Electroencephalography

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Introduction

Electroencephalogram (EEG) has already been used as a scientific tool for almost 100 years. Hans Berger, a German neurologist and psychiatrist, discovered a specific EEG rhythm, called alpha oscillations in 1924 and published his findings in 1929 (Berger 1929).
Since, EEG is one of the standard methods to measure brain activity in many fields and the main source of signals for non-invasive brain-computer interfaces (BCI). This chapter highlights the physiological foundation and properties of the EEG, different recording techniques and their implications. The final section describes current BCI research applications using different EEG signals.

General establishment of EEG

From Neuron to EEG

The human brain is estimated to comprise 100 billion neurons, with each neuron having approximately 10,000 connections to other neurons. This huge, electrically active neuronal network can be divided into many subnetworks. Ionic currents present in these subnetworks cause local extracellular potential changes. The superposition of these differences in potentials has been named local field potential (LFP) (Buzsáki et al. 2012). The frequency spectrum of LFPs is quite broad starting from DC (direct current) up to several hundred Hz. Synaptic transmissions and action potentials (APs) are regarded as main sources of LFPs (Einevoll et al. 2013). A plausible assumption is that synaptic transmissions are the source of low frequency components and APs are the source of high frequency components (>500 Hz) (Buzsáki et al. 2012). If ohmic impedances (i.e. the resistance is independent from frequencies) and electric dipole sources are assumed, the contribution of single sources to the LFP decays with the square of the distance (Nunez & Srinivasan 2006). However, the type of impedance of brain tissue is controversial. Typically, brain tissue is assumed to have high pass (i.e. high frequencies pass, low frequencies are dampened) properties, but there are also indications for low pass properties (Grimnes & Martinsen 2000; Bédard et al. 2004).
A paper of Logothetis et al. (2007) showed that pure ohmic impedance is a sufficient assumption for low frequencies (<1000 Hz)(Logothetis et al. 2007). A recent modeling of the LFP conducted by Linden et al. (2011) indicated that for uncorrelated activity, a reach of 200 µm is a realistic assumption. For correlated activity this assessment it is more difficult, but they concluded that “...the LFP recorded by an electrode is dominated by populations with substantial synaptic processes in the recording layer.” (Lindén et al. 2011). Hence, nearby sources contribute most to the LFP and distant sources contributions are subject to strong attenuation. Resulting from this, it is only possible to measure the collective activity of a large number of neurons at the scalp (Fabiani et al. 2007).
EEG is by far the most common non-invasive method for measuring electrical brain activity. It can measure the brain potentials through various types of electrodes (see Electrode principles to measure EEG) which get mounted at the scalp level with the help of an EEG cap. These measured scalp potentials are a modified version of the LFPs (Buzsáki et al.

2012). The modification has at least two causes. First, as described above, the electric field decays with the square of the distance from the source, and therefore, the LFP substantially attenuates until it reaches the scalp electrodes. Second, volume conductance of the head's tissues (mainly brain, cerebral fluid, skull and scalp) causes spatial smoothing over an area of about 10 cm² (Buzsáki et al. 2012).

Due to the attenuation and smoothing, only synchronous brain activity (i.e., brain activity that sums up over brain areas) can be measured at the scalp level. Rhythms that occur synchronously are typical for lower frequency ranges of the LFP. The low frequency components of LFPs are mainly caused by correlated synaptic transmissions and can be seen as neural dipoles in parallel pyramid cells (see Figure 1) (Buzsáki et al. 2012; Einevoll et al. 2013). Since only afferent APs lead to synaptic transmissions, it can also be assumed that the major contribution to LFP at lower frequencies comes from these afferent APs of cortex layers 1 to 4 (see Figure 1).

APs cause synaptic transmissions, but information coded in AP spike trains is not one-to-one equivalent to information in low frequency components of the LFP (Einevoll et al. 2013; Hodgkin & Huxley 1990). In fact, the connection from APs via synaptic transmissions to the LFPs is not entirely understood yet. Ionic transmembrane currents can be well described by models; however our understanding is limited by influences like the feedback of the LFP to surrounding cell activity and other effects (Einevoll et al. 2013; Hodgkin & Huxley 1952; Goldman 2004).

In summary, APs of afferent fibers in the cortex can cause synaptic transmissions. Correlated synaptic transmissions form parallel neural dipoles which contribute most to synchronous low frequency components of the LFP and therefore also contribute to the scalp EEG.

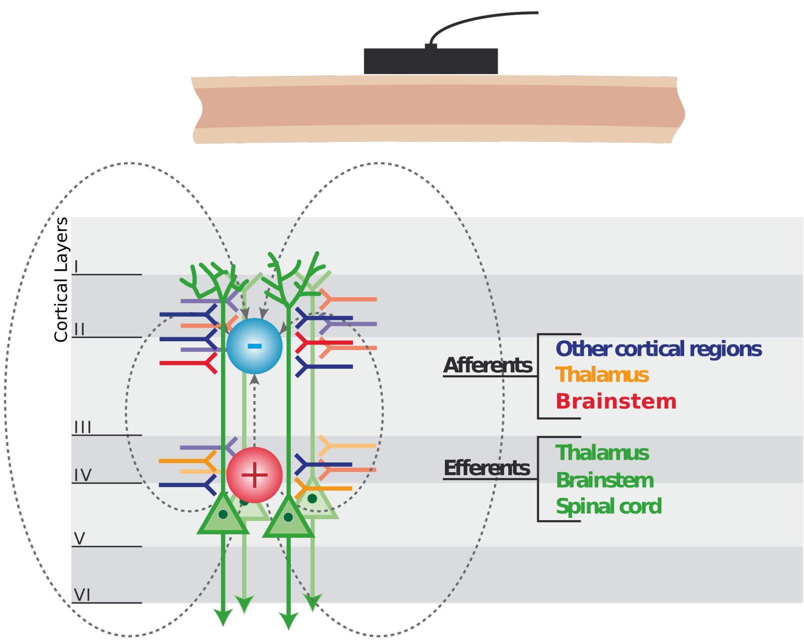

Figure 1: Sketch of BCI signal sources. I - VI mark the cortical layers. Cortical layer 5 and 6 pyramidal cells are highlighted in green. Their apical and basal synapses are color coded. The spatial and temporal dendritic integration of synaptic transmission leads to formation of dipoles. If millions of neurons receive synchronous basal or apical synaptic transmissions, the resulting electrical field propagates over large distances and is even detectable at the scalp where it is called EEG. Modified from (Steyrl et al. 2016)

The larger the synchronously active cell population, the higher the potential deflection, i.e. amplitude in the EEG. In contrast, in deep brain structures (e.g., amygdala), neurons' electric fields are typically oriented in different directions, which impedes the summation process (i.e., they cancel each other out) (Lorente de No 1947). Thus, such structures do not generate large summated dipoles (Harmon-Jones & Beer 2012) and therefore cannot be assessed by EEG oscillations at the scalp. This holds also to some extent for the orientation in sulci.

Considering EEG's physiological foundations that was outlined so far, an important implication for correctly interpreting EEG signals emerges. EEG oscillations recorded at the scalp only represent a subset of the electrical brain activity at a particular point in time. Research indicates that low-frequency oscillations (e.g., theta) span larger neural populations, while higher-frequency oscillations (e.g., gamma) span smaller neural assemblies (Buzsáki & Draguhn 2004).

Gevins and Smith outlined five major determinants of the degree to which potentials arising in the cortex are measureable at scalp level (Gevins & Smith 2006): 1) signal amplitude at the cortex, 2) size of the region over which post-synaptic potentials occur synchronously, 3) proportion of cells that are in synchrony in that region, 4) location and orientation of the activated cortical region in relation to the surface of the scalp, and 5), the amount of signal dampening and spatial smearing generated by conduction through the liquor, skull and other tissue layers.

Recording, Electrodes, Amplifiers and Artifacts

Electrode Positioning System

In EEG recordings, electrode locations are based on standard position systems. The 10-20 system originally proposed by Jasper (1958) is one of the most internationally recognized methods to describe the locations of the EEG scalp electrodes and it ensures that the inter-electrode distances are equal. Here, electrodes are placed at sites 10 percent and 20 percent from four anatomical landmarks: the nasion, inion, left, and right preauricular points. However, to achieve a higher spatial resolution, extra electrodes can be added to the 10-20 system, leading to more detailed systems such as the 10-10 or 10-5 systems. For that, intermediate positions between those of the original 10-20 system have been added (Oostenveld & Praamstra 2001). Figure 2 shows a 10-5 system where only the original 10-20 system electrodes are labeled. The existing naming convention for electrode positions is shown in Figure 2. The following rules apply:

(1) The first character refers to the cortical area (F = frontal area, C = central area, P = parietal area, T = temporal area, and O = occipital area). Electrodes between these areas are labeled using two characters (e.g., FC = frontal-central).
(2) A number (e.g., P3) or another character (e.g., Cz) follows after the first letter. Odd numbers indicate sites on the left hemisphere and even numbers indicate sites on the right hemisphere. Midline electrodes (i.e. on the virtual line connecting the nasion and the inion, where the vertex corresponds to its half-length) have "z" as indicator. Moreover, numbers increase as distance from the midline increases (see, for example, Fz, F3 F7 in Figure 2).

However, for specific BCI applications, researchers often choose individualized and end-user specific electrode positions. Still, the general rules described above are usually adopted.

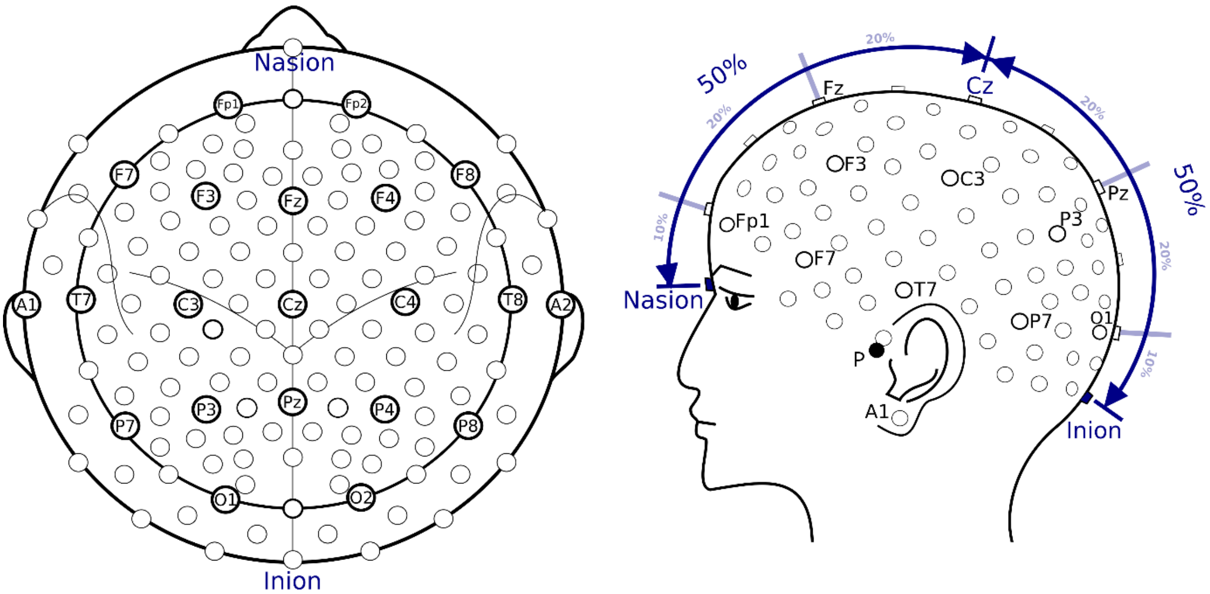

Figure 2: Scheme of a 10-5 electrode system, based on (Oostenveld & Praamstra 2001). Selected electrode positions are shown. A1 is the earlobe, P shows the preauricular point. It is on the line between Nasion and Inion above the tragus.

Electrode principles to measure EEG

At the very beginning, in 1924, scientists inserted steel needles into the subcutaneous tissue of the scalp and used galvanometers to visualize and interpret the recorded signals (Berger 1929). The quality and the interpretability of the signals improved with technological developments to amplify the very small signals. Still a standard nowadays, silver chloride (AgCl) covered electrodes were introduced by Berger in 1931 (Collura 1993).

When measuring EEG, a conductive connection to bridge the gap between the electrode and the skin surface has to be introduced. Currently, there are three common types of electrodes: gel-based, water-based, or dry-electrodes. The latter, as the name indicates, does not need an additional conductive substance. Figure 3 shows different types of EEG electrodes.

Gel-based electrodes can be subdivided based on the usage of abrasive gel or hydrogel. Abrasive gel is mainly used in combination with passive electrodes (i.e., direct connection between the electrode and the amplifier input). In contrast, the hydrogel is used for active electrodes. On active electrodes, a tiny pre-amplifier sits on the electrode and increases the robustness of the signals before being conducted to the main amplifier. The main difference between these two types of gels is that with the abrasive gel, the topmost layer of the skin, consisting of dead cells and a small amount of fat, is removed in a time-consuming procedure to decrease the impedance. This can lead to skin irritation, infection, or inflammation. For both types of gels, it is necessary for the participants to wash their hair after the measurement. Water-based electrodes use a felt or other fabric material soaked in water or saline solution to connect the electrode with the skin. Using tap water-soaked fabric to connect the two surfaces is a relatively new and practical method. This type of electrodes

should deliver a very good signal quality, the setup is less time-consuming, and no hair wash is needed after the measurement (Volosyak et al. 2010, Pinegger et al. 2016).
Dry electrodes, in contrast, work without any conductive substance. Pins made of metal alloy or conductive rubber are pressed directly onto the skin, and rely on small amounts of existing perspiration to get connected to the skin. Several studies highlighted the advantages of different dry electrode-based systems e.g., (Zander et al. 2011; Guger et al. 2012; Mota et al. 2013). However, experience shows that one main disadvantage of this type of electrodes is their sensitivity to movement artifacts.

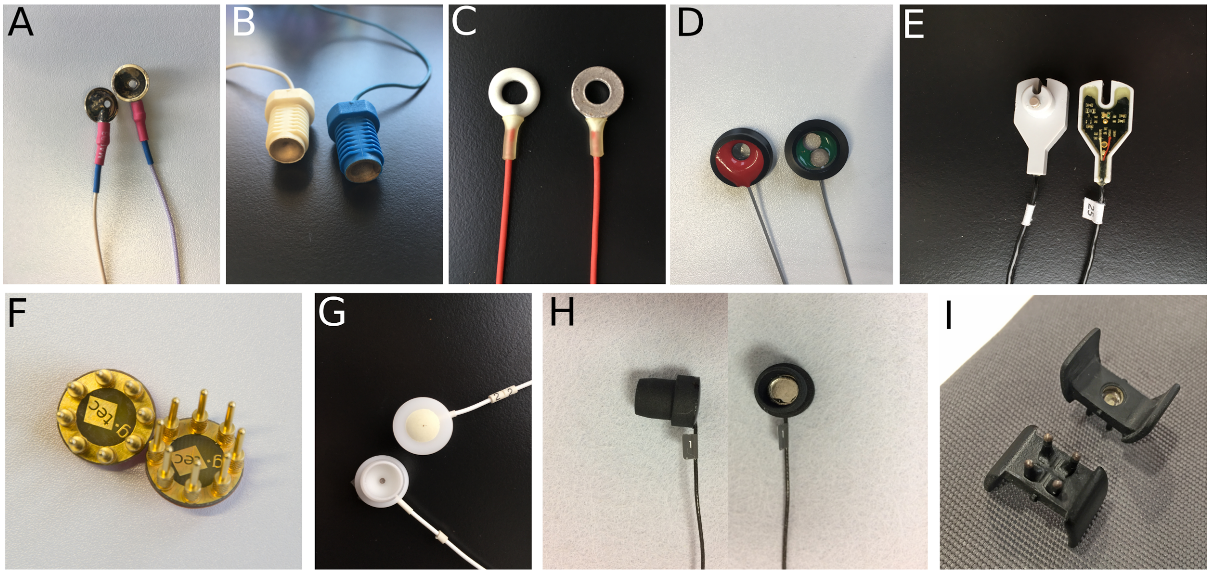

Figure 3: Examples of electrodes. (A) old cup electrode, (B) old passive sintered AgCl electrode, (C) gel-based passive Ag/AgCl ring electrode (from EasyCap), (D) gel-based active Ag/AgCl electrode (g.LADYbird from g.tec), (E) gel-based active Ag/AgCl (actiCAP, BrainProducts), (F) passive dry electrode with gold-coated pins (g.SAHARA electrode from g.tec), (G) (tap) water-based passive electrode (Mobita, TMSi), (H) (tap) water-based passive electrode (BitBrain Technologies), (I) passive dry electrodes with pins (BitBrain Technologies).

When looking on electrode technology from a BCI end-user perspective, comfort should be maximized and extra inconveniences eliminated (e.g., washing the hair). From a technical point of view, the signal quality has to be optimal to make the BCI perform effectively and efficiently. A system, which is user-friendly and provides, in the same time, the necessary signal quality is therefore challenging to develop. A recent work (Pinegger et al. 2016) evaluated three different commercially available EEG acquisition systems. They differed in the type of electrodes (gel-, water-, or dry-based), the amplifier technique, and the data transmission method. Every system was tested regarding three different aspects, namely, (i) technical, (ii) BCI effectiveness and efficiency (P300 for communication and control), and (iii) user satisfaction (comfort). The findings indicate that the water-based system had the lowest short circuit noise level, the gel-based system had the highest P300 spelling accuracies, and the dry electrode-based system caused the least inconveniences for the user (Pinegger et al. 2016).
Another recent study (Melnik et al. 2017) investigated the variance across different EEG systems compared to the variance across subjects or sessions. The authors tested four

different systems, one mobile EEG system with dry electrodes, one affordable system with a low number of channels and two standard gel-based research-grade systems. They recorded four subjects three times with each of the four EEG systems in six different standard EEG paradigms. The authors describe that the two standard research EEG systems had no significantly different means from each other across all paradigms. However, the two other EEG systems demonstrated different mean values from one or both of the two standard research-grade EEG systems in at least half of the paradigms.

It can be concluded that the type of application and its requirements are important to decide which electrode technology should be used (Nijboer et al 2015). Of course, this is often strongly coupled with the choice of the amplifier, since many of those electrodes are company-specific. Nowadays, all amplifiers have built-in analog-to-digital conversion and get connected to the computer via USB or network connection.

EEG Artifacts

When doing BCI research and single-trial classification it is of great importance to process clean EEG data. However, there is always the danger of having contaminated EEG signals and therefore BCI researchers must carefully consider artifacts. Generally, technical and biological artifacts exist.
The main sources of technical artifacts are primarily external electrical and electromagnetic noise coming from power lines, electric lights, or other fields. Poor contact can lead to high impedances und thus foster electromagnetic artifacts. Wrong electrode material can lead to high pass effects which can hide the requested signal. Also, mainly hidden to the BCI researcher are amplifier noise and quantization noise of the analogue-to-digital conversion. Aliasing effects due to wrong adjusted filters can be problematic. Experience show that major countermeasures for technical artifacts include: shielding the recording system, using filters (e.g., notch filters to remove power line noise) and high quality amplifiers. A properly grounding of the participants to reach potential equalization between participant and measurement system is mandatory.
The main sources of biological artifacts are participants' muscle - electromyogram (EMG)-activities (e.g., neck, face), eye blinks and eye movements. Slight baseline drifts (drift of the zeroline of the signal) due to sweating can also be problematic. While EMG occurs in a range between 20 and 1500 Hz, electrooculogram (EOG) cover a narrow low frequency range from DC up to 10 Hz. Depending on the type of BCI study or application, concurrent recording of the EOG and EMG are advised for applying detection or artifact removal algorithms. Artifacts must be detected and somehow indicated in an online system, where EEG data is processed and e.g. feedback to a user is generated. Depending on the type of processing - offline or online – both, visual and automatic artifact detection (e.g., Oostenveld & Praamstra 2001; Scherer et al. 2007) or removal (e.g., Schlögl et al. 2007, Daly et al. 2015) are important to record correct data (i.e. non-artifactual features) and therefore reliable classification results.

Brain signals and their use in BCI

EEG research distinguishes between two major types of brain activity. Consequently, there are also two major types of non-invasive and EEG-based types of BCIs: (i) spontaneous EEG (also referred to as endogenous or continuous EEG), which is based on internally-induced processes and mental tasks that generate mainly changes in the ongoing EEG, and (ii) event-related potentials, which are based on events or external stimuli.
In this section these two different phenomena are discussed and prominent BCI examples are given thereafter.

Spontaneous EEG

The spontaneous or continuous EEG is the measurable part of brain activity that goes on permanently in the living individual. In the healthy waking brain, the peak-to-peak amplitude of this signal is typically under 75µV but sometimes increases to 100µV (Gevins & Smith 2006). A considerable portion of the signal power originates from rhythmic oscillations in a frequency bandwidth from below 1Hz to approximately 40Hz, even though higher frequencies are also measureable up to 100 Hz (Schomer & da Silva 2012). This wide frequency range got subdivided into smaller, functional ranges with associated names (Schomer & da Silva 2012).
The *alpha rhythm* is characterized by medium-frequency activity (8-13 Hz) and generally indicates states of relaxed wakefulness in healthy adults (Berger 1929). The amplitude of these oscillations are typically very large and can be ten times µV. This wave type is also common during resting periods in which people have their eyes closed, then amplitudes are largest in the occipital areas. Based on this finding, researchers have argued that alpha waves constitute a neural correlate of cognitive inactivity, also referred to as cortical “idling” (Pfurtscheller et al. 1996). However, studies with evoked EEG activity (i.e., ERP investigations) have found that alpha rhythms may indicate different forms of information processing in which different alpha sub-bands (e.g., 8-10 Hz and 10-13 Hz) are dedicated to different functional processes (Klimesch 1999; Niedermeyer 1997). Alpha rhythms originating from sensorimotor areas are also known as mu rhythms and can be further subdivided into lower and higher mu rhythm (Pfurtscheller et al. 2000). Large amplitudes indicate resting sensorimotor areas.
Beta oscillations are characterized by medium to high-frequency activity (13-30 Hz) related to various mental states, such as active concentration, task engagement, excitement, anxiety, attention, or vigilance. Also, it is a marker for sensorimotor activity. The amplitudes of this waves are usually in the µV. Beta activity primarily constitutes an excitatory mechanism (Pfurtscheller & Lopes da Silva 1999) (see Figure 4.E).
Gamma oscillations are characterized by very high-frequency activity (30-200 Hz, but typically not measurable higher than 100 Hz by EEG). These oscillations are often associated with arousal and perceptual binding mechanisms (i.e., integration of various aspects of a stimulus into a coherent overall perception). The amplitudes are already rather small and usually between 1 and 2 µV (Hughes 2008).
Delta waves are characterized as very low-frequency activity (below 1 - 4 Hz) which usually relate to deep and unconscious sleep in healthy humans. Delta waves (amplitude can by several 10^{th} of µV) are also associated with pathological neural states, such as coma or the

loss of consciousness. Generally, delta activity diminishes with increasing age, which suggests that delta activity is primarily an inhibitory mechanism (Hobson & Pace-Schott 2002).

Theta waves occur as low-frequency activity (4 - 8 Hz) and are typically associated with specific sleep states, drowsiness, and meditation. However, in addition in the literature, also frontal midline theta is described. This type has been associated with mental effort, suggesting that attention is directed to an existing stimulus. In general, the amplitude of theta waves are typically between 8 and 10 μV (Cahn & Polich 2006).

It is important to mention that these rhythms can be time-locked to an event; however, they are always non-phase locked. This means, when one compares to similar trials the amplitude behavior may be similar, however, the oscillations of the EEG rhythms will not have the same phase. Therefore, with simple averaging techniques, it is not possible to extract meaningful information from the signals. The main challenge in BCI-research though is, to identify oscillatory patterns in EEG without knowing the time point of establishment – i.e., in an asynchronous BCI application an end user may wish to use the system without any external pace, stimulus or cue.

There are many methods to analyse spontaneous EEG, but in contrast to ERP analysis, the simple calculation of an average over trials does not work (see section Event-related potentials). To get a first and solid impression of spontaneous EEG activity related to various conditions, one of the standard methods used in BCI research is to compare power values with respect to a reference period. The so-called event-related (de)synchronization (ERD(S)) method introduced by Pfurtscheller in the late 1970s (Pfurtscheller & Aranibar 1977) and described in detail in (Pfurtscheller & Lopes da Silva 1999), compares band power values during an activity period with the band power of a reference (resting) period. This comparison results in relative band power changes given in %. By the calculation of these values for several frequency bands the ERD(S) maps represented as time-frequency maps, can be obtained (Graimann et al. 2002)) (See Figure 4.D).

There are many other methods available which exploit these EEG oscillatory components either for direct feedback (neuro-feedback, (Birbaumer et al. 1999)) or machine learning based BCIs. Exemplarily, most common are band power (Guger et al. 2000), common spatial patterns (Ramoser et al. 2000; Blankertz et al. 2008) and many others (Wolpaw & Wolpaw 2012)

Of high importance is, though, how these oscillatory components can be mentally changed or influenced by study participants or end-users.

Motor imagery and other mental tasks

One of the first mental strategies was to imagine hand movements (motor imagery, MI) (Pfurtscheller and Neuper 1997; Munzert et al. 2009; Cincotti et al. 2003). MI describes the mental rehearsal of a motor task without its execution. Typical kinesthetic MI tasks are: (1) sustained imagination of squeezing a training ball (Kaiser et al. 2014; Coyle et al. 2015), (2) repetitive opening and closing of the hand (Pfurtscheller et al. 2003; Ramoser et al. 2000) or (3) sustained/repeated movement imagination of both feet, e.g., dorsi- or plantar-flexion of both feet (Hashimoto and Ushiba 2013; Müller-Putz et al. 2007). Furthermore, this

phenomenon can be triggered by an external event, and users may induce it by actively performing the designated task (Pfurtscheller et al. 1997; Millan et al. 2003; Mason and Birch 2000). This fact is used in non-cue-guided, asynchronous BCI scenarios, where users decide for themselves when to establish control (Müller-Putz et al. 2005; Scherer et al. 2004; Leeb et al. 2007).
Motor imagery can be an efficient strategy for controlling a BCI based on the modulation of rhythms of the sensorimotor cortex also known as SMR-based BCI (Faller et al. 2012; Kreilinger et al. 2013; Neuper et al. 2009; Scherer et al. 2008; Blankertz et al. 2010; Pichiorri et al. 2011). The SMR-BCI uses the power decreases/increases as a feature for discriminating between two or more different MIs.
Beside motor imagination, there are also other mental tasks which can be used and lead to successful modulation of EEG patterns (Millán et al. 2002; Obermaier et al. 2001; Harmony et al. 1996; Cabrera et al. 2010; Jeunet et al. 2016). For example, distinct levels of kinesthetic attention (from focused attention to mind wandering) in a continuous passive mobilization task have been shown modulatory effects at the level of theta, alpha and beta frequency bands (Melinscak et al. 2016). Another study (Friedrich et al. 2013) explored seven mental tasks (mental rotation, word association, auditory imagery, mental subtraction, spatial navigation, left hand MI, both feet MI) and in a user-centered approach, the best four classes were used to build a BCI. Later on, this approach was successfully used to apply a BCI in end-users with disabilities (Scherer et al. 2015).

Event-related potentials

Event-related potentials (ERP) mainly originate from specific external stimuli. Regan (Regan 1989) gives the following definition:
„An EP is a transient wave complex elicited by a certain stimulus or event that is, to be precise, repeated only once. The averaged transient EP reflects a true response if the relevant brain mechanisms were in their resting states before each stimulus, and return to their resting states before the next stimulus. It is consequently assumed that the EP response to a single event does not depend on a previous one.“

When the stimuli are, for example, visual, auditory, somatosensory, or even olfactory, then they are called evoked potentials. However, ERPs can also be elicited by actions which are generated by a person's interval volition to perform a task, e.g, when starting a movement, or even when such a single movement is attempted or imagined (Shibasaki et al. 1980). This particular example of ERP illustrates the movement-related cortical potential (MRCP). Another example of an ERP is the error-related potential (ErrP). After a stimulus, which seems erroneous to a person due to a mismatch in his or hers expectation, the elicited brain wave can be recorded from the midline of the scalp (Falkenstein et al. 1991). Steady-state evoked potentials (SSEPs) are another type of potentials which get evoked only if a stimulus (visual or tactile) is presented with a high repetition rate, usually higher than 6 Hz. Regan (Regan 1989) defines:
"SSEPs occur when sensory stimuli are repetitively delivered at high enough rates so that the relevant neuronal structures are prevented to return to their resting states. [..] Ideally, the discrete frequency components remain constant in amplitude and phase within an infinitely long time period. [..] In practice, SSEPs never completely fulfil this definition of an ideal SSEP."

ERP signals are typically not very strong, and, hence, it is difficult to distinguish them from the spontaneous EEG in raw, single-trial, data. However, by repeated presentation of stimuli and averaging of the EEG responses, these ERPs can be made visible. Since ongoing EEG is not time-locked and not phase-locked to the stimulus, averaging increases the signal-to-noise ratio (Fabiani et al. 2007; Luck 2014; Regan 1989). In BCI research, however, our goal is usually to achieve single-trial detection, in which case specific paradigm design, signal processing techniques and machine learning approaches are necessary (see Chapters 7, 25, ZZ).

Various types of BCIs based on different ERPs as well as specific ERP-components are discussed next.

P300 Component

The P300 is regarded as indicator of information processing in relation to attentional and memory mechanisms and was first described by Sutton et al. (1965). Evidence that is more recent has shown that the P300 comprises two subcomponents: (i) the P3a, also referred to as "novelty P3" and (ii) the P3b, also referred to as "classical P300". The P3a is a positive potential having its maximum amplitude over frontal/central electrode sites and a peak latency in the range of 250-280ms. This wave has been associated with engaging attention (especially the orienting, involuntary shifts to changes in the environment) and processing novelty. In contrast, the P3b is a positive potential having the maximum around 300ms, though depending on the task, the peak can vary in latency from 250-500ms. Amplitudes are typically highest over midline parietal brain areas. Generally, the P3b is related to the likelihood of events, and the less likely an event, the larger the P3b (Katayama & Polich 1998; Simons et al. 2001).

The P300-component was used for the design of one of the first BCI systems. Already in 1988, Farwell and Donchin (Farwell & Donchin 1988) presented a first BCI paradigm based on a visual P300Subjects were presented with a matrix of characters displayed on a computer screen. The rows and column of the matrix were highlighted by flashes at short intervals. Subjects were asked to focus on the desired character (as an intersection of a row and column) and count internally its flashing occurrences (for each row and column) (see Figure 4.A). Since then, many BCI examples have been and are still published, exploring the different properties of the P300. One major contribution was made by Kaufmann et al. in 2011 (Kaufmann et al. 2011). Kaufmann introduced pictures of faces as stimuli instead of simple flashing characters since faces are known for eliciting particularly strong ERPs due to their psychological salience. In 2013 he published work where it was shown that this system increases significantly the accuracy of ALS patients (Kaufmann et al. 2013).

Since then, many applications have been developed, to name some of them: brain painting, web browsing, music composing (Pinegger et al. 2017).

Since many people are notable to focus their vision so precisely, tactile stimuli can be used to elicit the P300 (Herweg et al. 2016; Brouwer & Brouwer 2010).

Moreover, auditory P300 BCIs have also been developed and give now additional ways to help or assist end-users with limited visual pathways (Pokorny et al. 2013; Hohne et al. 2010; Schreuder et al. 2011).

Steady-state evoked potential

This potential appears as sinusoids with the same frequency as the stimulation frequency and sometimes with higher as well as sub harmonics (Müller-Putz, Scherer, Brauneis, et al. 2005; Herrmann 2001)). Since the early 2000s, steady-state visual evoked potential (SSVEP)-based BCIs are researched, first introduced by Middendorf and colleagues (Middendorf et al. 2000). Since then, many papers appeared investigating e.g., high number of classes (Gao et al. 2003), higher harmonics as shown in Figure 4.C (Müller-Putz, Scherer, Brauneis, et al. 2005) and other features like overlaying stimuli to avoid eye movements (Allison et al. 2008). A new application of an SSVEP BCI was shown by Pinegger et al. where they used this kind of analysis to check, whether a user was focusing a P300 spelling matrix. When the user's attention moves away also the SSVEP elicited by row-column flashing diminishes and the spelling could be stopped (Pinegger et al. 2014). Since not all end-users keep control of their eye movements Müller-Putz presented the idea of using steady-state somatosensory evoked potentials (SSSEPs) to create a BCI based on repetitive tactile stimuli applied to the two index fingers (Müller-Putz et al. 2006). As a basic concept the proof was made, however later attempts did not bring this kind of BCI to a level, where end-users could fully benefit from it (Pokorny et al. 2016; Breitwieser et al. 2016). Nevertheless, SSVEPs can be harnessed also in healthy BCI users when engaging in cooperative tasks (e.g., game playing) (Cruz et al. 2017).

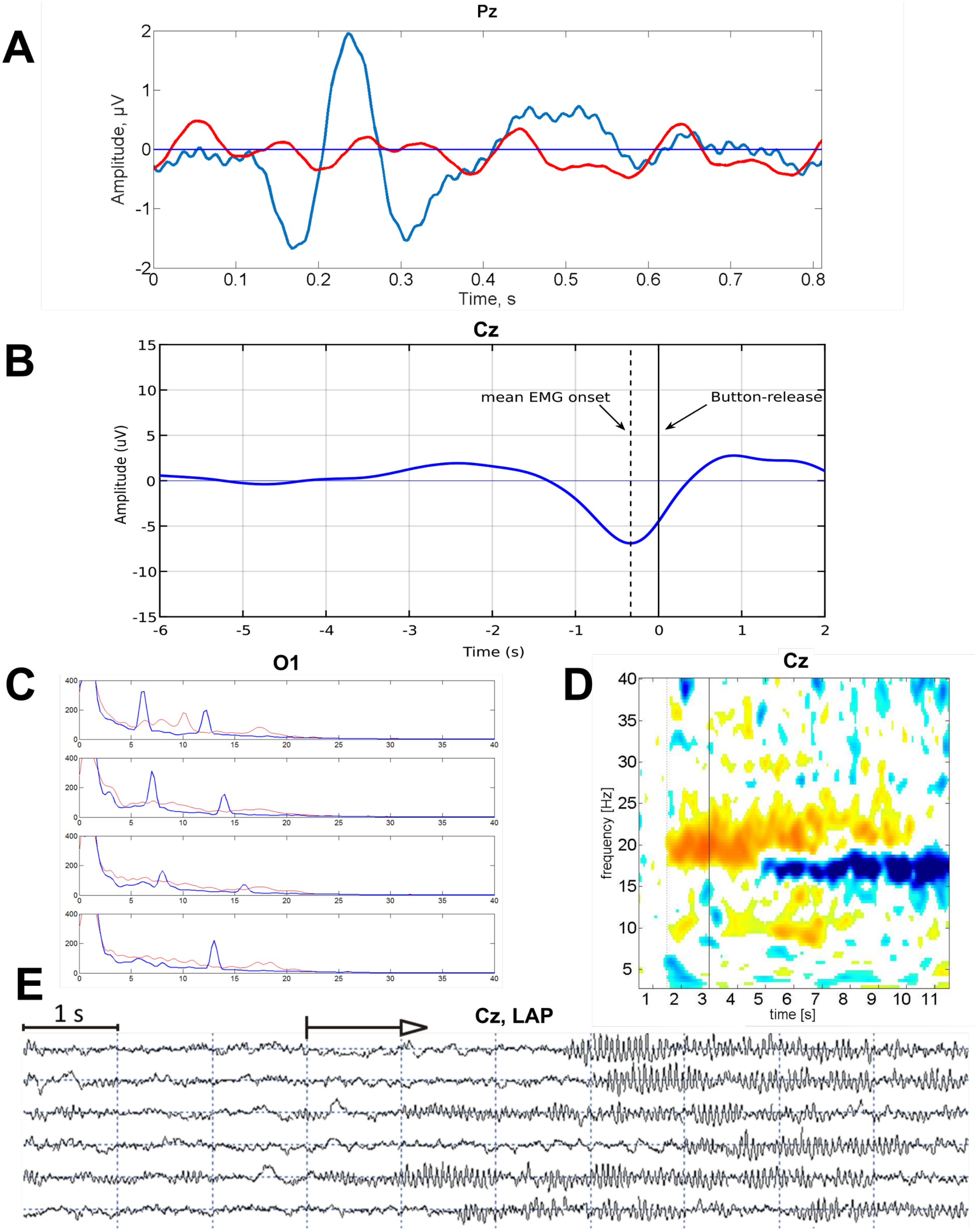

Figure 4: Various EEG signals and patterns. A) P300 target signal (blue) and average non-target responses (red). B) MRCP from 10 subjects averaged over 1000 trials (Sburlea, Montesano & Minguez 2015). C) SSVEP spectra of focused attention to 4 different flashing lights: 6 Hz, 7Hz, 8Hz, 13Hz (Müller-Putz, Scherer, Brauneis, et al. 2005). D) ERD map of a Laplacian derivation of Cz in an end-user with spinal cord injury during foot motor imagery. E) Examples of single EEG trials, Laplacian derivation, from Cz corresponding to D.

Error Potential

A possibility to increase the BCI performance is to automatically detect errors from recorded brain signals after reactions to particular decisions and thereby allowing a BCI system to either correct or inhibit erroneous commands.

In the early 1990s, the idea of the error potential (ErrP), often also referred to as error-related negativity (ERN) due to its negative polarity, came up. It is described as a characteristic wave complex measurable on frontal midline electrodes above the anterior cingulate cortex (ACC), a brain region to be known for its functional role in conflict monitoring and error processing (Botvinick et al. 1999; Botvinick et al. 2004; Carter 1998). ERN develops concurrently with response onset and often peaks within 100ms after onset; however, depending on the type of error peak, latencies may also range up until 500ms after response onset. Generally, the ErrP occurs after one perceives erroneous events.

Depending on the way these potentials are generated they are defined as either observation (Miltner et al. 1997), feedback (Miltner et al. 1997), response (Falkenstein et al. 1991), or interaction ErrPs (Ferrez & Millán 2008, Chavarriaga et al. 2014). Interaction ErrPs can be detected at the region over the anterior cingulate cortex (ACC) (Mathalon et al. 2003) and can be measured after a person witnesses a false execution of an intended command. From the user’s perspective, an interaction ErrP occurs whenever a command was misinterpreted by the used control interface.

In contrast to the other types of ErrPs, which either do not require the involvement of the user or do not emerge in self-paced scenarios, the interaction ErrP seems to be the most promising for increasing performance in BCI applications for end-users.

By using these interaction ErrPs, the performance of BCIs can be improved by detecting specific reactions to errors that differ from reactions to correct events. False actions can be inhibited which lead to increased accuracies of BCI-driven systems. Several studies have already mentioned the technical capabilities of error correction for various paradigms (Ferrez & Millán 2008). The paradigms used in these experiments have in common that they are designed to work well for ErrP processing. Because of the discrete nature of the feedback, ErrPs can be detected easily by evaluating time periods after discrete events.

However, modern BCI applications are no longer limited to discrete applications where only one discrete decision can be made at one given point in time. Instead, continuously controlled applications gain importance as they offer a more natural implementation of BCI for activities of daily living. Relevant examples are a continuously moving wheelchair for mobility (Galán et al. 2008) or moving cars in a computer game (Kreilinger et al. 2016).

A recent study showed that ErrPs can also be recorded and utilized during one of these continuous applications. A continuous feedback in form of a moving artificial arm was coupled with additional discrete events as triggers and ErrPs were successfully found in offline analysis (Kreilinger et al. 2012, Omedes et al. 2018), as well as asynchronously (Lopes Dias 2018).

An alternative and complementary BCI paradigm was presented by Iturrate and colleagues recently (Iturrate et al. 2015). In their approach a robotic arm executed actions that the participants evaluated as erroneous or correct, and exploited correlated brain patterns of this assessment to learn suitable motor behaviours.

Movement-related cortical potential

Movement-related cortical potentials (MRCPs) have been discovered in 1965 by Kornhuber and Deecke (Kornhuber & Deecke 1965) as EEG potentials that precede the electromyography (EMG) onset of voluntary action. These potentials have been observed over the motor and sensorimotor areas. In their study, the flexion of the index finger was investigated. Later, MRCPs have been studied in other types of movement such as, hand movements (Pereira et al. 2017; Jochumsen et al. 2015, Schwarz et al. 2018, Ofner et al. 2017), foot movements (Shibasaki et al. 1981; do Nascimento et al. 2005), and also in other actions such as walking (Jiang et al. 2015; Sburlea, Montesano & Minguez 2015), see Figure 4.B.

In all types of movements the MRCP emerges before the movement onset with a negative slope (the Bereitschaftspotential, BP) which has a similar distribution in both foot and hand movements, and starts between 1.2 and 0.5 s before the movement onset. The maximum negativity is reached between 0.5 and 0 s before the EMG onset. In the case of foot movement, the MRCP is visible on the midline precentral region and is symmetrically distributed, while for hand movements the MRCP is localized to the contralateral precentral region. It is considered that the maximum negativity of the MRCP is related to the movement, whereas the BP is more related to a non-specific preparation (or planning) of the cerebral cortex for voluntary movement (Shibasaki et al. 1980).

MRCPs are not only observed during movement execution, but are also present during attempt of execution and movement imagination. This corresponds to a very valuable property which can be exploited for BCIs based on EEG. MRCPs have been investigated especially in the lower delta frequency for the detection of movement intention in healthy subjects (Niazi et al. 2011; Lopez-Larraz et al. 2014; Jiang et al. 2015; Sburlea et al 2015, Jochumsen et al. 2015; Pereira et al 2017; Pereira et al 2018) and in patients (Miltner et al. 2016; Sburlea, Montesano, Cano de la Cuerda, et al. 2015; Sburlea et al. 2017). Ongoing studies that focus on the rehabilitation of motor impaired patients (stroke or spinal cord injured) use MRCPs to control assistive robotic devices or neuroprosthesis (López-Larraz et al. 2016; Müller-Putz et al. 2017). The detection of the MRCP's earliest component (BP) can also enhance positive neuroplasticity (Mrachacz-Kersting et al. 2012; Xu et al. 2014) and facilitate the recovery.

Intracortical research on primates (Nicolelis & Chapin 2002) and also humans (Hochberg et al. 2006; Collinger et al. 2013) has shown that brain signals contain information about hand movement trajectories in a 3-dimensional space. Following a similar research goal (of decoding movement trajectories) but from non-invasive EEG activity, some first results (Ofner and Müller-Putz 2012; Ofner and Müller-Putz 2015; Bradberry et al. 2010; Antelis et al. 2013) indicated that movement trajectory information can be recovered from the low-frequency EEG amplitudes. Although these studies report promising results, there is still a lot of research necessary before such non-invasive BCIs will be available for end-users. A more detailed review on this topic can be found in (Müller-Putz et al. 2016)

Discussion

In this chapter EEG was discussed in detail, from the neurophysiological foundations to EEG phenomena, signal recording methods, and respective signal patterns to be used in BCI research. With its high temporal resolution and its easy applicability EEG has played and will continue to play a major role in BCI applications for end-users with disabilities and furthermore in healthy users (Nijholt et al 2009, Gürkök et al 2017, Brunner et al. 2015) . Also, the combination of EEG with other recording techniques like near-infrared spectroscopy (Shin et al. 2017) or functional magnetic resonance imaging (fMRI) (Zich et al. 2015; Steyrl et al. 2017) gained importance during the last years. And finally, with particular interest for studies on movement neurophysiology, high density EEG recordings for source localization receive more and more attention. This is due to the fact that EEG, in contrast to fMRI, allows measurements while participants execute body movements (Wagner et al. 2016; Seeber et al. 2016).

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