F2	LfAw	DnAw	RtAw	PgDn	Pause
Caps	F5	Tab	EC	Esc	email	F11	Sleep

(b) Subject visible 8 x 9 matrix

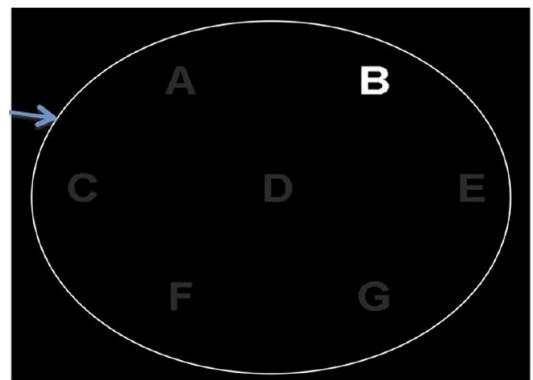
**Figure 4.3:** Checkerboard example

## Region based (RB)

Instead of flashing rows and columns, several regions flash. Character recognition is done in two levels (see figure 4.4). First, and left in the figure, the characters are placed in 7 groups at different regions of the screen. The subject is instructed to attend a specific character in one of the seven groups while each of the groups flashes at random. The group is identified after several flashes of each group, after which level 2 starts (right in the figure). Again different regions (characters) flash while the subject focuses on the desired character. The



(a) Set of characters



(b) Expanded set of characters

**Figure 4.4:** Example Region Based paradigm

RB paradigm significantly decreases the nearest target effect, human error, and adjacency problem. Two variations of RB scored averaged spelling accuracies of 90.6% and 98.1%, where for the RC and SC these were 85% and 72.2% respectively. The same set of subjects, trials, and characters were used.

## Moving & Alternative Stimuli

This approach involves motion rather than flashing stimuli. This can for example be achieved by showing controls (stimuli) with a vertical bar below each which moves left for 140ms at random intervals. Advantage of such an approach is a stronger (earlier) negative component such as the N2. A combination of both approaches is possible as well and has shown superior results as compared to either single approaches. Such studies suggest that the flash approach might possibly be not the best stimulation method and it is likely that other methods will be further improved like happened with the flashing based methods.

### 4.2.2 Applications

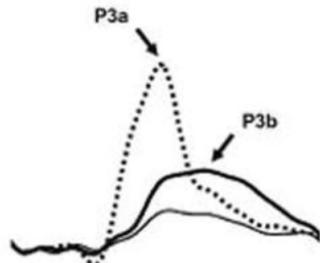
Some examples applications are a P300 speller<sup>1</sup> (Farwell & Donchin 1988), and based on the p300 speller controlling a robot arm<sup>2</sup> and music composition<sup>3</sup>. Also brain painting by Muenssinger et al. is a nice example, where the target group (ALS patients) paint by selecting

<sup>1</sup><https://www.youtube.com/watch?v=wKDimrzvwYA>

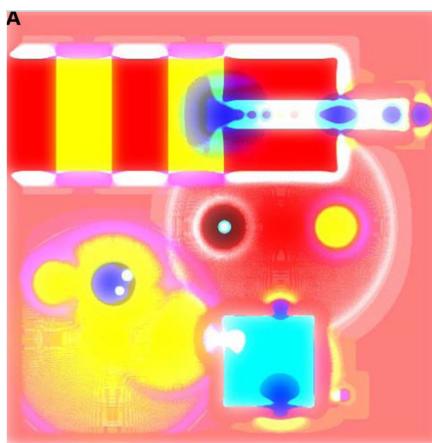
<sup>2</sup><https://www.youtube.com/watch?v=X51RiolKORw>

<sup>3</sup><https://www.youtube.com/watch?v=sFgounvwrYo&t=13>

appropriate symbols (see figure 4.6). Other examples of applications using the P300 in BCI include a P300 guilty knowledge test for lie detection and controlling games using a P300 game interface.



**Figure 4.5:** The P3a and P3b components



(a) The painting

L	Q	█	●	75	W	C
B	GR	⤒	⤓	⤔	3	7
25	50	⤕	⤖	⤗	M	63
S	100	⤑	⤒	⤓	255	511
1	2	A	M	Z +	Z -	
4	8	G	T	H	UD	RD

(b) Symbols

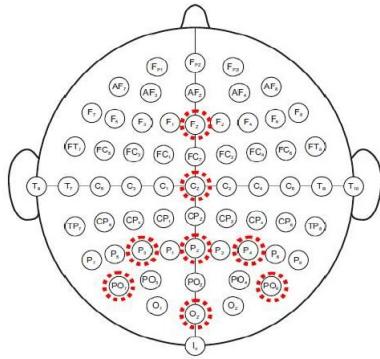
**Figure 4.6:** P300 brain painting

#### 4.2.3 Experiment protocol

Experiments utilizing the P300 usually require stimuli based on for instance the oddball effect. Electrodes are placed on the parietal lobe electrode sides (see figure 4.7). Active attention of the participant during multiple trials is required and averaging is applied. Finally the signal can be processed and analyzed. Influential factors include the probability of the oddball stimulus, identification of the target, individual variability, level of attention, mental state, motivation, and cognitive abilities. There are obstacles as well. The real-time accuracy is low, influence of repetition and habituation, the technology is currently not developed well enough to be suited for non-selection tasks such as the speller and/or home controllers.

#### 4.2.4 P300 Detection

To increase transfer rate, increase accuracy, and to properly detect the P300 several issues should be considered:



**Figure 4.7:** Electrode placement P300 experiments

- Attentional blink, occurring if intervals between two targets are less than 500 ms.
- Repetition blindness, occurring for the second target if two identical targets in a stream of non-targets are flashed at intervals between 100 to 500 ms.
- Target to target interval, the P300 amplitude is related to the interval between target events.
- Habituation, P300 amplitude often decreases with repeated presentation of the same stimulus. This may not occur in all BCI paradigms.
- Users may lose focus (and/or motivation) on the target character, causing for no elicited P300 and hence no accurate classification.
- Human error should be taken into consideration as well, as this too influences accuracy.

Furthermore, preprocessing, feature extraction, and classification is required for P300 detection. The first step is removing noise through preprocessing, for which commonly bandpass filtering is applied with typically a low cutoff frequency of 0.1 Hz and high cutoff frequency of 30 Hz. Its common practice to apply averaging to ERPs, enhancing the P300 amplitude and suppressing background EEG activity. After that features should be extracted for P300 detection for which methods like discrete wavelet transform, independent component analysis, and principal component analysis can be used. The final step is classification. Methods used include stepwise discriminant analysis (SWDA) followed by peak picking and covariance evaluation, support vector machine (SVM), and linear discriminant analysis (LDA). SWDA & Fisher's linear discriminant (FLD) provided the best overall performance and implementation characteristics for practical classification compared to Pearson's correlation method (PCM), linear kernel SVM and Gaussian kernel SVM.

#### 4.2.5 Challenges & Solutions

There are several practical concerns that limit wide P300 BCI adaption:

- Like any BCI, P300 BCIs require significant support. An expert is needed to identify and assemble components, customize parameters to each individual user, and address acute problems. Severely disabled users also need help with the electrode cap and washing hair and cap afterwards. Improvements in software and dry electrodes could help.
- For people unable to control gaze many P300 BCIs are less effective. Using non-visual stimuli or visual stimuli that don't require gaze shifting could help, but might also reduce information transfer.
- An external stimulation device is required for P300 BCIs, which are generally not reported to be distracting or annoying, but this might change with long term use.
- P300 BCIs are well suited for tasks like spelling, smart home control, and internet browsing, but are not as effective for other tasks so far. New paradigms or hybrid solutions could improve on that.

## 4.3 SSVEP

### 4.3.1 Fundamentals of steady-state visually evoked potentials (SSVEPs)

Visually Evoked Potentials (VEPs) are phase-locked to stimulus and can be enhanced using averaging techniques over many trials [22]. VEPs can be recorded in the visual areas of the brain. The most common types of stimuli that can evoke VEPs are flash (luminance) and pattern stimulation:

- Flash-VEPs
  - More variable across subjects
  - Little interocular asymmetry
  - Consist of a series of negative and positive waves, with the N2 (90 ms) and P2 (120 ms) as the most robust components
- Pattern reversal VEPs
  - The lowest waveform variability & peak latency within subject and over a normal population
  - Consists of the N75, P100, and N135 components
- Pattern offset/onset VEPs
  - More variable in appearance than pattern reversal VEPs.
  - Three main peaks. C1 (positive, 75 ms), C2 (negative, 125 ms), and C3 (positive, 150 ms)

The abbreviation SSVEP stands for Steady State Visual Event Potential, where steady state means here that frequency components remain close to constant in amplitude and phase over a long time period. The constant characteristic does not mean constant in time-domain, but rather in the frequency domain. Because of this characteristic, many applications can be derived from SSVEP propagation properties. SSVEPs are less sensitive to blink and eye movements and electromyographic noise contamination.

Although SSVEPs can be elicited by several types of visual stimuli, the underlying idea is always a blinking or moving visual stimulus at a constant frequency which is called the stimulus frequency. This elicits a response in the brain at the same frequency as the stimulus frequency and its even harmonics. Some scientist define the boundaries to be in the range from 3 to 50 Hz, however flickering stimuli at frequencies below 3 Hz and up to 80 Hz can elicit SSVEPs. A general definition of SSVEPs: *SSVEPs are evoked responses induced by flickering visual stimuli. SSVEPs are periodic, with a stationary distinct spectrum showing characteristic SSVEPs peaks, stable over time. SSVEPs are better observed in the frequency or time-frequency domains.* Regarding the complexity of distribution of the SSVEP, there are three theories:

1. SSVEPs originate in the primary visual cortex and propagate by the combined activity of locally and broadly distributed sources.
2. SSVEPs are generated by a finite number of electrical dipoles that are activated sequentially in time, starting with a dipole located in the striate cortex.
3. VEPs originate in the primary visual cortex, and propagate to other brain areas through cortical and standing wave.

All three have in common that SSVEPs propagate, starting at primary visual cortex and involve more than one single source dipole. Theory 1 offers better explanation regarding all available data (EEG and fMRI/PET), however introduces distinction between long distance and local brain dynamics which is a usual aspect of EEG models, but not for fMRI/PET models.

## **SSVEP components**

Usually three different components are distinguished:

- Primary component in the gamma 25 to 60 Hz range with small interindividual variability and latency of about 30 to 60 ms.
- Secondary component in the range from 15 to 25 Hz with higher interindividual variability and latency of about 85 to 120 ms.
- Rhythmic after-discharge below 15 Hz with latency of 135 to 350 ms (average 250 ms). For this component to reach steady-state level after stimulation starts takes several cycles. Also, it does not stop immediately after turning off stimulation.

The three components may appear by applying averaging, but are often extracted more effectively by applying Fourier analysis.

### **Visual attention**

Visual attention is the most well known cognitive mechanism studied regarding SSVEPs. Visual evoked responses are enhanced if the stimuli fall within the area of spatial range and this is more prominent in the right frontal hemisphere than in the left, but this distinction disappears after long exposure to the stimuli. When red and blue dots are flickering at differing frequencies and subjects focus on either one of the two, amplitudes for the stimuli that is focused on increases.

Binocular rivalry is a paradigm that regards conscious visual perception. Two incongruent visual targets are presented, one target in the visual hemifield and the second in the other hemifield, but only the subject knows which target he or she focuses on. It has however been shown that the amplitude of the target the subject focuses on is enhanced.

### **Applications in clinical neuroscience**

SSVEPs have potential for application in multiple fields of clinical neuroscience, both as a diagnostic and study tool, used to investigate pathological brain dynamics. Fields include:

- Aging and neurodegenerative disorders, like degrading memory due to natural aging, but also Alzheimer and Parkinsons disease.
- Schizophrenia
- Ophthalmic pathologies, dealing with diagnosis and characterization of neoplastic and non-neoplastic diseases of the eyes
- Migraine
- Depression
- Autism
- Anxiety & stress
- Epilepsy

#### **4.3.2 SSVEPs for BCI**

BCI systems have to react fast enough to human commands, so the brain signals that are used should have good time resolution. For SSVEP BCI the general idea is to encode human commands in flickering lights which induce SSVEP responses at different frequencies, allowing for users to control applications by focusing on the in different frequencies flickering lights. SSVEP based BCI can potentially achieve a higher ITR. Non-SSVEP based BCI can reach around 10-25 bits/min, compared to about 100 bits/minute for SSVEP based BCI. Also

SSVEP based BCIs can be used by around 90% of people without much training. Higher ITR is caused by the following reasons:

- Increasing the number of commands does not necessarily mean decreasing the ITR, whereas for many other BCI types this is the case.
- SSVEP is triggered by external stimuli, which are easier to control than internal stimuli.

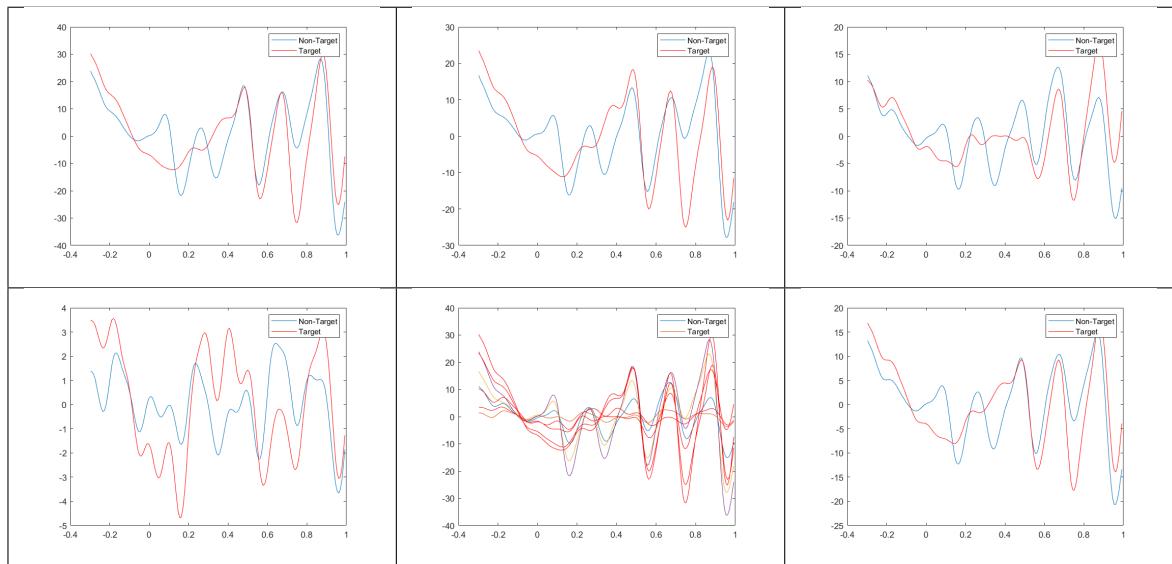
## 4.4 Lab session

The lab of this week deals with automatic detection of P300 signals (Part 1) and automatic detection of SSVEP signals (Part2).

### 4.4.1 Part 1

#### Exercise 1

In the first exercise we have to plot averaged P300 and non-P300 trials of several sets of electrodes. It is expected to see a third peak between 250 and 500 ms. The plots of the trials of electrodes Cz, Fz, Pz, Oz, [Fz,Cz,Pz,Oz] and the average of [Fz,Cz,Pz,Oz] can be seen in table 4.1.



**Table 4.1:** Exercise 1. Row one: Cz, Fz, Pz. Row two: Oz, [Fz,Cz,Pz,Oz], average [Fz,Cz,Pz,Oz].

For all trials we can see that there are higher amplitudes already before the stimulus which decrease then at  $t = 0$ , and increase again afterwards in an oscillating manner. We can see the P3 at roughly 500 ms for Pz, Cz and Fz as expected, however there are also higher peaks after the P3. The Cz has the highest amplitude with  $30 \mu V$ , while Fz and Pz have an amplitude about  $20 \mu V$ . The Oz electrode is located in the back of the brain and is related to visual processing of the brain. The signal does not look a typical P300 response but shows

phase locking in the target and non-target signal, in addition the amplitude is with  $3.5 \mu V$  considerably lower than the ones measured at the other electrodes. The phase locking is also visible after the stimulus in the averaged signal of the [Fz,Cz,Pz,Oz] electrodes after 500 ms.

### Exercise 2

In the second exercise we will analyze the classifications results when using different channels. We will compare only Pz, only Cz, [Fz, Pz, Cz, Oz], the mean of [Fz, Pz, Cz and Oz], and all channels. Running the algorithm for all of these channels gives accuracy, AUC, recall and precision values as depicted in table 4.2.

Channel	Accuracy	AUC	Recall	Precision
Pz	0.537	0.547	0.518	0.184
Cz	0.567	0.587	0.561	0.206
(Fz, Pz, Cz, Oz)	0.748	0.809	0.734	0.371
AVG (Fz, Pz, Cz, Oz)	0.553	0.562	0.554	0.198
All	0.911	0.920	0.806	0.704

**Table 4.2:** Accuracy, AUC, recall and precision values for the classification using only Pz, only Cz, [Fz, Pz, Cz, Oz], the mean of [Fz, Pz, Cz and Oz], and all channels.

We can see that using all channels gives the best results with an of 0.911, AUC of 0.920, recall of 0.806 and precision of 0.704, 'slightly' followed by using the Fz, Pz, Cz, Oz channels. Using just the Pz, just the Cz or the average of the Fz, Pz, Cz, Oz channels performs considerably worse.

### Exercise 3 & 4

Initially a time span of 0 to 0.5 seconds and a down sampling factor of 4 has been used. In this exercise we will change the down sampling time and select different time segments, using all channels as these gave the best results so far. First, the start time will be limited, afterwards the end time. based on the best result, we will then decrease / increase the down sampling factor. The results of this can be seen in tables 4.3 and ??

Time	Accuracy	AUC	Recall	Precision
0.1 - 0.5	0.915	0.922	0.827	0.710
0.2 - 0.5	0.904	0.931	0.842	0.669
0.3 - 0.5	0.884	0.906	0.813	0.614
0.2 - 0.6	0.914	0.938	0.849	0.698
0.2 - 0.7	0.912	0.933	0.813	0.706
0.2 - 0.8	0.893	0.904	0.777	0.651

**Table 4.3:** Changing start and end time for the classification using all channels.

Limiting the start time increases all values, but decreases however after a start time of 0.3 seconds. ]Using a start of 0.2 seconds, first a better result with an end time of 0.6 seconds

<b>Factor</b>	<b>Accuracy</b>	<b>AUC</b>	<b>Recall</b>	<b>Precision</b>
2	0.892	0.924	0.755	0.652
3	0.910	0.934	0.813	0.698
5	0.898	0.928	0.799	0.661
6	0.898	0.929	0.806	0.659
7	0.881	0.910	0.791	0.611

**Table 4.4:** Changing down sampling factor for the classification using all channels and a time span of 0.2-0.6 seconds.

but starts to decrease with increasing end times. Using a time span of 0.2 - 0.6 second, we get decreasing values for increasing and decreasing the down sampling factor. Thus, the best result is achieved using all channels, a time span of 0.2 - 0.6 seconds and a down sampling factor of 4, giving an accuracy score of 0.914, AUC of 0.938, recall 0.849 of and precision of 0.698.

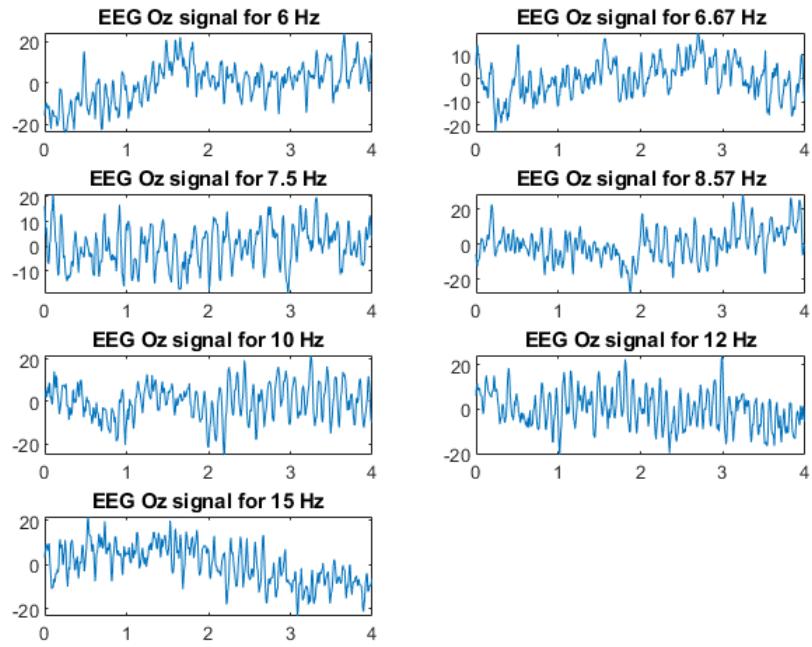
However, important to note is that we use all channels it might be that we not detect the P300 but correlating signals and possibly other artifacts which means that the classifier is then not necessarily build on the P300 response. In that case the classifier might work for these data set, but for another data set / person it is likely that the classifier needs other parameters to achieve high performance metrics.

#### 4.4.2 Part 2

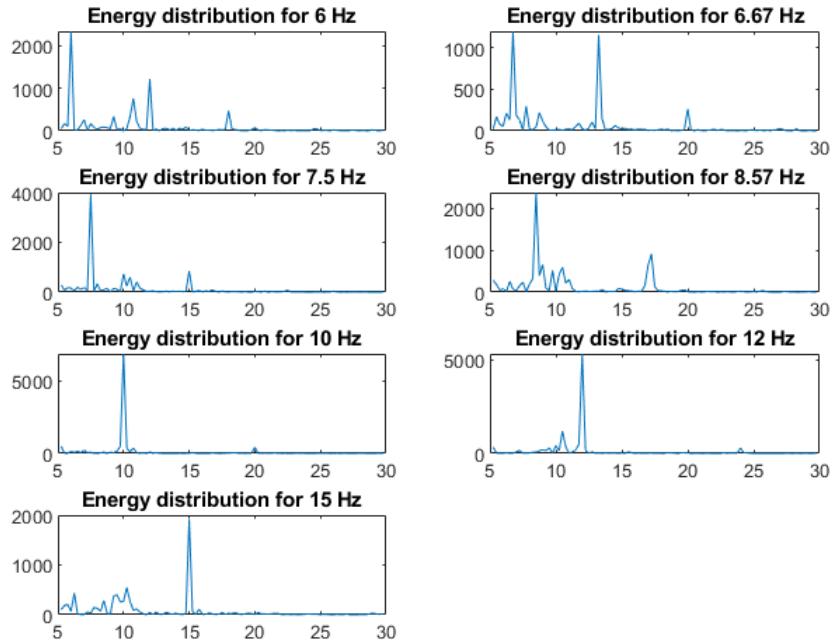
##### Exercise 1

In the first exercise of the second part of this lab we have to compute for a given set of stimulation frequencies( 10Hz, 12Hz, 15Hz, 6.67Hz, 6Hz, 7.5Hz, 8.57Hz) the average of all trials corresponding to the stimulation frequency and compute and visualize the frequency power plot using the FFT. The dataset corresponds to the paper "Comparison of PSDA and CCA detection methods in a SSVEP-based BCI-system" by G. Hakvoort et al. [23], where 25 trials have been conducted per stimulation frequency. Plotting the EEG signal for channel OZ for the various stimulation frequencies in the time and frequency domain can be found in figures 4.8 and 4.9. Plotting the average of all trials per stimulation frequency in the frequency domain can be found in figure 4.10.

We can see in figure 4.9 that all stimulation frequencies are easily identifiable with a large peak at the corresponding frequency, except for the stimulation frequency of 6.67 Hz, which has a peak at 6.67 Hz but also a peak at 13.25 Hz, both having a roughly equal magnitude. Calculating the average of all trials in the frequency domain as shown in figure 4.10 gives similar results as in the previous graph, however the 2nd peak for the 6.67 Hz stimulation frequency has significantly diminished. In addition, the plot for the stimulation frequency of 8.57 Hz shows now at 5, 10.25, and 17 Hz but not at 8.57 Hz. At this point it is not clear to us why this is happening.



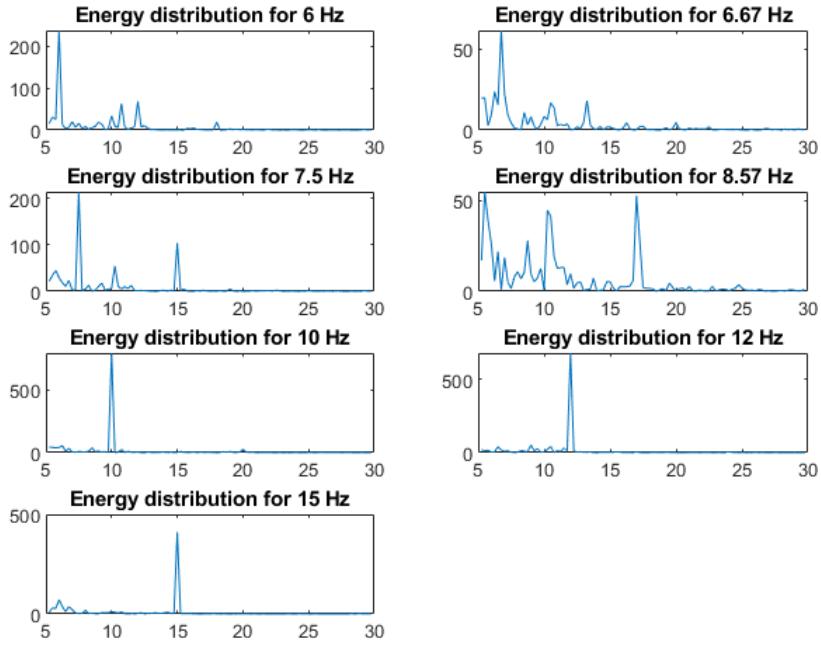
**Figure 4.8:** Plotting stimulation frequencies in the time domain.



**Figure 4.9:** Plotting stimulation frequencies in the frequency domain.

### Exercise 2

In this exercise we will know try to classify the signal using the FFT of the signal with a LDA classifier. In addition, we will first apply a Tukey window with a cosine fraction of 0.5 and detrend the signal. Doing so we obtain the confusion matrix shown in figure 4.11 and an accuracy of 94.3%.



**Figure 4.10:** Plotting the average of all trials of the stimulation frequencies in the frequency domain.

8	0	0	0	0	0	0
0	12	0	0	0	0	0
0	0	15	0	0	0	0
0	0	0	16	0	0	0
1	0	2	0	11	1	0
0	0	0	0	0	12	0
0	0	1	0	0	0	9

**Figure 4.11:** Confusion matrix for the LDA classifier.

### Exercise 3

In this exercise we investigate the effect of windowing and detrending. EEG data can drift due to changes in temperature of the experiment room for example. One way of dealing with this is to detrend the data in order to make it stationary. Not detrending the data gives in this case a performance of 0.932%. Next, the FFT function assumes that input signals are periodic, however, if they are not periodic, discontinuities will appear in the output signal. Windowing can be used to make the input signal period by multiplying it for example with a sinusoidal function. Not windowing the data in this case gives a performance of 86.4% accuracy. Not windowing and not detrending however gives a performance of 89.8% accuracy, which is higher than not windowing but detrending. At this point it is not known to us why this is happening.

#### Exercise 4

In this exercise will implement a canonical correlation analysis (CCA) and compare it with the performance of the FFT approach when classifying the SSVEP data. CCA is a correlation method that focuses on two sets of variables [23]. The goal of CCA is to find pairs of linear transformations for the two sets such that when the transformations are applied the new sets of variables have a maximal correlation. In the case of SSVEP, CCA-based detection techniques calculate the correlations between the brain signals and the given stimuli frequencies by creating various reference signals. After having implemented the CCA, we obtain an accuracy of 94.9% and the confusion matrix shown in figure 4.12. Comparing to the accuracy of the FFT approach (94.3%), the CCA approach gives a slightly better performance in terms of accuracy.

25	0	0	0	2	0	0
0	25	0	0	4	0	0
0	0	25	0	0	0	0
0	0	0	23	1	0	0
0	0	0	1	18	0	0
0	0	0	0	0	25	0
0	0	0	1	0	0	25

**Figure 4.12:** CCA confusion matrix.

# 5 | Week 5

In week 5 we are going to explore adaptivity and machine learning, error potentials, neuro-feedback, neuromarketing and imaginary movement.

## 5.1 Adaptivity and Machine Learning

How can we utilize machine learning to adapt a BCI to a specific person [8]?

### 5.1.1 Adaptivity in BCIs

For most BCI applications, the parameters needed for the best accuracy are *a priori* unknown. They depend on highly variable factors such as sensor placement and subject state, vary from person to person, but also depend on hard to measure factors such as functional brain map as well as expensive to measure factors such as brain folding. We can use calibration / training data to estimate these parameters from and a separate calibration step to build a BCI model. Ideal calibration data is collected with the same measurement equipment as used for online applications, comprises multiple independent trials in order to quantify variability, is collected under conditions that are as close to those of the online application as possible (e.g. same person, same sensor arrangement, task parameters should be similar, etc.). If the data is biased by for example the use of different sessions, the data should cover multiple sessions to capture variability. Plain EEG recordings that are unlabeled means that there is no knowledge about the association between raw observed signal and the cognitive state variable of interest. However, labeled data (e.g. person is (not) surprised) is far more useful than unlabeled data as these relate to input / output pairs of the envisioned BCI application. Next to calibration data, we can also utilize prior knowledge which may include anatomical atlases and functional atlases (if available), but also timing information (e.g. neural latencies, reaction times) and frequency bands of oscillatory processes(alpha, beta, theta, etc.).

### 5.1.2 Machine learning

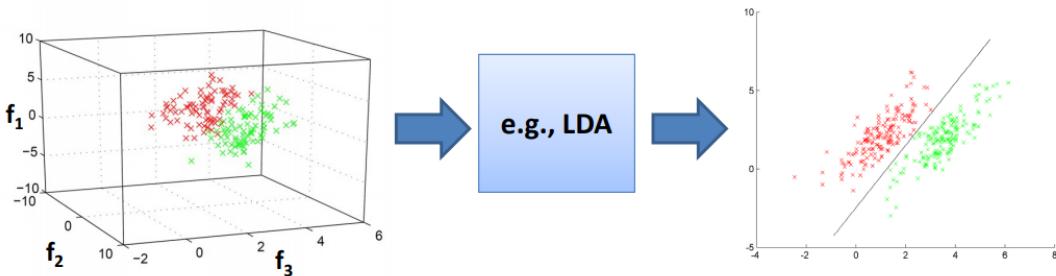
Machine learning is a very rich field in computer science that employs various algorithms to classify data based on a set of certain features and is related to other fields such as probability theory, statistics, optimization, neural networks, artificial intelligence. Most methods are based on supervised learning which entails the training a model on a training data set (commonly 75% of the total set) and testing the model on new, unseen data, the test set

(the remaining 25%). The data typically consists out of 2 matrices, a X matrix that holds various features with numerical values and the Y matrix that provides information about the labels. Other sub-types of machine learning include unsupervised learning, where given a set of training example with no labels, the structure in the input space is learned (e.g. clusters, manifolds, probability density); semi-supervised learning, where some training examples have labels and others do not; and other sub-types such as active learning or online learning.

In the context of BCI applications, often one trial segment is extracted for every target marker in the calibration recording and used as a training exemplar  $X_k$  while the associated label  $Y_k$  can be deduced from the target marker. The training function then computes a parameter of the prediction function such that the performance on the given data is optimal. Common machine learning methods typically do not work well when applied to raw signal segments of the calibration recording as the data is too high dimensional which will lead to over-fitting and also has a too complex structure to be captured which leads to too much modelling freedom. To obtain meaningful models, feature extraction needs to be utilized that transforms raw data into feature vectors, which lowers the dimensionality of the data. Feature selection depends on the process of interest, for oscillations, the log-variance or parts of the Fourier spectrum might be of interest while for ERPs, peak latency, height, width, as well as the mean in one or more time ranges relative to the event and subsets of wavelet coefficients might be of interest.

### 5.1.3 Case: LDA classifier

Given the task that a person is presented with a sequence of images of which one half is exciting and the other half is not, how can we design a BCI that can determine whether a person is shown an exciting or a non-exciting image? One approach to solve this problem is as follows: First, cut out an epoch  $X_k$  of 1s length for each trial and extract a short vector of features  $f_k$ , and assign a label  $y_k$  in exciting (E) or non-exciting (NE). Prominent peaks can be characterized by width, height and latency. Plotting the 3-element feature vectors for all exciting trials in red, and non-exciting trials in green, we obtain two distributions in a 3d space, where the feature vectors are passed on to a machine learning function as shown in figure 5.1.



**Figure 5.1:** On the left, feature vector with 3 dimensions (Height, width, latency), on the right, both classes E and NE are separated by the LDA [8].

In this case, a relatively simple model is being used, the Linear Discriminant Algorithm (LDA), which generates parameters of a linear mapping. The LDA model assumes that the data in each class is distributed according to a Gaussian distribution and that the shape of the distribution is identical for all classes. This way we obtain a simple, fast and optimal in the large-sample limit if assumptions are true. However, this model is very sensitive to outliers, in addition, the covariance matrix estimates become unreliable / unusable for too few trials and too many dimensions

#### 5.1.4 Performance Evaluation

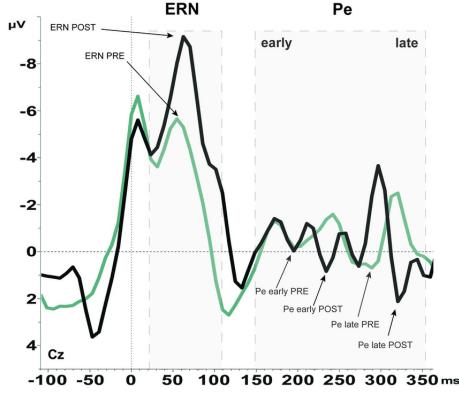
Common evaluation strategies compute the loss estimate between a vector of predictions  $p$  and a vector of targets  $t$ , such as the mean-square-error or the miss-classification rate. Other typically used evaluation metrics are accuracy, precision, recall or the F1 score. If there is only one data set available, cross validation can be used, which means that the data set is split multiple times into training/test blocks where each trial is used once for testing. In machine learning, typically randomized cross validation is preferred, however as EEG data is time related, block wise cross validation is preferred. In addition, as neighboring trials are more closely related than training and test online data, a margin of several trials/seconds should be left between the training and test set. Usually 5 or 10 fold cross validation is done to evaluate the data.

## 5.2 Error Potentials

In this section, we will describe what error potentials are and how they can be used for BCI applications, based on the slides from Bhowmick and Gulhane [24], and the paper "EEG-based communication: presence of an error potential" by Schalk et al. [25].

Error related potentials (ErrP) are responses that can be measured when a person recognizes an error during a task. ErrPs can consist out of 2 components as shown in figure 5.2, the error-related negativity (ERN or Ne) which occurs at around 50–100 ms after an erroneous response; and depending on the task, an error positivity (Pe) that follows the ERN which can be further divided into frontocentral and centroparietal components. The frontocentral Pe, which appears to be related to the P3a, appears directly after the ERN, while the late Pe seems to be related to the P3b and appears in the centroparietal region with a latency of 200–400 ms after the error. Furthermore, studies suggest that the negative components are linked to error processing and reward prediction [26], [27], while the positive component is associated with conscious error perception [28].

As EEG-based applications often face errors due to transmission, the paper "EEG-based communication: presence of an error potential" by Schalk et al. [25] compares EEG data immediately after correct target selection to data after incorrect selection in order to develop a method to detect error potentials. The results of the experiment showed that mistakes are followed by a positive potential centered at the vertex, peaking about 180 ms after the incorrect selection. This "suggest that this error potential might provide a method for



**Figure 5.2:** Error-Related-Negativity (ERN) and Error Positivity (Pe) [29].

detecting and voiding errors that requires no additional time and could thereby improve the speed and accuracy of EEG-based communication”.

### 5.3 Neuromarketing

This section is about neuromarketing and how and whether neuroscientific technologies can be effectively employed to better understand the human (consumer) behaviour in real decision-making contexts [30]. One of the most important question in marketing is what drives consumers to decide on one product instead of another and why consumers interact with a specific brand? This lead to a growing interest in understanding how brain responses reflect the decision-making process of consumers. The practical use of neuroimaging / neuroscientific tools in real contexts and stimuli is termed neuromarketing and is defined as ”the application of neuroscientific methods to analyse and understand human behaviour in relation to markets and marketing exchanges”. Neuromarketing studies investigate different brain regions while experiencing marketing stimuli in order to relate customer behaviour and neurophysiological states, measure processes such as decision-making, reward processing, memory, attention, approach and withdrawal motivation, but also emotional processing. Combining knowledge from brain anatomy and physiological functions of brain areas, it is possible to model neuronal activity based on specific human behaviours, describe the dynamics of human decisions but also understand the usual mismatches between consumers’ thoughts and their actions.

#### 5.3.1 Added Value of Neuromarketing

Traditional techniques in marketing research allow to measure the cognitive and emotional experiences only as verbally expressed at the conscious level during the interview and are hence dependent on the good faith and accuracy of the experimental subject reporting his own sensations and opinion. By employing brain imaging techniques, it is possible to distinguish the unconscious states related to processes determine influencing behaviours, integrating what can be found by verbal or written declarations. Other added values in marketing are for example that neuromarketing allows us to identify advertising elements that trigger positive

feelings and select visual and audio features, as well as the timing and selection of appropriate media. In addition it may be possible to identify causes of purchasing disorders such as compulsivity and develop more effective social campaigns (e.g. anti-smoking). Furthermore, neuromarketing can be used to evaluate the strength of emotional attachments to a brand and what stimuli should be implemented accordingly to encourage purchases. Moreover, whereas traditional marketing research focuses on system 2 processes in our brain (slow, voluntary, and under our control), neuromarketing allows us to measure system 1 process as well (fast, automatic, and outside our volitional control), providing new insights to understand how and why consumers respond to marketing stimuli. However, there has also been some critique of neuromarketing. Some researchers argue that the use of neuromarketing would affect consumers' ability to avoid marketed products, leaving them unable to resist such efforts and making them easy targets for the company's campaigns. Other researchers claim that neuromarketing is "science fiction rather than reality-based science, given that thoughts are individual and strictly dependent on personal experiences and character, which makes virtually and practically impossible to find people with identical thoughts".

### **5.3.2 Main Brain Areas and Processes of Interest for Neuromarketing**

Next, brain regions that are of interest for neuromarketing will be described. For decision making, studies suggest that several regions of the prefrontal cortex (PFC), situated in the frontal lobe of the brain, are relevant. In particular the orbitofrontal cortex (OFC), the dorsolateral prefrontal cortex (DLPFC) and the ventromedial prefrontal cortex (VMPFC) are of interest for decision making. The OFC is associated with the evaluation of trade-off and plays central role in choosing appropriate behaviours, especially in unpredictable situations. The DLPFC is also an important factor in decision-making due its involvement in cognitive control over emotion and contribution to impulse control for complying with social norms. Moreover, research suggests that the VLPFC contributes to motivating social norm compliance by projecting the threat of punishment from others in case of noncompliance.

Next, reward system of the brain is mainly based on the activation of the striatum, a striped mass of white and grey matter located in the basal ganglia inside the forebrain. Research suggests that the striatum and its components (putamen, caudate nucleus, and nucleus accumbens) play an important role in the evaluation of expectations compared to actual rewards received and the influence of social factors on this region's reward-related activity. In the addition, the ventral tegmental area (VTA) is also part of the reward system, as it passes the neurotransmitter dopamine to other brain regions, enabling the modulation of decision making and affecting in goal-seeking behaviours. Measuring activities in these regions can help to determine which kinds of product design or brands can be considered as rewarding stimuli within consumers' brains.

Another key question in marketing is to what consumers direct their attention towards once they are exposed to several rapidly identified choice alternatives (i.e., brands and communications). The prefrontal cortex has been identified to direct towards and focus on attention and has been shown to connect with the neurons responsible for processing visual stimuli

in the occipital lobe. In addition to attention, memory-related mental processes might provide useful insights into variables influencing consumer behaviour such as brand awareness, product experience, and advertising recall. The hippocampus, plays an important role in generating different forms of memory as well as in memory processing and consolidation, in long-term memory, and in the acquisition and recall of declarative memory. Moreover, the amygdala, located next and closely related to the hippocampus, is an important modulator of the memory system, especially in memory consolidation.

mental workload is the level of effort to process information, caused from both the external and internal environment of a person, where the internal environment reflects the thoughts of that person. In addition, mental workload can be defined as "as a hypothetical construct that describes the extent to which the cognitive resources are required to perform a task actively engaged by the operator" or as "the process that emerges from the interaction between the requirements of a task and the circumstances under which it is performed and the skills, behaviours, and perceptions of the operator". Several studies have shown the correlation of spectral power of the EEG with the complexity of the task that the subject is performing. In particular, an increase in the theta band spectral power (4–7 Hz), especially on the frontal cortex can be observed as well as a decrease in the alpha band (8–12 Hz), over the parietal cortex. In marketing research, it is very important to measure mental workload when customers are involved in a specific operational task, e.g. For example, in usability test when people look for a landing page on a website or when people visit a store.

Another brain process relevant for neuromarketing is emotional involvement in the context of marketing stimuli. Emotional processing has been linked to activity in prefrontal and frontal cortices (PFC and FC, respectively), where the PFC region plays an important role in the generation of emotions. In addition, studies regarding EEG spectral power analysis indicate that the anterior cerebral hemispheres are differentially lateralized for approach and withdrawal motivational tendencies and emotions. In particular, the left PFC mediates appetitive approach behaviour, while the right PFC appears to play an important role in instantiating defensive withdrawal. Furthermore, fMRI research suggests that, when a reward is being enjoyed, activity in the orbitofrontal cortex (OFC), especially in its medial parts, correlates with subjective reports about the pleasantness or valence of the experience. However, it is still an open question is which neural systems encode negative experiences. Studies have shown that unpleasantness of taste correlates with brain activity in the lateral OFC and left dorsal anterior insula/operculum, whereas the size of abstract punishments (i.e., losing money) activates lateral parts of the OFC. However, the problem in investigating negative experience is to dissociate it from intensity, as negative experiences are usually perceived to be more intense and thus are often confounded. Neuromarketing studies are based on the theory of a left-right asymmetry of frontal EEG signals, where relatively greater activity in the left frontal region is associated with either positive emotional experience. The paper leaves the question open whether negative emotions are related with just the right frontal region. Studies suggest that the amygdala is involved in the regulation of emotional responses and in the processing of negative emotions and unknown stimuli, as well as in aversive responses to inequity. In addition, it is also known as a locus of aversive and fear

memory and has been shown to be involved for positive emotions even with minor extents of negative emotions, usually in relation to rewarding stimuli. Another brain region that plays an important role in the processing of negative experiences is the insula (or insular cortex) which is involved in the perception and expectation of risks, especially when making decisions for which a social or financial risk is expected. Moreover, the activation of the insula has been associated with anger and disgust in response to unfair economic situations. Another region of interest is the anterior cingulate which has been associated with the experience of an internal conflict between alternative options, and its activation could reflect the conflict between cognitive and emotional motivations.

Important to note is that there is "not a single brain region responsible for emotional processes, and no single brain region is activated in relation to one particular type of emotion as the interconnected cerebral network involved in emotion is very complex". However, it is possible to assess the emotional state of the subject by monitoring autonomic activity such as the heart rate (HR) and skin conductance (SC), as emotions are accompanied by physical reactions that are partially beyond an individual's control and can therefore be used to overcome the validity problem of self-reports. These autonomic reactions include facial expressions but also physiological reactions (e.g., sweating) primarily caused by changes in the autonomic nervous system (ANS). SC is a frequently used measure of activation of the autonomic nervous system as it is related to the level of sweat in the eccrine sweat glands, which are involved in emotion-evoked sweating. Because the increase in activation of the ANS is an indicator of arousal, SC can be used as a measure of arousal. HR can be, for both attention and arousal, a valid, real-time, and continuous measure, as there is a phasic deceleration when attention increases. Arousal on the other hand is accompanied by a tonic acceleration in the heart rate. Furthermore, HR can give an indication of the valence of an emotional response, "compared to neutral stimuli, both positive and negative stimuli first exhibit a phasic decrease in the HR. [...] At a tonic level, positive stimuli evoke an increase in the heart rate, while negative stimuli generally lead to a decrease in the heart rate".

### 5.3.3 Neuropolitics

Neuropolitics is defined by A. Gutierrez-Rub, as a "new discipline capable of understanding the brain of people in their capacity as citizens, voters or activists that allows knowing and understanding how it works, how it articulates images, values, feelings and channels its decisions". Neuropolitics includes a set of techniques aimed at predicting the outcomes of the electoral process and success, as well as the design and elaboration of communication campaigns meant to seduce it. Based on the theory of affective intelligence, the most important emotions for political behaviour are enthusiasm and fear. Using Neuromarketing, researchers claim that it is possible to analyse how effective political campaigns are and how they can influence votes for candidates from an unconscious level. Kanai [31] suggests that, at a physical level, there are differences in the brain of conservatives and liberals and, therefore, a difference between cognitive systems. Studies claim that the more liberal people were, the more volume of grey matter in the cortex of the anterior cingulate could be found, while the

more conservative people were, more volume of grey mass in the right amygdala of the brain could be found. In another study, Vecchiato [32] investigated the brain activity of swing voters and supporters during a speech of the Italian prime minister in 2009, claims that for "for the supporters, a greater power spectral activity was observed throughout the speech than the swing voters, who were less attracted by the speech".

#### 5.3.4 Ethical Issues

Neuromarketing is a new and emerging research field but it is also seen very controversial under researchers. On the one hand, it raises concern regarding protection of different parties that may be harmed or exploited, consumer autonomy protection, as well as transparency. Vulnerable populations such as children, people with neurological or pathological disorders or people sensitive to advertisements should not be capitalized on by Neuromarketing methods. In addition, critique has been expressed regarding the autonomy of consumers, companies might be able by examining the cognitive processes related to individuals' consumption preferences to identify and trigger buying mechanisms that suggest unconsciously the purchase of otherwise unwanted items, making consumers more transparent and promoting addiction and overconsumption. Furthermore, concerns have been raised regarding the transparency in the methodologies used by neuromarketing companies that employ proprietary methods that are not fully validated or disclosed to the scientific community which makes it difficult to classify supported and unsupported claims of validity of the services offered by those companies which in turn can create misperception and overestimation of the actual capacity of these methods.

On the other hand, Neuromarketing also has positive "aspects", such as advancing the understanding how human beings create, store, recall, and relate to information such as brand messages in everyday life. In addition, Neuromarketing may help to discover whether "certain aspects of advertisements and marketing activities are able to trigger negative effects, such as overconsumption" or compulsive purchases. In order to make use of these more beneficial traits of Neuromarketing, researchers suggest an ethical code that includes amongst other things the protection of research subjects and vulnerable niche populations from marketing exploitation, full disclosure of procedures and results as well as goals, risks and benefits, which would facilitate accurate media and marketing representation as well as internal and external validity. Cherubino et al. [30] state that if Neuromarketing would comply with such an ethical code, "here should not be any ethical or moral problems: on the contrary, neuromarketing could actually help marketers understand consumer behaviour and as well help companies find business solutions that precisely respond to their needs".

### 5.4 Neurofeedback

In this section we will investigate what neurofeedback is, what types of neurofeedback exist, electrode placements as well as protocol treatments and applications [33]. Neurofeedback is a method that assists participants to control their brain waves consciously by measuring brain

waves and providing a (usually audio or visual) feedback signal. During this process, subjects become aware of the changes that appear during training and are able to assess their state in order to achieve optimal performance.

#### **5.4.1 Electrode Placement**

Commonly, two types of unipolar and bipolar montage are used in the neurofeedback treatment. For the unipolar mode, the active electrode is placed on the skull and the recorded signal by the active electrode is compared to a reference electrode where the activity from the reference electrode is subtracted from the activity of the active electrode in order to obtain the brain activity at the active electrode. In contrast, the bipolar mode uses two active electrodes that are separately placed on the scalp which allows for the common mode rejection that occurs during the recording procedure. For any external artifact occurring at both channels and at the same time, the amplitude and phase of this artifact can be subtracted and the spatial selectivity can be improved.

Electrode placement is applicable to various brain functions, dependent on specific symptoms specific symptoms. For example, frontal lobes are associated with immediate and sustained attention, time management, social skills, emotions, empathy, working memory, executive planning. Parietal lobes are associated with solving problems conceptualized by the frontal lobes. For example, complex grammar, naming of the objects, sentence construction, and mathematical processing are related to the left parietal lobe while map orientation, spatial recognition, and knowing the difference between right and left are related to the right parietal lobe. Temporal lobes have various functions such as reading & word recognition, memory, learning (left hemisphere); and music, anxiety, facial recognition, and sense of direction (right hemisphere). Occipital lobes are associated with visual memories, accurate reading and traumatic memories accompanying visual flashbacks. In addition, occipital lobes are also related to proxemics, colour recognition, identifying objects, reading, writing, and spelling. Finally, the central lobes (sensory and motor cortex) are related to conscious control of all skeletal movements such as typing, playing musical instruments, handwriting, operation of complex machinery, speaking.

Researchers suggest that the motor cortex helps the cerebral cortex to encode both physical and cognitive tasks. Thus, subjects who have difficulties seeing the logical sequence of cognitive tasks may benefit from neurofeedback training along the left hemisphere sensorimotor cortex. Subjects may trained along the sensorimotor cortex for the treatment of stroke, epilepsy, paralysis, ADHD, and disorders of sensory/motor integration or epilepsy.

#### **5.4.2 Types of Neurofeedback**

There are 7 types of Neurofeedback: The most frequently used form of neurofeedback is frequency / power neurofeedback, which uses of 2 to 4 surface electrodes and is used to change the amplitude or speed of particular brain waves in specific brain locations to treat ADHD, anxiety, and insomnia. Slow cortical potential neurofeedback (SCP-NF), which improves the direction of slow cortical potentials to treat ADHD, epilepsy, and migraines. Low-energy neu-

rofeedback system (LENS) is a method that sends a weak electromagnetic signal to change the patient's brain waves while they are not moving with their eyes closed. This technique has been used to treat amongst others traumatic brain injuries, ADHD, insomnia, fibromyalgia, restless legs syndromes, anxiety, depression, and anger. Hemoencephalographic (HEG) provides feedback on cerebral blood flow to treat migraine. Live Z-score neurofeedback is a method that employs continuous comparison of variables of brain electrical activity to a systematic database to provide continuous feedback and has been used to treat insomnia. Low-resolution electromagnetic tomography (LORETA) monitors phase, power, and coherence and has been used to treat addictions, depression, and obsessive-compulsive disorder. Finally, functional magnetic resonance imaging (fMRI) is one of the more recent neurofeedback techniques and regulates brain activity based on the activity feedback from deep subcortical areas of the brain.

### 5.4.3 Protocol Treatments

Various protocol treatments exist for neurofeedback which mainly focus on the alpha, beta bands or a combination of them such as alpha/ theta ratio, beta/theta ratio. Protocol treatments have a range of applications. Alpha training is commonly used for treating pain relief, reducing stress and anxiety, memory improvement, improving mental performance, and treatment of brain injuries; whereas beta training is used for improving focus and attention, reading ability, computational performance, cognitive processing as well as for reducing of over-thinking, obsessive compulsive disorders (OCDs), alcoholism, and insomnia. A table giving an overview of recent protocol treatment studies and clinical applications can be found in figure 5.3 and 5.4.

However, there are methodological limitations and clinical ambiguities: for example, for alpha wave treatments it is unclear " how many sessions are needed before can learn to exert an alert control over their own alpha waves, or how many sessions are needed before such training procedures produce the expected effect on the optimal performance, and how long the desired effects last without feedback (long-term effects)". Marzbani et al. thus urge for standard protocols to perform neurofeedback in order to improve validity and effectiveness of treatments. Just like most treatments, neurofeedback has its pros and cons. Although it is a safe and non-invasive procedure that demonstrated improvement in the treatment of many problems and disorders (e.g. ADHD, anxiety, depression), the validity has been questioned in terms of conclusive scientific evidence of its effectiveness. In addition, it is an expensive procedure which is not covered by many insurance companies while it is also time consuming and long term benefits are not guaranteed.

	Site of treatment	Enhance/inhibit	Number of sessions	Outcome
(Allen, Harmon-Jones, & Cavender, 2001)	$F_3, F_4$	Enhance alpha (8-13 Hz)	5	Impact of self-reported emotional responses and facial EMG
(Angelakis et al., 2007)	$F_{o3}$	Enhance peak alpha (8-13 Hz)	31-36	Improve cognitive processing speed and executive function
(Hanslmayr, Sauseng, Doppelmayr, Schabus, & Klimesch, 2005)	$F_3, F_4, F_z, P_3, P_4, P_z$	Enhance upper alpha	1	Improvement in cognitive performance
(Hardt & Kamiya, 1978)	$O_z, O_1, C_3$	Enhance alpha (8-13 Hz)	7	Decrease anxiety
(Hord, Tracy, Lubin, & Johnson, 1975)	$O_2$	Enhance alpha		Help maintain performance such as counting and auditory discrimination
(Markovska-Simoska et al., 2008)	$F_3-O_1, F_4-O_2$	Enhance individual upper alpha	20	Increasing the quality of musical performance
(Martindale & Armstrong, 1974)	$O_z, P_4$	Reduction alpha (7-13)	1	High creative
(Plotkin & Rice, 1981)	$O_z$	Enhance alpha	5-7	Decrease anxiety
(Regestein, Buckland, & Pegram, 1973)	Parietal-occipital	Enhance alpha (8-13 Hz)	2	Decrease sleep need
(Schmeidler & Lewis, 1971)	Right occipital	both	2	Mood changes
(Zoefel, Huster, & Herrmann, 2011)	$P_3, P_z, P_4, O_1, O_2$	Enhance individual upper alpha	5	Enhancement of cognitive performance

**Figure 5.3:** Summary of studies using alpha protocol training [33]

	Site of treatment	Enhance/inhibit	Number of sessions	Outcome
(Rasey, Lubar, McIntyre, Zoffuto, & Abbott, 1995)	Central-posterior region ( $C_{pz}, P_{cz}$ )	Enhance beta (16-22 Hz) and inhibit high theta and low alpha	20	Improvement in attentional performance
(Egner & Gruzelier, 2001)	(12-15 Hz) at right central region ( $C_2$ ) and (15-18 Hz) at the left central region ( $C_3$ )	Enhance low beta (12-15 and 15-18 Hz), inhibiting theta (4-7 Hz) and high beta (22-30 Hz)	10	Successful enhancement of attentional performance
(Vernon et al., 2003)	$C_2$	Enhance low beta (12-15 Hz), inhibiting theta (4-8 Hz) and high beta (18-23 Hz)	15	Enhance cognitive performance
(Egner & Gruzelier, 2001)	$C_z$	Enhance SMR (12-15 Hz) and inhibit theta (4-7 Hz) and high beta (22-30 Hz)	10	Improve perceptual sensitivity
(Egner & Gruzelier, 2001)	$C_z$	Enhance low beta (15-18 Hz), inhibiting theta (4-7 Hz) and high beta (22-30 Hz)	10	Increase cortical arousal
(Vernon et al., 2003)	$C_z$	Enhance SMR (12-15 Hz) and inhibit theta (4-7 Hz) and high beta (18-22 Hz)	8	Increased recall in semantic working memory
(Lubar, Swartwood, Swartwood, & O'Donnell, 1995)	$F_{cz}, C_{pz}$	Enhance beta (16-20 Hz) and inhibit theta	40	Reduction of inattention, hyperactivity and impulsivity
(Fuchs, Birbaumer, Lutzenberger, Gruzelier, & Kaiser, 2003)	$C_3, C_4$	Enhance beta (15-18 Hz) and SMR (12-15), inhibit theta	36	Improvement in attention and intelligence
(Heinrich, Gevensleben, & Strehl, 2007)	$C_a, C_z$	Enhance SMR and inhibit theta		Treatment epilepsy disorder and ADHD
(Heinrich, Gevensleben, & Strehl, 2007)	$C_z, C_3$	Enhance beta (13-20 Hz) and inhibit theta		Treatment ADHD

**Figure 5.4:** Summary of studies using beta protocol training [33].

## 5.5 Motor Imaginary based BCI Feedback

This section will discuss imaginary movement (IM) BCI feedback and applications, as well as relevant feature extraction and classification methods. IM is defined as the cognitive process of imagining the movement of your own body part without actually moving that body part. IM in combination with BCIs has many applications such as mental practice (Visuo-motor imagery, improving motor behavior, simulating an action through imagination), sports, neurological rehabilitation, music, as well as cognitive neuroscience and psychology. Limitations of imaginary movement BCI applications include a lack of reliability, slow learning progress & long training times, poor performance, and fatigue; in addition, these factors can lead to demotivation and frustration which can in turn influence the performance negatively.

Relevant feature extraction methods for IM include fast fourier transforms (FFTs), auto-regressive models (AMs), wavelet transforms (WTs) as well as common spatial patterns (CSPs). On the one hand, FFT provides an accurate description of the frequency composition of a signal while being very efficient in terms of speed; on the other hand it does not take into account time information while also being challenging to use for non-linear signals. AM has advantage that it provides good frequency resolution and provides reasonable spectral estimates for short segments. However, the validity of the model depends highly on proper selection of the model order. WT provide improved balance between window length and spectral resolution and are better suited for sudden changes in signal. However, also it is important to select appropriate model parameters. CSP has the advantage that it is suitable for multichannel signal analysis and can be tuned to a subject specific frequency range. Howbeit, CSP does not able to handle temporal dynamics and has a slow convergence. Dependent on the IM application the right features must be chosen.

Common classification models for IM include linear discriminative analysis (LDA), support vector machine (SVM), neural networks (NN) and deep neural networks (DNN). LDA has the advantage that it is on the one hand very simple to use and requires on the other hand only very low computational power. However, as this algorithm is very simple, it is not suitable for complex non-linear EEG data. Next, SVM has better generalisation properties while being insensitive to dimensionality, however, it is not suitable for handling dynamic signals. NN provide reasonable trade-off between accuracy and speed but its need careful selection of model parameters. Finally, on the one hand, DNN is able to learn discriminant features and classifier simultaneously from raw EEG data but on the other hand it requires significant computational complexity for training and testing.

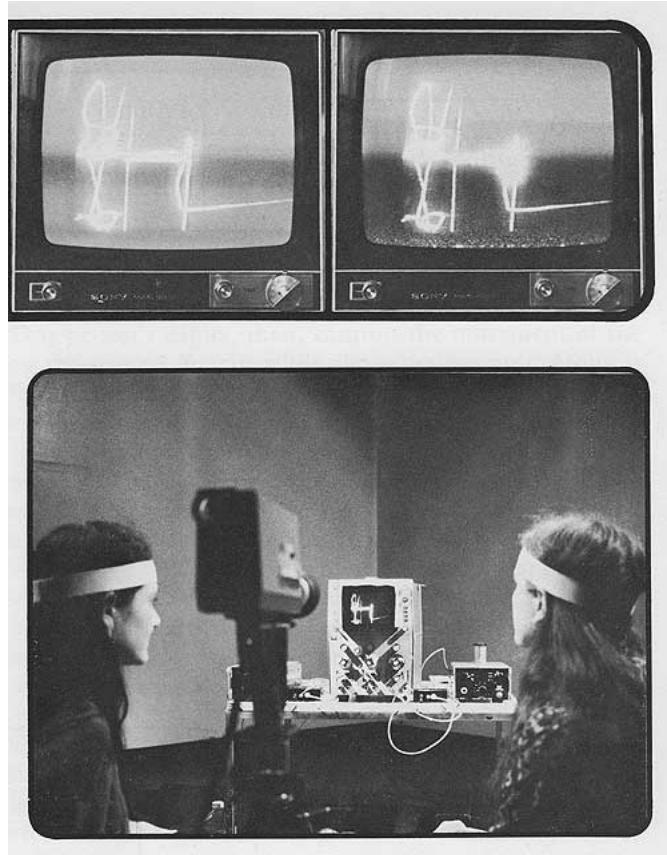
# 6 | Week 6

In this week we will explore the topics BCI art, mental state detection, Readiness potentials, CNV, and Multi-Brain interfaces.

## 6.1 BCIs & Art

In this section will be exploring how BCIs have been developed throughout history in relation to art [34]. The first art BCI installations appeared already in the early 1960s, many years before Jacques Vidal coined the term BCI in 1973. The so called “brain wave artists” were highly interested in the results of neuroscience research and the possibility to use brain waves in their installations and performances. They often cooperated with scientists and researchers, introducing ideas that were ”far away from the research of those days but could nevertheless be illustrated as ‘artistic hypotheses’ in their playful and artistic applications”. The artists often assumed that two persons interacting with each other’s brain waves, giving brain feedback to each other, were needed to get a certain artistic or playful task done. Most explorations in BCI related art evolved around using alpha waves which might be caused by the increasing association between recorded alpha waves and meditative and spiritual states at the time.

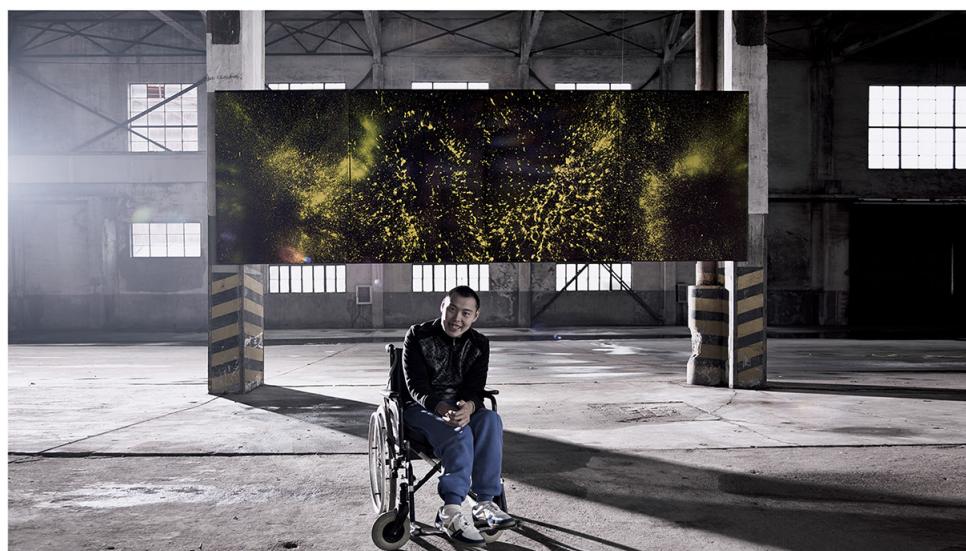
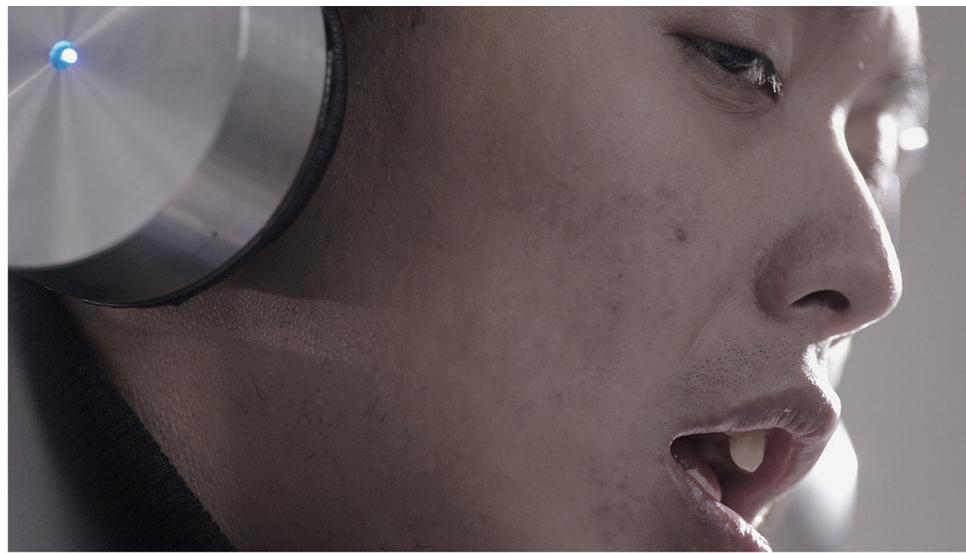
Early installations mostly involved audio-visual media as feedback from the brain waves. For example, the (best to our knowledge) first art BCI application was Lucier’s ”Music for Solo performer” in 1965 [34]. This installation used the alpha waves of a solo performer to excite percussion instruments while an assistant channeled the signals to the loudspeakers in various combinations. Another early art BCI installation was Rosenboom’s ”EEG-installation Ecology of the Skin” in 1970. Rosenboom combined alpha-feedback, synthesizers, phosphene stations, and oscilloscope displays to create group encounter brain bio-feedback performance system” for multiple participants. Other early art BCI installations include Jacqueline Humbert’s Alpha Garden (1973), in which two persons control the flow of water through a garden hose and sprinkler system by synchronizing their alpha activity; and Brainwave Etch-a-Sketch (1974), in which two participants control horizontal and vertical movements on an oscilloscope to create drawings, as depicted in figure 6.1.



**Figure 6.1:** Jacqueline Humbert, Brainwave Etch-a-Sketch, 1974 [35].

More recent installations include for example Mind art (2014), (Un)Focussed (2017), State dependency (2019) and Solaris (2016). In Mind art, the artist J. Xiong [36] collaborated with multiple handicapped individuals and gave them the chance to create art by triggering colour explosions via their brain waves, as shown in figure 6.2. The installation (Un)Focussed by A. Novello, M. Traenkle & I. Bol [37] is a live EEG performance that translates the brainwaves of the performers into sound, light and laser control, as can be seen in figure 6.3. The installation State Dependency - Audiovisual interaction through brain states by P. Neff is an audiovisual installation driven by entropy measures on motor imagery and various sensory modalities that "generates a highly accessible, reactive and immediate experience transcending common limitations of the BCI technology" [38].

Solaris [39] is an interactive BCI installation that aims to visualize the brain state of the user by dynamic movements of ferroelectric liquids. While some participants reported that the experience felt like a dialogue between user and installation, reflecting their thoughts and inner state, other participants reported that they had difficulties communicating with the installation and their interest shifted more towards the environment around them. Moreover, participants stated that they gained more control over the installation over time, indicating that here the participants learn to use the installation instead of the system having algorithms implemented that interpret the affective / mental state of the user.



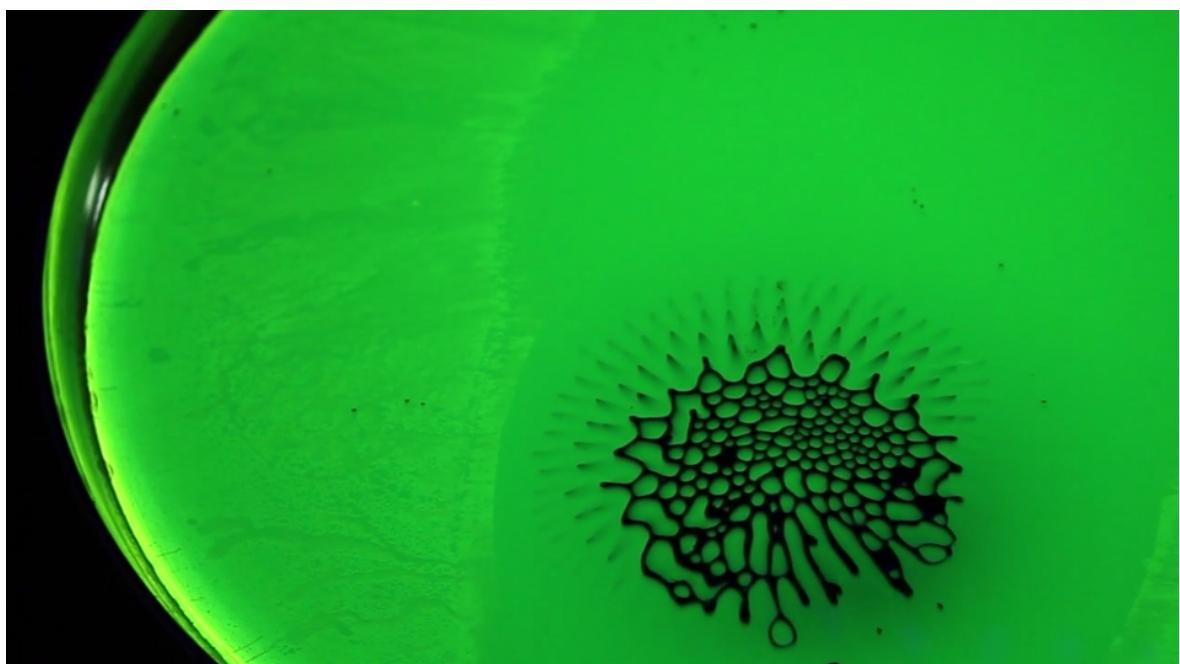
**Figure 6.2:** J. Xiong, Mind art, 2014 [36].



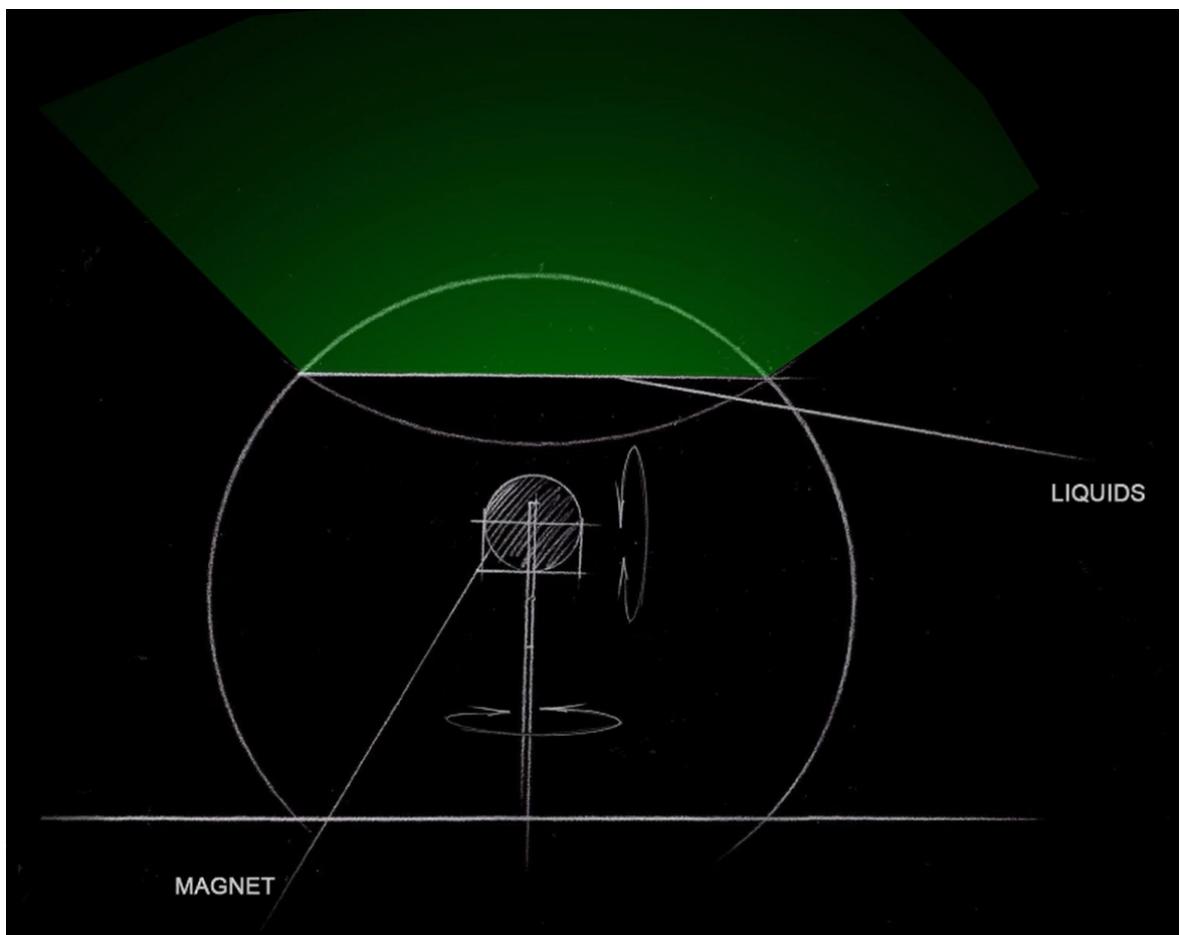
**Figure 6.3:** A. Novello, M. Traenkle & I. Bol, (Un)Focussed, 2017, [37].



**Figure 6.4:** P. Neff, J. Schacher & D. Bisig, State Dependency, 2019, [38].



**Figure 6.5:** ::vtol::, Solaris, 2014, [39]



**Figure 6.6:** ::vtol::, Solaris, 2014, [39]

## 6.2 Mental State Detection

In this section we will investigate mental state detection, the process of detecting mental states, in particular emotions and workload; and ethical considerations relating to mental state detection [40].

### 6.2.1 Definition & Background

In cognitive psychology, mental states are defined as hypothetical states that correspond to thinking and feeling, and consists of a collection of mental representations and attitudes. Mental states include for example arousal, stress, attention, or vigilance. As mental states are a result of natural perception, activities and thoughts, they are inherently linked to passive BCIs. The subject matter of mental states in relation to evoked EEG responses has been studied since the early 1960's as for example by Haider et al. in 1964, who investigated attention and vigilance in relation to cortical evoked-potentials. Mental state detection as a research field is highly interdisciplinary and is linked to other fields such as physiological computing, affective computing, augmented cognition, and neuro-ergonomics.

### 6.2.2 Mental State Detection Process

Traditional neuroimaging techniques typically try to determine how a specific perceptual or cognitive state is encoded in brain activity, by determining which regions of the brain are involved in a given task. This is commonly done by measuring activity from multiple locations in the brain repeatedly, but then analysing each location separately, yielding differences in activity, which allows to compare two or more mental states at each individual sampled location. In theory, if the responses at any brain location differ between two mental states it should be possible to analyze which one of those two mental states currently reflects the mental state of the subject. However, in reality it is often difficult to find individual locations where the differences between conditions are significantly large to allow for reliable decoding. Contrary to strictly location-based conventional decoding methods, recent studies shows that the sensitivity of mental state detection can be considerably increased by taking into account the full spatial pattern of brain activity, measured simultaneously at many locations. Due to time constraints, we will only focus on two mental states in the next two subsections, emotion detection and workload detection, as these are the most common studied mental states.

#### Emotion Detection

For mental state detection, commonly the valence-arousal model is being used. Valence is related to power spectral density in the alpha band in the frontal lobes while arousal is associated with activities in the theta band. Whereas negative valence is correlated with decreasing power in the left lobe, positive valence is related to an asymmetry within the right lobe.

## **Workload Detection**

Workload is one of the most studied mental states and is defined as the quantification of mental activity resulting from performance of a task or set of tasks. Several mental processes are involved in workload such as alertness, vigilance, attention, fatigue, or drowsiness. In order to create meaningful BCI applications relating to workload, the system has to be sensitive to cognitive fluctuations without intruding in the user's primary task, therefore only noninvasive BCIs such as EEGs or FNIRs are adequate for this kind of application. Brain regions that are related to mental workload include the prefrontal cortex and posterior parietal cortex, while in the frequency band alpha and theta frequencies are related to working memory.

### **6.2.3 Challenges in Mental State Detection**

Challenges in mental state detection consist out of technological as well as methodological challenges. On the technical side, limitations of current neuroimaging technology restrict spatial and temporal resolution. In addition, fMRI signals might not reflect the information present in spiking activity of neural populations as the neural basis of the blood-oxygen-level dependent (BOLD) signal is not yet fully understood. Moreover, high cost and limited transportability of fMRI and MEG scanners limit real world applications; only EEG or NIRS might be considered portable and reasonably affordable. However, even if highly sensitive and portable alternatives were available, there are still many methodological obstacles present that hinder a generalized and possibly even practical brain reading device, including generalization and invariance, measuring concurrent cognitive or perceptual states, and extrapolation to novel perceptual or cognitive states.

### **Generalization and Invariance**

In most mental state studies, the decoding algorithm is trained for each participant individually, for a fixed set of mental states and based on data measured in a single recording session, which presents a highly simplified situation compared to real world applications. In order to move forwards, we need to answer the question to what extent can classification-based models generalize over time, across subjects and to new situations.

Generalization over time is possible if appropriate spatial resampling algorithms are used. However, more challenging is the generalization across different instances of the same mental state, as typically, mental states can occur in many different situations, but with subtle variations. Thus, reliable classifiers require accurate detection of the invariant properties of a specific mental state in order to avoid training the model on the full set of possible mental states. To achieve this, the classifiers requires a certain flexibility that is able to ignore irrelevant differences between different instances of the same mental state. In addition, careful categorization of mental states is required as highly heterogeneous sets of mental states might impede the correlation of a unique brain pattern to invariant properties. Moreover, one must note that generalization is typically achieved at the cost of decreased discrimination

of individual exemplars. Any model for mental state detection must not only detect invariant properties of a mental state but also allow sufficient discrimination between individual exemplars.

Finally, an ideal mental state detection algorithm must not only be able to generalize across time and mental states but also across different subjects. Whether this is achievable is highly dependent on whether it is possible to identify functionally matching brain regions across subjects associated with a particular mental state. Haynes and Rees state that "algorithms for spatially aligning and warping individual structural brain images to stereotactic templates are well established, however, at the macroscopic spatial scale there is not always precise spatial correspondence between homologous functional locations in different individual brains, even when sophisticated alignment procedures are used; many situations where spatial matching is unlikely to be successful" [40].

### **Measuring concurrent cognitive or perceptual States**

Currently, it is unclear if it is possible to independently detect several simultaneously occurring mental states. Decoding multiple mental states simultaneously requires a method to address superposition, however, spatial patterns indicating different mental states might spatially overlap. Recent research has shown some level of separation using the simplified assumption that the patterns linearly superimpose. However, to date it is not known how to handle cases where different mental states are encoded in the same neuronal population. Further improvement of statistical pattern recognition algorithms is needed to create reliable measurements of concurrent perceptual or cognitive states.

### **Extrapolation to novel perceptual or cognitive States**

The possibly biggest obstacle in mental state detection is that the range of possible perceptual or cognitive states is infinite, whereas the range of training categories is inherently limited. Due to the limited amount of available training sets, it is therefore necessary to be able to extrapolate from a sparsely sampled set of measured categories to completely new categories. In order to achieve this, the underlying representational space of mental states must be determined. Techniques such as multidimensional scaling suggest that it is possible to classify response patterns to new object categories based on their relative location in an abstract shape space that is spanned by responses to measured training categories. In addition, extrapolation is not only needed to decode mental processes but also specific contents of cognitive or perceptual states, or even sentence-like semantic propositions. To date, decoding of sentences has required training on each individual example sentence until now, "generalizing such an approach to new sentences will ultimately depend on the ability to measure the neural structure of the underlying semantic representations", according to Hayson and Rees [40].

#### 6.2.4 Ethical considerations

Neural correlates have been identified for various mental states that could potentially be used to reveal sensitive information without the knowledge or consent of a person. These include for example "neural correlates of conscious and unconscious racial attitudes, emotional states and attempts at their self-regulation, personality traits, psychiatric diseases, criminal tendencies, drug abuse, product preferences and even decisions" [40]. Important to note is that the presence of these correlates alone does not mean that they can be used to accurately decode ones mental state, as this has been empirically not addressed yet. However, one must realize that recent technology advances will likely enter new areas and applications and must therefore be ethically addressed. As many potential applications are very controversial, one must weigh the benefits against the potential abuse of this emerging technology. On the one hand, benefits include a high amount of potential clinical applications, such as "the ability to reveal cognitive activity in fully paralysed 'locked-in' patients, the development of brain-computer interfaces for control of artificial limbs or computers, or even the reliable detection of deception" [40]. On the other hand, there exist also potentially controversial applications, such as decoding covert mental states without an individual's consent. While common forms of communication, such as body language and speech can usually be controlled to some extent by a person, mental states might be used to detect concealed or undesirable attitudes and could potentially lead to significant violations of mental privacy. Although the field of mental state detection is still severely limited in practice, "the effectiveness of brain reading has nevertheless been considered sufficient to justify the founding of several commercial enterprises offering services such as neuromarketing and the detection of covert knowledge". As there is still very little, scientifically validated information on the reliability of these commercial services, it is unclear to what extent these services are reliable, which also contributes to the tendency of the media and the general public to overestimate the findings of neuroimaging findings. Haynes and Rees highlight the need of ethical guidelines regarding transparency in the methodology outside medical and scientific settings as well as ethical guidelines regarding acquisition and storage of brain scanning data.

### 6.3 Multi brain BCIs [2]

#### 6.3.1 Human performance enhancement with BCI

Several studies are mentioned that look into the use of BCI to enhance human performance and these can be categorized into the following four paradigms:

1. **Motor action paradigm:** The conventional pathway of peripheral nerves & muscles in motor control can be bypassed with BCI, since BCI offers a direct link between the brain and an output device. Delays between other (early) stages of sensory information processing and motor control can be eliminated as well and motor behaviours can be predicted more rapidly than the actual motor reaction time.
2. **Mental-state monitoring paradigm:** Signal changes related to alertness, arousal,

and cognition are presented in EEG. Human performance can be enhanced by sending warnings or control commands when BCI is used to characterize this information and can provide understanding of human cognitive states. An example is using changes of EEG power spectrum while performing a driving task for auditory arousing feedback to improve attention level.

3. **Visual target detection paradigm:** Targets can be indicated by brain activities like a P300 ERP (see section 4.2). This means that instead of a manual response to confirm target detection also a mental response from the brain can provide target detection. An example is image based target detection using rapid serial visual representation paradigm, which then can improve human performance.
4. **Additional input paradigms:** BCIs, when combined with more traditional manners of input, have potential to improve input speed. An example is combining BCI-based controls with traditional controls in gaming in order to make operations faster. Another example is for situations where traditional input is not accessible. BCIs can for instance provide hands-free control for astronauts to facilitate operations in conditions with gravity being absent.

A challenging problem for deploying BCI for performance enhancement for healthy human beings is the low signal-to-noise ratio (SNR) of EEG signals which makes BCI a more frustrating modality compared to other alternatives. In order to enhance the SNR averaging methods can be used on multiple trials as well as on multiple subjects. In environments where real-time operations are necessary, multi trial averaging is not practical and averaging using multiple subjects can be an alternative. The authors of [2] propose a collaborative method for improvement in BCI performance through collaborative brain activity from multiple users.

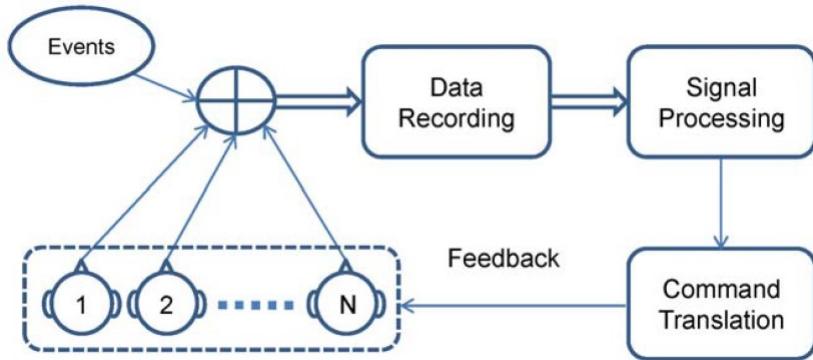
### 6.3.2 Collaborative BCI system diagrams

Where a conventional BCI is often mainly focused on helping individuals with motor disabilities to communicate with their environment, collaborative BCIs are designed for improvement of human performance for healthy users. A collaborative BCI consists of three major parts (and procedures) (see figure 6.7):

1. A data-recording module. (acquiring brain signals from a group of users by multiple EEG recording devices and synchronizing them with common environmental events)
2. A signal processing module. (processing integrated EEG and event data for feature extraction for user intention decoding)
3. A command translation module. (direct translation of features into operation commands which can also be used to provide sensory feedback to users)

In order to implement collaborative BCI, several specific hardware and software design requirements exists due to the multiple users:

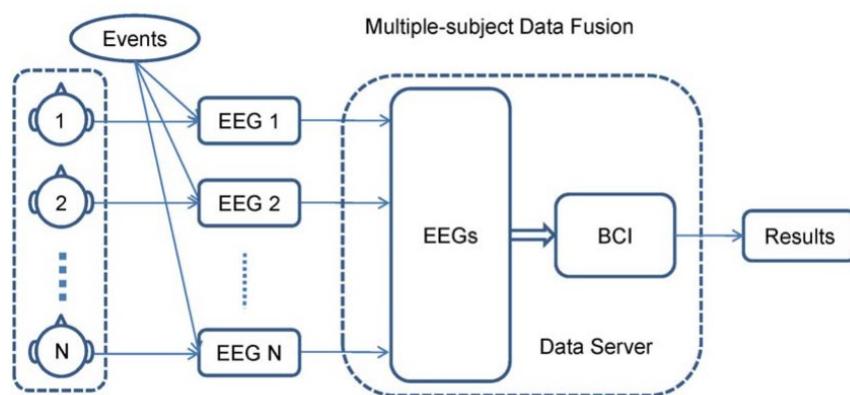
1. Multiple EEG recording systems need to work independently and simultaneously.
2. Multiple-subject data needs to be received and synchronized with environmental events.
3. Multi-subject data recording and processing has to be done in (near) real-time.



**Figure 6.7:** System paradigm of a collaborative BCI

### Centralized paradigm

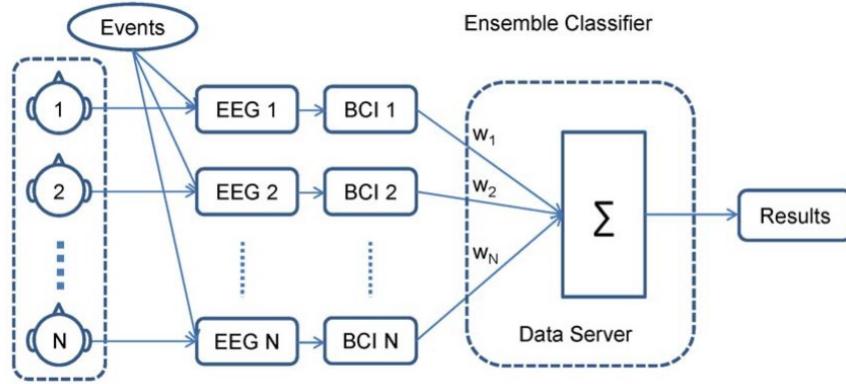
See figure 6.8 for the system diagram for the centralized paradigm. EEG data from multiple subjects is received, recorded, and thrown into a conventional BCI module for signal processing and command translation using a data server. This paradigm is optimal for collaborative BCI system design, but practicality and hardware/software robustness of implementation may be limited due to heavy loads of data transmission, computational costs of advanced signal processing and machine learning techniques, and the involvement of multiple BCI subsystems.



**Figure 6.8:** Centralized paradigm system diagram for collaborative BCI

## Distributed paradigm

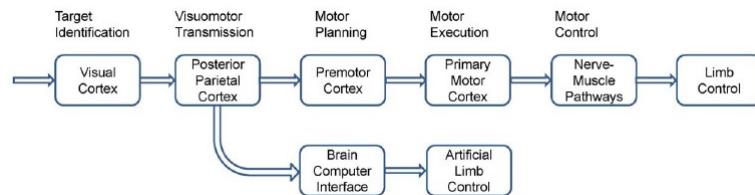
See figure 6.9 for the system diagram for the distributed paradigm. The distributed paradigm was proposed following the issues with the centralized paradigm. The system in a distributed paradigm consists of multiple distributed BCI subsystems and a simplified data server. The BCI subsystems work independently for each user, each subsystem has its capability in EEG data acquisition and processing. The between subsystem and data server data transmission amount is significantly reduced, as well as computational costs of data processing. Robustness is improved as well, as the data server only functions as ensemble classifier for integration of classification results from the subsystems. The only disadvantage is that the costs of subsystems may increase due to data processing requirements for each subject individually.



**Figure 6.9:** Distributed paradigm system diagram for collaborative BCI

### 6.3.3 The experiment

The experiment described in [2] used the motor action paradigm. The motor response task was a visually guided reaching or gazing. Brain activities in the posterior parietal cortex (PPC) were extracted for prediction of the direction of upcoming movements, to improve human performance. The five stage of the response time of a cue-guided reaching movement can be seen in figure 6.10.



**Figure 6.10:** Information flow in a visuomotor control pathway and a BCI control pathway for a motor response.

## Subjects

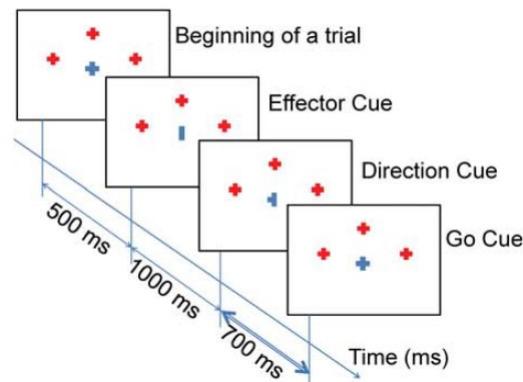
Twenty right handed participants (12 male, mean age 25) with (corrected to) normal vision participated in the EEG experiment. A group of 18 participants (12 males, mean age 23) participated in the behavior experiment.

## Stimuli and procedure

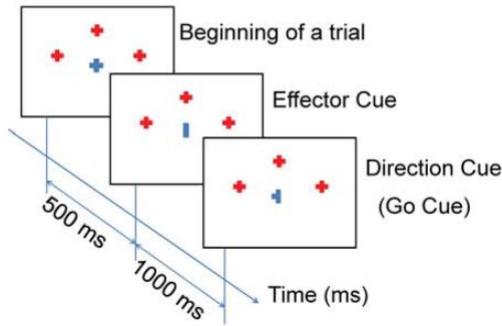
The task used in the EEG study was a *delayed saccade-or-reach task*. The experiment had nine conditions:

- Movement types
  - Saccade to target
  - Reach without eye movement
  - Visually guided reach
- Movement directions
  - Left
  - Center
  - Right

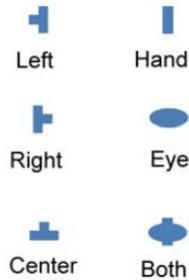
Subjects were instructed on the to perform task by an effector cue (type of action), a direction cue, and an imperative action cue. Subjects were seated at a distance of 40 cm from a 19-inch touch screen. Figure 6.11 shows the time sequence of an EEG trial, figure 6.12 of a behavioral trial, and figure 6.13 the visual cues indicating effector and direction of task. A fixation cross plus the potential positions of targets were displayed. The behavioral experiment was designed to measure the actual reaction time, without delay after the direction cue (direction cue also used as Go cue). Subjects were instructed to react as fast as possible.



**Figure 6.11:** EEG trial time sequence of cue presentation and task-specific visual cues



**Figure 6.12:** Behavioral trial time sequence of cue presentation and task-specific visual cues



**Figure 6.13:** Visual cues indicating effector and direction of task

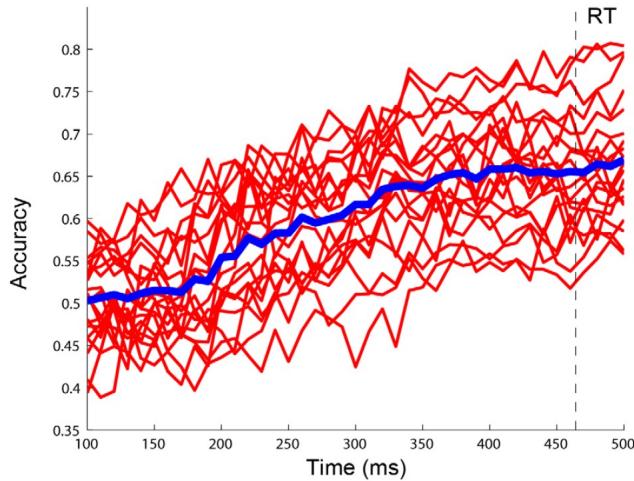
#### 6.3.4 Collaborative BCI data analysis and results

Left vs right was classified using a standard machine-learning paradigm. Three approaches to fuse the information from multiple subjects were used for collaborative classification based on data from multiple subjects:

1. ERP averaging across subjects
2. Feature combination (concatenating features from multiple subjects)
3. Voting using an ensemble classifier.

The accuracy of single-trial classification for all 20 subjects is shown in figure 6.14. Accuracy increased in accordance to the increase of the time window length used for feature extraction. EEG activities near the PPC can provide useful information for predicting the intended movement direction. Although single-trial classification performance for single subject is low, it provides a substantial basis for building collaborative BCI. Figure 6.15 show the prediction accuracy for the three collaborative methods as function of the number of subjects. Three major findings:

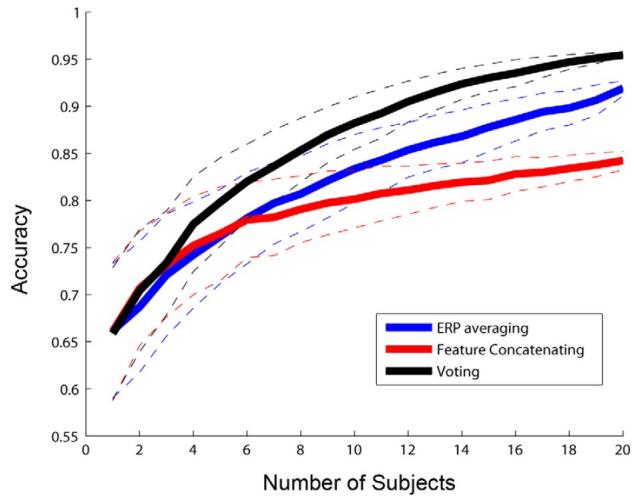
1. Classification performance for all three methods improved significantly when data from multiple subjects were combined and integrated. Combining data of 2 subjects showed significant difference between individual performance and collaborative performance when using Voting and Feature concatenating methods. For the ERP averaging method at least 3 subjects were required to reach significance. Although individual classification performance was low, high collaborative classification performance could still be reached.
2. Classification accuracy enhanced and standard deviation decreased when the number of subjects increased. These results proved independence between subjects which made all subjects contribute to the improvement of system performance and robustness.
3. The Voting method is optimal for collaborative EEG classification and always outperformed the ERP averaging method when multiple subjects were involved.



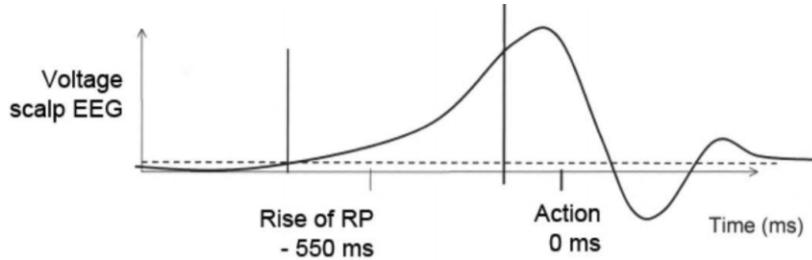
**Figure 6.14:** Time course of single-subject classification accuracy

## 6.4 Readiness Potentials

Readiness potentials (RP) are defined as measure of activity in the motor cortex and supplementary motor area of the brain leading up to voluntary muscle movement [41]. Typically, RP are not visible in single trial sessions due to their nature of being slow cortical potentials close to direct-current; however, they can be observed by averaging the signals. A landmark in the field of RP research were the experiments of Libet in the 1980s, who measured the time when subjects became consciously aware of the decision to move, trying to answer the question whether humans have a free will [42]. In his study, subjects were asked to voluntarily flex their fingers and to report the clock position in seconds, in relation to performing the self-initiated act. Libet found a pre-movement buildup of electrical potential called readiness potential (RP) starting 550 ms before the movement, however the conscious awareness of the decision emerged only 200 ms before movement, as shown in figure 6.16.



**Figure 6.15:** Classification accuracy of different collaborative classification methods as a function of the number of subjects



**Figure 6.16:** Readiness potential.

Libet "interpreted the early rise in the RP as a reflection of neuronal computation that unconsciously prepare for the voluntary action" [42]. The "conscious" would emerge at 200ms to either allow or block a process to complete, resulting, respectively, in the execution or withholding of the motor act. Libet thus concluded that "brain unconsciously plans our behavior but allows for a conscious "veto" to alter the outcome of our volition". However, critique has been expressed regarding Libet's findings as it is unclear how the RP is related to several factors during the execution of the action, including action preparation, general anticipation of the occurrence of an action, variable waiting time intervals between the onset and the end of the experiment, choice of whether and when to move, and the impulsive urge to move; of which all could be reflected in the RP.

Throughout history the definition of RP changed multiple times. First, in 1983, Libet defined RP as potentials that "initiate or, at least, prepare to initiate the act at a time before there is any reportable subjective awareness that such a decision has taken place" [41]. Recent studies show that subjects are still able to cancel the initiation of a movement, even after the onset of the RP up to a point of no return 200 ms before movement onset. While Alexander et al. (2016) interpret these RP as reflection of general anticipation, Schultze-Kraft et al. (2016) state that RP might reflect simply background neuronal noise as robust

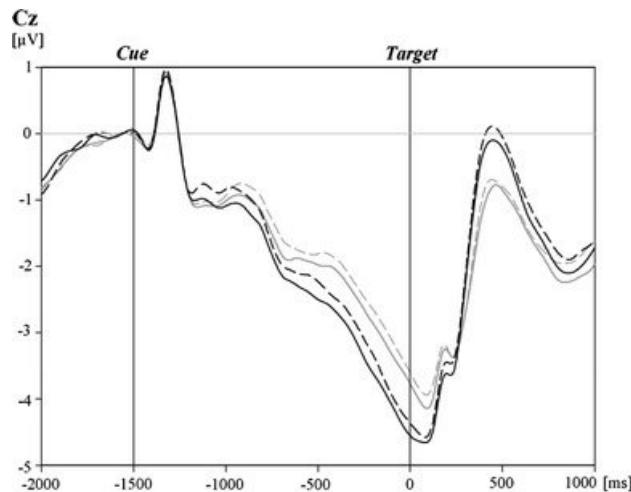
RPs occurred in their study, even in the absence of movement. Uri Maoz et al. (2019) found that expected RPs for arbitrary decisions were significantly absent for deliberate ones. They interpret Rp as "accumulation of noisy, random fluctuations that drive arbitrary—but not deliberate—decisions" [41].

## 6.5 Contingent Negative Variation

In this section we will learn about Contingent Negative Variation, how to set up experiments, influencing factors as well as applications for contingent negative variations.

### 6.5.1 Definition

Contingent Negative Variation (CNV) are defined as negative shift of the cortical electrical potentials that increases over time [41], see figure 6.17. A CNV is associated with an anticipated response to an expected stimulus and indicates a state of readiness or expectancy.



**Figure 6.17:** Contingent Negative Variation [43].

A CNV occurs between a warning signal and a go signal. It consists out of two phases: first an early CNV, which appears mostly in the frontal cortex as response to the warning signal; which is then followed by a late CNV, which appears mostly in the motor cortex and signals the preparation for a motor response. Late CNVs are very similar to RPs as it occurs just before the participant is signaled to respond while an RP occurs just before the participant carries out a self-paced action. CNVs are associated with attention processes, have been found to correlate with concentration on a task as well as task performance.

### 6.5.2 Protocol

To induce a CNV, a participant is presented with an initial stimulus followed by a short pause (500 ms - 3000 ms), after which a second stimulus is presented at which the participant is meant to perform some action (e.g. motoric or cognitive). Often the reaction time between

the two stimuli is measured, to apply time pressure. This process is then repeated multiple times, affecting the CNV. The signal is usually recorded in Cz, Fz or Oz electrodes and filtered by a low pass filter to reduce noise.

### **6.5.3 Influencing Factors**

Influencing factors include the number of trials as the CNV naturally declines with increasing number of repetitions as well as the consistency of the trials, the more consistent they are, the more CNV will be present. In addition, the learnt probability of the second stimuli occurring will influence the CNV as well. Furthermore, time between stimuli and type of stimuli can influence the CNV. The less time between stimuli exists the more CNV will be present, while more intrusive types of stimuli can also lead to more CNV. Finally, the type of action (motoric / perceptual) can also influence the response of the CNV.

### **6.5.4 Applications**

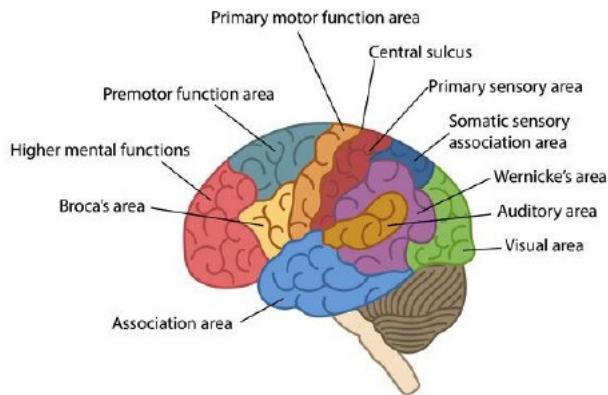
CNVs have multiple applications including applications in clinical research as well as applications for disabled individuals. For example, the heightened amplitude of CNVs predict migraine attacks one day prior; sleep deprivation is correlated with increased CNV peak latencies; and CNVs with low amplitudes are associated with posttraumatic stress disorders. In addition, CNVs may be used as decision device for patients that are unable to move, for example patients with locked-in syndrome.

# 7 | Week 7

## 7.1 BCIs & Music

The first musical work using brainwaves was that of Alvin Lucier, Music for solo performer [34]<sup>1</sup>. In this work Alpha waves were send to amplifiers and percussion instruments were used. This work was highly experimental and non-scientific. Another pioneer in the use of neurofeedback in composing is David Rosenboom. Again Alpha waves were used and the signals were vocalised and used as additional instrument<sup>2</sup>.

Music is integrated into everyone, is related to language, and can be highly complex. Areas of the brain (figure 7.1) related to listening to music are: auditory, premotor, and to a lesser extend the primary motor area. Regarding making music: the auditory, premotor, primary motor, frontal lobe, and somatic sensory association area.



**Figure 7.1:** Functional areas of the Cerebral Cortex

Also more serious applications are possibly, such as the brain stethoscope<sup>3</sup> developed by researchers from the Stanford university, which is explained in more detail in the next section.

### Detecting silent seizures by their sound [44]

This paper describes a study done on the effectiveness of sonified EEG waveforms so that users can hear the sound of rhythmic fluctuations. The authors focus on altered mental status

<sup>1</sup><https://www.youtube.com/watch?v=bIPU2ynqy2Y&t=439>

<sup>2</sup><https://www.youtube.com/watch?v=dWfoDjwcttw&t=525>

<sup>3</sup>[https://www.youtube.com/watch?v=pnGzVW\\_7cfM](https://www.youtube.com/watch?v=pnGzVW_7cfM)

(AMS) patients and for which EEG is the gold standard method for subclinical seizure (especially nonconvulsive status epilepticus) detection. However, for the interpretation of EEG features an EEG reading trained profession is required, causing delays in obtaining diagnostic information. Using sonified EEG waveforms professionals not trained in EEG can determine whether seizures are represented in the EEG waveforms by listening to the rhythmic fluctuations of the waveforms. Although this method is not a replacement for traditional approaches, it can provide meaningful and fast assessment of patients with suspected subclinical seizures.

## Methods

EEG samples (84) were collected with a duration of 15 seconds, as this is the same time range that would be displayed for visual inspection. Only "silent" seizure cases were selected, which means the patients showed no clinical signs of a seizure. Each 15 second EEG sample was reviewed by three senior epileptologists as reference standard. Samples were defined as *seizure* ( $n = 7$ ), *seizure-like abnormalities* ( $n = 25$ ), and *slowing or normal* ( $n = 52$ ) based on the majority agreement of the 3 experts.

Two surveys were conducted. One with a visual representation of 18 channels of the EEG samples and one with single channel audio representations using the same samples as with the visual survey. The order of the samples was randomized in both surveys. The visual survey showed samples on one page, the auditory survey presented clips from left and right channels separately. For the auditory survey participants were shown a video prior to completing the survey, in which the appearance of seizures and seizure-like patterns were described as well as the correlation of specific visual features that define these patterns with the sound of the sonified brainwaves.

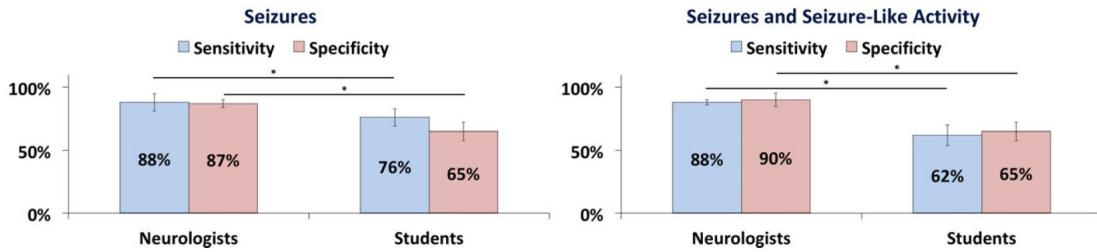
A sonification algorithm was used to translate the low-frequency EEG signals to the audible range. This was done by using the signals as modulators of a voicelike synthesized sound. For each visual EEG channel two sonified EEG clips were produced, one for each hemisphere. This method produced speech like declamations with a loud and strong rhythmic character for seizure cases, which is easily distinguished by ear from the quieter non-seizure cases.

## Results

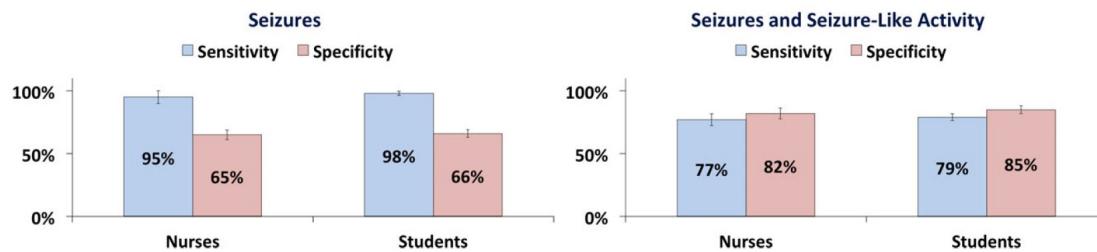
The results are shown below. Figure 7.2 contains the results for visual inspection of the EEG, figure 7.3 for the auditory inspection of the sonified EEG, and figure 7.4 the comparison of visual and auditory EEG seizure detection performance for medical students.

### 7.2 Kessel Run [3]

BCI devices becoming smaller, easier to use, and more affordable has lead to usage outside the medical field and towards user industries like entertainment with especially the gaming



**Figure 7.2:** Visual EEG results. Sensitivity and specificity are shown of visual EEG for seizures (left) and seizure/seizure-like activity (right) when read by neurologists and medical students. Asterisks denote  $P < .05$ . Error bars represent 95% confidence intervals.



**Figure 7.3:** Audio EEG results. Sensitivity and specificity are shown of audio EEG for seizures (left) and seizure/seizure-like activity (right) when read by nurses and medical students. Statistical differences between neurologists, nurses, and students did not reach statistical significance. Error bars represent 95% confidence intervals.

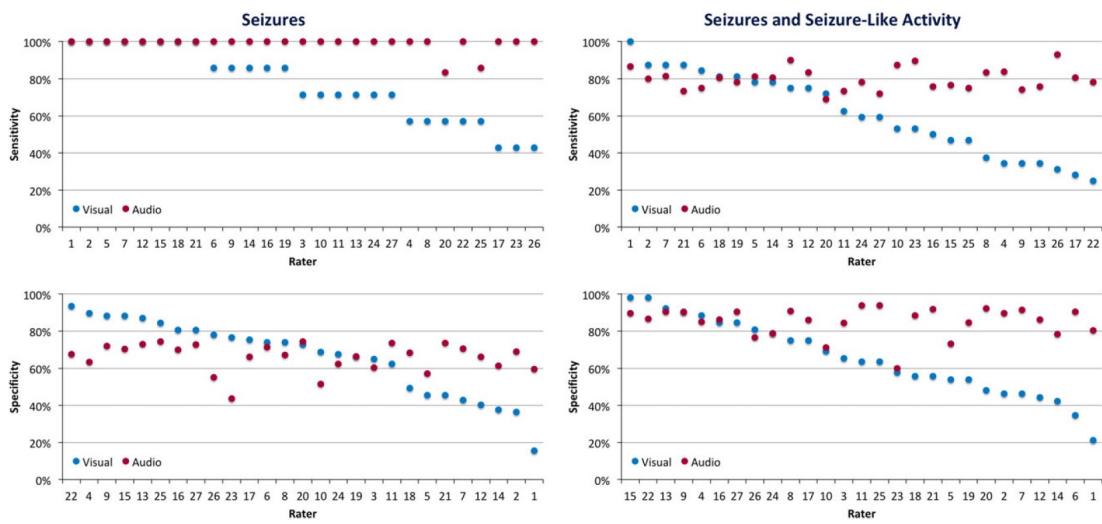
industry BCIs as interaction modality. At first adaptation of traditional input games emerged as trend, like Pacman, Pinball, or Tetris. Later or newly developed games were developed, but these were usually proofs of concept without taking proper game design into account.

Kessel Run is a multiplayer BCI game for 2 players, to breach the gap between fun games and BCI games. The goal of the developers was to create a BCI game that could be played outside of the laboratory, with a short training period, and that was as exciting as a non-BCI game.

### 7.2.1 The game and design requirements

Kessel Run is build using Unity 5. The game world consists of a moving spaceship navigating through an asteroid field (see figure 7.5). The goal for the players is to survive a two minute space race by cooperating with one another and losing as little fuel as possible. Steering of the ship is shared by both players, each player controls one of the propellants' movements so cooperation is an important part in order to win the game. The game is lost when all fuel is lost before the end of the race.

In order to provide a fun experience for the players, a set of rules and concepts were derived from good design theories in BCI games, mostly from the Flow theory (a state of



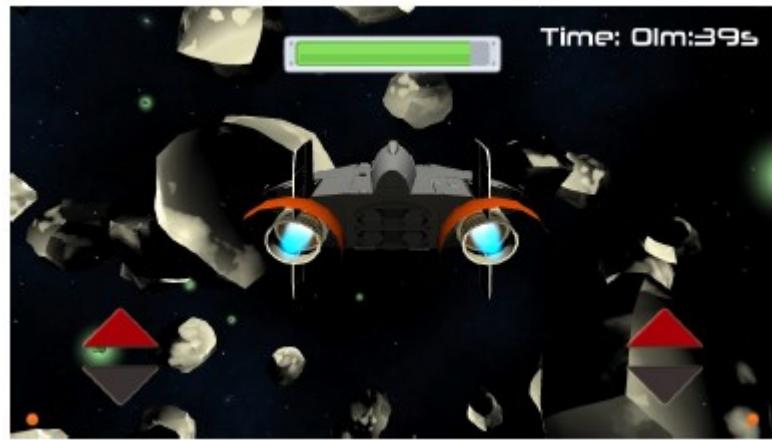
**Figure 7.4:** Comparison of medical student performance using visual and audio EEGs. Medical student ( $n = 27$ ) detection of seizures (left column) and seizures and seizure-like activity (right column) by visual inspection (blue) versus listening to sonified EEG (red) demonstrates variable performance using visual EEG but consistently high performance using audio EEG.

active involvement and a challenge level matching the players skill level) and Paradox of Control (the player when in flow must feel in control of the events as well as feeling the possibility to lose control due to failure). The requirements that must be fulfilled in order to achieve good game design:

- The game must feature a clear goal
- The game must have clear rules
- The game must challenge the players' skills
- The game should be controlled by the BCI paradigm

Additional requirements were listed regarding achievement of the desired interaction between players in a cooperative game:

- The players must have a common success
- The game must feature collaborative tasks
- The players should have inter-dependent roles
- The game should allow for communication between the players



**Figure 7.5:** Screenshot of gameplay

### 7.2.2 Importance of selecting the right paradigm

Selection of the right BCI paradigm fitting the game is very important. Among the three types of paradigms (active, passive, and reactive), the reactive paradigm was selected because of the low illiteracy rate (89% of users are able to get 80% accuracy or higher after only a short training). Making use of SSVEP (see section ?? for the control provides continuous control since the BCI detects user's intention for as long as he attends the stimuli (flickering lights). Another benefit of using SSVEPs is that external LEDs can be used, thus saving screen space for the game itself. A downside of using SSVEPs is that players need to concentrate on the stimuli constantly which can become very tiresome and uncomfortably. This could potentially also break or reduce game immersion. Using external LEDs also don't suffer from a screens refresh rates for flickering. Flickering is done at 15 and 12 Hz, detected on the 10-20 system's Pz and/or Oz electrodes.

### 7.2.3 Methods

#### Participants

Participants in the experiment were university students who were asked to bring a friend to play the game with and if no friend was available participants were teamed up. There were a total of 12 participants aged 22 to 31 years old, 5 females and 7 males, for a total of 6 game sessions. Half of the participants had no prior BCI experience.

#### Materials

The EEG signals were acquired at 512 Hz sampling rate using a Biosemi ActiveTwo system on a dedicated PC (for EEG data acquisition, processing, and recording) for each participant. Two active electrodes (Pz and Oz) were placed according to the 10-20 system. A third computer was used to run the game. Participants were seated as shown in figure 7.6, they sat opposite to each other in order to see each other and interact during gameplay without

having to move their head too much. Two pairs of red LED lights were mounted on top and bottom of the player's monitors.



**Figure 7.6:** Gaming setup

### Procedure

After introduction and a questionnaire, EEG caps and electrodes are placed on each of the participants. Electrolyte gel was applied until all electrode offsets were lower than approximately 20 mV. A short SSVEP session of 80 s was recorded for offline performance analysis and participant's Canonical Correlation Analysis (CCA) parameter definition. Players were given some time to get acquainted with the gameplay before playing eight actual rounds of Kessel Run. After playing each player filled in a questionnaire on Game Experience and Social Presence.

### Data Analysis

Data Analysis was done using Matlab and R. The SSVEP performance of the participants was evaluated using the short training session prior to playing the game. Trials of 80 samples

	$\bar{X}(\sigma)$	Max	Min
Overall	55.3 (14.1)	78.9	34.1
12 Hz	62.7 (12.6)	85.6	47.8
15 Hz	37.8 (19.5)	80.0	20.0

**Table 7.1:** SSVEP performance descriptives from CCA classification (33% chance level)

were extracted from the raw EEG signals (Pz & Oz electrodes) for the conditions looking at the 12 Hz light (bottom), 15 Hz light (top), and center of the computer monitor. CCA with sine and cosine reference signals at 12 & 15 Hz was done for each trial, after which the best electrode(s) and an empirical correlation threshold were set for the participants by visual inspection, and classification for each condition followed.

#### 7.2.4 Results

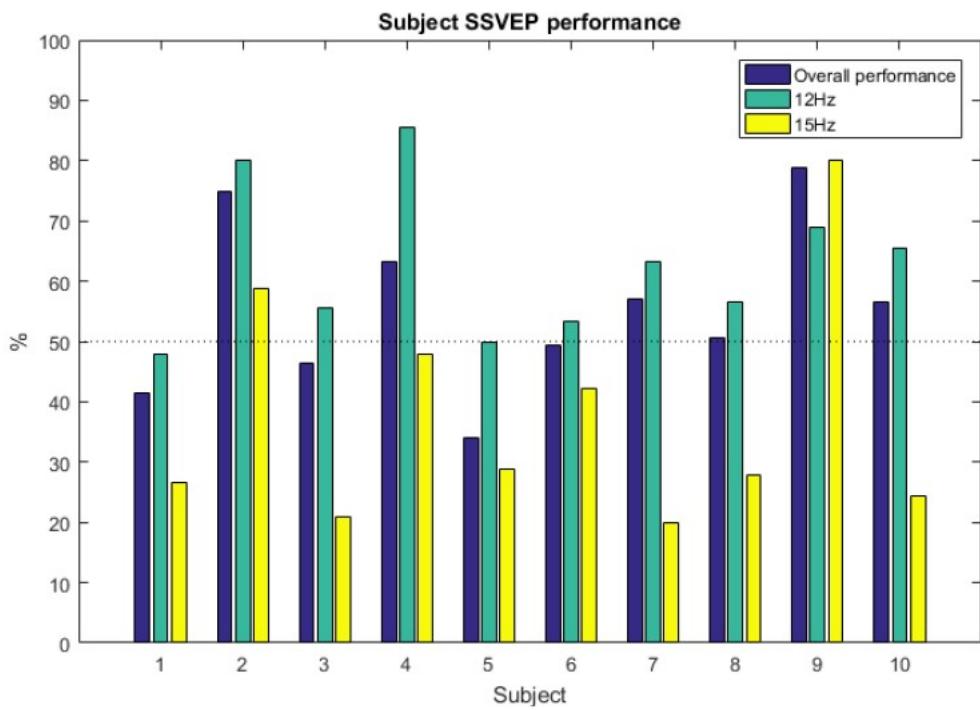
Instead of the data of the total of 12 participants, only data of 10 participants was used due to changes in the experimental setup after two participants participated. Overview of the performance can be found in table 7.1. The main factors identified as influence on rather low performance were darkness of the room and participant detection of the used frequencies. Good quality SSVEP requires to isolate visual stimuli from other light sources and although the rooms was darkened, there was still some light from windows present as can be seen in figure 7.6.

Figure 7.7 contains an overview of the performance per participant. Here it is clear that subject's performance for 12 Hz is consistently higher than for 15 Hz and that the maximum and mean performance are also the highest of the classes. Other research shows consistent results in that precision in a CCA-based detection method differs according to used frequencies. Although the BCI performance is quite low, participants were still able to play the game by adapting their strategy. This was done by for instance using different positions for their heads (closer to LEDs for example) or focusing on using only 1 of the controls (12 Hz LEDs usually). This could have resulted in a higher feeling of control than is reflected by the classification performance.

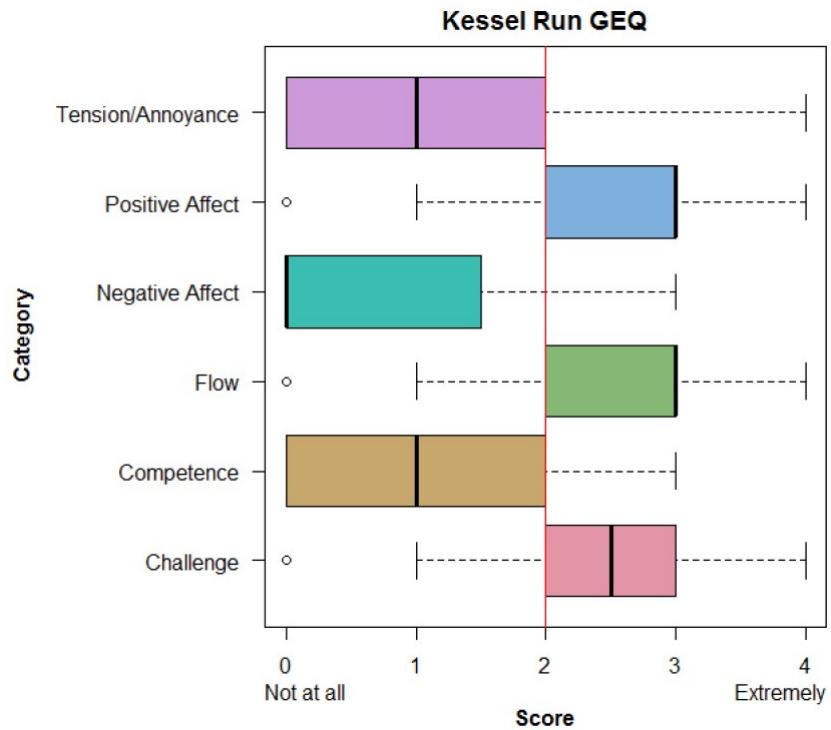
#### Game experience & social presence questionnaires

A summary of the results of the game experience questionnaire can be found in figure 7.8. Participants felt only slightly competent to play the game, probably due to low classification performance. Also due to low classification performance, players needed to adapt their strategies by moving in only one direction or splitting directional tasks (when one player had better results with a certain direction). This means collaboration became more important and this resulted in a greater bond between players and a positive affect, greater feeling of immersion, and a moderate to fair sense of challenge during the game.

Regarding the social presence, the summary can be found in figure 7.9. The Behavioral Involvement component measures the degree to which players feel their actions are dependent



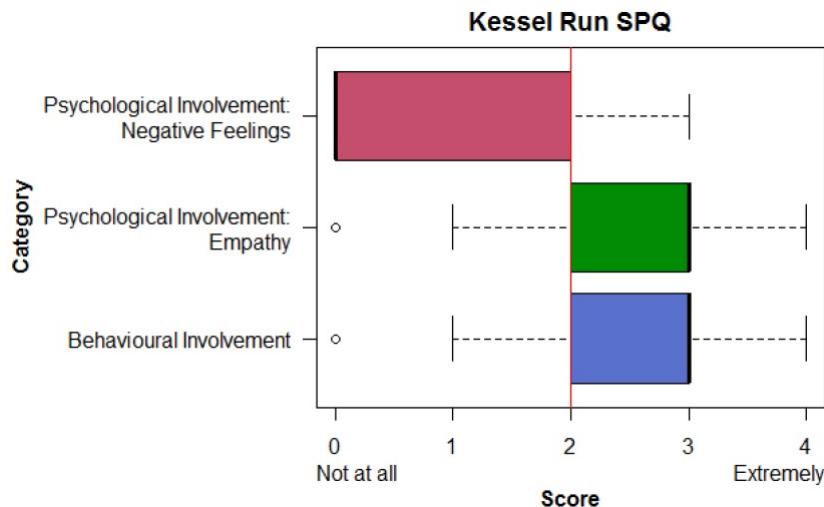
**Figure 7.7:** Classification performance overview per participant



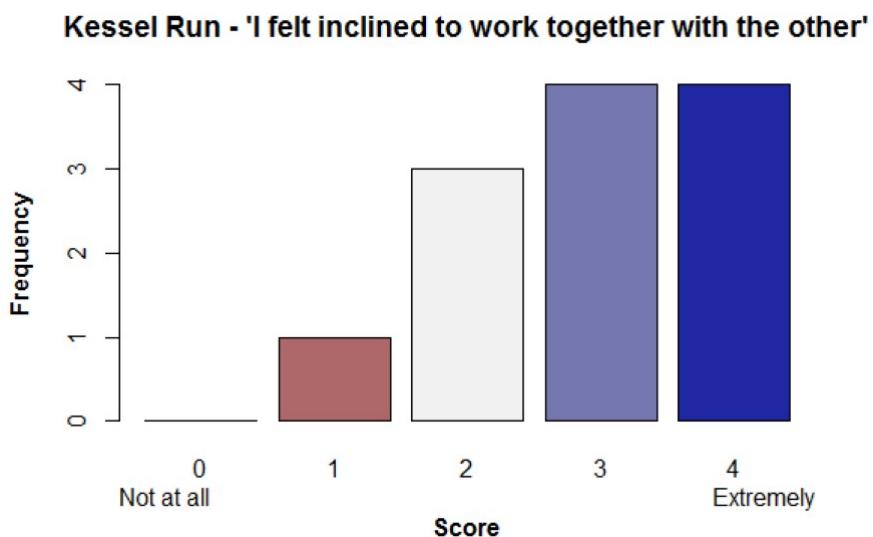
**Figure 7.8:** Boxplot for the answers on the Game Experience Questionnaire

on their co-players actions and all had positive scores. Of the Psychological Involvement - Empathy, only the component *I admired the other* had a negative mean score (mean = 1.0

'slightly'). This could be caused by players feeling not much competent in playing the game due to low classification performance and therefore did not feel their co-players would be competent as well. For Psychological Involvement - Negative Feelings the overall mean score was negative (mean under 2). Players did not feel jealous or revengeful of the other, but did feel moderately influenced by the others mood. Figure 7.10 contains responses to the question whether players felt inclined to work together with the other.



**Figure 7.9:** Boxplot for the answers on the Social Presence Questionnaire



**Figure 7.10:** Frequency bar plot of answers to 'I felt inclined to work together with the other'.

# 8 | Research Project

## 8.1 Introduction

This project will focus on the P300 speller, specifically on the evaluation of the row/column (RC), checkerboard (CB), and checkerboard with color (CBC) paradigms. This research experiment will attempt to replicate the study done by Ryan et al., titled "Evaluating Brain-Computer Interface Performance in an ALS Population: Checkerboard and Color Paradigms" [45] with non-ALS subjects. The three paradigms mentioned, RC, CB, and CBC are all visual P300 paradigms, which are explained in section 4.2.1.

The P300 can be generated by the oddball principle, where for instance flashing of targets and non-targets is used. The occurrence of the more rare event in the two classes elicits a P300 response most visible in parietal lobe electrode sites. In the case of a P300 speller, the rare event would be the letter the user focuses on. Using the P300 in such applications is fast, easy to measure, non-invasive, and requires very little training since it depends on endogenous attention-based brain function. Application of P300 spellers is very suitable for users with serious neurological diseases like ALS, but has limitations as well. EEG patterns are unique for individuals, which means individual calibration is required. Moreover, an individual's EEG pattern can change due to factors like motivation, level of attention, fatigue, mental state, and learning. Detection of the P300 in real-time can prove to be difficult as well, as errors can occur due to a subject's attentional blinking, repetition blindness, and habituation.

Important in visual P300 paradigms is eliciting large differences between the target and non-target classes. The RC paradigm has been the most common paradigm for a long time. This paradigm makes use of a 6 by 6 matrix of all letters and digits ranging from 0 to 9 in grey color. Rows and columns are then flashed sequentially while the user focuses on a single character. Flashes of rows and columns containing this character that is focused on will elicit a P300 response after which, using the column and row, the character can be determined. However, as mentioned in section 4.2.1, there were improvements made based on two issues with the RC paradigm, namely subsequent flashing of the same character (double target item flash) and distraction due to apparent flashing of non-targets (whole rows and columns flashing). From this the CB paradigm emerged.

The CB paradigm makes use of a 8 by 9 matrix on which a virtual checkerboard is superimposed. In order to fill the 8 by 9 checkerboard, two 6 by 6 matrices which are not visible to the users are filled randomly, one with white characters and the other with black

characters. Flash groups are made to prevent simultaneous adjacent flashing characters, but for the user the flashing on the checkerboard still appears to be random. Ryan et al. [45] investigated two variants of the CB paradigm, namely a greyscale version and colored version. This project aims to produce an indication of similar results as obtained by Ryan et al., with hypothesis of increased performance, increased information transfer rate, and participant preference in the paradigm order RC, CB, CBC. The reason we are only aiming at an indication of similar results is that in the assignment description of the course we were strongly advised to limit our number of participants to a maximum of 2.

## 8.2 Set up and Preparation

### 8.2.1 Participants

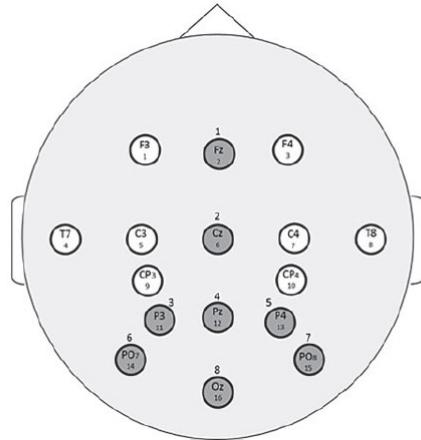
The original study was done with 11 participants, all were diagnosed with ALS. Due to feasibility only non-ALS patients will be selected to participate in this study, aiming at a maximum of only 2 participants since the assignment description advised to have a maximum of 2. It should be noted however, as Ryan et al. [45] pointed out as well, that BCI research should be conducted with the target population in the target environment in order to reach full potential. When this study will be executed, participants selection will be done on the University of Twente and will consist of students with no prior experience regarding any of the three mentioned paradigms. This to account for potential bias towards the colored paradigm, which was mentioned as a limitation in the original study (see section 8.4).

Prior to participating in the study participants are informed by the researchers verbally, requested to read the information brochure and sign the consent form. See appendix A.1 for the information brochure and the consent form. The information brochure contains global information about the nature of the research, what (personal) information is gathered, why this information is gathered, and how this information is handled (anonymization, storage encryption, and storage duration). The brochure also informs participants about their rights to withdraw consent without reason at any time during the experiment as well as after the experiment has been completed. Finally the brochure also contains contact information of one of the researchers (contact person) as well as contact information of the project supervisor of the course. After the participant is informed, he or she is requested to sign the consent form in two fold.

### 8.2.2 Experimental Set Up

Participants take place in front of a monitor at a distance of 1 m. Stimulus presentation and online processing is done using BCI2000. The three conditions, RC, CB, and CBC, are completed by the participants in pseudo-randomized order (Latin square). Participants are requested to focus on the target character, ignore non-target characters and either count the number of target flashes or repeat the target character silently in their head each time the target character is flashed. Five six letter words are obtained by using a random word

generator, requiring a total of 30 character selections. Resulting EEG data from the 30 character selections is then used as training data, further outlined in section 8.2.3 which is then used for online response classification and feedback for an additional 30 selections. The number of stimulus presentations is held constant at seven sequences per character selection during calibration and online testing. In the context of the three conditions applicable for this study the number of flashes required to complete a sequence (two target character flashes) differs per paradigm and is therefore further clarified for each condition below.



**Figure 8.1:** Electrode placements. Channels used for classification are in grey

### RC condition

A 6 by 6 matrix of grey characters (all letters, a space, and digits 1 to 9) on a black background is used. Rows and columns are flashed in a random order in white color. Stimulus-on duration (the duration of the flash) is 187.5 ms and stimulus-off duration (time between flashes) is 62.5 ms. A sequence (two target character flashes) for the RC conditions requires a total of 12 flashes, 6 for each row and 6 for each column. An example of the RC condition where the letter C is the target for the word Combat is shown in figure 8.2.

COMBAT (C)						
A	B	C	D	E	F	
G	H	I	J	K	L	
M	N	O	P	Q	R	
S	T	U	V	W	X	
Y	Z	Sp	1	2	3	
4	5	6	7	8	9	

**Figure 8.2:** Example of the RC condition, current letter C of the word Combat

## CB condition

For the non-colored CB condition grey characters are shown on a 6 by 6 matrix again containing all letters, a space, and digits 1 to 9 on a black background. Stimulus-on and stimulus-off duration is equal to the RC condition, 187.5 ms and 62.5 ms respectively. In this condition a sequence (two target character flashes) consists of 18 flashes, caused by the constraint prohibiting adjacent character flashes. This results in an increase of 3000 ms of character flashing per selection. An example of the matrix for the CB condition is shown in figure 8.3.

ADVICE (A)						
A	B	C	D	E	F	
G	H	I	J	K	L	
M	N	O	P	Q	R	
S	T	U	V	W	X	
Y	Z	sp	1	2	3	
4	5	6	7	8	9	

**Figure 8.3:** Example of the CB condition, current letter A of the word Advice

## CBC condition

For the CBC condition grey characters are shown on a 6 by 6 matrix again containing all letters, a space, and digits 1 to 9 on a black background. Stimulus-on and stimulus-off duration is equal to the RC and non-colored CB condition, 187.5 ms and 62.5 ms respectively. A sequence for this condition is equal to the non-colored condition, namely consisting of 18 flashes and an increase of 3000 ms of character flashing per selection as compared to the RC condition, caused by the constraint prohibiting adjacent character flashes. An example of the matrix for the CBC condition is shown in figure 8.4.

DRAGON (D)						
A	B	C	D	E	F	
G	H	I	J	K	L	
M	N	O	P	Q	R	
S	T	U	V	W	X	
Y	Z	sp	1	2	3	
4	5	6	7	8	9	

**Figure 8.4:** Example of the CBC condition, current letter D of the word Dragon

### 8.2.3 Signal Processing & Classification

In the study by Ryan et al. it is not explicitly mentioned what type (dry or wet) electrodes were used other than that the method was non-invasive. Expected is that wet electrodes were used, which require longer to set up as compared to dry electrodes. In order to attempt to produce results consistent with Ryan et al., wet electrodes will be used. 16 channel EEG is recorded using electrodes placed as depicted in figure 8.1. Electrodes in grey are electrodes that will be used for classification. These were used by Ryan et al. and selected based on results of a previous study [46].

The EEG data is first band pass filtered (0.5Hz and 30Hz) to remove unwanted artifacts, detrended to remove drift from e.g. temperature changes and then downsampled to 20 Hz. Samples collected before the stimulus onset can be used to correct for baseline signal shifts before the stimuli [12]. Finally, the data can then be averaged. In the study by Ryan et al. the resulting data recorded from the 30 character selections is then used as training data for a stepwise linear discriminate analysis (SWLDA), which is then used for online response classification and feedback for an additional 30 selections. While the study by Krusienski et al. [47] showed that the SWLDA and Fisher's linear discriminant (FLD) provided the best overall performance as in comparison to Pearson's correlation method (PCM), linear support vector machine (LSVM), and a Gaussian kernel support vector machine (GSVM); Manyakov et al. [48] found that the Bayesian linear discriminant analysis (BLDA) performed best followed by the (non)linear SVM as in comparison to other traditional methods, including SWLDA. Moreover, a recent study by Xiao et al. [49] demonstrated that the novel discriminative canonical pattern matching (DCPM) algorithm outperformed the SWLDA significantly. Based on these studies, we will compare SWLDA as has been used in the study by Ryan et al. with BLDA and DCPM to examine whether better results are achievable with different classification algorithms.

## 8.3 Evaluation

In the study by Ryan et al. [45] accuracy and information transfer rate (ITR) has been used as performance metrics. Accuracy was calculated based on the number of correct selections out of the total number of selections made in the online session. ITR is an objective metric that combines number of possible selections, accuracy and the number of selections completed in a minute. To obtain accuracy and ITR measures, an offline simulation using dynamic stopping was performed by Ryan et al., which examines the probability of character selection after each flash. If a character is a higher than the probability of 0.9, then the flashing is stopped and the character is selected. Both accuracy and ITR have been analyzed with via a analysis of variance (ANOVA). In addition, each participant was given a survey with regard to which paradigm they preferred in their final session, which has been analyzed with a chi-square goodness-of-fit test.

## 8.4 Influencing Factors and Limitations

There exist some limitations regarding this study and the method used. First of all, some limitations were already mentioned by Ryan et al. in the original study [45]. The main limitation mentioned there is the small number of participants and lack of statistical power. Since our study aims to use an even smaller number of participants, expected is that this will increase the effect of these limitations on our results. Also, as mentioned in section 8.2, in order to reach full potential BCI research should be preferably carried out in target population and environment. This would mean that the experiment should be carried out using ALS patients as participants, but due to feasibility of the project this is not possible. Another limitation mentioned in [45] is the prior experience of the participants with the RC and CB paradigm and no experience with the CBC paradigm. Participants could therefore be biased towards the colored paradigm. In our experiment we aimed at using participants with no prior experience in using any of the three paradigms to account for this potential bias. Finally, only three stimulus presentation conditions were used in the study (RC, CB, CBC). These are not representative of all possibilities and future work could focus on further examination and performance comparison of other paradigms.

Apart from limitations due to participant selection and the existence of more paradigms than RC, CB, and CBC, there exist limitations arising from challenges in P300 paradigm design [12]. See also section 4.2. Possible limitations include:

- **Crowding effect** - Crowded interfaces can cause sensory overload and influence results, since P300 relies heavily on sensory load through the visual channel. Expected is that this won't effect our results that much, partly because for the CB paradigms a smaller matrix size is used (6 by 6) than originally (8 by 9).
- **Adjacency problem** - The adjacency problem is caused by items adjacent to the target also sending scattered stimulation to the visual organ. Expected is that this limitation is most present in the RC condition, since the CB and CBC condition account for adjacent flashing by the use of flash groups.
- **Repetition blindness** - This occurs when presentation of the target object is followed by the presentation of the same object, which results in a lowered probability of detection. Expected is that this limitation will not significantly effect our results. RC, CB, and CBC conditions both flash target characters twice in total. Rows and columns in the RC condition are flashed at random (rows first, then columns) and in the CB/CBC conditions flashgroups are flashed at random, therefore the probability of two consecutive target flashed will be low.
- **Fatigue** - Visual fatigue can be caused by longer fixation duration as well or in combination with the influence of display resolution.
- **User comfortability** - Constant staring at the targets on the screen can result in decrease in the participant's comfort. Participants should be comfortable enough to be able to stare at the display for the required amount of time.

- **User training** - An amount of training is necessary prior to the experiment, however one should balance this very well to not cause exhaustion before the actual experiment even starts.

# Bibliography

- [1] J. Ward, *The Student's Guide to Cognitive Neuroscience*. Psychology Press, 2010.
- [2] Y. Wang and T.-P. Jung, “A collaborative brain-computer interface for improving human performance,” *PloS one*, vol. 6, no. 5, 2011.
- [3] H. Ferreira and A. Nijholt, “Kessel run-a cooperative multiplayer ssvep bci game,” in *Intelligent Technologies for Interactive Entertainment: 9th International Conference, INTETAIN 2017, Funchal, Portugal, June 20-22, 2017, Proceedings*, vol. 215. Springer, 2018, p. 77.
- [4] G. Edlinger and et al, *Springer Handbook of Medical Technology*. Springer, 2011. [Online]. Available: [https://doi.org/10.1007/978-3-540-74658-4\\_52](https://doi.org/10.1007/978-3-540-74658-4_52)
- [5] S. Abdulkader and et al, “Brain computer interfacing: Applications and challenges,” *Egyptian Informatics Journal*, vol. 16, no. 2, pp. 213–230, 2015. [Online]. Available: doi:10.1016/j.eij.2015.06.002
- [6] L. Nicolas-Alonso and J.Gomez-Gil, “Brain computer interfaces, a review,” *Sensors (Basel)*, vol. 12, no. 2, pp. 1211–1279, 2012. [Online]. Available: doi:10.3390/s120201211
- [7] T. Zander and S. Leske, “Detecting affective covert user states with passive brain-computer interfaces,” in *3rd International Conference Affective Computing and Intelligent Interaction*, 10 2009, pp. 1 – 9. [Online]. Available: doi:10.1109/ACII.2009.5349456
- [8] C. Kothe, “Introduction to modern brain-computer interface design, lecture 1,” [sccn.ucsd.edu/pub/bcilab/lectures/01\\_Introduction.pdf](http://sccn.ucsd.edu/pub/bcilab/lectures/01_Introduction.pdf), online, accessed: 07.02.2020.
- [9] *Readings week 2, Basic Neuroscience*.
- [10] S. center for computational neuroscience, “Single subject data processing tutorial.”
- [11] K. Gopan and et al, *Distribution Based EEG Baseline Classification*. Springer International Publishing, 2017.
- [12] C. Nam, A. Nijholt, and F. Lotte, Eds., *Brain-Computer Interfaces Handbook: Technological and Theoretical Advances*. United Kingdom: CRC Press, 2018.

- [13] J. Ward, Ed., *The student's guide to cognitive neuroscience*. USA: Psychology Press, 2015.
- [14] X. Hu and et al, “Ten challenges for eeg-based affective computing,” *Brain Science Advances*, vol. 5, no. 1, pp. 1–20, 2019. [Online]. Available: doi: 10.26599/BSA.2019.9050005
- [15] B. Fredrickson, “Positive emotions,” *Advances in Experimental Social Psychology*, pp. 1–53, 2013. [Online]. Available: doi:10.26599/BSA.2019.9050005
- [16] X. Hu and et al, “fnirs evidence for recognizably different positive emotions,” *Front Hum Neurosci*, vol. 13, p. 120, 2019.
- [17] Y. Liu and et al., “Real-time movieinduced discrete emotion recognition from eeg signals,” *IEEE T Affect Computing*, vol. 9, no. 4, pp. 550–562, 2018.
- [18] X. Hu and et al, “Eeg correlates of ten positive emotions,” *Front. Hum. Neurosci.*, vol. 11, p. 26, 2017.
- [19] “Brain vital sign monitoring of concussion in hockey.” [Online]. Available: <https://www.surreynewleader.com/news/game-changing-surrey-born-technology-tests-brain-vital-signs/>
- [20] R. Fazel-Rezai, B. Allison, C. Guger, E. Sellers, S. Kleih, and A. Kübler, “P300 brain computer interface: current challenges and emerging trends,” *Frontiers in Neuroengineering*, vol. 5, p. 14, 2012. [Online]. Available: <https://www.frontiersin.org/article/10.3389/fneng.2012.00014>
- [21] L. A. Farwell and E. Donchin, “Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials,” *Electroencephalography and clinical Neurophysiology*, vol. 70, no. 6, pp. 510–523, 1988.
- [22] F. Vialatte, “Steady-state visually evoked potentials: focus on essential paradigms and future perspectives,” *Progress in neurobiology*, vol. 90, no. 4, pp. 418–438, 2010.
- [23] G. Hakvoort and et al., “Comparison of psda and cca detection methods in a ssvep-based bci-system,” *University of Twente, Faculty EEMCS*, 2011.
- [24] A. Bhowmick and D. Gulhane, “Error potentials,” Brain Computer Interfacing, University of Twente, 2020.
- [25] G. Schalk and et al, “Eeg-based communication: presence of an error potential,” *Clinical Neurophysiology*, vol. 111, pp. 2138–2144, 2000.
- [26] C. Holroyd and et al., “When is an error not a prediction error? an electrophysiological investigation,” *Cogn. Affect. Behav. Neurosci.*, vol. 5, p. 59–70, 2009.
- [27] O. E. Krigolson and C. Holroyd, “Hierarchical error processing: different errors, different systems,” *Brain Res.*, p. 70–80, 2007.

- [28] J. R. Wessel and et al., “Error awareness revisited: accumulation of multimodal evidence from central and autonomic nervous systems,” *J. Cogn. Neurosci.*, vol. 23, p. 3021–3036, 2011.
- [29] L. Konicar and et al., “Brain self-regulation in criminal psychopaths,” *Scientific Reports*, vol. 5, 03 2015.
- [30] P. Cherubino and et al., “Consumer behaviour through the eyes of neurophysiological measures: State-of-the-art and future trends,” *Neurophysiological Measures for Human Factors Evaluation in Real World Settings*, pp. 0–41, 2019.
- [31] R. Kanai and et al., “Political orientations are correlated with brain structure in young adults,” *Current Biology*, vol. 21, no. 8, pp. 677–680, 2011.
- [32] G. Vecchiato and et al., “Eeg analysis of the brain activity during the observation of commercial, political, or public service announcements,” *Intelligence and Neuroscience*, vol. 2010, 201.
- [33] H. Marzbani and et al., “Methodological note: Neurofeedback: A comprehensive review on system design, methodology and clinical applications,” *Basic and Clinical Neuroscience*, vol. 7, no. 2, pp. 143–158, 2016.
- [34] A. Nijholt, *Brain Art: Brain-Computer Interfaces for Artistic Expression*. Springer, 2019. [Online]. Available: [https://doi.org/10.1007/978-3-540-74658-4\\_52](https://doi.org/10.1007/978-3-540-74658-4_52)
- [35] T. Moody, “Brainwave etch a sketch,” <https://rhizome.org/editorial/2007/mar/12/j-humbert-brainwave-etch-a-sketch-1974/>, online, accessed: 18.04.2020.
- [36] J. Xiong, “Mind art,” <https://www.behance.net/gallery/22054167/Mind-Art->, online, accessed: 18.04.2020.
- [37] M. Tränkle, “(un)focussed,” <http://mariontraenkle.eu/portfolios/unfocussed/>, online, accessed: 18.04.2020.
- [38] P. Neff and et al., “State dependency - audiovisual interaction through brain states,” *Proceedings of the 16th Sound & Music Computing Conference*, 2019.
- [39] ::vtol::, “Solaris,” <http://vtol.cc/filter/works/solaris>, online, accessed: 18.04.2020.
- [40] J. Haynes and G. Rees, “Decoding mental states from brain activity in humans,” *Nature Reviews Neuroscience*, vol. 7, no. 7, pp. 523–534, 2006.
- [41] M. Riefel, “Cnv & rp,” Brain Computer Interfacing, University of Twente, 2020.
- [42] K. Fifel, “Readiness potential and neuronal determinism: New insights on libet experiment,” *Journal of Neuroscience*, vol. 38, no. 4, 2018.
- [43] P. Ahmadian, “Development of soft computing algorithms for the analysis and prediction of motor task from eeg data,” 03 2014.

- [44] J. Parvizi, K. Gururangan, B. Razavi, and C. Chafe, “Detecting silent seizures by their sound,” *Epilepsia*, vol. 59, no. 4, pp. 877–884, 2018.
- [45] D. B. Ryan, K. A. Colwell, C. S. Throckmorton, L. M. Collins, K. Caves, and E. W. Sellers, “Evaluating brain-computer interface performance in an als population: Checkerboard and color paradigms,” *Clinical EEG and Neuroscience*, vol. 49, no. 2, pp. 114–121, 2018, pMID: 29076357. [Online]. Available: <https://doi.org/10.1177/1550059417737443>
- [46] D. J. Krusienski, E. W. Sellers, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, “Toward enhanced p300 speller performance,” *Journal of neuroscience methods*, vol. 167, no. 1, pp. 15–21, 2008.
- [47] D. Krusienski and et al., “A comparison of classification techniques for the p300 speller,” *Journal of Neural Engineering*, vol. 4, pp. 299–305, 2006.
- [48] M. Manyakov and et al., “Comparison of classification methods for p300 brain-computer interface on disabled subjects,” *4th International Conference on Bioinspired Systems and Cognitive Signal Processing*, 2011.
- [49] X. Xiao and et al., “A comparison of classification methods for recognizing single-trial p300 in brain-computer interfaces,” in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2019, pp. 3032–3035.

# A | Title of first appendix

## A.1 Information Brochure & Consent Form

### Purpose of the Study

This research is being conducted in the context of the brain computer interfacing course of the University of Twente. The purpose of this research study is to replicate the study done by Ryan et al., titled "Evaluating Brain-Computer Interface Performance in an ALS Population: Checkerboard and Color Paradigms" [45] with non-ALS subjects.

### Procedure of Study

You will participate in an experiment where you will wear an EEG cap, interacting with a spelling program which consists out of a matrix of all 26 letters plus digits from 0 to 9. Each row and column flashes in random order, you are asked to focus on a desired letter and silently count the number of flashes for this character. The flashing of (the row and column) of the desired character elicits a special brain signal, a so called P300 response. By matching the detected P300 response to the flashed row and column, the selected character can be determined. You are asked to move as little as possible which includes not moving your head, eyes, neck, etc.. This is to prevent unwanted artifacts in the EEG data.

*Please tick the appropriate boxes*

#### Taking part in the study

I have read and understood the study information dated [DD/MM/YYYY], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.

- Yes
- No

I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.

- Yes
- No

I understand that taking part in the study involves ...

- Yes
- No

**Use of the information in the study**

I understand that information will be used for educational purposes only.

- Yes  
 No

I understand that personal information collected about me that can identify me, such as [e.g. my name or where I live], will not be shared beyond the study team.

- Yes  
 No

**Future use and reuse of the information by others**

I give permission for the usage of the EEG data that I provide to be archived in the repository of the Human Media Interaction group at the University of Twente so it can be used for future research and learning. The data will be anonymised, that is, no personal information will be stored in correspondence with the data. In addition, the data will be encrypted in a way that only authorized personnel will have access to the data, commercial use of the data will be prohibited. The data will be stored for the maximum duration of one year.

- Yes  
 No

**Signatures**

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Name of participant (printed)	Signature	Date
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Name of researcher (printed)	Signature	Date
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**Contact Information for Questions about Your Rights as a Research Participant**

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Dr. Mannes Poel, m.poel@utwente.nl

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee of the Faculty of Behavioural, Management and Social Sciences at the University of Twente by ethicscommittee-bms@utwente.nl