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Brain-Computer Interfaces – conjunctions between two worlds

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Abstract

Ever since humans have started interacting with computers, they have seen them as companions in their lives. Even more so nowadays where advanced technologies such as smartphones make computers even more ubiquitous. However, it is clear that we could consciously tell our counterpart only what is expressible with muscles (e.g. using keyboards or speaking). The study of brain-computer interfaces (BCIs) makes a new, more direct, method possible.

BCIs are means to express intentions without the use of muscles. Instead, they perform actions by reading out and interpreting brain signals.

In this paper, the reader will be familiarized with the realm of BCIs. Many people still see utilization of technology in conjunction with the brain as an anachronistic science fiction scenario. However, the reader may find the overview of the topic helpful in understanding the implications, applications and principles behind this contemporary technology.

Moreover, this paper introduces not only a clear idea about the topic, but also offers a broad overview of different methods and applications of BCI systems.

Additionally, the mathematical principle behind a specific algorithm of preparing data is introduced.

Lastly, the reader may find a chapter discussing the future towards which BCIs are heading.

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Introduction

The 21st century is often considered as the century of neuroscience. This view is expressed by Francis S. Collins, M.D., Ph.D., a doctor, scientist and educator of high renown. He claims that

How the brain works and gives rise to our mental and intellectual lives will be the most exciting and challenging area of science in the 21st century. As a result of this concerted effort, new technologies will be invented, new industries spawned, and new treatments and even cures discovered for devastating disorders and disease of the brain and nervous system.¹

This trend in interest becomes particularly clear when analyzing the number of scientific papers published on the topic of BCIs over the years.

Plotting the number of topic-related scientific papers published on Google Scholar over the last decades illustrates the increasing interest since the beginning of the century. Figure 1 below visualizes this trend. The analyzed search term was ‘brain-computer interface’ on <https://scholar.google.com>.

It has to be kept in mind that this is just an approximation. While Google Scholar reliably lists older papers (even far back into the 19th century), this graph should be interpreted with caution and only viewed as a means of illustration.

¹Davis, 2017

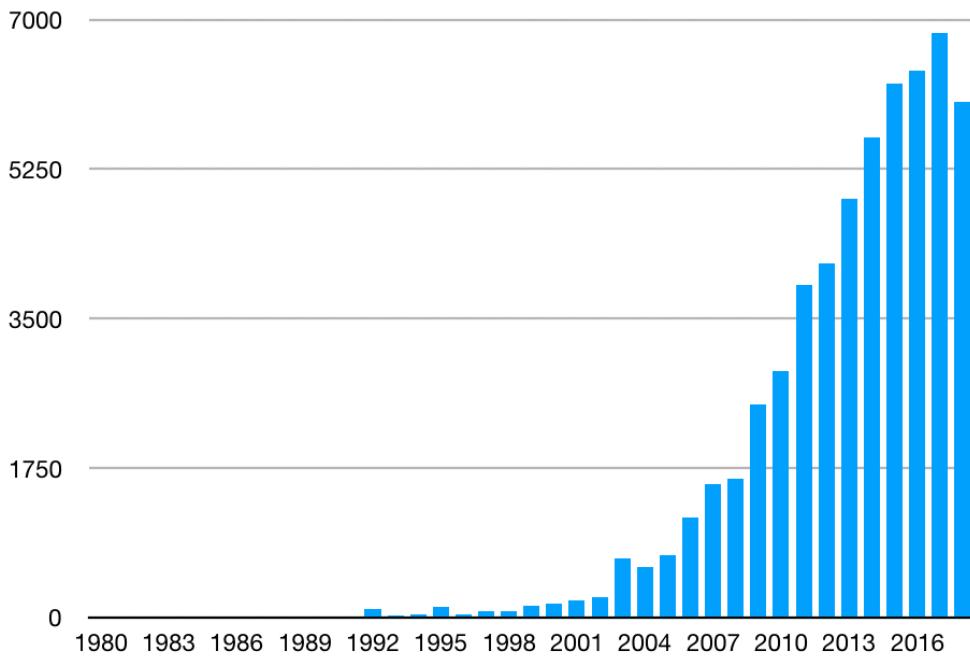


Fig. 1: Google Scholar BCI related results from 1980 to 2018 illustrating an increase in interest in BCIs in the last two centuries (Python analysis tool by [Volker Strobel, 2018](#)).

This paper aims to give an overview of BCIs and clear up questions the reader might have.

Additionally, this paper ought to create an interest in the reader and make the topic more appealing. After reading this paper, the reader may be more open to this technology, will understand important limitations and implications and will look forward to (rather than fear) the upcoming developments.

This paper's two main parts are *BCI Principles*, which outlines the theory of BCIs and the steps necessary for a BCI device to work and *BCIs in Practice*, which describes current BCIs and the future of BCIs.

To start off, however, a basic notion of BCIs and what they are about has to be established. The following chapter *Preliminary Questions* will serve this purpose.

1 Preliminary Questions

Since the 1930s people have known that electrical signals produced by the brain can be captured. The pioneer of this idea of monitoring brain signals was the German psychiatrist Hans Berger in 1929.²

Ever since then, scientists have been fascinated by the idea that people could consciously act and communicate without using their muscles. Every kind of action we perform (think about the vocal cords or your facial muscles e.g.) is ultimately based on muscular activity and so it is understandable why many scientists are excited by this completely novel way of communicating by using BCIs.

With the onset of more advanced and powerful technology as well as machine learning algorithms, reliably using BCIs as a means of communication has become reality more and more.

A very comprehensive definition of a BCI taken from an eminent textbook will outline this chapter:

A BCI is a system that measures CNS activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external environment.³

In this preliminary chapter of the paper the definition above will be dissected and a crucial foundation for understanding subsequent topics will be constructed. The discussed parts of the definition are:

- CNS Activity
- Signal Conversion
- Manipulation of Output
- Change of Interactions

²cf. Berger, 1931, p. 1

³Wolpaw & Winter Wolpaw, 2012, p. 3

1.1 CNS Activity

Fundamentally, the central nervous system (CNS) consists of the spinal cord and the brain. The signals that are to be picked up when a BCI is used have their origin in different, primarily cortical (i.e. the outer), areas of the brain, as seen in Figure 2.

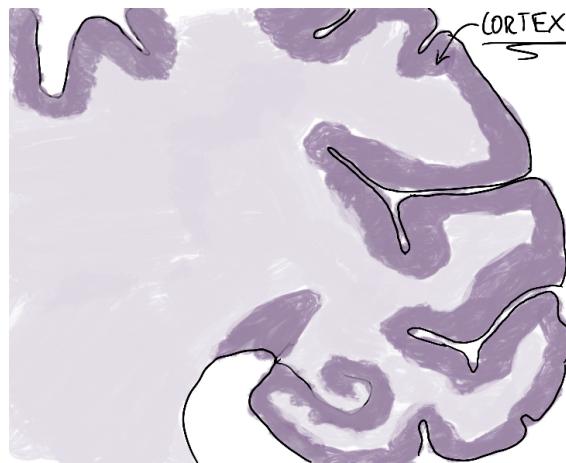


Fig. 2: The cerebral cortex, in this case of a rhesus macaque monkey, is the outer layer painted in dark violet (from brainmaps.org, 2008).

Depending on the kind of BCI device, different characteristics of brain communication are being. The most commonly recorded signals are *electric* or *magnetic* fields measured from the scalp or close electric fields on the surface of the brain.

Another signal that can indirectly be picked up is the blood flow in the brain. These signals are called *metabolic* signals (outlined in Chapter 2 *Signal Acquisition*).

As the most commonly measured characteristics are electrical and magnetic signals, their origin will be discussed briefly. The origin of metabolic signals is simply the need for blood in brain cells so that they can operate correctly.

Electrical signals have their origin in the communication of neurons. Neurotransmitters are being released into the synaptic cleft when excited by a nerve impulse and bind to the ionic channels of the postsynaptic neuron (as seen in Figure 3). This allows the channels to open, allowing an influx or outflux of ions to change the local membrane potential.⁴

⁴cf. Rao, 2013, p. 9

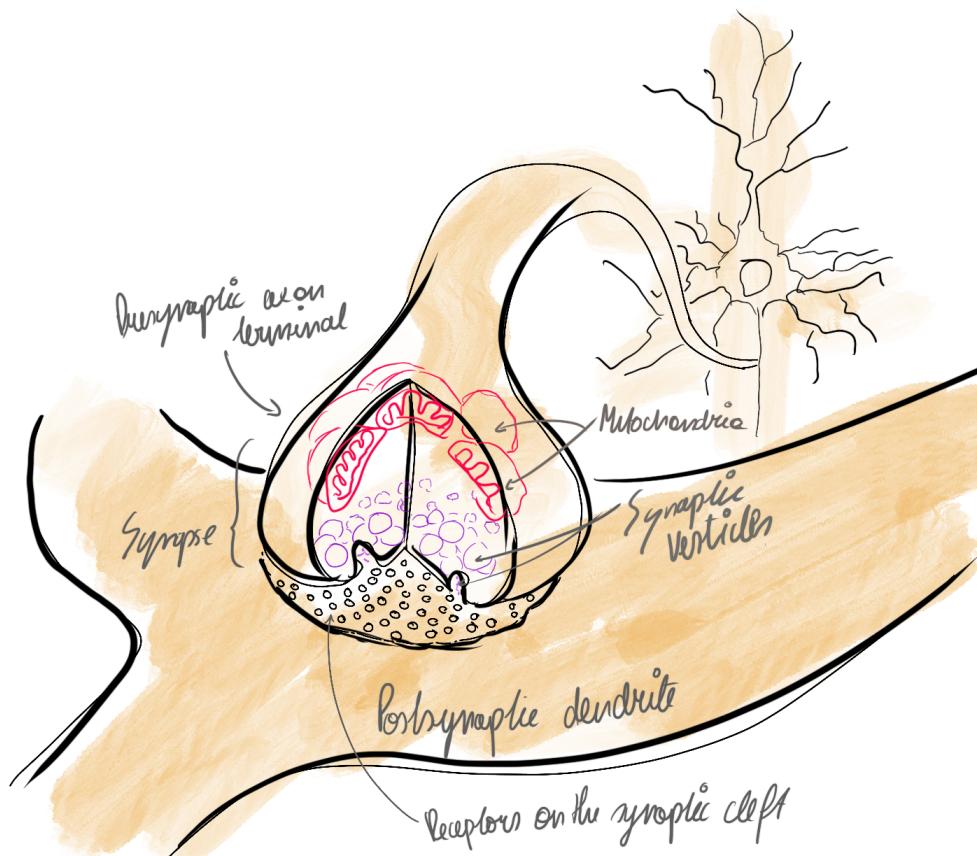


Fig. 3: A synapse visualized. When a nerve impulse arrives in the presynaptic axon terminal, neurotransmitters are released (from Bear et al., 2016, p. 42).

These potential changes are ultimately what will be picked up and interpreted (in higher quantitative numbers).⁵

1.2 Signal Conversion

The signals that are picked up have to go through signal manipulation and machine learning algorithms for their meaning to be interpreted. These algorithms can be highly complex.

For this preliminary chapter it suffices to say that the picked up signals are being *cleaned* of artifacts such as EMG (electromyogram) signals produced by muscle activation or ambient disturbances such as WiFi or power line noise.⁶

⁵cf. Taylor & Stetner, 2010, pp. 205, 206

⁶cf. Rao, 2013, p. 18

This is done to have a signal that is as uncluttered as possible for exact interpretation. The importance of a clear signal was also stressed by Dr. Seeber, a researcher from the University of Geneva and an expert in the study of BCIs.⁷

In future references Dr. Seeber will be denoted as a source in the subsequent footnote (his ResearchGate profile can be looked up in the reference section of this paper).

1.3 Manipulation of Output

The ultimate goal of a BCI is to use the signals that have been measured and converted to manipulate natural CNS output. Reasons for the need of this manipulation could be the impairment of movement or the need for an artificial limb, to name only two.⁸ BCIs can then help by manipulating CNS output (natural CNS output may not be possible anymore).

Different types of manipulations will be outlined in Chapter 5 *Usage*.

1.4 Change of Interactions

There is one last crucial step when using a BCI. This step is called *feedback*.

Feedback is the last and most important act when the BCI user's brain is supposed adapt to a newly established means of interacting with the environment (e.g. via an artificial arm).⁹

When touching a table, the arm and fingers can be seen moving towards the table and subsequently the surface of the table can be felt. This gives the brain feedback by reporting that something happened successfully when the arm and fingers were told to move towards the table.

This feedback has to be established at any cost if the BCI is to be functional and long-lasting.

⁷cf. Dr. Seeber

⁸cf. Wolpaw & Winter Wolpaw, 2012, p. 197

⁹cf. Rao, 2013, p. 208

BCI Principles

Having built a sturdy foundation, more in-depth topics will be discussed.

This major chapter will deal with the principles underlying BCIs. It will be based on Figure 4, which portrays the steps involved in the operation of a BCI.

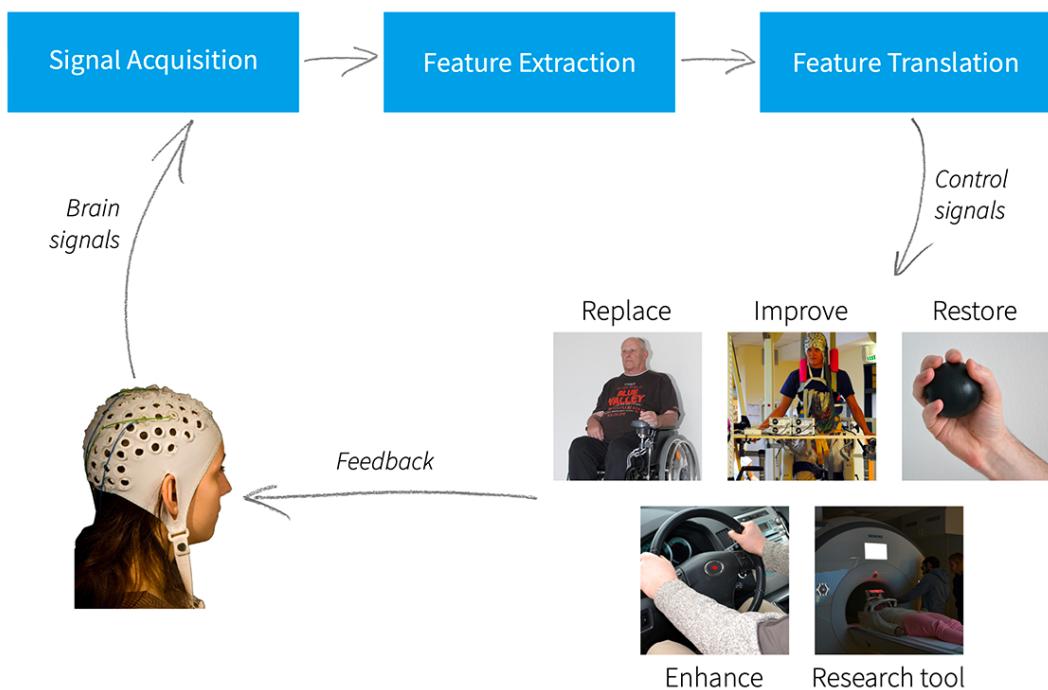


Fig. 4: The process of brain-computer interfacing illustrated (from Brunner et al., 2015, p. 14).

Explicitly, topics that will be examined are:^{10,11}

- Signal Acquisition
- Signal Processing¹² (Extraction & Translation)
- Feedback

Note that the process depicted in Figure 4 illustrates a loop that repeats itself until the user has successfully performed his desired action.

2 Signal Acquisition

This chapter gives an overview of the different means of signal acquisition and which advantages and disadvantages make them useful or impractical for BCIs.

The most fundamental way to distinguish means of acquiring signals from the brain is by their *invasiveness*. First, *non-invasive* systems will be considered, which means that there is no surgery required for their application. Afterwards *invasive* methods will be discussed. For these methods surgery is mandatory.¹³

Two fundamental terms, temporal and spatial resolution, have to be reviewed before means of acquiring signals are discussed.

Temporal and Spatial resolution¹⁴

Temporal and spatial resolution are the most important performance characteristics for methods of acquiring brain signals.

Temporal resolution refers to how long it takes for the user's intention to be picked up by the device. Undoubtedly, a small temporal resolution is desirable for quick BCI usage and feedback.

Spatial resolution refers to how precise the method can measure brain signals. Usually a higher spatial resolution is desirable. This allows for more complex movements (e.g. the fingers of an artificial hand).

¹⁰cf. Brunner et al., 2015, p. 14

¹¹cf. Shih et al., 2012, p. 271

¹²cf. Wolpaw & Winter Wolpaw, 2012, p. 123

¹³cf. Shih et al., 2012, p. 272

¹⁴cf. Wolpaw & Winter Wolpaw, 2012, p. 66

2.1 Non-Invasive Methods

For brevity reasons, two eminent means of acquiring brain signals will not be discussed in this main part, namely PET and fMRI systems. They are non-invasive, but are currently not practical for BCI usage. The user has to lie down in order to use them and they have poor temporal resolution. The reader will find detailed discussions about those methods in the Appendix at the end of this paper.

2.1.1 fNIR

Functional near infrared (fNIR) imaging is based on the fact that oxygenated blood absorbs infrared light to a different degree than de-oxygenated blood. This is due to different hemoglobin levels and gives information about where in the brain the most activity is taking place (i.e. how much blood is circulating).¹⁵

By placing infrared detectors on the scalp, the amount of reflected light (having been sent out beforehand) can be measured. Therefore the area with the most activity can be determined (see Figure 5).

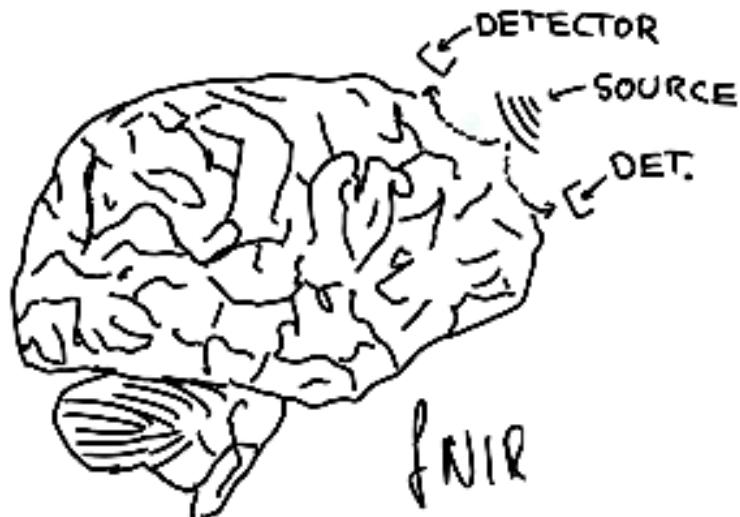


Fig. 5: The principle behind fNIR. The detectors catch the reflected infrared light sent out by the source (from [BIOPAC Systems® Inc.](#)).

However, fNIR can only detect neural activity in the outer layers (the cortex) of the brain. This might pose a problem depending on whether sub-cortical (i.e. below

¹⁵cf. Shih et al., 2012, p. 270

the cortex) signals are required in the BCI.^{16,17}

Compared to other methods, fNIR, relying solely on optical measurements, is not susceptible to interfering artifacts (e.g. muscular activity or WiFi signals). If it were not based on slow metabolic activity, it would be a perfect candidate for every-day BCI usage.¹⁸

2.1.2 MEG

While the previous methods were based on metabolic activity, this method (magnetoecephalography or MEG) is based on measuring the magnetic fields (originated from neuronal activity as discussed in Chapter 1 *Introduction*) propagating through the skull.

Because this procedure is ultimately based on electrical activity in the brain (magnetic fields result from electric activity), a huge advantage is the temporal resolution. Contrary to metabolic signals, the electrical currents in brains move almost instantly (up to $120 \frac{m}{s}$ ¹⁹). Therefore the measured activity is visible virtually immediately.²⁰

While the incredible temporal resolution sounds great, there are many inconveniences connected with using this means of recording.

MEGs are not portable at all (as is seen in Figure 6), which would be impractical for BCIs that are to be used on a daily basis. One has to sit in an enclosed room which has to be shielded from all external magnetic fields.

¹⁶cf. Wolpaw & Winter Wolpaw, 2012, p. 66

¹⁷cf. Shih et al., 2012, p. 270

¹⁸cf. Rao, 2013, p. 30

¹⁹cf. Bear et al., 2016, p. 423

²⁰cf. Rao, 2013, p. 29



Fig. 6: A MEG device in use. The user has to sit down cannot move (from Rao, 2013, p. 29).

Two examples for magnetic field sources that can interfere with the brain's fields are the Earth's magnetic field and power line magnetic fields.²¹ They are around a billion times larger than the signals which are to be measured in the subjects (even though there are about 50.000 – 100.000 neurons excited together).²²

Additionally, MEG instruments are tremendously expensive, using so-called *superconducting quantum interference devices* (SQUIDS). SQUIDS can only detect these minuscule magnetic fields when their impedance (resistance to current changes) is very low, which means they have to be cooled down to about –269 degrees Celsius in a liquid helium bath.²³

To not only talk poorly about MEGs, they are exceptionally precise, since magnetic fields are not hindered by the layers between the brain and the device. This is not the case with BCIs based on electric fields (such as EEGs discussed shortly), where the signals will be spread quite a bit along the way.²⁴

²¹cf. Bear et al., 2016, p. 648

²²cf. Washington, 2012

²³ibid.

²⁴cf. Singh, 2014

2.1.3 EEG

While MEG devices are quite expensive and not portable at all, *electroencephalography* (EEG) devices are the exact opposite. They are easy to apply and can be totally portable and are thus commonly used in research. They are widely seen as the future of BCIs. EEGs measures the electric fields on the scalp of the subject.²⁵

EEGs are very inexpensive, being based simply on metal electrodes (such as in Figure 7) that are attached to the scalp. The electric field is then induced and current is created. It will be amplified and recorded afterwards.²⁶

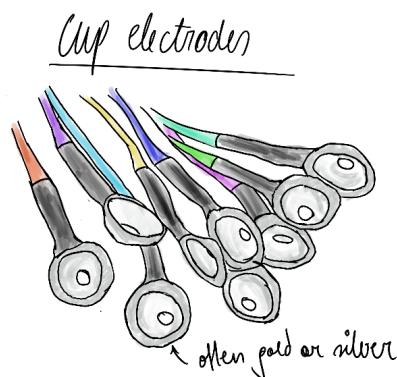


Fig. 7: Simple silver cup electrodes (from bio-medical.com®).

Characteristic for EEGs is the use of conductive paste for the electric field to have as few obstacles as possible. This lowers the impedance (resulting in a clearer signal).²⁷

The fields picked up by the BCI should have their origin mainly in the cerebral cortex. But even though they are very close to the electrodes, their amplitudes are just around a few μV .²⁸

For EEGs it is crucial to keep in mind that the electric fields can have their origin in a manifold of places. The most obvious being EMG muscular electric fields or those of the subject's surroundings. To account for these, one has to apply artifact-reduction techniques. Sophisticated artifact recognizing machine-learning approaches are being used to clear the signal of those disruptions.

²⁵cf. Rao, 2013, p. 26

²⁶cf. Marcuse et al., 2016, p. 8

²⁷cf. Lifelines Neuro®

²⁸cf. Marcuse et al., 2016, p. 8

Figures 8 to 11 depict four examples for artifacts in EEG devices:

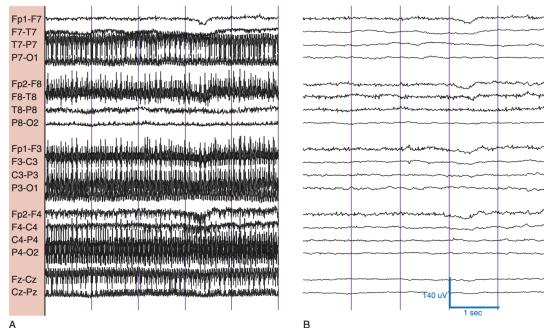


Fig. 8: 60Hz power line artifacts without (A) and with (B) an applied filter (from Marcuse et al., 2016, p. 34).

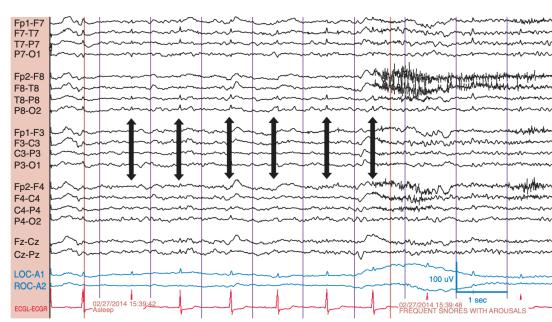


Fig. 9: The arrows indicate ECG (electrocardiography - heart muscle) artifacts (from Marcuse et al., 2016, p. 20).

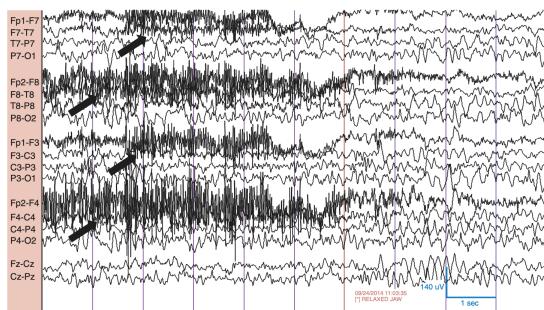


Fig. 10: Marked by the arrows are jaw muscle artifacts (from Marcuse et al., 2016, p. 27).

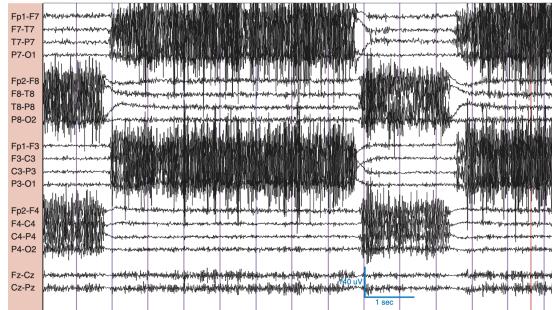


Fig. 11: These highly disruptive artifacts were produced by alternating tooth grinding (from Marcuse et al., 2016, p. 28).

The outstanding temporal resolution of EEGs is currently being combined with improved spatial resolution by means of developing *hdEEGs* (high-density EEGs). They are very promising and quite accurately address one of the problems conventional EEGs have, namely bad spatial resolution.^{29,30}

Development in this direction will go a long way in finding a BCI that is useful for more complicated tasks, which are not yet able to be achieved accurately using conventional BCIs.³¹

²⁹cf. Schiaffi, 2014

³⁰cf. Lustenberger & Huber, 2012, p. 1

³¹ibid.

2.2 Invasive Methods

While having many advantages (e.g. concerning spatial resolution), invasive methods do have the disadvantage of requiring surgery before they can be used. This makes them currently only relevant in clinical settings. All relevant invasive methods will be discussed in the following.

2.2.1 ECoG

Electrocorticography (ECoG) is a highly promising method of picking up electrical fields *on the surface* of the brain. The signals are acquired by placing electrodes underneath the skull either above or below the dura mater, which is labelled in Figure 12 as epidural and subdural respectively.³²

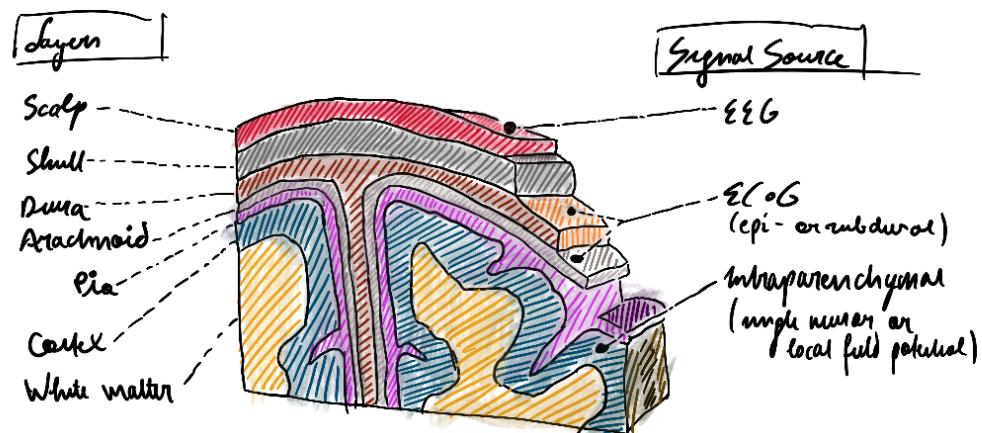


Fig. 12: Reference for recording domains and some neurophysiology (from Schalk & Leuthardt, 2011, p. 140).

The electrodes (typically made of platinum) are arranged in a grid, which is then placed on the cortex. Macrogrids (as seen in Figure 13 D) have a padding of 10mm. Other methods include microgrid arrays (as seen in Figure 13 A and B), which have an even better spatial resolution due to their minuscule padding.

³²cf. Schalk & Leuthardt, 2011, p. 140

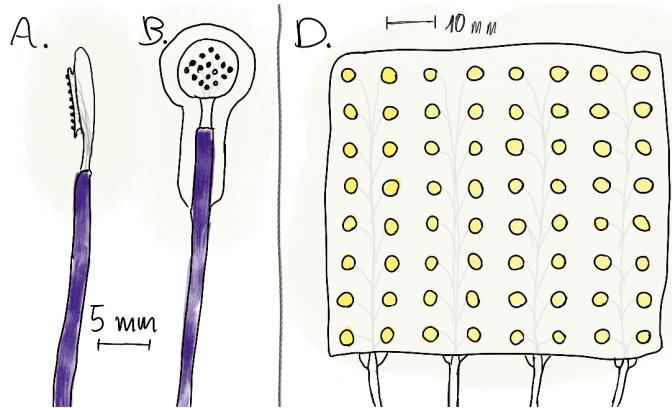


Fig. 13: Microgrids (A and B) and macrogrids (D) as commonly seen in clinical applications (from Schalk & Leuthardt, 2011, p. 141).

Generally speaking, ECoGs are very special as they pose a great balance between the convenience and practicality of EEGs and a performance which no other method of recording can achieve.

Concerning performance, the unreliability of EEGs regarding artifacts and noise is not present to such an extent in ECoGs. EMG and EOG (electrooculogram signals due to eye movements) artifacts, e.g., are picked up only to a negligible amount.

Because there are fewer layers for the electric fields to permeate, the signal is much clearer and much stronger than that of EEGs, for instance (ECoG: 50 – 100 μ V; EEG: 10 – 20 μ V). This is also where the amazing spatial resolution comes from. Because electric fields spread in every direction, it is of great value that the electrodes are as close to the source as possible (ECoG: 1.25mm and 1.4mm, subdural and epidural respectively; EEG: several centimeters).³³

Another effect of the crystal clear signal is the ability to pick up frequencies that would in other methods be lost in the noise (ECoG frequency range: 0 – 500Hz; EEG: 0 – 40Hz). These frequencies can help decipher the intentions of subjects that would simply be invisible when using other methods.³⁴

Due to the necessity of surgery, ECoG devices are still mainly used in clinical settings. Nevertheless, it is already proclaimed that long-term use of ECoGs is possible for several months without problems.³⁵

³³cf. Schalk & Leuthardt, 2011, p. 140

³⁴ibid., p. 141

³⁵ibid., p. 143

2.2.2 Intracortical Methods

An even more invasive method is the insertion of microelectrodes in the brain tissue itself. Electrodes such as these are typically made of platinum or iridium and are united into so-called microelectrode arrays (as in Figure 14).³⁶

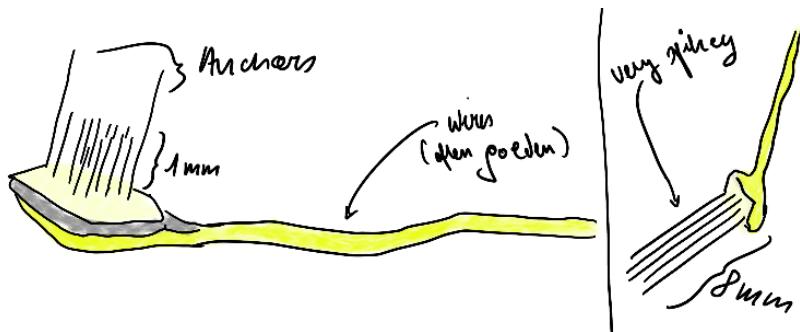


Fig. 14: Minuscule electrodes combined to form an intracortical electrode array (from Wolpaw & Winter Wolpaw, 2012, p. 84).

The electrodes either record the neuronal spikes themselves (the earlier discussed potential differences) or LFPs (local field potentials) of nearby neuron populations that are transduced into the electrodes.^{37,38}

While intracortical microelectrodes have impeccable temporal as well as spatial resolution, there are multiple difficulties connected with their usage.

One of the most important element to consider when using this method is the right choice of electrode material. It is integral that a low-impedance material which is not too rigid is chosen. Neglecting the latter would make it hard for the electrodes to move with the brain, which it naturally does to a slight degree as the subject moves.³⁹ Several research teams are working on finding a perfectly flexible material that is compatible with brain tissue.⁴⁰

However, the biggest problem is the integration of the electrodes into the brain's structure. The brain should - as with prosthetics - not view the material as a foreign object which would lead to inflammation or infection. Another problem is

³⁶cf. Wolpaw & Winter Wolpaw, 2012, pp. 82-84

³⁷ibid., p. 87

³⁸cf. Taylor & Stetner, 2010, p. 205

³⁹cf. Wolpaw & Winter Wolpaw, 2012, p. 98

⁴⁰cf. Jorfi et al., 2015, p. 1

the initial injury when inserting the electrodes into the brain. This insertion can lead to edemas (swelling due to excess liquid) or scar tissue.⁴¹

Since there is often no way to restore the initial neuronal health of these areas, this still poses a huge problem.⁴²

2.3 Comparison

In Figure 15, all the discussed methods can be seen in comparison to each other. The two key factors are spatial resolution and temporal resolution (clarified at the beginning of the chapter).

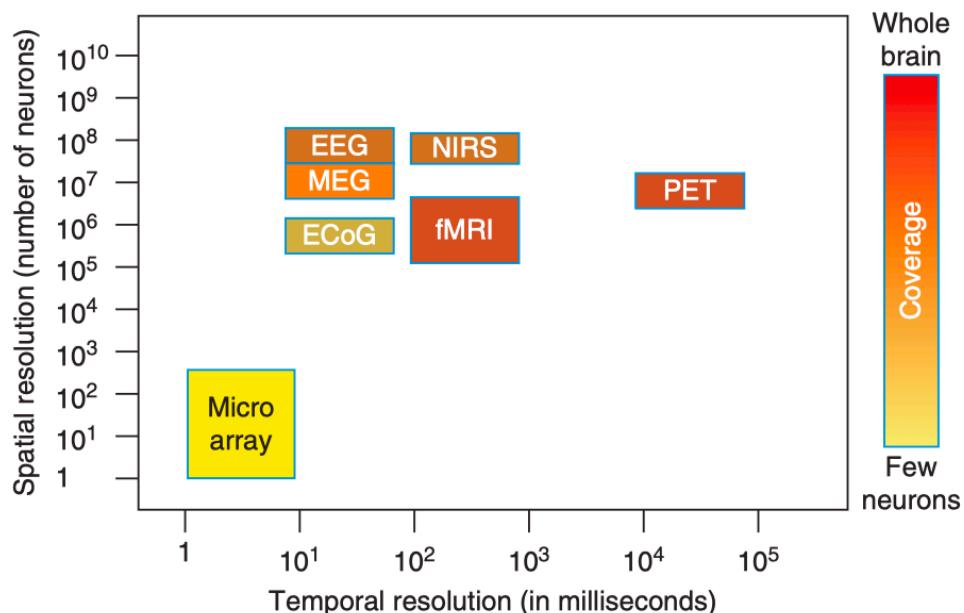


Fig. 15: Different imaging techniques compared based on their temporal and spatial resolution. Here, NIRS is equivalent to fNIR (from Wolpaw & Winter Wolpaw, 2012, p. 66).

⁴¹cf. Polikov et al., 2005, p. 1

⁴²cf. Wolpaw & Winter Wolpaw, 2012, pp. 22, 87-98

3 Signal Processing

After the user's brain signals are acquired, the BCI has to ascertain which action is to be executed. This process, broadly called *Signal Processing*, consists of two sub-processes:

1. **Feature Extraction**
2. **Feature Translation (also called Classification)**

To build a sturdy foundation, a *feature* has to be defined. A self-made explanation will facilitate comprehension.

What is a feature?

A feature is a certain pattern of brain signals that can be categorized into specific groups of action (e.g. movement of the right arm upward). When these features are identified (they are highly user-specific), the user's intention can be guessed. It is essential for a stable BCI that the device's guess is very precise.⁴² The feature extraction process is far from straightforward, since various kinds of artifacts and noise disturbances happen all the time, which particularly for EEGs have to be accounted for (see previous chapter).

3.1 Feature Extraction Generally

Feature extraction can best be introduced by using this quote by Hoffmann et al. (2006):

*A good feature extraction method should reduce the dimension of the input data as much as possible while keeping all the information necessary for classification.*⁴³

⁴²cf. Woon & Cichocki, 2007, pp. 1-3

⁴³Hoffmann et al., 2006, p. 2

When attempting to extract features in a BCI, there are three main sources of information that are relevant for identification:⁴⁴

- **Spatial information:** Spatial information is crucial when the feature is originated in a specific area of the brain. In this case the information about the signal strengths in certain electrodes can be analyzed and features can be extracted.

This is especially important for actions that have their origin in specific areas of the motor cortex, the area are in the brain responsible for movement.

In Figure 16, the locations of bodily functions on the motor cortex are illustrated. This map can be used to specify the optimal position for electrodes if one wants to stimulate or read activity.

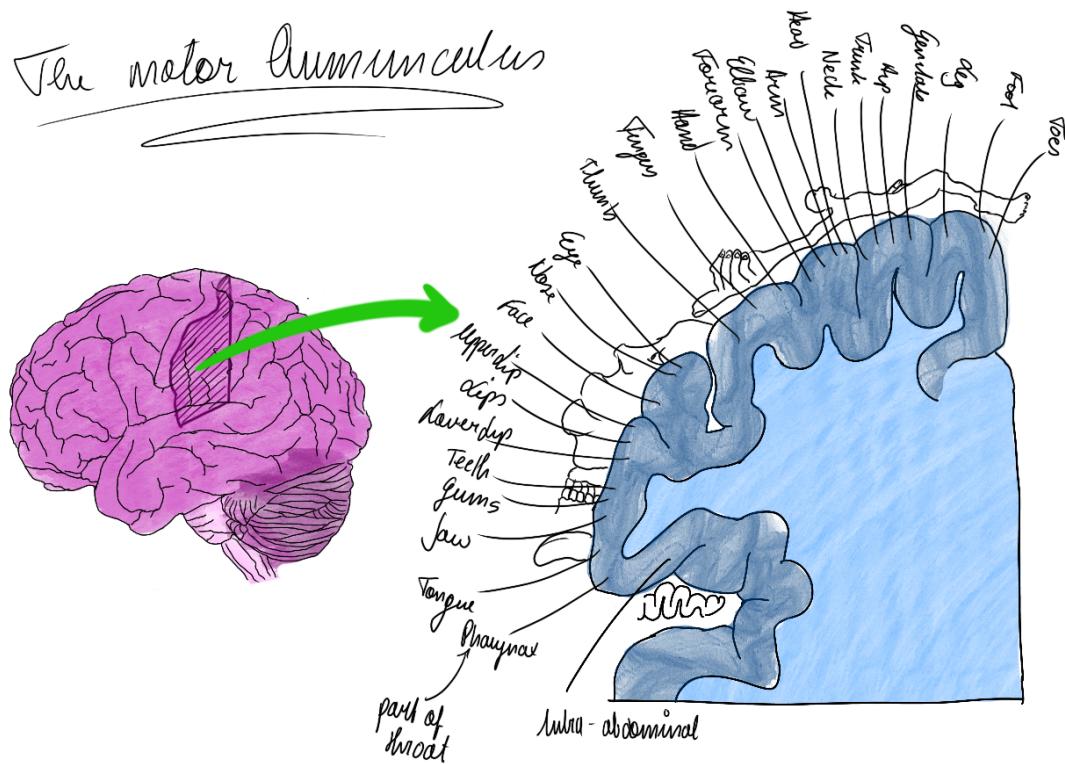


Fig. 16: The motor homunculus, schematically illustrating the approximate location of bodily functions (from Bear et al., 2016, p. 432).

⁴⁴cf. Lotte, 2014, p. 6

- **Spectral information (frequency):** Generally, the reason why electric or magnetic fields-based BCIs pick up different frequencies is that thousands of neurons fire together and create oscillatory signals due to time delays. Certain actions can be characterized by their signal frequency.⁴⁵

Features of this sort will be characterized by higher amplitudes in certain frequency bands. For example, executed and imagined movements activate premotor and primary sensorimotor areas (front and center of the brain respectively). This results in amplitude/power changes in the μ (mu), β (beta) and γ (gamma) rhythms.⁴⁶ Mu rhythms are equivalent to alpha waves in Figure 17.⁴⁷

For reference, R. Douglas Fields offers an overview of the different frequencies of brainwaves and their properties (see Figure 17).⁴⁸ This is a general overview of how brain signal frequencies give information about events in the body.

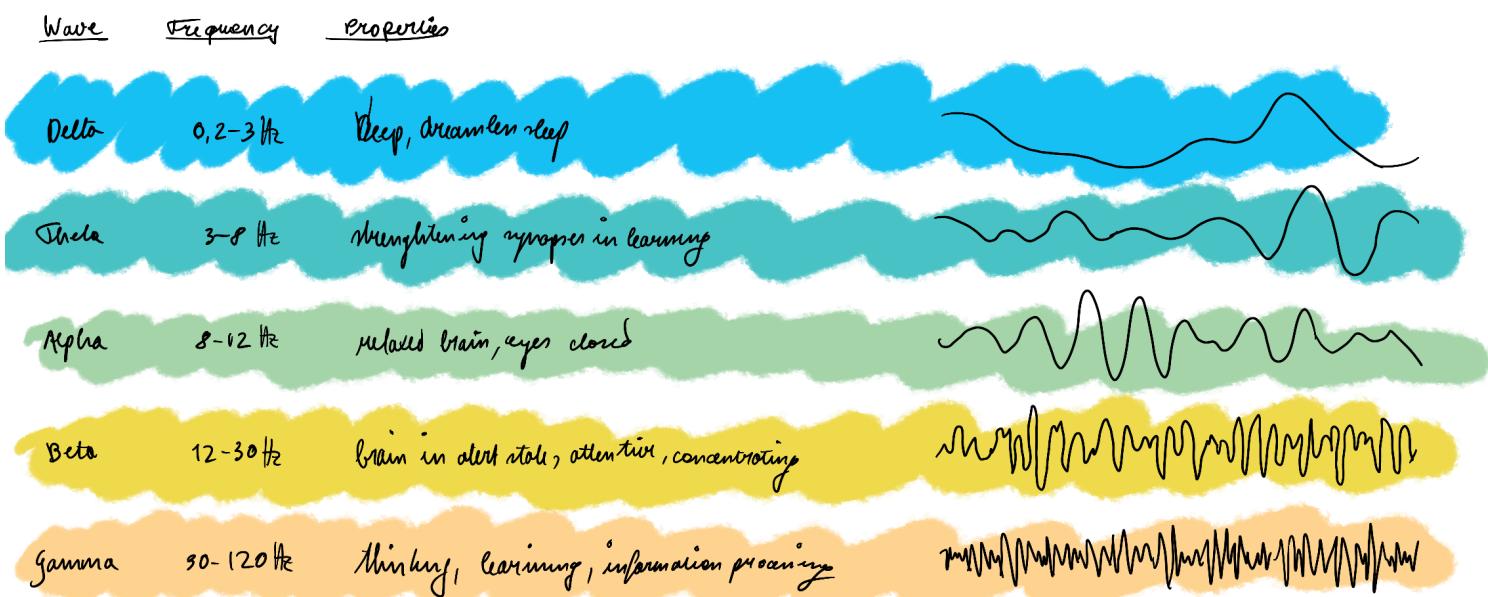


Fig. 17: Different brainwaves and their properties (from Fields, 2016, p. 60).

⁴⁵cf. Rao, 2013, p. 40

⁴⁶ibid.

⁴⁷cf. Fields, 2016, p. 60

⁴⁸ibid.

Generally, an increase in frequency-band amplitude is called an *Event Related Synchronisation* (ERS), whereas a decrease in frequency-band amplitudes is called an *Event Related Desynchronisation* (ERD).⁴⁹

To name a more specific example, imagination of a *left* hand movement leads to a *contralateral* (i.e. *right* side in this case) ERD in the motor cortex (located centrally on the brain's cortex) in the μ and β bands during movement imagination, and to an ERS in the β band just after the movement imagination ending. This is also called *beta rebound* and just one example of how a frequency-based feature would look like.⁵⁰

- **Temporal information:** Features that are analyzed temporally are characterized by the change of their signal over time. In practice, to extract temporal features, one has to observe the amplitudes of brain activity at different points in time to make predictions about the intention of the user.⁵¹

A feature which is predominantly based on temporal characteristics will be outlined in great depth in the following paragraphs. Any questions concerning temporal characteristics in features will then be answered.

High precision BCIs often extract information of several types of features to get a clearer picture of the intention the user might have. Furthermore, there is no one-size-fits-all solution to feature extraction, since different characteristics are important for different applications.⁵²

For instance, BCIs based on oscillatory activity (such as imagined or overt movement) mostly use spectral and spatial information. On the other hand, BCIs based on so called *event-related potentials* mostly use temporal and spatial information for extraction.

One example for an event-related potential is the notorious and well researched *P300 potential*, which is crucial in BCIs based on recognizing decision-making actions.⁵³ In order to illustrate how the path from recording the signal from the brain to the action the BCI performs looks like, in the following the details of one of the most commonly used potential will be covered.

⁴⁹cf. Pfurtscheller, 2001, p. 1

⁵⁰cf. Lotte, 2014, p. 3

⁵¹ibid., pp. 2-5

⁵²ibid., pp. 3-6

⁵³cf. Picton, 1992, pp. 1, 2

In a paper of this length it is sheer impossible to cover all the methods of feature extraction and feature translation currently known, so it is appropriate to use this very specific example to illustrate the steps necessary to obtain a BCI action. This will aid in understanding the nature of feature extraction methods in general.

3.2 Feature Extraction for P300 Potentials

More specifically, an *event-related potential* (ERP) is the brain's response to a certain stimulus perceived by the user. As already mentioned, one of the most well-known ERPs is the P300 potential, which is a positive deflection of the signal occurring 300ms after the relevant stimulus is perceived.^{54,55} A relevant stimulus could be a desired letter on a screen in the case of a *speller* BCI (discussed on the next page).⁵⁶ The behavior of a P300 potential can be observed in Figure 18 below.

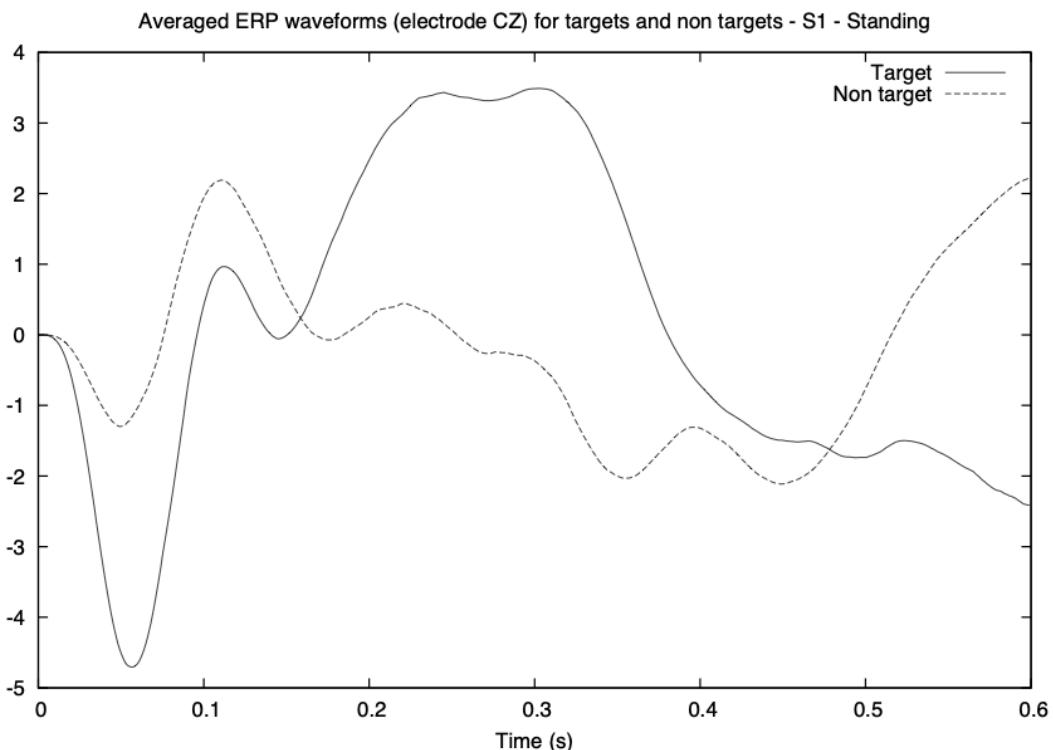


Fig. 18: An averaged P300 potential. The ‘Target’ graph peaks 300ms (therefore the name) after the stimulus at Time = 0s (from Lotte, 2014, p. 18).

⁵⁴cf. Lotte, 2014, p. 6

⁵⁵cf. Picton, 1992, p. 1

⁵⁶cf. Rezeika et al., 2018, p. 1

As mentioned, a speller BCI is a common application of an ERP-based BCI. The following will clear up some questions.

A speller BCI

A speller BCI alternates between rows (as seen in Figure 19) and stops when a P300 potential is ascertained. The computer can then construct the user's intended message.⁵⁷

CRT	N/A	N/A	N/A
B C I	B		
A	B	C	D
G	H	I	J
M	N	O	P
S	T	U	V
Y	Z	L	R
F		W	X
K		3	4
L		9	-

Fig. 19: The interface of a so-called matrix speller BCI (from Rezeika et al., 2018, p. 9).

To account for the spatial characteristics of P300 potentials, P300-based BCIs focus on electrodes located over the parietal lobe (an area in the brain located in the rear). Only features of the relevant electrodes are extracted. This is where the origin of P300 potentials are.⁵⁸ For that reason, Krusienski et al. recommends an electrode setup such as in Figure 20.

⁵⁷cf. Rezeika et al., 2018, p. 9

⁵⁸cf. Lotte, 2014, p. 19

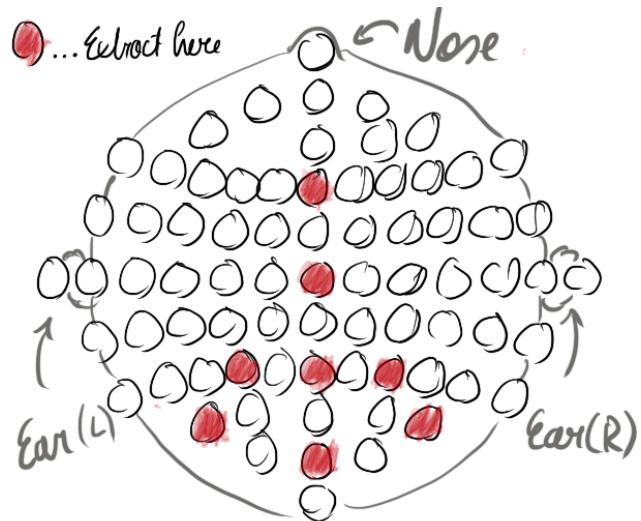


Fig. 20: Recommended electrode setup for P300-based BCIs by Krusienski et al. (from Lotte, 2014, p. 19).

The following steps are generally taken to prepare a P300 potential for its analysis.⁵⁹ This can also be seen in Figure 21.

1. Low-pass or band-pass filtering of the signals (for P300 ERPs that is between 1Hz and 12Hz). Generally, ERPs are slow waves.
2. ‘Downsampling’ of the filtered signals. This will reduce the dimensionality and facilitate signal analysis.
3. Combining the remaining time points into a ‘feature vector’ to be inserted into the classifier (for feature translation)

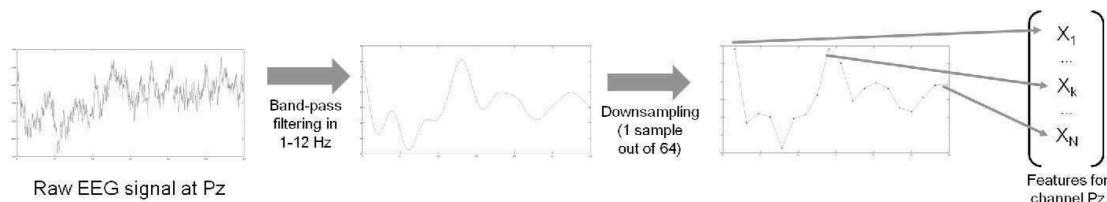


Fig. 21: Typical process of extracting features from a channel (P_z in this case) in a P300-based BCI design. The P300 potential is becoming more visible with the different processing steps until it is converted to a vectorized form (from Lotte, 2014, p. 20).

⁵⁹cf. Mallick & Kapgate, 2015, pp. 1, 2

In Figure 21, the process is illustrated for the central electrode P_z , whose position can be seen in Figure 20.

The resulting feature vector can then be put into a classifier, which assigns it to certain classes. In the context of a P300-based BCI, classes of ‘target’ or ‘no target’ make sense. Examples for each of the two can be seen in Figure 18 at the beginning of this chapter.

The ‘target’ class refers to having received a rare stimulus (e.g. choosing a character in a BCI letter-speller⁶⁰), as opposed to the ‘no target’ class, which refers to not receiving a relevant stimulus (not having a target in mind).

Generally, the number of time points (samples) needed for an ERP-based BCI is much higher than for a BCI based on oscillatory activity. If a reduction of dimensionality is necessary (e.g. due to insufficient computational power to handle high-dimensional datasets), feature selection, channel selection or spatial filtering methods can be used.⁶¹

3.2.1 Feature selection

Feature selection algorithms are widely used in machine learning and are therefore also very commonly used in BCI design.

Generally, the discriminative power of each feature is measured (in this case the time points or *samples*) and their usefulness is assessed by using statistical relevance concerning the class assignment. If they are not very descriptive, they will not be used for further analysis and thus not included into the feature vector.⁶²

In the case of many data points, however, this algorithm can demand a lot of computational power, so it makes sense to use more than one dimensionality-reducing algorithm.⁶³

⁶⁰cf. Rezeika et al., 2018, p. 1

⁶¹cf. Lotte, 2014, p. 20

⁶²ibid., p. 9

⁶³ibid., p. 11

3.2.2 Channel selection

With channel selection, statistical usefulness of each channel is calculated and thus one can determine the discriminative power (i.e. how much new information it provides) of each channel. Subsequently, the unnecessary channels will be excluded. While both, channel selection and feature selection, reduce dimensionality, channel selection has additional advantage. In particular, using fewer channels means a faster setup time for the BCI (e.g. less electrodes for EEGs) and also a lighter and more comfortable setup for the subject.^{64,65}

3.2.3 Spatial filtering

Another method to reduce feature dimensionality, besides feature and channel selection, is *spatial filtering*. Spatial filtering is a method to increase discriminative power of the feature vectors by finding a linear filter to apply to the features. In the following, a spatial filtering method by Hoffmann et al. (2006) is presented.⁶⁶

Even though this filtering method is very specific and unique to the application (P300 potentials), it is important for the reader to grasp the complexity of such algorithms and understand the way to the goal of making the BCI perform an action (for P300 potentials, a speller BCI seems the natural choice⁶⁷). The algorithm's objective goes as follows:

Aim of the algorithm proposed by Hoffmann et al.⁶⁸

The algorithm aims to simplify the dataset to minimize the work the feature translation algorithm (discussed later on) has to do, substantially shortening processing time. The unnecessary data (i.e. data that is very similar to other data and thus has not much meaning) will 'distract' the algorithm, giving less meaning to the relevant information. This unnecessary data has to be removed or combined.

⁶⁴cf. Lotte, 2014, p. 9

⁶⁵cf. Alotaiby et al., 2015, pp. 1, 2

⁶⁶cf. Hoffmann et al., 2006

⁶⁷cf. Rezeika et al., 2018, p. 1

⁶⁸cf. Hoffmann et al., 2006

As a foundation, a primer in matrix operational methods is necessary, which the following info boxes intend to do:

Basics of tracing a matrix⁶⁹

Tracing a matrix is denoted by $\text{tr}(A)$ and simply means taking the sum of the diagonal values of the entries of a square matrix, as described in the following equation:

$$\text{tr}(A) = \sum_{i=1}^n a_{i,i} = a_{1,1} + a_{2,2} + \dots + a_{n,n} \quad (1)$$

Basics of transposing a matrix⁷⁰

A transposed matrix A is denoted by A^\top where

$$[A]_{n \times m} = \begin{bmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,m} \\ a_{2,1} & a_{2,2} & \dots & a_{2,m} \\ \dots & \dots & \dots & \dots \\ a_{n,1} & a_{n,2} & \dots & a_{n,m} \end{bmatrix} \rightarrow [A^\top]_{m \times n} = \begin{bmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,n} \\ a_{2,1} & a_{2,2} & \dots & a_{2,n} \\ \dots & \dots & \dots & \dots \\ a_{m,1} & a_{m,2} & \dots & a_{m,n} \end{bmatrix} \quad (2)$$

As you can see, the rows and columns are just switched, which will prove to be practical for calculating the squared distances later on.

Note for the following chapters

Equations 3 to 10 have been adopted from the paper of Hoffmann et al. (2006).⁷¹ This is mentioned, because a clutter of footnotes in the subsequent chapters should be avoided, lest it makes the process of understanding the theory more difficult.

⁶⁹cf. Broyden, 1975, p. 21

⁷⁰ibid., p. 7

⁷¹Hoffmann et al., 2006, pp. 1, 2

Mathematical nomenclature and goal

For subsequent formulas, the basic matrix E_i is needed. This represents the recorded *epochs* (i.e. the recordings).

The array of all the recordings is $E = \{E_1, E_2, \dots\}$.

One recording matrix can be written as follows:

$$E_i = \begin{bmatrix} e_{i,1}(t_1) & e_{i,1}(t_2) & \dots & e_{i,1}(t_m) \\ e_{i,2}(t_1) & e_{i,2}(t_2) & \dots & e_{i,2}(t_m) \\ \dots & \dots & \dots & \dots \\ e_{i,n}(t_1) & e_{i,n}(t_2) & \dots & e_{i,n}(t_m) \end{bmatrix} \quad (3)$$

where $e_{i,3}(t_5)$, for instance, is the value of the 3rd electrode of the BCI at time 5 at the i^{th} recording. Generally $e_{i,j}(t)$ is the function that depicts the values of voltage of an electrode. So t is the time and j is the index of an electrode.

Equally important is the definition of the classification categories. In the current example, 2 classification sets are feasible ('target' and 'no target'). The index lists C_{target} and $C_{\text{no target}}$ contain all indices of the recording matrices that were classified as *target* and *no target* respectively. An example:

$$C_{\text{target}} = \{1, 5, 7\}$$

where E_1 , E_5 and E_7 are classified as having shown a P300 potential (i.e. belonging to the 'target' class).

The method's goal is then to find a linear filter f , which will reduce the dimensions of E_i from $n \times m$ to a $n' \times m$ where n' should ideally be *much* smaller than n . Mathematically, this means:

$$E_i = \begin{bmatrix} e_{i,1}(t_1) & e_{i,1}(t_2) & \dots & e_{i,1}(t_m) \\ e_{i,2}(t_1) & e_{i,2}(t_2) & \dots & e_{i,2}(t_m) \\ \dots & \dots & \dots & \dots \\ e_{i,n}(t_1) & e_{i,n}(t_2) & \dots & e_{i,n}(t_m) \end{bmatrix} \rightarrow x_i = \begin{bmatrix} x_{i,1}(t_1) & x_{i,1}(t_2) & \dots & x_{i,1}(t_m) \\ x_{i,2}(t_1) & x_{i,2}(t_2) & \dots & x_{i,2}(t_m) \\ \dots & \dots & \dots & \dots \\ x_{i,n'}(t_1) & x_{i,n'}(t_2) & \dots & x_{i,n'}(t_m) \end{bmatrix} \quad (4)$$

Here, x_i is one feature vector with less dimensions, since $n' \ll n$.

Mathematical meaning

The theory behind this method is as follows: Hoffmann et al. propose a spatial filtering method for event-related potentials which aims to reduce the dimensionality of the samples and thus make the application simpler and more efficient. They start with the following formula:

$$J = \frac{\text{tr}(S_b)}{\text{tr}(S_w)} \quad (5)$$

In Equation 5, J can be interpreted as the separation of two classes with S_b being the between-class scatter matrix and S_w being the within-class scatter matrix (schematically illustrated in Figure 22 and 23).

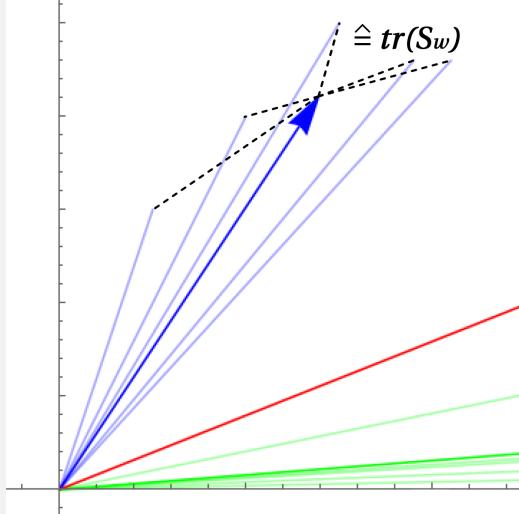


Fig. 22: Simplified, $\text{tr}(S_w)$ corresponds to the illustrated dashed black lines (the within-class distances). This is to be minimized in order to get a distinction between the two classes that is as clear as possible

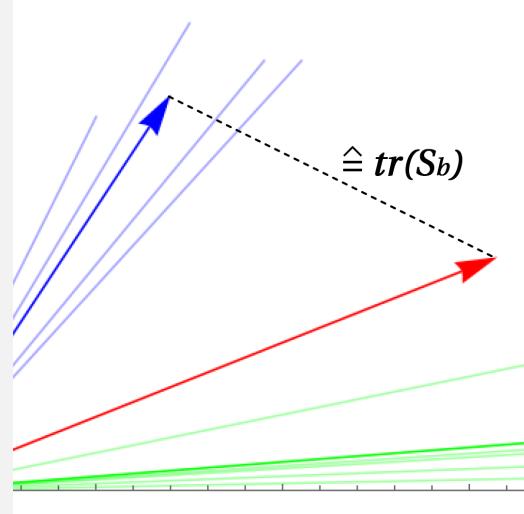


Fig. 23: Similarly, $\text{tr}(S_w)$ corresponds to the between-class distances (distances between the overall mean vector (red) and the class mean-vectors discussed shortly). This is to be maximized in order to have a clear distinction

For a P300-based BCI, the classes should be ‘target’ and ‘no target’. Maximizing J means maximizing the space between the two classes ($\approx \text{tr}(S_b)$) and minimizing the space between all the features that belong to a one certain class ($\approx \text{tr}(S_w)$).

This will help making the distinction between the two classes more evident.

$\text{tr}(S_b)$ can be calculated by maximizing the sum of the squared distances of the mean feature vectors (i.e. the feature vector that is the average of all feature vectors of one class) to the overall mean vector (of *all* feature vectors).

The following equation is being used for calculating the overall average vector (i.e. the vector that is the average of *all* the feature vectors)

$$\bar{x} = \frac{1}{N} \sum_{i \in C} x_i \quad (6)$$

where \bar{x} is the average feature vector, N is the number of overall feature vectors, C is the set that contains the indices of all feature vectors and x_i is the feature vector of the index i . Figure 24 will facilitate understanding by visualizing a possible mean vector \bar{x} .

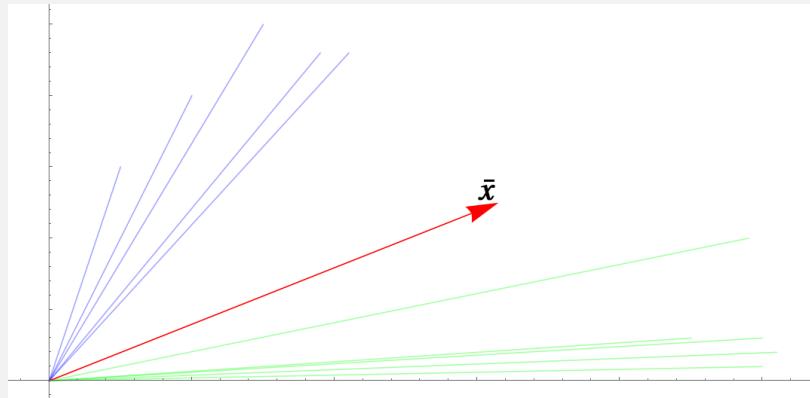


Fig. 24: A possible low-dimensional mean vector \bar{x} (red) illustrated as calculated in Equation 6. The mean vector is used to separate the two classes (here green and blue).

When calculating the average vector for one of the classes, the following formula is needed. This is very similar to Equation 6 above.

$$\bar{x}_k = \frac{1}{N_k} \sum_{i \in C_k} x_i \quad (7)$$

where \bar{x}_k is the average feature vector for the class k ('target' or 'no target' as seen in Figure 25), x_i is the feature vector of index i , the set C_k contains all indices of the feature vectors that belong to class k and N_k is the number of feature vectors that exist in class k .

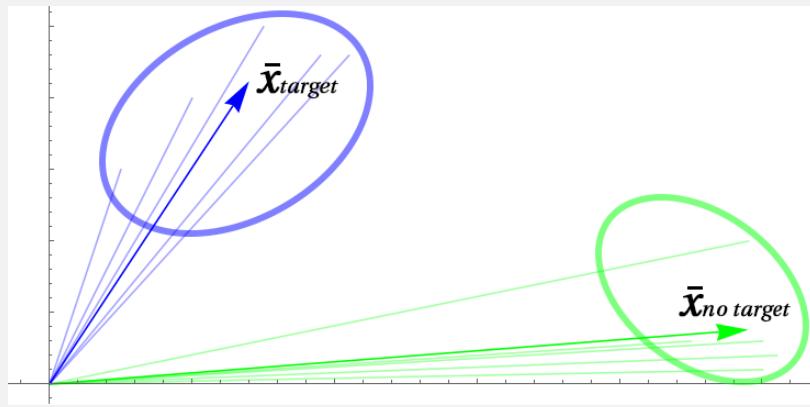


Fig. 25: Inter-class mean vectors \bar{x}_{target} and $\bar{x}_{no\ target}$ for the classes 'target' (blue) and 'no target' (green) respectively (class data shown as lines in the respective colors).

The next step is to calculate the between-class scatter matrix S_b :

$$S_b = \sum_{k=1}^K p_k (\bar{x}_k - \bar{x}) \cdot (\bar{x}_k - \bar{x})^\top \quad (8)$$

where K is the number of classes given in the example (2) and p_k is the probability for class k to occur. The value of p_k can be used to fine-tune the classifier.

In Equation 8, one can see the difference of the mean class vectors and the mean feature vector are multiplied by the transpose of the same matrix. This can be thought of as squaring the trace values. The following example will facilitate understanding.

The vector v is given as:

$$v = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}$$

then

$$v^\top = \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix}$$

The rules of matrix multiplication say that

$$v \cdot v^\top = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} \cdot \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} = \begin{bmatrix} v_1^2 & v_1 \cdot v_2 & v_1 \cdot v_3 \\ v_2 \cdot v_1 & v_2^2 & v_2 \cdot v_3 \\ v_3 \cdot v_1 & v_3 \cdot v_2 & v_3^2 \end{bmatrix}$$

When traced in our case this results in attaining all the deviations to the mean vector squared.

The within-class scatter matrix (i.e. the distances of the feature vectors that belong to one class to the class-specific mean vector) can be calculated as follows:

$$S_w = \sum_{k=1}^K p_k \cdot S_k, \quad (9)$$

where

$$S_k = \frac{1}{N_k} \sum_{i \in C_k} (x_i - \bar{x}_k) \cdot (x_i - \bar{x}_k)^\top \quad (10)$$

Basically, the same step as before is executed, but for all vectors inside all different classes. Therefore, the two sum operators Σ are needed. One for the vectors and one for all the classes. This $\text{tr}(S_w)$ value is what is to be minimized in order to have a densely packed class.

With these foundations, Hoffmann et al. manage to minimize Equation 5 and find an optimal filter f to apply to the epochs E . This is a very common optimizing problem. However, for brevity reasons, it will not be elaborated any further.

This chapter introduced a reputable method of dimension-reduction in the context of a P300 potential-based BCI. For brevity reasons, the part based on complicated and cloudy mathematics was excluded.

Analogy to daily life

Humans also act according to these *dimension-reducing* algorithms. They choose to simplify the information they get in order to see only the relevant characteristics. One example would be the purchase of a television set:

There are dozens or hundreds of characteristics describing the performance and quality of a television, however, only a few relevant ones are ever considered: resolution, energy saving performance, frame-rate and price. This is done instinctively to avoid *information overflow*.⁷²

Figures 25 to 23 (inspired by Hoffmann et al. 2006) have been created using Wolfram Mathematica[©] 11 and Adobe Photoshop[©] 2017.

3.3 Feature Translation or Classification

The features now have to be classified for the BCI system to understand what it has to do. There are lots of different types of classifiers, however, only the most interesting and common types, namely linear classifiers and neural networks are briefly discussed.

3.3.1 Linear Classifiers

This category of classifiers can be further divided into different types, however, they are mostly based on the same principle, namely using linear functions to distinguish classes. Two well-known linear classifiers are logistic regression and support vector machines.⁷³

The following introduction will explain *classification* by comparing the former, logistic regression, with the well-known linear regression method.

⁷²cf. Melinat et al., 2014, p. 1

⁷³cf. Lotte et al., 2007, p. 6

What is classification?

In *linear regression* (well known in mathematics and informatics), a straight line is fitted through a set of data. It is based on minimizing the squared distance between the hypothesis (i.e. the straight line through the data) and the points of data. The parameters of the linear function are then θ and the prediction is called $h_\theta(x) = \theta_0 \cdot x_0 + \theta_1 \cdot x_1 + \dots + \theta_n \cdot x_n = \theta^\top \cdot x$ where both θ and x are column vectors with n rows.⁷³ This kind of function can be seen in Figure 26.

It is important to know that the fitted function can take on values of larger than 1 or smaller than 0, which is impractical for a classifier, which should only return values between 0 and 1 (probabilities).

This is why logical regression is used. A so-called *sigmoid* or *logistic* function is introduced (famous in classification problems), which looks like the function in Figure 27 (the red data points are either 0 or 1):

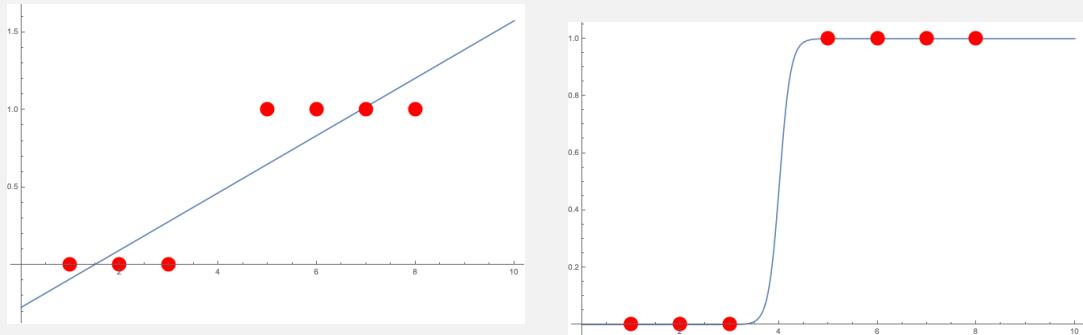


Fig. 26: Linear regression is not suitable for classification. In $h_\theta(x) = \theta^\top \cdot x$ the optimal parameter vector θ should be found (inspired by Ng 2015).

Fig. 27: Logistic regression, using a *sigmoid* function to classify a dataset (assign probability of reaching 1) (inspired by Ng 2015).

Generally, a sigmoid function is written as seen in Equation 11 where the optimal θ vector is to be found

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^\top \cdot x}} \quad (11)$$

The sigmoid classification function (Equation 11) outputs a probability of the input being 1 (this could be ‘target’). The input x that the function would take is the feature vector (uncommonly used one-dimensional feature vectors are used in Figure 26 and 27 for illustrative purposes) and an output is returned, providing information concerning the probability for the vector being part of the ‘target’ class. The parameters θ can be found by using gradient descent e.g. (trial and error parameter fitting for θ), which is an easy algorithm also used in linear regression.^{74,75}

Support Vector Machine

The support vector machine (SVM) method uses a separator (discriminant hyperplane) to identify different classes. SVMs use so-called *support vectors* to build the optimal segregation boundary, which then determines future classifications of data points.⁷⁶

The separation is determined by maximizing the paddings around the separating line between data points. Depending on the distance of a given feature vector to this line, conclusions about the certainty concerning a certain feature belonging to the class can be made. In the case of a P300-based BCI this means that it can be said that there is a high certainty that a certain feature is a ‘target’ feature if the vector is far away from the hyperplane.

It is crucial to note that feature vectors are almost never 2- or 3-dimensional, but will have many tens or hundreds of dimensions and that it needs a powerful computer to execute all these calculations, which makes it clear why it is important to reduce the data points.

Winston (2014) illustrates the principle strikingly in his MIT Course, describing the algorithm as searching the ‘broadest street’ between the features.⁷⁷ This is illustrated in Figure 28.

⁷³cf. Ng, 2015

⁷⁴ibid.

⁷⁵cf. Ruder, 2017, p. 1

⁷⁶cf. Hsu et al., 2016, p. 1

⁷⁷cf. Winston, 2014

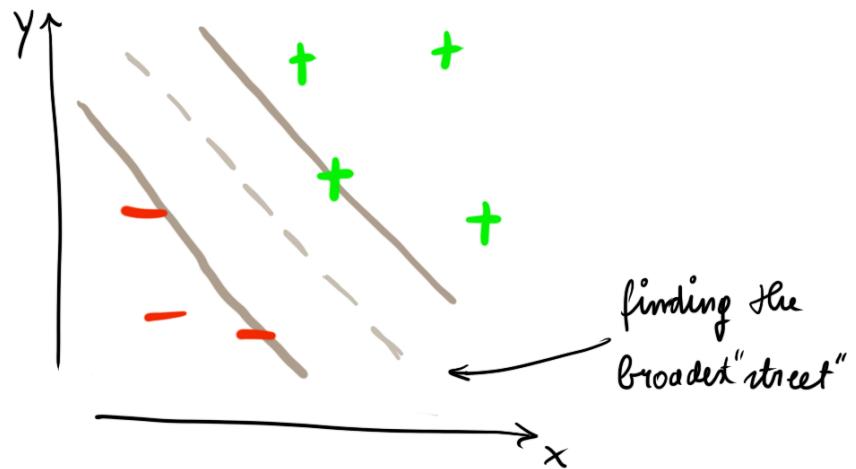


Fig. 28: The principle of support vector machines (finding a line with the largest padding between data points, here + and -) (from Winston, 2014).

It is important to know that most of these algorithms need a training set determining the initial separation boundary for future classification.⁷⁸

3.3.2 Neural Networks

'Neural networks' are also frequently used. They classify in a non-linear way and are used widely in every day life (in facial recognition, for instance).⁷⁹

Currently, neural networks have enjoyed lots of attention, however, describing them in a detailed way will go beyond the scope of this paper.

Relevant for this paper is to remember that brain-like neural networks are often used to classify brain signals. This should illustrate how much collaborative processes humans have already developed with technology (see Chapter 1 *Introduction*).

Figures 26 and 27 have been created by using Wolfram Mathematica[©] 11.

⁷⁸cf. Lotte et al., 2007, p. 7

⁷⁹cf. Shiruru, 2016, pp. 1, 2

4 Feedback

There is still one crucial step to be done. When intending to keep up the connection between the brain and the computer, the brain has to adapt to the new way of expressing its actions.

For that reason *feedback* is necessary. Feedback has to close the loop when adapting to a new, often unprecedented, action.

Analogy to daily life

Without feedback, the human brain could not learn how to do anything. It is unimaginable for humans to never have known whether their actions were correct in their childhood. By a means of parental advice or first-hand experience they have learned to differentiate between correct and incorrect actions. They could never have learned to not touch a hot stove had they not felt the extreme heat and pain immediately after having done it the first time.

The principle of feedback relies on the neuroplasticity of the brain, meaning that neuronal connections become stronger with frequent use.^{80,81}

With most of the actions a BCI executes feedback is inextricably intervened. A user's brain seeing their artificial arm move after having told it to do so, for instance will provide it with visual feedback.

Other forms of natural feedback are hearing sounds or feeling objects. As long as the user perceives a change in their environment, their brain adapts to this new means of communicating with the rest of the body.⁸²

When such natural means are not possible, the user has to be provided with artificial stimulation such as sensors on their prosthetic hand and subsequent stimulation of the brain areas that should be connected with that action.⁸³

⁸⁰cf. Bear et al., 2016, p. 866

⁸¹cf. Rao, 2013, pp. 11-12

⁸²cf. Chan et al., 2015, p. 2

⁸³cf. Rao, 2013, p. 2

BCIs in Practice

5 Usage

We are living in an exciting time when it comes to science and particularly BCIs, which are now on the verge of leaving their lab-prototype status and finding their way to commercially available products.

This chapter is concerned with how and where BCIs are being used currently. A division into four categories for which BCIs can be used is useful and will guide this chapter.^{84,85}

1. Replacement
2. Restoration
3. Improvement
4. Enhancement

At the end of every sub-chapter a demonstration of the respective category will be elaborated. This will be based on a recent development or application. To indicate these parts, they have been highlighted by a grey box.

5.1 Replacement

Using BCIs as a means of replacement can sometimes be the last resort for people who are in need of those BCIs. They have often suffered from injury or disease which has lead to the loss of bodily functions. Those functions can then be *replaced* by a BCI.⁸⁶

⁸⁴cf. Wolpaw & Winter Wolpaw, 2012, p. 4

⁸⁵cf. Brunner et al., 2015, p. 14

⁸⁶ibid., p. 17

One example would be speech synthesizers for people who have suffered from strokes and are now unable to talk.⁸⁷ Another instance would be when somebody is unable to walk, in which case a BCI-controlled wheelchair would enable them to move.⁸⁸

Researchers at the Old Dominion University have developed a BCI-controlled wheelchair which is based on *steady-state visual evoked potentials* (SSVEPs). SSVEPs are signals that are the brain's responses to visual stimulation.⁸⁹ The frequencies generated in the brain are then picked up by an EEG device.

On the screen, the phone is displaying flashing lights of different frequencies and by focusing on them, the user can control the wheelchair. The BCI picks up different SSVEPs (different frequencies) for each flashing field the user focuses their vision on.⁹⁰



Fig. 29: The SSVEP-based BCI wheelchair built by scientists of the Old Dominion University (from Waytowich, 2014).

⁸⁷cf. Brumberg et al., 2010, p. 1

⁸⁸cf. Wolpaw & Winter Wolpaw, 2012, p. 4

⁸⁹cf. Prueckl & Guger, 2009, p. 1

⁹⁰cf. Waytowich, 2014

5.2 Restoration

Restoring a body function via a BCI is helpful for people who have been inflicted by an injury. The connection between the brain and the limb might have gotten destroyed and therefore their bodies have lost some of their functions. BCIs stimulate the limbs via connections that can be attached from the inside or from the outside of the body.⁹¹

Bill Kochevar, a 53 year old man was able to move his arm again for the first time in years by using a BCI. His spine had been injured in a bike accident and body is paralyzed from below his neck.

His brain signals are converted in a computer and are used to stimulate his arm. The scientists of the Case Western Reserve University say that this first experiment is just a proof of concept and that this is the first step to it becoming generally used for paralyzed people.⁹²

*In the future I will be able any time I want to take a drink of something or feed myself, Kochevar says.*⁹³



Fig. 30: Bill Kochevar raising his arm for the first time in years (from Boseley, 2017).

⁹¹cf. Wolpaw & Winter Wolpaw, 2012, p. 4

⁹²cf. Boseley, 2017

⁹³ibid.

5.3 Improvement

The method of improving bodily functions is particularly interesting for rehabilitation. People who have had a stroke and cannot fully operate their limbs anymore can regain this vital connection via a BCI. It acts as a bridge in the action-loop. The BCI detects signals on the scalp and rewards movements that have been executed correctly.

This helps the brain regain control (see Chapter 4 *Feedback*). Through feedback, the brain learns to reestablish the connection.⁹⁴ After some time, the BCI might not be necessary anymore, since the brain has gained control again.

Researchers at the Technical University of Iasi and the University of Bucharest in Romania managed to create a rehabilitation setup which is based on a BCI, Virtual Reality Feedback and *Functional Electrical Stimulation* (FES) (i.e. augmented stimulation of muscles). They were even nominated for the official 2018 BCI-award.⁹⁵



Fig. 31: The setup used for the rehabilitation experiment, using Virtual Reality, BCI techniques and FES (from Lupu et al., 2018).

⁹⁴cf. Brunner et al., 2015, p. 25

⁹⁵cf. Lupu et al., 2018

5.4 Enhancement

Various methods are already used that enable an enhancement of body functions. For instance, BCIs can be used to detect loss in attention and immediately restore it by means of auditory or visual hints.⁹⁶

This could help students who lack attention. It could also detect drivers lacking attention, notify them and thus reduce the number of traffic accidents that happen due to lack of attention.⁹⁷

Figure 32 shows a young kid using a wireless EEG headset to monitor his engagement in reading. It was mentioned that the electrical brain signals have different frequencies (as discussed in Chapter 3.1 *Feature Extraction Generally*), which is the main principle by which this device works.



Fig. 32: A kid using the FOCUS EEG headset to monitor concentration (from Huang et al., 2014).

⁹⁶cf. Brunner et al., 2015, p. 29

⁹⁷cf. Wolpaw & Winter Wolpaw, 2012, p. 4

The device measures the attention level E by the following formula:⁹⁸

$$E = \frac{\beta}{\alpha + \theta} \quad (12)$$

As outlined in Figure 17, α waves are related with relaxation and flowing thoughts, θ waves are associated with emotional states and imagery, and β waves are present when concentration on certain tasks is prevalent. When the β brainwaves are dominant (higher value), the subject is concentrated.

For optimal concentration, α and θ wave values have to be as low as possible.⁹⁹

⁹⁸cf. Huang et al., 2014

⁹⁹cf. Fields, 2016, p. 60

6 The Future of BCIs

Wolpaw & Winter Wolpaw (2012) describe the fields of improvement in future BCIs in 3 areas:¹⁰⁰

1. Signal acquisition hardware
2. Dissemination
3. Reliability

These areas have to be addressed for BCIs to have practical and effective applications in the future.

6.1 Signal Acquisition Hardware

Comfort is arguably the most important aspect in future BCIs, this aspect is discussed by Wolpaw & Winter Wolpaw (2012). He argues that the following improvements could be made for *non-invasive* BCIs (only some mentioned).

- No need for conductive gel (*dry electrodes* are more convenient¹⁰¹)
- Small system (full portability)
- Easy setup
- Little maintenance
- Utilizable in all environments (no artifacts or noise)
- Wireless signal transfer (no cables)

These changes could be made in order to prepare BCIs for commercial use, which is a necessary step for making BCI development more attractive and ubiquitous.¹⁰²

Considering the advantages and disadvantages of the different signal acquisition methods outlined in Chapter 2 *Signal Acquisition*, fNIR- and EEG-based BCIs seem to be the methods showing the most potential, since the remaining methods can not be worn while moving and are therefore impractical.

¹⁰⁰cf. Wolpaw & Winter Wolpaw, 2012, p. 387

¹⁰¹cf. Sellers et al., 2009, p. 1

¹⁰²cf. Brunner et al., 2015, p. 23

However, fNIR-based BCIs will have to be improved concerning their slow BOLD signals (blood oxygenation level dependent).

With invasive BCIs, the goal seems similar: make them more practical, less prone to problems and safer. This could include finding novel materials that do not damage brain tissue as much or establishing wireless communications with the external computer. Also, long-term performance is of importance (usually with invasive BCIs the signal tends to degrade over time).¹⁰³

Convenience is The Future

Having talked to Dr. Seeber from the University of Geneva, I have gained a lot of insight about future applications and development. Dr. Seeber's idea of applying the electrodes below the skin on the head (still outside of the skull) seems very logical. This method will provide stronger signals (the skin significantly dampens the signal), while still being only invasive to a small degree. Another argument which speaks for this means of application is the increase in convenience (enabling comfortable daily use) when not having to apply a conductive gel multiple times a day.¹⁰⁴

This conversation makes it clear that the future of BCIs really lies in convenience. With more convenience, BCIs will find more means of application, boosting public interest and development in this direction.

6.2 Dissemination

Dissemination in this context refers to the distribution of BCI system (e.g. to different sections in commercial use). Wolpaw & Winter Wolpaw (2012) argue that BCI technology is a so-called *orphan technology*.

This means that the technology is proven to work in laboratories, however, has yet to be introduced commercially (there is no incentive to do so).¹⁰⁵ While there are great companies (such as OpenBCI[®]), which have a set mission of spreading the technology, there has not been a lot more commercial interest in this domain.

¹⁰³cf. Wolpaw & Winter Wolpaw, 2012, p. 388

¹⁰⁴cf. Dr. Seeber

¹⁰⁵cf. Wolpaw & Winter Wolpaw, 2012, p. 388

Commercial incentive

One company that offers BCIs commercially is OpenBCI[©]. Their goal is to evoke enthusiasm and make BCIs commercially available and interesting to the public. One of their products, the Ultracortex ‘Mark IV’ EEG Headset, can be seen in Figure 33

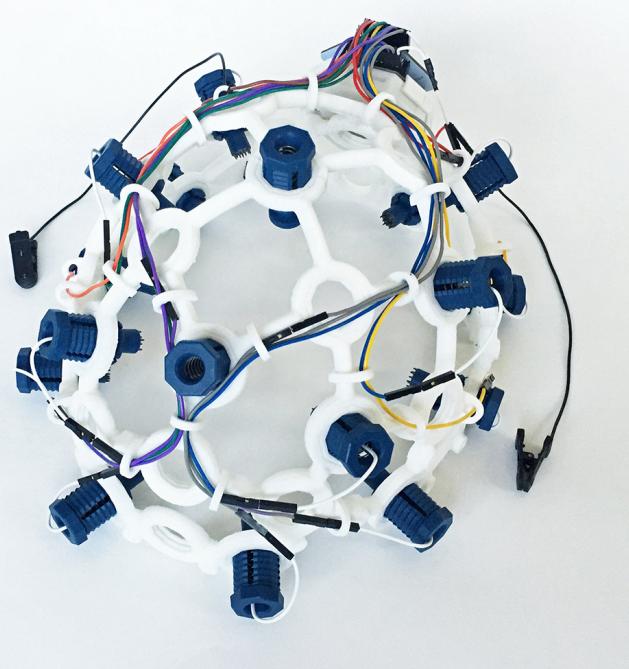


Fig. 33: The Ultracortex ‘Mark IV’ EEG Headset by OpenBCI[©] (from [OpenBCI[©] store](#)).

They describe their company as follows:

*OpenBCI specializes in creating low-cost, high-quality biosensing hardware for brain computer interfacing. Our [...] biosensing boards provide high resolution imaging and recording of EMG, ECG, and EEG signals. Our devices have been used by researchers, makers, and hobbyists in over 60+ countries as brain computer interfaces to power machines and map brain activity. OpenBCI headsets, boards, sensors and electrodes allow anyone interested in biosensing and neurofeedback to purchase high quality equipment at affordable prices.*¹⁰⁶

¹⁰⁶OpenBCI[©] website

An optimal scenario would undoubtedly be achieved if there was a *commercial incentive* and large-scale distribution taking place at the same time as *scientific development and testing* of BCI technology.

The former is still in its early stages, but a commercial incentive is not inconceivable. The latter could be achieved if BCIs continue to help people with severe disabilities.

The first kind of development would utilize BCIs belonging to the category *repair* and *restore*, while the second kind would belong to *improve* and *enhance* (see Chapter 5 *Usage*).

6.3 Reliability

Reliability will most likely determine the future of BCI systems. Up to now, the concept has been proven, however, intricate movements and unmitigated reliability are still far off.

During one's lifetime, a person's brain changes its wiring constantly. How should a BCI be able to know what the user wants to do when the features change constantly? The answer can be found in *adaptive algorithms*.¹⁰⁷

Like the brain changes over time, those algorithms also change how they classify the intended movements. It is a synergy that has to be employed for BCIs to work reliably in the long-term.¹⁰⁸

How reliable a BCI works is also determined by how many parameters (feature types) it can work with (see Chapter 3 *Signal Extraction*).

Generally, the future of BCIs hinges on hardware (as established before) as well as software and algorithm improvements. They have to work together seamlessly to create practical and reliable BCIs.

The future of BCIs will doubtlessly prove to be an extraordinarily exciting one. It is undoubtedly going to be a road riddled with obstacles and problems, but that is what makes developing, exploring and experimenting so interesting.

¹⁰⁷cf. Wolpaw & Winter Wolpaw, 2012, p. 390

¹⁰⁸ibid., p. 391

Concluding Remarks

Science has come a long way from the 1920s and 30s when Hans Berger discovered neuroelectrical activity.¹⁰⁹ The technology of BCIs has gained great attention in the last decades particularly, which is mostly due to the advancement of computational power.

In this paper the reader has been familiarized with the study of BCIs. A few key insights are:

- The main purpose of a BCI is to offer an alternative output method (in lieu of muscle usage).
- There are many different ways of picking up signals from the brain. They all have their different applications, advantages and disadvantages. Currently, there is no one-size-fits-all way of recording brain signals.
- Mathematics plays a big role in BCI algorithm development. The algorithms used are often highly sophisticated.
- BCIs are commonly used in medicine, helping many people live comfortably with their handicap (additional to some non-medical applications).
- For BCIs to flourish in the future, there has to be a commercial incentive for public development and production.

This paper should have excited the reader and made them look forward to a future where the computer, a ubiquitous companion, can be used even more productively in medical as well as non-medical environments.

¹⁰⁹cf. Berger, 1931, p. 1

Appendix A: OpenBCI

In the course of writing this paper for my high school graduation, I have had the honor of trying out the OpenBCI[®] Mark IV Headset with the Cyton biosensing board.

Being extremely grateful for this chance, I would like to present to the reader how they would go about setting up their own OpenBCI[®] kit. This will just be a quick tour and will solely illustrate what they can expect from the free OpenBCI software and whether it is difficult to set up the device or not (hint: it is very easy).

First, I would recommend just exploring the OpenBCI[®] website and taking a look at all their products and tools and browsing through the community page and connecting with thousands of other BCI enthusiasts.

All of this can be found on <https://openbci.com>.

In ‘shop’ you can find all of their products. In my case, I have ordered the Cython board, which allows for reading data from eight electrodes, which was sufficiently enough for my use (there are also 4 or 16). It can be seen in figure 34.

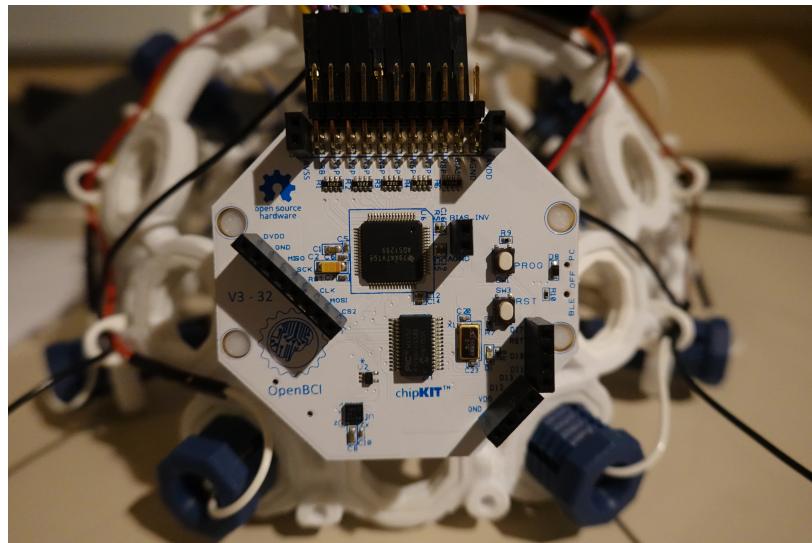


Fig. 34: The OpenBCI[®] Cython board with all electrodes connected

Additionally, with the Cython board there will also be the USB dongle included, which can be seen in figures 35 and 36. This will just be plugged into the computer and you will be ready to go.

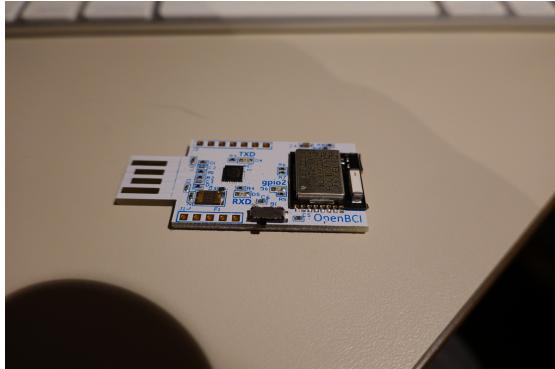


Fig. 35: OpenBCI[©] Cython USB connector (front)



Fig. 36: OpenBCI[©] Cython USB connector (back)

While it is also possible to 3d-print the headset (Mark IV) itself, I ordered the finished product, which you can see (already connected) in figure 37.

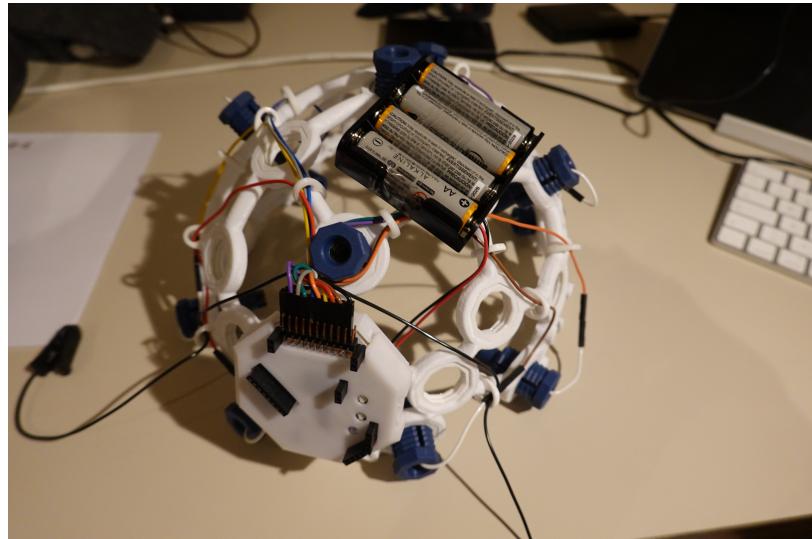


Fig. 37: fully equipped OpenBCI[©] Mark IV headset

For people with a great volume of hair, they can also buy special dry comb electrodes. These will not be single-time use like most other electrodes, but will enable

a clear contact with your head multiple times even if you have lots of hair. They are visible in figure 38.



Fig. 38: OpenBCI[®] dry comb electrodes

Next, after ordering, receiving and assembling the BCI device (it only took 5 minutes with the instruction booklet), I installed the OpenBCI_GUI software. With this software (see figure 39) you will be able to display all the data that the device sends to your computer. It can be downloaded here: <https://github.com/OpenBCI>.

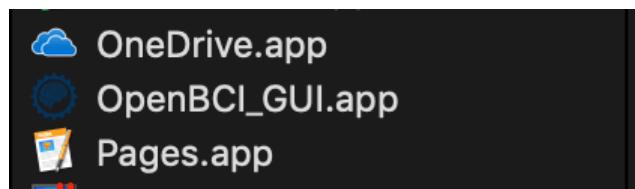


Fig. 39: OpenBCI_GUI application

When starting the application you will really only need 2 or 3 clicks to be able to read all kinds of data from your device. First, you have to choose where you want to read the data from. If you have the same device I ordered, reading it from the dongle would be the best approach. So click ‘System Control Panel’ (see figure 40) and choose ‘Serial (from Dongle)’. Click ‘Start stream’ to start reading your BCI data.

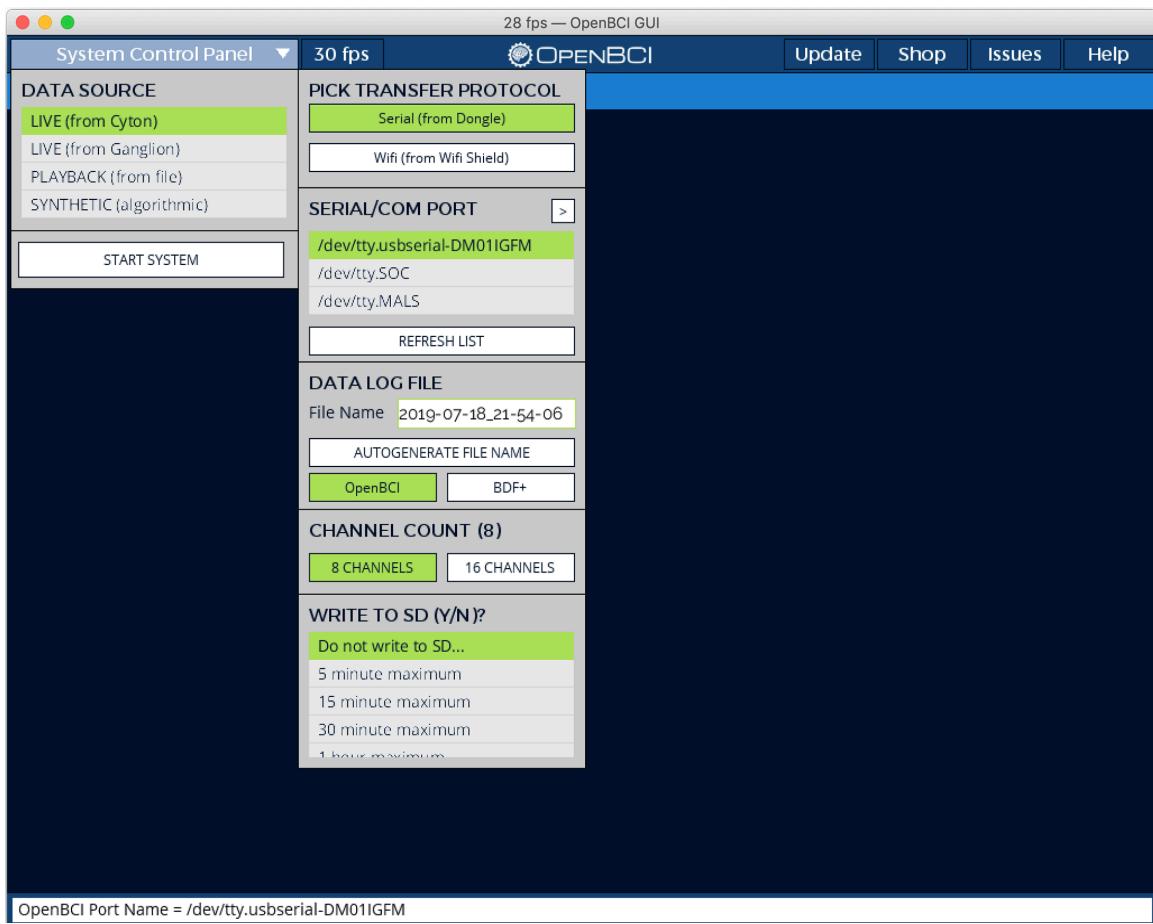


Fig. 40: OpenBCI[®] first application screen

You will be sent to a screen like the one in figure 41 after clicking ‘Start data stream’ again.

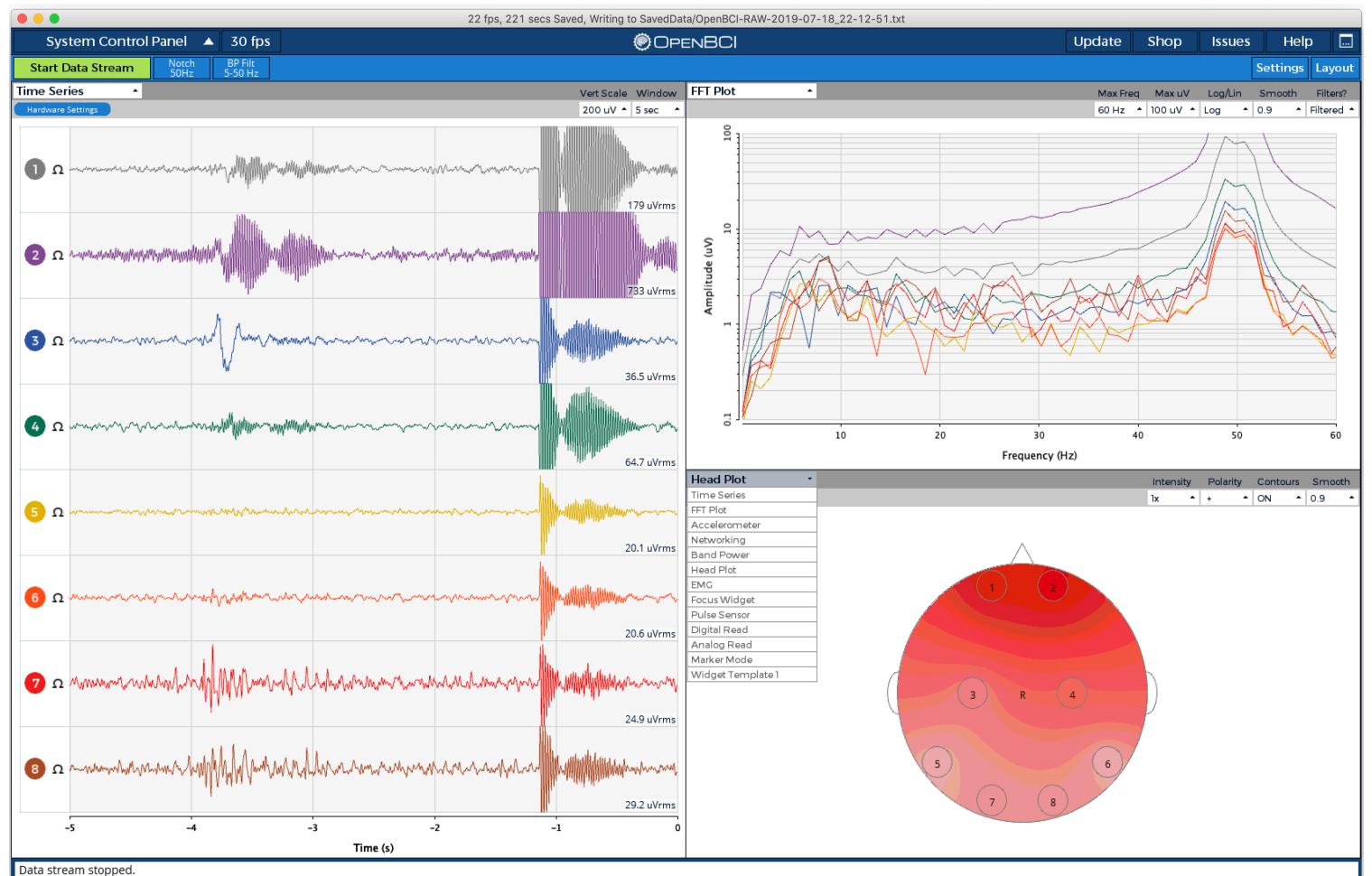


Fig. 41: OpenBCI[®] data stream

Here you have reached the most interesting part of the BCI process. You can now read out all active parts in your brain. You should change the 'Notch' filter to fit your local power outlet frequency, so your signal is much cleaner. From here on you can play around and if you want to, you could even program your own widgets (you can see one 'Widget template' in the dropdown menu in figure 41)

Now you are ready to go to explore your brain with OpenBCI[®].

Thanks again to OpenBCI[®] for making this possible.

Appendix B: Additional Signal Acquisition Methods (PET & fMRI)

PET

Positron emission tomography (PET) is a long-established method of measuring brain signals. It is based on injecting radioactive material (called a *tracer*) into the body.

When different areas of the brain are active, they will require more blood than usual. The blood that has previously been blended with the radioactive tracer (most frequently flourine-18) will emit gamma rays.

In most modern PET scanners these rays can be recorded by an x-ray camera.¹¹⁰ By computational analysis, a 3-dimensional image of the active areas of the brain will be constructed and analyzed.¹¹¹

Being based on metabolic activity, this approach has a remarkably poor temporal resolution.

Consequently, it has to be kept in mind that it might take some time for changes to be visible. This slow temporal resolution is due to the comparatively slow speed of blood distribution. For a result to be shown, a PET scanner can take up to a minute.¹¹²

Another significant drawback is the need for radioactive material to be injected into the patient's body. This limits the number of measurements that can be done on one subject in a given time, which is more than sub-optimal for long-term BCI usage. While portable scanners are imaginable, the lack of portability is another huge drawback (see Figure 42).

¹¹⁰cf. Basu et al., 2011, p. 2

¹¹¹cf. Penny & Friston, 2007

¹¹²cf. Ogawa & Sung, 2007



Fig. 42: In a typical PET machine the subject has to lie down, making it impractical for mobile, every-day BCI use (from Rodman Media[©]).

Concludingly, PET scans are very practical when intending to study neurophysiology and neurochemistry (you can create a 3-dimensional model of the brain), however, there are far better approaches for signal acquisition in BCIs.¹¹³

fMRI

Functional magnetic resonance imaging (fMRI) is based on a similar principle as fNIR. However, fMRI uses the difference in magnetism of de-oxygenated and oxygenated hemoglobin. Blood containing hemoglobin is exchanged to supply the active brain areas with oxygen to keep it working properly.

De-oxygenated hemoglobin is more magnetic and this difference can be recorded by a fMRI scanner to construct a 3-dimensional model of the active areas of the subject's brain. The signals that are being recorded by fMRIs are called *blood oxygenation level dependent* (BOLD) responses.

Once again, this process is not very practical for long-term BCIs, since the subject has to lie down and remain immobile for the duration of the procedure for it to work accurately (as seen in Figure 45).¹¹⁴

¹¹³cf. Ogawa & Sung, 2007

¹¹⁴cf. Rao, 2013, p. 30



Fig. 43: A typical fMRI apparatus. The patient has to lie down, making it impractical for BCIs similarly to PET in Figure 42 (from [Tung](#)).

List of Acronyms

BCI	Brain-Computer Interface
CNS	Central nervous system
ECG	Electrocardiogram
EOG	Electrooculogram
EMG	Electromyogram
LFP	Local field potential
EEG	Electroencephalography
hdEEG	High-density EEG
MEG	Magnetoencephalography
ECoG	Electrocorticogramm
PET	Positron emission tomography
fNIR	Functional near-infrared spectroscopy
fMRI	Functional magnetic resonance imaging
FES	Functional electrical stimulation
BOLD	Blood-oxygen-level dependent
SQUID	Superconducting quantum interference device
SSVEP	Steady state visually evoked potential
ERP	Event-related potential
ERS	Event-related synchronisation
ERD	Event-related desynchronisation
SVM	Support Vector Machine

Code References

```
In[370]:= markerImage = Graphics[{Red, Disk[]}]

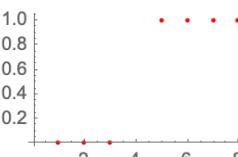
(*This creates the red circle image that is used in the data plots*)

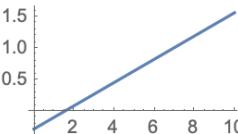
In[371]:= A single red circular marker, representing the plot marker defined in In[370].
```

```
data = Table[{{1, 0}, {2, 0}, {3, 0}, {5, 1}, {6, 1}, {7, 1}, {8, 1}}]
(*This is an arbitrary test dataset. It is created to illustrate the difference
between logistic and linear regression as simply as possible*)

Out[372]= {{1, 0}, {2, 0}, {3, 0}, {5, 1}, {6, 1}, {7, 1}, {8, 1}}
```

```
a = ListPlot[data, PlotMarkers -> {markerImage, .05}]
(*This plots the data that is defined above*)
b = Plot[model["BestFit"], {x, 0, 10}]
(*This creates the linear regression fit for our data*)

Out[377]= A scatter plot showing data points and a linear regression line. The x-axis ranges from 0 to 10 with ticks at 2, 4, 6, and 8. The y-axis ranges from 0.2 to 1.0 with ticks at 0.2, 0.4, 0.6, 0.8, and 1.0. The data points are red circles at approximately (1, 0), (2, 0), (3, 0), (5, 1), (6, 1), (7, 1), and (8, 1). A blue line represents the linear regression fit.
```

```
Out[378]= A separate plot showing the linear regression line from Out[377]. The x-axis ranges from 0 to 10 with ticks at 2, 4, 6, 8, and 10. The y-axis ranges from 0.5 to 1.5 with ticks at 0.5, 1.0, and 1.5. The blue line passes through the origin and extends to approximately (10, 1.5).
```

```
In[380]:= Show[b, a] (*This displays both the data and the linear regression in one plot
(this is the image used in the paper)*)

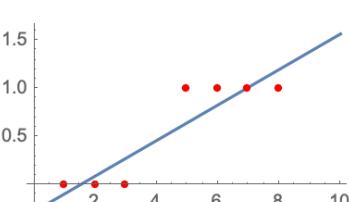
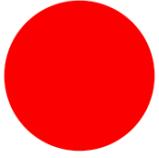
Out[380]= A combined plot showing the data points and the linear regression line. The x-axis ranges from 0 to 10 with ticks at 2, 4, 6, and 8. The y-axis ranges from 0.5 to 1.5 with ticks at 0.5, 1.0, and 1.5. The data points are red circles at approximately (1, 0), (2, 0), (3, 0), (5, 1), (6, 1), (7, 1), and (8, 1). A blue line represents the linear regression fit.
```

Fig. 44: Mathematica code for linear regression of data points

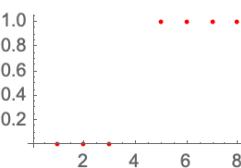
```
In[11]:= markerImage = Graphics[{Red, Disk[]}]
(*This creates the red circle image that is used in the data plots*)

Out[11]= 
```

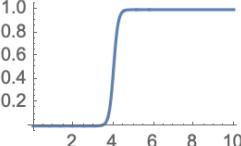
```
In[12]:= data = Table[{{1, 0}, {2, 0}, {3, 0}, {5, 1}, {6, 1}, {7, 1}, {8, 1}}, {8}]
(*This is an arbitrary test dataset. It is created to illustrate the difference between logistic and linear regression as simply as possible*)

Out[12]= {{1, 0}, {2, 0}, {3, 0}, {5, 1}, {6, 1}, {7, 1}, {8, 1}]

In[22]:= a = ListPlot[data, PlotMarkers -> {markerImage, .05}]
(*This plots the data that is defined above*)
cf = Classify[data[[All, 1]] -> data[[All, 2]], Method -> "LogisticRegression"]
b = Plot[cf[x, "Probability" -> 1], {x, 0, 10}]
(*This creates the logistic regression fit for our data*)

Out[22]= 
```

```
Out[23]= ClassifierFunction[  Input type: Numerical
Classes: 0, 1 ]
```

```
Out[24]= 
```

```
Show[b, a] (*This displays both the data and the logistic regression in one plot
(this is the image used in the paper)*)

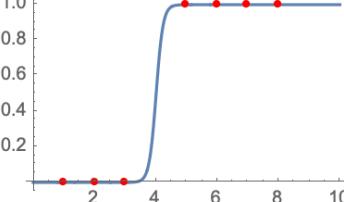
Out[25]= 
```

Fig. 45: Mathematica code for logistic regression of data points to classify

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