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Chapter 2

Brain Signal Acquisition

In this chapter, a comprehensive and systematic introduction of brain signals used in brain–computer interface (BCI) systems is presented. Figure 2.1 shows a new taxonomy of brain signals including invasive and noninvasive signals based on the signal collection method. Invasive signals are collected from the cortex surface or under the cortex surface (Section 2.1); noninvasive signals are collected by the external sensors (Section 2.2). Electroencephalogram (EEG) plays a dominant role among noninvasive signals. Therefore, the EEG signal and its subordinate categories in specific are introduced in Section 2.3. The basic characteristics of various brain signals are summarized in Table 2.1.

2.1 Invasive Approaches

Here we only briefly introduce the basic knowledge about invasive methods as this book mainly focuses on noninvasive approaches. Invasive recordings are acquired by electrodes deployed under the scalp. Figure 2.2 (Leuthardt *et al.*, 2009) shows both "intraparenchymal signals" gathered from the cortex and "electrocorticography (ECoG)"[1] gathered from the surface of the cortex (dura and arachnoid).

Invasive techniques can provide high-quality brain signals as electrodes collect signals directly from locations near the brain neurons. The collected

[1]Some studies refer to intracortical as "invasive," and ECoG as "semi-invasive." In this book, we combine the so-called "invasive" and "semi-invasive" into "invasive" because they both require surgery.

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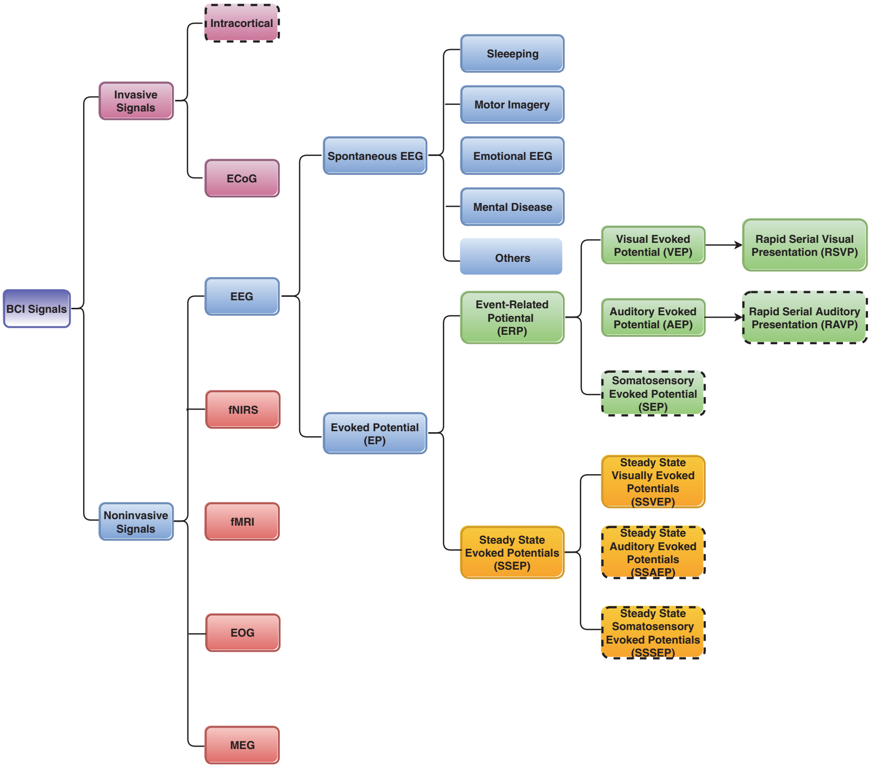

Fig. 2.1: The brain signal acquisition methods. The dashed quadrilaterals (intracortical, RAVP, SEP, SSAEP, and SSSEP) are not included in this chapter because there is no existing work focusing on them involving deep learning algorithms. P300, which is a positive potential recorded approximately 300 ms after the onset of presented stimuli, is not listed in this signal tree because it is included by ERP (which refers to all the potentials after the presented stimuli). In this classification, other brain signals beyond EEG (e.g., MEG and fNIRS) could also include visual/auditory tasks theoretically, but we omit them since there is no existing work adopting deep learning on these tasks.

signals have high temporal and spatial resolution[2] and high signal-to-noise ratio (SNR). Nevertheless, invasive methods suffer from two challenges. First, the implantation of electrodes requires a surgical procedure, which is expensive and risky because of potential medical complications such as transplant rejection. Second, implanted electrodes are fixed and, therefore,

[2]Spatial resolution refers to how well the signal discriminates among nearby locations.

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Table 2.1: Summary of the characteristics of brain signals.

	Invasive		Noninvasive				
Signals	**Intracortical**	**EcoG**	**EEG**	**fNIRS**	**fMRI**	**EOG**	**MEG**
Invasiveness	High	High	Low	Low	Low	Low	Low
Spatial Resolution	Very high	High	Low	Intermediate	High	Low	Intermediate
Temporal Resolution	High	High	High	Low	Low	Intermediate	High
Signal-to-Noise Ratio	High	High	Low	Low	Intermediate	Intermediate	Low
Portability	Intermediate	Intermediate	High	High	Low	High	Low
Cost	High	High	Low	Low	High	Low	High
Characteristic	Electrical	Electrical	Electrical	Metabolic	Metabolic	Electrical	Magnetic

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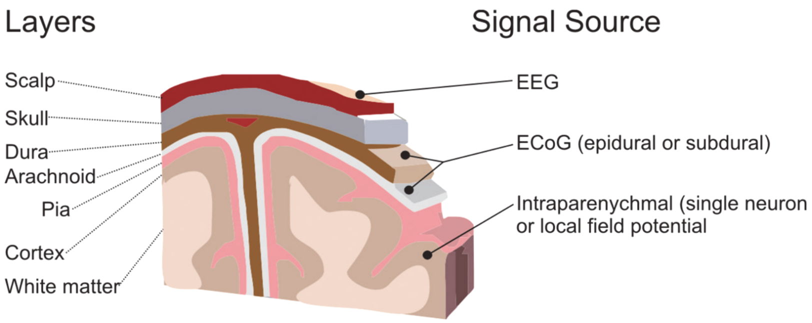

Fig. 2.2: Signal source locations in the brain (Leuthardt *et al.*, 2009).

can only measure the brain signals from the same locations. For these reasons, invasive brain signal techniques are mainly used in animals (e.g., monkeys and rats) and for people with severe disabilities (e.g., individuals with amyotrophic lateral sclerosis (ALS)) (Abdulkader *et al.*, 2015).

2.1.1 *Intracortical Approaches*

The intracortical recording technique involves the insertion of electrodes into the cortex of the subject's brain (Figure 2.2). The implanted micro-electrode can be a single electrode or an array of electrodes. Generally, the intracortical electrodes provide high-resolution motor control brain signals, as movement is the most easily observable phenomenon compared to other phenomena, such as hearing. Under the cortex, the electrodes are sensitive enough to pick up the discrete all-or-none output of single neurons, the action potential, commonly referred to as a "spike", as well as the summed voltage fluctuations from small to large numbers of neurons, called field potentials. Each electrode provides spiking from up to a few neurons, yielding the time-evolving output pattern of the population. These represent but a small sample of the entire set of neurons in this limited region, as spiking can only be detected by microelectrodes closely approximated to a neuron (Homer *et al.*, 2013). Pandarinath *et al.* (2017) developed a high-performance BCI system for communication among patients with ALS. This work implanted a 96-channel silicon microelectrode array in the motor cortex corresponding to hand area and recorded the motor intention of users by the microelectrode array. The array was then decoded into point-and-click commands to control a cursor.

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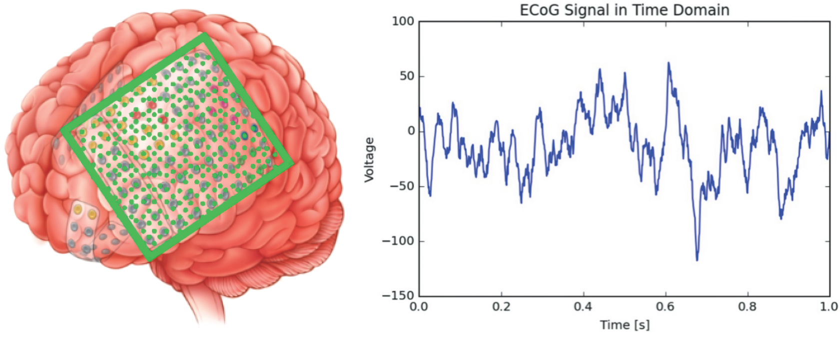
2.1.2 *Electrocorticography*

ECoG is an extracortical invasive electrophysiological monitoring method to record brain activity. The electrodes collecting ECoG are attached under the skull, above (epidural) or below (subdural) the dura mater, but not within the brain parenchyma itself (Figure 2.2) (Leuthardt *et al.*, 2009). ECoG provides a tradeoff between higher SNR compared to noninvasive recordings and lower risk compared to intracortical recordings. It provides a higher spatial resolution and a rather high SNR with a lower surgical risk. Therefore, ECoG has a better prospect in the medical arena than intracortical recordings.

The ECoG collection approach and signals are shown in Figure 2.3 (Bandt *et al.*, 2017). ECoG signals have a higher amplitude compared to noninvasive brain wave signals. For instance, ECoG amplitude is higher than 50 μV, whereas the EEG amplitude is generally lower than 20 μV. The higher amplitude renders ECoG less vulnerable to artifacts such as eye blink activity. Moreover, ECoG has a bandwidth of 0–500 Hz, which is much wider than EEG (0–40Hz), because of the low-pass filtering effects of the skull. The wider frequency bands take substantial information from functional areas of a brain (e.g., motor and language) and thus can be used to train a higher performance BCI system. However, the disadvantages of an invasive methods like ECoG (such as the risky surgery and inconvenience of permanently attached devices) naturally limit its wide deployment in real-world scenarios.



(a) ECoG microelectrodes (b) ECoG signals

Fig. 2.3: ECoG grid on cortical surface and ECoG signals (Bandt *et al.*, 2017).

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2.2 Noninvasive Approaches

Noninvasive recordings can gather user's brain information without electrodes being inserted. Signals can be collected using electrical, magnetic, or metabolic methods. Noninvasive signals mainly include EEG, functional near-infrared spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), electrooculography (EOG), and magnetoencephalography (MEG). EEG-related studies represent the considerable majority of noninvasive signals and have numerous subclasses. We will introduce more details and subcategories of EEG in Section 2.3.

2.2.1 *Electroencephalography*

EEG is the most commonly used noninvasive technique for measuring brain activities. EEG monitors the voltage fluctuations generated by an electrical current within human neurons. Electrodes placed on the scalp measure the amplitude of EEG signals. EEG signals have a low spatial resolution because the number of electrodes is limited. EEG electrode locations generally follow the international 10–20 system or the intermediate 10% electrode positions (Malmivuo and Plonsey, 1995). The international 10–20 system divides the scalp in 10% and 20% intervals and totally contains 21 electrode locations (Figure 2.4). The intermediate 10% electrode position is standardized by the American Electroencephalographic Society and splits the scalp with 10% intervals, containing 75 electrodes. The existing EEG collection system is generally less than 75 electrodes, specifically, 64 electrodes (BCI 2000 system), 32 electrodes (openBCI headset), 14 electrodes (Emotiv EPOC+ headset), 5 electrodes (Emotiv insight headset), and 1 electrode (Mindware headset).

The temporal resolution of EEG signals is much better than spatial resolution. The ionic current changes rapidly, which offers a temporal resolution higher than 1000 Hz. The SNR of EEG is generally very poor because of both objective and subjective factors. Objective factors include environmental noises, the obstruction of the skull and other tissues between cortex and scalp, and various stimulations. Subjective factors contain the mental stage of the subject, fatigue status, and the variance among different subjects.

EEG-recording equipment can be installed in a cap-like headset. As shown in Figure 2.5 (Zhang *et al.*, 2018h), the EEG headset can be mounted on the head of the user to gather signals. Compared to other

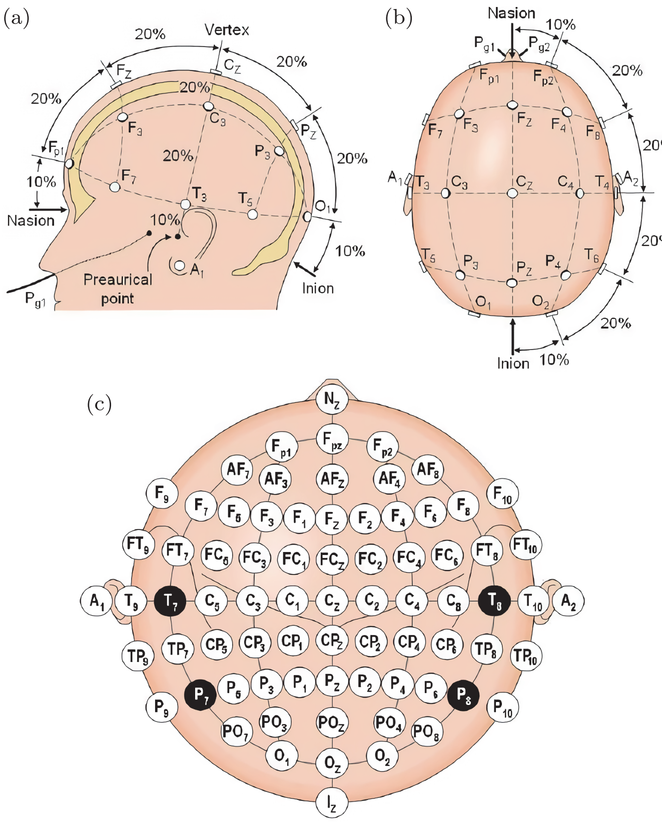
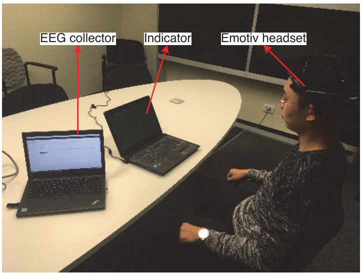
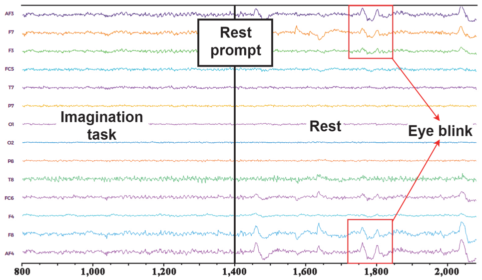


Fig. 2.4: (a) and (b) are the left and above view of the international 10–20 system; (c) presents the intermediate 10% electrodes positions (Sazgar and Young, 2019).



(a) EEG



(b) EEG signals

Fig. 2.5: EEG collection scenario and the gathered signals. The subject is undertaking an imagination task.

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Table 2.2: EEG patterns and corresponding characters. Awareness degree denotes the degree of being aware of an external world. Consciousness represents the subject's normal state of being awake.

Patterns	***Hz***	**Amplitude**	**Brain State**	**Awareness**	**Produced Location**
Delta	0.5–4	Higher	Deep sleep pattern	Lower	Frontally and posteriorly
Theta	4–8	High	Light sleep pattern	Low	Entorhinal cortex, hippocampus
Alpha	8–12	Medium	Closing the eyes, relax state	Intermediate	Posterior regions of head
Beta	12–30	Low	Active thinking, focus	High	Most evident frontally
Gamma	30–100	Lower	Cross-modal sensory processing	Higher	Somatosensory cortex

equipment used to measure brain signals, EEG headsets are portable and more accessible for most applications.

The EEG signals collected from any typical EEG hardware have several nonoverlapping frequency bands (Delta, Theta, Alpha, Beta, and Gamma) based on the strong intraband correlation with a distinct behavioral state (Zhang *et al.*, 2018h). Each EEG pattern contains signals associated with particular brain information. Table 2.2 shows EEG frequency patterns and the corresponding characteristics. The degree of awareness denotes the perception of individuals when presented with external stimuli. It is mainly defined in physiology instead of psychology. Each frequency band represents a brain state and a qualitative assessment of awareness:

- Delta pattern (0.5–4 Hz) corresponds to deep sleep when the subject has lower awareness.
- Theta pattern (4–8 Hz) corresponds to light sleep in the realm of low awareness.
- Alpha pattern (8–12 Hz) mainly occurs during eyes closed and deeply relaxed state and corresponds to the medium awareness.
- Beta pattern (12–30 Hz) is the dominant rhythm while the eyes of the subject are open and is associated with high awareness. Beta patterns capture most of our daily activities (such as eating, walking, and talking).

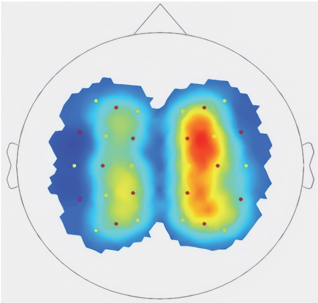
- Gamma pattern (30–100 Hz) represents the co-interaction of several brain areas to carry out a specific motor and cognitive function.

2.2.2 *Functional Near-infrared Spectroscopy*

fNIRS is a noninvasive functional neuroimaging technology using near-infrared (NIR) light (Naseer *et al.*, 2016). In specific, fNIRS employs NIR light to measure the aggregation degree of oxygenated hemoglobin (Hb) and deoxygenated-hemoglobin (deoxy-Hb) because Hb and deoxy-Hb have higher absorbance of light than other head components such as the skull and scalp. fNIRS relies on blood-oxygen-level-dependent (BOLD) response or hemodynamic response to form a functional neuroimage. The BOLD response can detect the oxygenated or deoxygenated blood level in the brain blood. The relative levels reflect the blood flow and neural activation, where increased blood flow implies a higher metabolic demand caused by active neurons. For example, when the user is concentrating on a mental task, the prefrontal cortex neurons will be activated, and the BOLD response in the prefrontal cortex area will be stronger (Hennrich *et al.*, 2015).

Figure 2.6 shows the fNIRS collection hardware and the collected signals. Single or multiple emitter–detector pairs measure the Hb and deoxy-Hb: the emitter transmits NIR light through the blood vessels to the detector. Most existing studies use fNIRS technologies to measure

(a) fNIRS collection equipment



(b) fNIRS signals

Fig. 2.6: fNIRS collection equipment and the gathered signals.[3]

[3]https://www.artinis.com/fnirs. Accessed Jan. 20, 2017.

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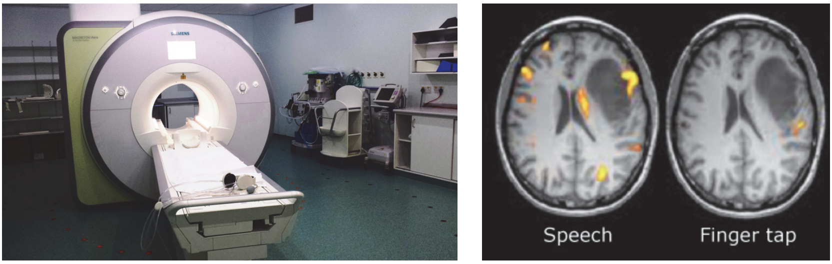
the status of prefrontal and motor cortex. The former is a response to mental tasks, whereas the latter is a response to motor-related tasks (e.g., motor imagery). The monitored Hb and deoxy-Hb change slowly since the blood speed varies in a relatively slow ratio compared to electrical signals. Therefore, fNIRS signals have lower temporal resolution[4] compared with electrical or magnetic signals. The spatial resolution depends on the number of emitter–detector pairs. In current studies, three emitters and eight detectors would suffice for adequately acquiring the prefrontal cortex signals; and six emitters and six detectors would suffice for covering the motor cortex area (Naseer and Hong, 2015). A drawback of fNIRS is that it cannot be used to measure cortical activity occurring deeper than 4 cm in the brain, because of the limitations in light emitter power and spatial resolution.

2.2.3 *Functional Magnetic Resonance Imaging*

fMRI monitors brain activities by detecting changes associated with blood flow in brain areas (Wen *et al.*, 2018). Similar to fNIRS, fMRI relies on the BOLD response. The main differences between fNIRS and fMRI are as follows (Liu *et al.*, 2018a). First, as the name implies, fMRI measures BOLD response through magnetic instead of optical methods. Hemoglobin differs in how it responds to magnetic fields, depending on whether it has a bound oxygen molecule. The magnetic fields are more sensitive to and are more easily distorted by deoxy-Hb than Hb molecules. Second, the magnetic fields have higher penetration than NIR light, which gives fMRI greater ability to capture information from deep parts of the brain than fNIRS. Third, fMRI has a higher spatial resolution than fNIRS since the latter's spatial resolution is limited by the emitter–detector pairs. However, the temporal resolutions of fMRI and fNIRS are at an equal level because they both constrained by the blood flow speed.

fMRI has several flaws compared to fNIRS: (1) fMRI requires an expensive scanner to generate magnetic fields; (2) the scanner is heavy and has poor portability. Figure 2.7 shows the fMRI acquisition machine, and the resulting brain images. fMRI images of speech perception and finger tapping have a significant difference, indicating high SNR.

[4]Temporal resolution refers to the smallest time period of neural activity reliably separated out.



(a) fMRI collection equipment (b) fMRI images

Fig. 2.7: fMRI collection equipment and the gathered fMRI signals while the subject is speaking and finger tapping.[5]

2.2.4 *Electrooculography*

EOG is a technique for measuring the corneo-retinal standing potential that exists between the front and the back of the human eyes. Most patients who have lost voluntary motor movements (e.g., locked-in syndrome patients) remain in partial control of the eyes (Yang *et al.*, 1989). The eye movements can be detected by EOG signals to interact with the external devices. Therefore, we regard EOG signals as one class of brain signals in this book. EOG can be used to bridge the user and the outer world because different eye movements will cause different electrical potentials. Pairs of electrodes are typically placed above/below the eye or to the left/right of the eye to measure EOG signals. The EOG collection equipment (Aungsakun *et al.*, 2011) and the collected signals (Rusydi *et al.*, 2014) can be found in Figure 2.8. Figure 2.8(a) shows EOG electrode placements, where electrodes Ch.V+ and Ch.V− measure the vertical movements, and Ch.H+ and Ch.H− measure the horizontal movements. G electrode representing the ground line works as a reference point. Figure 2.8(b) shows the vertical EOG in the time domain under six scenarios (looking upward, looking downward, single blink, double blink, looking leftward, and looking rightward). We can observe EOG signals have large variances among different scenarios, indicating they have a relatively high SNR and are easily recognizable by machine learning algorithms. EOG has low spatial resolution compared to other brain signals since we can

[5]https://www.jameco.com/Jameco/workshop/HowItWorks/what-is-an-fmri-scan-and-how-does-it-work.html. Accessed Jan. 5, 2017.

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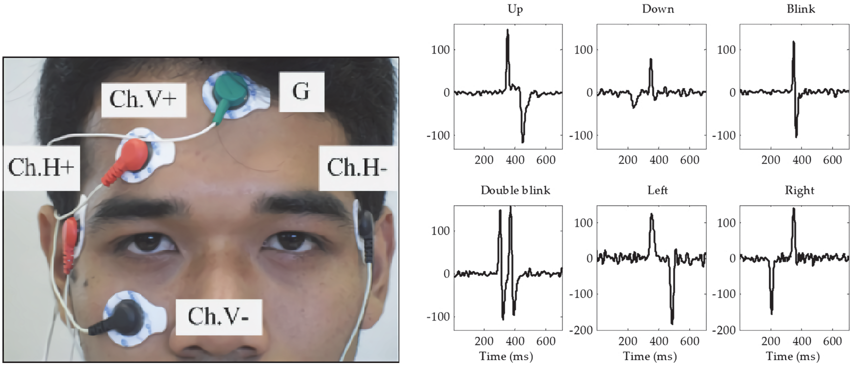

(a) EOG collection (b) EOG signals

Fig. 2.8: EOG collection equipment (Aungsakun *et al.*, 2011) and the gathered vertical signals while the subject is looking in different directions and blinking (Rusydi *et al.*, 2014).

only detect the vertical and horizontal potentials. The temporal resolution of EOG is higher than neuroimaging techniques because the electrical potentials vary faster than metabolic features (e.g., blood flow).

2.2.5 *Magnetoencephalography*

MEG is a functional neuroimaging technique for mapping brain activity by recording magnetic fields produced by electrical currents occurring naturally in the brain, using very sensitive magnetometers (Cichy *et al.*, 2017). The ionic currents of active neurons will create weak magnetic fields. The generated magnetic fields can be measured by magnetometers like SQUIDs (superconducting quantum interference devices). However, producing a detectable magnetic field requires massive (e.g., 50,000) active neurons with similar orientation. The source of the magnetic field measured by MEG is the pyramidal cells which are perpendicular to the cortex surface.

MEG has a relatively low spatial resolution because the signal quality highly depends on the measurement factors (e.g., brain area, neuron orientations, neuron depth). However, MEG can provide very high temporal resolution ($\geq$1000 Hz) because MEG directly monitors the brain activity from the neuron level, which is in the same level of intracortical signals. The MEG equipment (Ukil, 2006) is shown in Figure 2.9. MEG equipment is expensive and not portable, which limits its real-world

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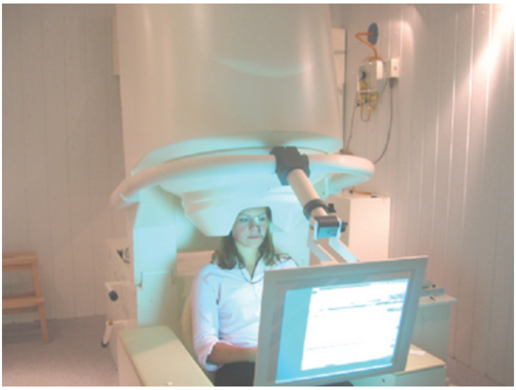

Fig. 2.9: MEG collection equipment (Ukil, 2006).

deployment for brain signal. The gathered MEG signal is similar to EEG signals.

2.3 EEG Paradigms

Compared to other noninvasive signals (e.g., fMRI, fNIRS, EOG, MEG), EEG has several important advantages: (1) the hardware has higher portability with much lower price; (2) the temporal resolution is very high (milliseconds level)[6]; (3) EEG is relatively tolerant of subject movement and artifacts, which can be minimized by existing signal processing methods; (4) the subject doesn't need to be exposed to high-intensity (>1 Tesla) magnetic fields. Thus, EEG can serve subjects that have metal implants in their body (such as metal-containing pacemakers).

As the most commonly used signals, there are a huge number of subcategories of EEG signals. In this section, we present a systematic introduction of EEG subclass signals. As shown in Figure 2.1, we divided EEG signals into spontaneous EEG and evoked potentials (EPs). EPs can be split into event-related potentials (ERPs) and steady-state evoked potentials (SSEP) based on the frequency of the external stimuli. Each potential contains visual-, auditory-, and somatosensory-potentials based on the external stimuli types. The dashed quadrilaterals in Figure 2.1, such as intracortical, SEP, SSAEP, SSSEP, and RSAP, are not included in this

[6]http://www.biomagcentral.org/biomagnetism/meg.html. Accessed Feb. 23, 2020.

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book because there are very few existing studies working on them with deep learning algorithms. We list these signals for systematic completeness.

2.3.1 *Spontaneous EEG*

Generally, when we talk about the term "EEG," we refer to *spontaneous* EEG, which measures the brain signals under a specific state without external stimulation. For example, spontaneous EEG includes the EEG signals while the user is sleeping, undertaking a mental task (e.g., counting), under fatigue stage, suffering brain disorders, undertaking motor imagery tasks, and so on.

The EEG signals recorded while a user stares at a color/shape/image belong to this category. While the subject is gazing at a specific image, the visual stimuli are steady without any change. This scenario differs from the visual stimuli in EP, where the visual stimuli are changing at a specific frequency. Thus, we regard the image stimulation as a particular state and categorize it as spontaneous EEG. BCI systems based on spontaneous EEG are challenging to train, because of the lower SNR and the larger variation across subjects (Pfurtscheller and Neuper, 2001).

2.3.2 *Evoked Potential*

EP or evoked responses refer to EEG signals which are evoked by a event stimulus instead of spontaneously. An EP is time-locked to the external stimulus, whereas the aforementioned spontaneous EEG is non-time-locked. In contrast to spontaneous EEG, EP generally has higher amplitude and lower frequency. As a result, the EP signals are more robust across subjects. According to the stimulation method, there exist two categories of EP: the ERP and the SSEP. ERP records the EEG signals in response to an isolated discrete stimulus event. To achieve this isolation, stimuli in an ERP experiment are typically separated from each other by a long inter-stimulus interval, allowing for the estimation of a stimulus-independent baseline reference (Norcia *et al.*, 2015). The stimuli frequency of ERP is generally lower than 2 Hz. In contrast, SSEP is generated in response to a periodic stimulus at a fixed rate. The stimuli frequency of SSEP generally ranges within 3.5–75 Hz.

2.3.2.1 *Event-Related Potential*

There are three kinds of EPs in extensive research and clinical use: visual evoked potentials (VEP); auditory evoked potentials (AEP); and

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somatosensory evoked potentials (SEP) (Cecotti and Ries, 2017). The VEP signals are mainly on the occipital lobe, and the highest signal amplitudes are collected at the calcarine sulcus.

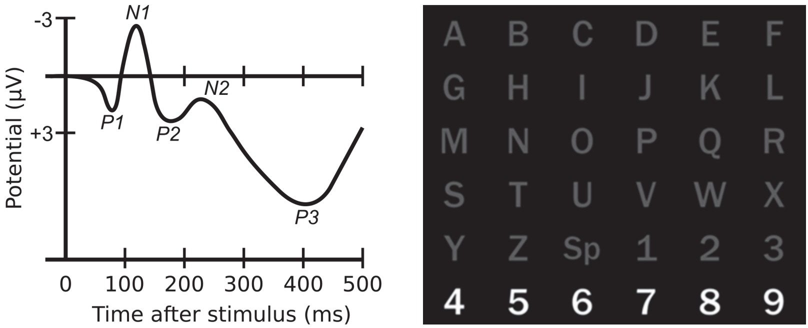
(1) VEP. VEPs are a specific category of ERP caused by visual stimulus (e.g., an alternating checkerboard pattern on a computer screen). VEP signals are hidden within the normal spontaneous EEG. To separate VEP signals from the background EEG readings, repetitive stimulation and time-locked signal-averaging techniques are generally employed.

Rapid serial visual presentation (RSVP) (Lees *et al.*, 2018) can be regarded as one kind of VEP. An RSVP diagram is commonly used to examine the temporal characteristics of attention. The subject is required to stare at a screen where a series of items (e.g., images) are presented one by one. There is a specific item (called the target) that separates from the rest of the other items (called distracters). The subject knows which is the target before the RSVP experiment. Generally, the distracters can either be a color change or letters among numbers. RSVP contains a static mode (the items appear on the screen and then disappear without moving) and a moving mode (the items appear on the screen, move to another place, and finally disappear). Nowadays, brain signal research mainly focuses on the static mode RSVP. Usually, the frequency of RSVP is 10 Hz which means that each item will stay on the screen for 0.1 s.

(2) AEP. AEPs are a specific subclass of ERP in which responses to auditory (sound) stimuli are recorded. AEP is mainly recorded from the scalp but originates at the brainstem or cortex. The most common AEP measured is the auditory brainstem response that is often employed to test the hearing ability of newborns and infants. In BCI, AEP is mainly used in clinical tests for its accuracy and reliability in detecting unilateral loss (Chiappa, 1997). Similar to RSVP, rapid serial auditory presentation (RSAP) refers to experiments with rapid serial presentation of sound stimuli. The task for the subject is to recognize the target audio among the distractors.

(3) SEP.[7] SEP is another commonly used subcategory of ERP, which is elicited by electrical stimulation of the peripheral nerves. SEP signals include a series of amplitude deflection that can be elicited by virtually any sensory stimuli.

[7]Generally, SEPs are abbreviated as SSEP or SEP. In this chapter, we choose SEP as the abbreviation in case of conflict with SSEPs.



(a) ERP components (b) P300 speller

Fig. 2.10: P300 waves and visual-based P300 speller (Farwell and Donchin, 1988).

2.3.2.2 *P300*

P300 (also called P3) is an important component in ERP (Guger *et al.*, 2009). Here we introduce P300 signal separately since it is widely used for BCI systems. Figure 2.10(a) shows the ERP signal fluctuation in the 500 ms after the stimuli onset.[8] The waveform mainly contains five components, P1, N1, P2, N2, and P3. The capital character P/N represents positive/negative electrical potentials. The following number refers to the occurrence time of the specific potential. Thus, P300 denotes the positive potential of ERP waveform at approximately 300 ms after the presented stimuli. Compared to other components, P300 has the highest amplitude and is easiest to detect. Thus, a large number of brain signal studies focus on P300 analysis. P300 is more of an informative feature instead of a type of brain signal (e.g., VEP). Therefore, we do not list P300 in Figure 2.1. P300 can be analyzed in most of ERP signals such as VEP, AEP, SEP.

In practice, P300 can be elicited by rare, task-relevant events in an "oddball" paradigm (e.g., P300 speaker). In the oddball paradigm, the subject receives a series of stimuli where low-probability target items are mixed with high-probability nontarget items. Visual and auditory stimuli are the most commonly used in the oddball paradigm. Figure 2.10(b) shows an example of visual-based P300 speller, which enables the subject to spell letters/numbers directly through brain signals (Farwell and Donchin, 1988). The 26 letters of the alphabet and the Arabic numbers are displayed

[8]The negative voltage of ERP is plotted upward, which is common in ERP research.

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on a computer screen which serves as the keyboard. The subject focuses attention successively on the characters they wish to spell. The computer detects the chosen character online in real time. This detection is achieved by repeatedly flashing rows and columns of the matrix. When the elements containing the selected characters are flashing, a P300 fluctuation is elicited. In the 6×6 matrix screen, the rows and columns flash in mixed random order. The flash duration and interval among adjacent flashes are generally set as 100 ms (Belitski *et al.*, 2011). The columns and rows flash separately. First, the columns flash six times with each column flashing one time. Second, the rows will flash for six times. After that, this paradigm repeats for several times (e.g., N times). The P300 signals of the total $12N$ flash will be analyzed to output a single outcome (i.e., one letter/number).

2.3.2.3 *Steady State Evoked Potentials*

SSEPs are another subcategory of EPs, which are periodic cortical responses evoked by certain repetitive stimuli with a constant frequency. It has been demonstrated that the brain oscillations generally maintain a steady level over time, whereas the potentials are evoked by steady state stimuli (e.g., a flickering light with fixed frequency). Technically, SSEP is defined as a form of response to repetitive sensory stimulation in which the constituent frequency components of the response remain constant over time in both amplitude and phase (Regan, 1977). Depending on the type of stimuli, SSEP can be divided into three subcategories: steady-state visually evoked potentials (SSVEP), steady-state auditory evoked potentials (SSAEP), and steady-state somatosensory evoked potentials (SSSEP). In the brain signal area, most studies are focused on visual evoked steady potentials, and papers only rarely focus on auditory and somatosensory stimuli. Therefore, in this book, we mainly introduce SSVEP rather than SSAEP and SSSEP.

2.3.2.4 *Commonly Used Visual-Related Potentials*

VEPs are the most commonly used potentials. Therefore, it is essential to distinguish the three different VEP paradigms: VEP, RSVP, and SSVEP. Here, we theoretically introduce the characteristics of each paradigm. First, the frequencies are different: the frequency of VEP is less than 2 Hz, whereas the frequency of RSVP is around 10 Hz, and the frequency of SSVEP ranges from 3.5 to 75 Hz. In addition, they have various presentation protocols. In the VEP paradigm, different visual patterns will be presented on the screen *in turn* to check the changes in the brain signals of the user. In an RSVP diagram, several items will be presented on a screen *one by one*. All the items are shown in the same place and share the same frequency. In SSVEP paradigm, several items will be presented on a screen *at the same time* while the items are shown at *variant positions* with different frequencies.

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