6 Brain–Computer Interfacing with Interactive Systems—Case Study 2

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6.1 Introduction

The brain can be described as an electrochemical machine, inducing a combination of electrical and chemical signals. The existence of the electrical activity of the brain was initially captured and demonstrated almost a century ago, first by Richard Caton in animals [Caton 1875] and later by Hans Berg in humans [Berger 1933]. Berg achieved the capturing of electrical activity exhibited in human brain by using a novel method at the time, the electroencephalography (EEG). To date, non-invasive EEG is the most common brain signal acquisition technology. EEG utilizes surface electrodes—over a layer of bone and tissue—for capturing the combined electrical activity of populations of excitable cells called neurons. These "firing" neurons have characteristic intrinsic electrical properties, producing electrical and magnetic fields when activated [da Silva 2010].

The electrical activity manifested in neurons reveals discrete potential patterns, which in turn characterize different states of mental activity. These patterns are distinguished by different wave oscillations in the frequency domain [Buzsáki and Draguhn 2004]. Through this electrical activity, it was discovered that different potential patterns are produced by different states of mental activity. These patterns are distinguished by different wave oscillations in the frequency domain called EEG bands or rhythms.

These EEG rhythms are divided into different frequency ranges (see Figure 6.1), namely delta (δ) (1–4Hz), alpha (α) (8–12Hz), beta (β) (13–30Hz), theta (θ) (4–8Hz),

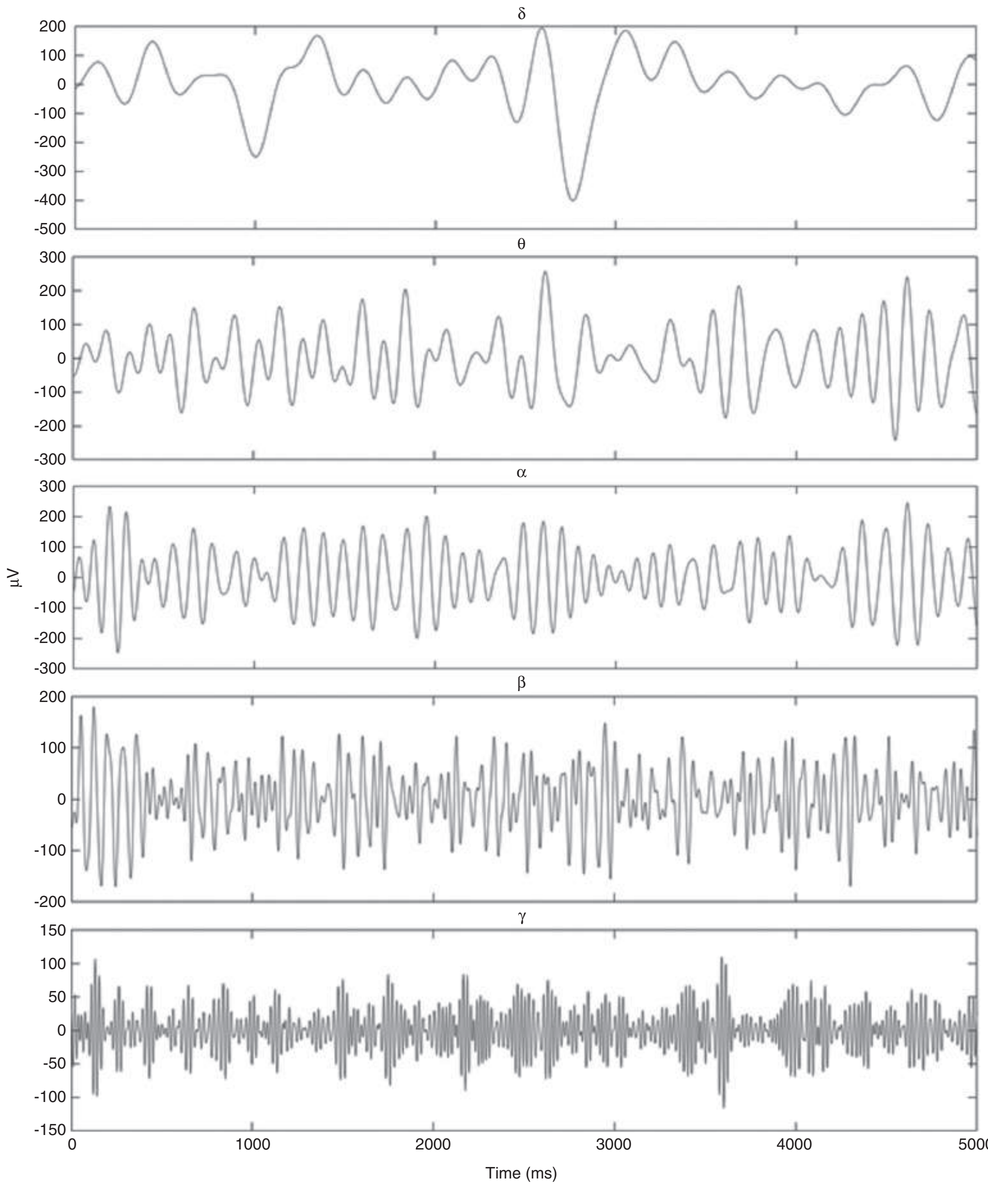

Figure 6.1 Frequency ranges of EEG rhythms: δ (1–4Hz), α (8–13Hz), β (13–30Hz), θ (4–8Hz), and γ (40–100Hz).

and gamma (γ) (40–100Hz), and each rhythm or combination of rhythmic activity is related with different mental states, including motor planning [Schomer and de Silva 2011]. For example, rhythms in the α and β frequency bands are functionally related to major sensorimotor systems [Crone et al. 1998], which are activated primarily through motor preparation or execution [Pfurtscheller and Neuper 1997]. α and θ oscillations are known to reflect cognitive and memory performance [Klimesch 1999, Schack et al. 2002], and θ was found by early EEG studies to be closely related with problem-solving, perceptual processing, and learning [Schacter 1977]. Furthermore, δ rhythm is related to concentration, attention, and internal processing [Harmony et al. 1996], while γ rhythm has been shown to be modulated during volitional meditation (concentration focused on a visualization), consciousness, and sense of self [Lehmann et al. 2001]. Translating cognitive states or motor intentions from different EEG rhythms is a complex process, and it is impossible to associate a single frequency range or cortical location to a brain function.

This oscillatory brain activity—recorded through EEG—is currently used for the interfacing between humans and computers. This connection is achieved through the use of communication systems called brain–computer interfaces (BCIs) or brain–machine interfaces (BMIs) [Wolpaw et al. 2002]. Some of the benefits of using EEG for BCI include the high temporal resolution (1ms), relatively lightweight and portability, and finally the cost compared to other brain imaging technologies (e.g., magnetoencephalography [MEG] or functional magnetic resonance imaging [fMRI]), allowing for more flexible data collection in real-world environments [Vourvopoulos et al. 2019c]. On the downside, EEG signals are noisy, non-stationary, and have low spatial resolution, making source localization hard to achieve and rendering their utilization cumbersome [Lotte et al. 2007].

A unidirectional brain-to-computer communication is elicited first by a stimulus (visual, auditory, or somatosensory), which generates endogenous or exogenous potentials. Endogenous potentials are those whose occurrence is not related to the physical attributes of a stimulus (e.g., frequency or intensity) but to a person's reaction to it. For example, motor imagery BCI (MI-BCI) involves the imagination of limb movements and is considered a BCI paradigm that evokes endogenous potentials since the user generates motor-related brain patterns unrelated to the stimulus attributes. In addition, P300 BCIs use brain responses that are generated 300ms after stimulus onset (hence the name P300) [Fazel-Rezai et al. 2012] but are considered to be also endogenous potentials, since after the stimulus presentation, there is a stimulus validation process (a cognitive function) by the brain. In contrast, the steady-state visually evoked potentials (SSVEPs) are considered an exogenous potential since they are caused by visual stimulation of flashing lights, which occur at the primary visual cortex of the brain [Creel 1995]. Both SSVEP and P300 paradigms are mostly used mainly for patients in the locked-in state, while MI-BCI captures activity over the motor and somatosensory cortices and is used primarily for motor restoration and rehabilitation [Vourvopoulos et al. 2019b].

BCIs not only offer an alternative communication channel between the user and the machine for restorative or assistive applications, but they can also broaden the communication bandwidth of healthy users with a system [Niforatos et al. 2017], for example, measuring drivers' cognitive load (see Chapter 11 CS7). BCI is an emerging research area in the fields of virtual reality (VR) and interactive systems, providing a wide new range of possibilities in the way users interact with games and virtual environments. VR feedback in BCIs offers a more compelling experience to the user through immersive virtual environments [Lotte et al. 2013a]. The fusion of BCI and VR (BCI-VR) enables a wide range of experiences where participants can control various aspects of their (VR) surroundings—either in an explicit or implicit manner—by using mental imagery alone [Friedman 2017]. For example, to be able to walk through a virtual street without muscular activity, only imaginary feet movements [Pfurtscheller et al. 2006].

This direct brain-to-VR communication can induce illusions mostly relying on the sensorimotor contingencies between perception and action that could potentially increase the sense of presence and embodiment in VR [Slater 2009]. This harnesses the benefits of immersive VR into transferring the physical body into the virtual world [Slater et al. 2010].

The use of BCIs in games has become progressively prevalent, particularly in the last few years, due to the introduction of low-cost EEG systems that render EEG technology accessible for non-medical research [Vourvopoulos et al. 2019c]. High-end, medical-grade, EEG acquisition systems range between 10,000 and 250,000 EUR (e.g., Biosemi [Biosemi B.V., Amsterdam, The Netherlands], Brain Products [Brain Products GmbH, Gilching, Germany], Advanced Brain Monitoring [Advanced Brain Monitoring Inc., Carlsbad, CA, USA], or EGI [Electrical Geodesics, Inc., Eugene, OR, USA]), while low-cost commercial EEG devices are accessible between 100 and 1000 EUR (e.g., Emotiv EPOC [Emotiv, San Francisco, CA, USA], Neurosky Mindwave [NeuroSky, San Jose, CA, USA], Muse Headband [Toronto, Ontario, Canada]), offering low-cost, off-the-shelf systems for developers. Moreover, open hardware and open-source projects are now offered as alternatives to commercial and patented equipment through open-source projects for hobbyists and EEG "hackers" (e.g., OpenBCI [OpenBCI, Brooklyn, NY, USA] or open EEG project), ranging from 300 to 1,000 EUR. In fact, prior research analyzing and comparing EEG systems ranging from open-source devices to medically certified systems has demonstrated that effective BCI interaction can be accomplished without requiring high-end/high-cost devices [Nijboer et al. 2015, Vourvopoulos and Bermúdez i Badia 2016a].

Nowadays, EEG-based BCI systems are starting to gain ground in enhancing interactive systems and as a result play an important role in human–computer interaction (HCI) research. However, major challenges must still be tackled for BCIs to mature into an established communications medium for VR applications [Lécuyer et al. 2008].

6.2 Interfacing with the Brain

EEG signals are acquired through surface electrodes usually coated with silver chloride (AgCl) or other metals such as silver (Ag), tin (Sn), steel (alloy of iron [Fe] and carbon [C]), and gold (Au). EEG electrodes conduct the acquired EEG signals to a signal amplifier for amplification. Signal amplification is necessary, since EEG signal amplitude is very weak, and thus needs to be amplified several thousand times before it can be captured. This innate EEG signal faintness implies a high susceptibility to noise, particularly in the bands of 50/60Hz, transmitted inductively by an adjacent electric field, such as those generated from building wiring. Amplifiers boost EEG signals into a range where they can be digitized accurately (e.g., microvolts [μV]) by an analog-to-digital converter (ADC). When the signal is digitized, it is then directed to a computer system via communication interfaces such as an S-232 serial port, USB, or Bluetooth.

On the side of the computer system, specialized software is acquiring the quantized signal originating from the ADC and provides it as input to the other layers of the existing software architecture, including dedicated EEG client software. The most common EEG client software provides visualization, basic filtering, and/or logging features. These and additional post-processing features are available through commercial software or for free in open-source software.

6.2.1 Requirements

6.2.1.1 Hardware

EEG systems differ in the sampling rate (the number of samples per second) they can support, the number of electrodes, type of electrodes (active vs. passive or dry vs. gel), their portability, and extendibility.

Sampling rates: Sampling rates are expressed in samples per second with the unit Hertz (Hz). For example, an EEG system with a sampling rate of 250Hz can measure 250 samples per second. For analyzing the acquired digitized signal, one should be aware of the Nyquist theorem. The Nyquist theorem states that all of the information in an analog signal (such as EEG voltages) can be captured digitally as long as the sampling rate is higher than twice the highest frequency of interest in the signal [Srinivasan et al. 1998]. For example, if you sampled your data at 256Hz, you should only analyze frequencies up to $256/2 = 128$Hz, if not less.

Number of electrodes: The number of electrodes required depends on the BCI paradigm one wants to use (e.g., P300 or MI) or the type of application (e.g., spellers for communication, control of prosthetic limbs, workload measurement, etc.). For example, for SSVEP or P300 paradigms, eight-electrode systems are sufficient, since a subset of four electrodes are utilized on average, covering mainly the occipital area of the head (the occipital lobe is the area of most of the brain's visual cortex). On the other hand, for MI cases where spatial filtering is used for improving classification performance, a large number of electrodes is desired over the motor and sensorimotor areas [Farquhar et al. 2006]. In cases of two-class MI classification, 16-electrode systems provide a safe choice. On the other hand, there are MI paradigms that could use fewer electrodes (with the additional reference and ground electrodes). For example, locomotion detection (imagination of walking) could be sufficiently detected with one- to four-electrode configuration over the target area (e.g., over location Cz depicted in Figure 6.3, and the adjacent electrodes).

Type of electrodes: Electrodes require conductive paste or gel to be applied first on the scalp of the user. Although a new generation of dry electrodes has been developed to minimize the preparation time, to date, there is no study reporting better performance of dry electrodes over the gel electrodes, with artifact levels being consistently and significantly higher during the use of dry electrodes [Searle and Kirkup 2000]. Gel-based electrodes are divided between active and passive electrodes. Active electrodes have embedded built-in circuitry which amplifies the electrical current (ultra-low noise pre-amplifier) before sending it to the EEG amplifier (see Figure 6.2[f]). This greatly improves the signal quality received by the EEG amplifier, yielding significant advantages over passive electrodes. In addition, due to lower impedance levels, active electrodes usually take a shorter time to set up. The downside is their increased cost. Overall, the use of active gel electrodes is the most robust solution for high signal-to-noise ratio.

Portability: There are two types of EEG amplifiers, namely wired (RS-232 serial port or USB) and wireless (Bluetooth). Wireless options can provide independence for field studies but also lighter setup with less cables, reducing artifacts of movable parts. On the other hand, wired solutions offer more bandwidth, uninterrupted connection, no missing data packets due to poor signal, and do not rely on batteries.

6.2.1.2 Software

The available EEG software is highly diverse, and it depends on the use case and/or application scenario at hand. For example, the EEG software involved in measuring

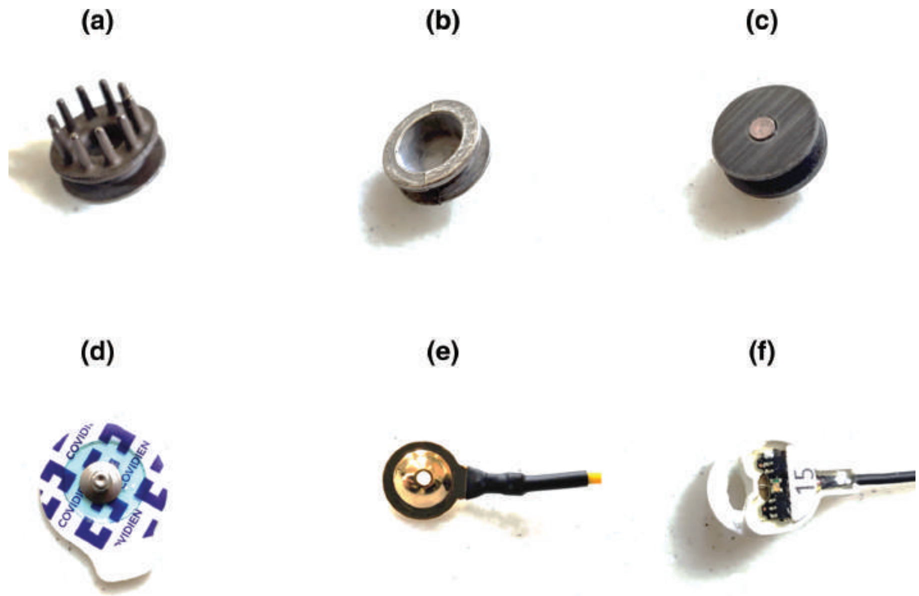

Figure 6.2 Main electrode types: (a) dry electrode, (b) gel electrode, (c) frontal semi-dry electrode, (d) disposable adhesive electrodes for referencing over the mastoid, (e) disc electrode, (f) active electrode (with embedded circuitry for pre-amplification).

brain activity changes in response to external stimuli (e.g., visual) may differ from the EEG software used for classifying EEG activity as input to a game (e.g., move an avatar right or left). Despite often being implemented in an integrated and holistic fashion, EEG software can be divided into two broad categories: *collection*, and *analysis* and *visualization*.

Collection: Perhaps the most well-known EEG protocol for collecting EEG signals is the lab streaming layer (LSL) (Kothe 2014). The LSL is a transmission control protocol (TCP) for the unified collection of measurement time series in research experiments that handles both the networking, time-synchronization, (near-) real-time access as well as, optionally, the centralized collection, viewing, and data storage. For real-time acquisition and storage, Openvibe (Inria, Rennes, France) [Renard et al. 2010], Neuropype (Intheon Labs, San Diego, CA, USA), and BCI2000 [Schalk et al. 2004] support the majority of the commercial and open EEG devices (more than 20). The collected data can be stored in the European Data Format (EDF and EDF+), a simple and flexible format for the exchange and storage of multi-channel biological and physical signals [Kemp and Olivan 2003], extended by eXtensible Data Format (XDF, https://github.com/sccn/xdf) (Swartz Center for Computational Neuroscience, University of California, San Diego [UCSD]) for handling data with high sampling rates such as audio, or data with a high number of channels such as fMRI or raw video.

Analysis and visualization: For analyzing EEG data, a comprehensive set of specialized tools have been developed as toolboxes in MATLAB, but also as standalone versions. EEGLAB (Swartz Center for Computational Neuroscience, UCSD) [Delorme and Makeig 2004] is one of the most widely used tools for EEG analysis, incorporating independent component analysis (ICA), time/frequency analysis, artifact rejection, event-related statistics, and several visualization features. FieldTrip is a MATLAB toolbox for EEG, MEG, and near-infrared spectroscopy (NIRS) analysis. Like EEGLAB, it offers pre-processing and advanced analysis methods, such as time-frequency analysis, source reconstruction using dipoles, and nonparametric statistical testing [Oostenveld et al. 2011]. One of the oldest and still active EEG processing toolbox for MATLAB is Brainstorm (University of Southern California, Los Angeles, CA, USA) [Tadel et al. 2011], incorporating the same important features for continuous or event-related EEG data as EEGLAB. Standalone processing tools include BrainVision Analyzer (Brain Products GmbH, Gilching, Germany), BrainVoyager (Brain Innovation B.V., Maastricht, The Netherlands), and LORETA (KEY Institute for Brain-Min Research, Zurich, Switzerland) for estimating cortical connectivity [Pascual-Marqui 2002].

Despite most of the MATLAB toolboxes being available for free, MATLAB requires a paid license. Despite the fact that the GNU Octave project is a free alternative to MATLAB, Octave does not support the entirety of the tools available (such as EEGLAB), with many of the functions not properly working, including the graphical user interface (GUI).

In the last few years, open-source Python software for exploring, visualizing, and analyzing EEG and other neurophysiological data have been developed. A major example is MNE-Python. MNE is tightly integrated with the core Python libraries for scientific computation (NumPy, SciPy, Sklearn) and visualization (matplotlib and Mayavi) [Gramfort et al. 2013]. In addition, Wyrm is a BCI toolbox written in Python and is suitable for running online BCI experiments as well as offline analysis of EEG data together with Mushu [Venthur and Blankertz 2012] for signal acquisition and Pyff, a BCI feedback and stimulus framework [Venthur et al. 2010].

Finally, although MATLAB has been established for many years, with a big community, using Python has the benefits of being free and open, and it is object-oriented, portable, and powerful (supports threading) with a fast-growing community.

6.2.2 Study Setup

EEG studies are notoriously tedious, both for the participant and the experimenter, and often resulting in the collection of EEG signals indistinguishable from noise. However, the technological advancement has made it possible for EEG to escape the narrow boundaries of a clinical lab, and find its way into field studies and deployments. Nonetheless, this EEG democratization often comes at the cost of adhering to low quality standards, thus greatly affecting credibility and reproducibility of results. Therefore, adequate preparation is of utmost importance before conducting an EEG study. In the following sections, we present a concentrated set of best EEG practices on acquiring and analyzing EEG signals based on the theoretical background introduced in Chapter 3.

6.2.2.1 Preparation

Before employing EEG in a study, one needs to understand what EEG exactly measures. EEG measures the potential difference (i.e., voltage difference) between electrodes. Therefore, when an EEG headset with electrodes is worn by the user, a reference electrode should always be placed. Typical locations of the reference is the left/right mastoid, the earlobe, the nose, the cheek, or the frontal mid-line electrode location. The measured electrical potential differences (i.e., the EEG signals) are the voltage drops between, and for each, electrode and the reference electrode. As we have seen previously, EEG electrodes come in a variety of metallic coating in an effort to improve conductivity. Conductive paste is another way one can increase electrode conductivity in EEG, and comprises a variety of substances aiming at reducing skin impedance when using EEG electrodes. After carefully removing dead skin cells and hair oil with alcohol, the conductive paste is applied on the EEG electrode, as an inset between the electrode and the scalp. As a rule of thumb, a good impedance is considered somewhere in the range of 5–20kΩ, and the lower the better [Kappenman and Luck 2010]. Hence, conductive paste provides the right balance of conductivity and adhesiveness, keeping EEG electrodes in place, while being non-toxic and easily washable. EEG electrodes that employ conductive paste are also known as wet or gel electrodes for differentiating from dry electrodes that do not use conductive paste. Dry electrodes are usually more pointy, in an attempt to compensate for adhesiveness, and thus often considered uncomfortable for long periods of measurement (Figure 6.2).

The electrode location (i.e., electrode topology) over the user's head is defined by the 10–20 international system [Jasper 1958]. The 10–20 system indicates the electrode name and position based on the hemisphere and the lobes it is located over the head. For instance, electrodes starting with the letters F, T, C, P, and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. Next

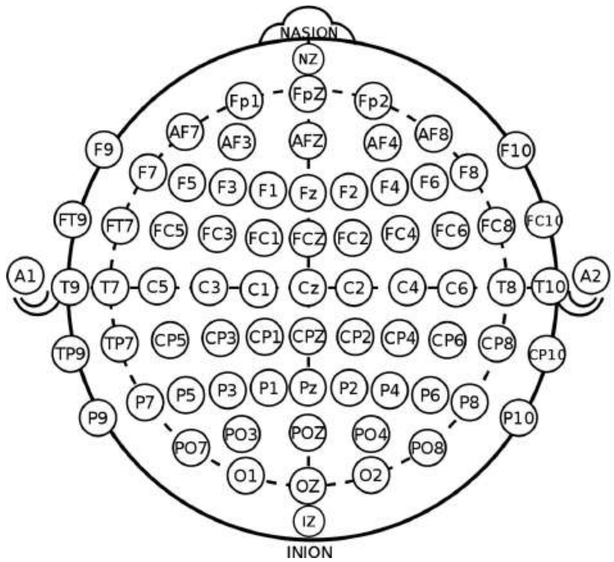

Figure 6.3 The 10–20 international system describing the location of scalp electrodes with letters for each lobe and numbers for each hemisphere. Typical reference locations are above the nose (Nz), frontal-central (FCz), ears (A1, A2), or over the mastoids (TP9, TP10).

to each letter, even numbers (2, 4, 6, 8) refer to electrode positions on the right hemisphere, whereas odd numbers (1, 3, 5, 7) refer to electrode positions on the left. Finally, the "z" letter next to each lobe letter (e.g., Cz) indicates the mid-line of the head (Figure 6.3). The topology should be decided based on which areas of the brain are expected to be activated the most during an EEG study. As a rule of thumb, one should place the EEG electrodes closer to the brain areas most prominently involved in the subsequent experiment. For example, an EEG experiment that aims to measure visual brain activity implies altering the electrode topology for including more electrodes on the back of the head (e.g., locations O1,O2,Oz).

6.2.2.2 Signal Acquisition

Typically, during the signal acquisition process, the EEG device, including the amplifier, the ADC, as well as the EEG data collection software (e.g., LSL), should be active and in continuous communication for registering the generated EEG signals. Depending on the experimental design (e.g., number of conditions, within/between subjects), one should record the EEG signals corresponding to a period with the minimum number of stimuli. This is intended for forming a baseline of neutral brain activity for forming a control condition. EEG signals collected in the control condition will be used later for testing against an experimental condition, where certain brain activities are expected to manifest in response to some stimuli and are subsequently captured via EEG. For example, in the experimental scenario where one wants to measure brain activity to visual stimuli, first a neutral image (e.g., a picture of a beach) can be utilized for obtaining the baseline (i.e., control condition). Then, the participant undergoes the experimental condition during which one is exposed to the visual stimuli under investigation. Another approach for forming a baseline, but for cognitive workload, is the n-back task. During the typical n-back task, an experimenter asks the participant to count backwards from 100 with a step of $-n$ (e.g., -2) [Berka et al. 2007]. This task generates sufficient workload for simulating a baseline for comparing against a cognitively demanding experimental condition (e.g., the task of solving a puzzle).

Often, one seeks to investigate the direct impact of specific stimuli on brain activity rather than comparing between periods of extended brain activity (i.e., experimental vs. baseline conditions). Events that are considered capable of triggering a direct effect on brain activity are known as event-related potentials (ERP). ERPs are defined as the measured brain response that is the direct result of a specific sensory, cognitive, or motor event. In a more formal and generic definition, ERP is any stereotyped electrophysiological response to a stimulus and can be measured with EEG and MEG; however, in the case of MEG, these are known as event-related fields (ERFs). ERPs are widely investigated in neuroscience, cognitive psychology, and psycho-physiological research, since they are considered a reliable measure of time for the brain to process information [Allen 2002, David et al. 2005]. For example, a well-known experiment that generates ERPs via visual stimuli is the flashing checkerboard paradigm, typically employed for detecting any damage or trauma in one's visual system. A flashing checkerboard is presented to the subject with alternating flashing patterns in a frequency of 1–12Hz. The healthy brain response to such flashing patterns maximizes at around 8Hz, with a healthy participant's first response (i.e., ERP) of the visual cortex at 50–70ms (Walsh et al. 2005). It is therefore evident that ERPs should be recorded with an accuracy in the order of ms, and in absolute synchronization with the employed modality that generated the stimulus (e.g., a presentation of a series of pictures on a screen). For executed and imagined movements, ERPs are recorded from the supplementary motor/premotor area (SMA/PMA) and primary motor area (M1) [Romero et al. 2000]. This is very useful in neurorehabilitation since M1 is considered a prime target of post-stroke rehabilitation [Sharma et al. 2006].

6.2.2.3 Participant Recruitment

Normally, participants are recruited based on their desire to participate, although previous neurological disorders need to be considered. Specifically, participants with systemic disorders with the involvement of the central nervous system (CNS; e.g., endocrine or metabolic disorders), neurological disorders including traumatic brain injury, history of childhood neurological disorders, and neurodegenerative diseases (e.g., dementia, Alzheimer's, Parkinson's, etc.), psychiatric disorders, alcohol and drug abuse or dependence should be excluded. Also, users who receive CNS-active medications including any psychotropic medications, and those with first-degree relatives with a family history of psychiatric disorders, including personality disorders and mental sub-normality, should be not admitted [Boutros 2013].

6.2.3 *A Posteriori* Analysis

When it comes to EEG analysis and feature extraction, an extensive list of pre-processing steps needs to be completed in order to convert raw signals to results. In this chapter, we present the basic steps one needs to perform in *a posteriori* analysis.

As an example, let us consider an MI-based BCI, a BCI that can recognize imagined movements such as left-hand or right-hand movements. In this case, the two mental states to identify are imagined left-hand movement on one side and imagined right-hand movement on the other side. For identifying mental states from EEG signals, we utilize band power as typical features (i.e., the power of the EEG signal in a specific frequency band). For MI, band power features are usually extracted in the μ (about 8–12Hz) and β (about 13–30Hz) frequency bands for electrodes localized over the motor cortex areas of the brain (around locations C3 for right-hand and C4 for left-hand movements, respectively) [Pfurtscheller and Neuper 2001]. Such features are then typically classified between left- or right-hand movements using a linear classifier.

6.2.3.1 Pre-processing

The basic pre-processing steps involve the following:

Downsampling: The first step after loading the data is to downsample the signals in order to reduce the data size. Based on the Nyquist theorem mentioned in Section 6.2.1.1, the re-sampled signal should be more than twice as large as the highest frequency of interest. In addition, low-pass filtering is necessary before downsampling for anti-aliasing.

Bandpass filter: The purpose of the application of a bandpass filter is to allow frequencies within a certain range to pass while rejecting (attenuating) frequencies outside that range. It is generally recommended to use lower cutoff frequencies, for example 0.1–1.0Hz [Luck 2005], applying also a high cutoff frequency at 50–60Hz to remove the powerline noise.

Bad channel removal: It is common during the acquisition to have a few sensors that are failing, with really bad connection quality between the electrode and the scalp. This bad connection propagates the bad signals to all channels, making the artifact removal from the signals more difficult. Bad channel removal can be done manually through visual inspection or also using automated techniques such as the artifact subspace reconstruction (ASR) method [Mullen et al. 2013], but it is out of the context of this chapter. Finally, any potential missing channels need to be interpolated in order to minimize a potential bias in the re-referencing stage.

Re-referencing: As described in Section 6.2.2.1, typical locations of the reference is the left/right mastoid, the earlobe, and the nose. In data analysis, the average of all electrodes is often chosen as the reference. As a rule of thumb, the position of a reference electrode should not be close to that of an electrode where you expect your main effects to manifest. For example, the Cz is often used as a reference electrode, but it should not be used if the task-related activity (e.g., MI over C3, C4) is centered around this electrode. It is also not advisable to reference your data to an electrode of one hemisphere, as this could introduce a lateralization bias into your data.

Artifact removal: Electrodes pick up electrical activity from other sources in the environment besides cortical activity. The recorded activity that is not of brain origin is termed an “artifact” and can be divided into physiological and non-physiological artifacts. Physiological artifacts may include cardiac pulse, respiratory, sweat, glossokinetic (tongue movement), eye movement (blink, spikes from lateral eye movement), and muscle and movement artifacts. Non-physiological artifacts include power line noise at 50–60Hz and movement of an electrode or headset. Majorartifacts, such as big spikes from electrode or head movement, can be removed through visual inspection of the data in addition to the application of ICA [Makeig et al. 1995]. ICA is a computational method for separating a multivariate signal into additive subcomponents, and it is widely used for removing a wide variety of artifacts, also including the use of blind source separation [Jung et al. 2000].

Data epoching: EEG epoching is a procedure in which specific time windows are extracted from the continuous EEG signal. These time windows are called "epochs," and usually are time-locked events with respect to a stimulus (e.g., a visual stimulus). For extracting epochs from the signal, data tagging/labeling is necessary during acquisition, indicating specific timestamps of interest related to the stimulus.

6.2.3.2 Feature Extraction

The next step in EEG signal processing is known as "feature extraction," which aims at describing the EEG signals by (ideally) a few relevant values called "features" [Bashashati et al. 2007]. Such features should capture the information embedded in EEG signals that is relevant to describe the mental states we seek to identify while rejecting the noise and other non-relevant information [Lotte et al. 2013a]. Typical features are band power features (i.e., the power of the EEG signal in a specific frequency band). For MI, band power features are usually extracted in the μ (8–12Hz) and β (13–30Hz) frequency bands, over the motor cortices located around the C3 and C4 electrodes. Next, we get a power estimation of the filtered signal (squaring) which we usually averagefor every second (temporal average) and logarithmize for creating our first feature. All features extracted are usually arranged into a vector, known as a feature vector.

6.2.3.3 Classification

As a last step, our target is to assign a class to a set of features (from the feature vector), translating the features into commands [Lotte et al. 2007]. Each class corresponds to the kind of mental state identified. As explained in Chapter 4, the type of algorithms that are dedicated into classifying the selected features are known as "classifiers." Typical classifiers used in BCIs include: linear classifiers, artificial neural networks (ANNs), non-linear Bayesian classifiers, K-nearest neighbor (KNN) classifiers, and classifier combinations [Lotte et al. 2007]. Linear classifiers include linear discriminant analysis (LDA), regularized LDA, and support vector machines (SVMs). Both LDA and SVM are the most popular types of classifiers for real-time BCIs due to their low computational demand and low complexity. ANNs are computational models bio-inspired from the functioning patterns of biological neurons of the human brain. ANNs are arranged in layers, which can be used to approximate any non-linear decision boundary. One of the most common types of NN currently used for BCI is the multi-layer perceptron (MLP). Moreover, non-linear Bayesian classifiers are instances of linear classifiers modeling the probability distributions of each class using Bayes' theory to select the class to assign to the current feature vector. The KNN algorithm is a non-parametric method used for assigning a class to the current feature vector according to its nearest neighbors. Further, KNN could be used as an output for feature vectors or class. Finally, classifier combinations are configurations which combine multiple classifiers, either by combining their outputs and/or by training them in ways that maximize their outcome. Classifier combinations used for BCI include boosting, voting, or stacking combination algorithms [Lotte et al. 2007].

Merging classifiers is considered to be the best performing configuration for EEG-based BCIs, but it comes at a computation cost as well as speed. Therefore, merging classifiers can only be used for offline evaluations and not in real time.

6.3 Interacting with VR

Despite the increased attention that BCI technology has attracted with the launch of low-cost commercial EEG devices, BCIs are hardly used outside laboratory environments [Lotte et al. 2013b]. Unfortunately, BCIs are not yet as accurate as other types of interfaces [Lotte 2012], and users require long training periods—of up to several months—to achieve accuracy levels of 80% using cortical potentials [Wolpaw et al. 2002]. Although accuracy varies among the different BCI paradigms, most are not 100% accurate, require extensive training, and have low information transfer rates and long response delays [Friedman 2017].

In the following sections, we illustrate our systematic approach toward enhancing BCI performance in interactive VR systems in three different levels: (1) the feedback level, by illustrating the role of multimodal feedback and immersive VR; (2) the system level, through adaptive performance based on prior training data; and finally, (3) the user level, by highlighting the role of prior gaming experience and demographics.

The following approaches are implemented through the MI-BCI paradigm, since it is the only paradigm that can offer self-paced control, in that the user can voluntarily trigger responses without the need for external stimulus evocation. In addition, MI-BCI is the only paradigm which can contribute in a novel way to augmenting neuroplastic changes in the brain for neurorehabilitation [Dobkin 2007].

Finally, a consistent feature extraction method and classifier configuration have been implemented across all the following sections. The extracted features involved the μ and β band power over the motor and sensorimotor areas with the help of spatial filters as described in Section 6.2.3.2. This was achieved by using a common spatial patterns (CSPs) filter. CSP is a spatial filter that helps in maximizing the difference between the signals of the two classes (e.g., left- and right-hand MI) which have maximum differences in variance. Next, for classification, an LDA classifier was used. The LDA is used due to the very low computational requirements, as described in Section 6.2.3.3, rendering it ideal in generalizing for unseen data, and thus establishing it as the most used classifier for BCI design [Lotte 2014a].

6.3.1 Feedback: Designing VR for BCI interaction

In order to be able to harness the benefits of BCI in interactive systems, two questions need to be addressed: (a) how can we increase user performance of naïve users through immersive VR?, and (b) how can we engage the activation of specific brain areas through multi-modal feedback?

6.3.1.1 Effect of Immersive VR

Previous research in learning states demonstrates that a poorly designed feedback can actually deteriorate motivation and impede successful learning [Shute 2008]. On the other hand, providing extensive feedback to the user can lead to efficient and high-quality learning [Hattie and Timperley 2007]. Lotte et al. recommended a set of guidelines for a good instructional design in BCI training as follows: (1) the user should only be presented with the correct classified action for enhancing the feeling of competence; (2) a simplified and intuitive task should be provided; (3) the task should be meaningful and self-explanatory; (4) it should be challenging but achievable, with feedback on the progress of achievement; and finally (5) it should be in an engaging three-dimensional (3D) virtual environment [Lotte et al. 2013b].

Recent findings with the use of virtual arms have shown that the combination of motor priming (physical rehearsal of a movement) preceding BCI-VR MI training can improve performance as well as the capacity to modulate and enhance sensorimotor brain activity rhythms [Vourvopoulos and Bermúdez i Badia 2016a]. The protocol consisted of three BCI conditions to which users were exposed in a randomized order, and their EEG activation patterns were then also compared to the activity during overt motor-execution (see Figure 6.4).

By exposing users to three BCI training conditions in a within-subject design, a repeated-measures analysis of variance (ANOVA) (see Chapter 2) revealed statistically significant differences across conditions for: α ($F[2.524, 20.191] = 4.800, p < 0.05$) and β ($F[1.599, 12.796] = 7.541, p < 0.05$) bands (see Figure 6.5). In these results, there are two control conditions. First is the the extracted EEG data during motor execution (see "Motor" in Figure 6.4), and second is the control condition is the Graz standard feedback through arrows and bars (see "Control" in Figure 6.4).

α and β bands are motor-related bands and show that the brain activation of VR and virtual reality with motor priming (VRMP) conditions is really close to overt motor execution ("Motor"). In addition, the differences between α and β bands compared to the Graz feedback ("Control") is of high importance for BCI training,

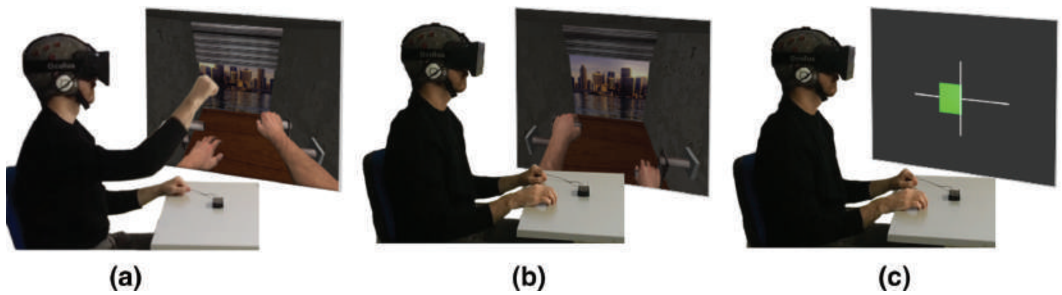

Figure 6.4 BCI training conditions. (a) VRMP: the user is performing motor priming by mapping his/her hand movements into the virtual environment. (b) VR: the user has to perform training through simultaneous motor action observation and MI. (c) Control: MI training with the Graz standard feedback through arrows and bars. Figure adapted from Vourvopoulos and Bermúdez i Badia [2016b].

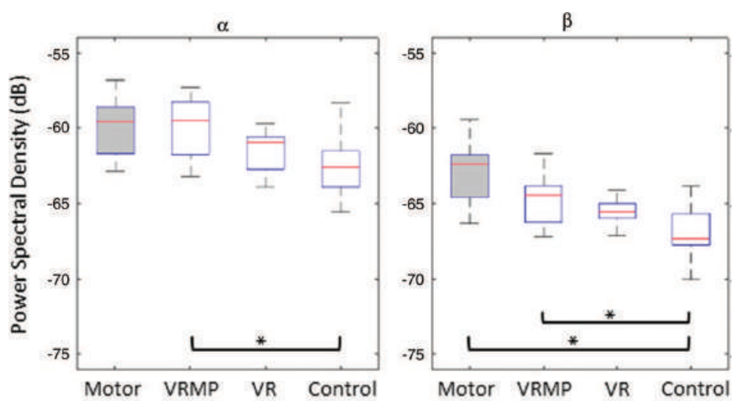

Figure 6.5 Power of α and β EEG band modulation during BCI training. $^*p < 0.05$. Figure adapted from Vourvopoulos and Bermúdez i Badia [2016b].

since VR is closer to actual movement compared to abstract feedback. This shows that there is a better correspondence to cortical activation of sensorimotor areas during voluntary movement [Jeannerod and Frak 1999].

Finally, performance in terms of the classification score revealed that the multimodal setup with motor priming condition (VRMP) provided the highest performance (median [Mdn] = 65.8, interquartile range [IQR] = 3.32) when compared with the VR only condition (Mdn = 64.5, IQR = 5.41) and control condition with the traditional feedback (Mdn = 62.3, IQR = 7.63) (see Figure 6.6).

These findings highlight the effect of immersive VR in the evoked EEG activity during MI, the incremental tendency in classification accuracy, and also the importance of using VR in ecologically valid BCI training. This means that BCI

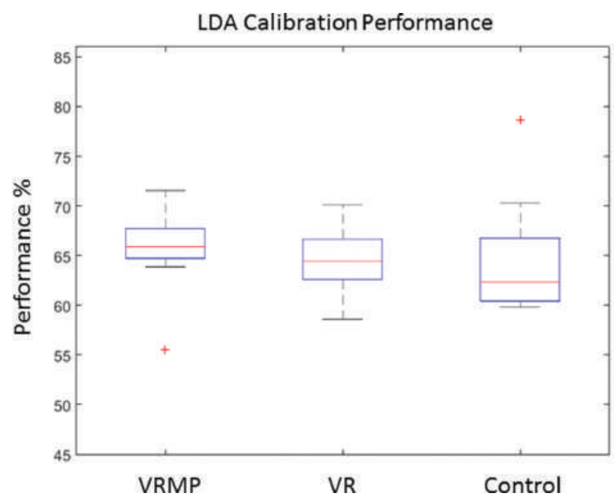

Figure 6.6 LDA classifier score. Calibration score of the LDA classifier illustrating the ability of the classifier to distinguish the left or right imaginative hand movement. Figure adapted from Vourvopoulos and Bermúdez i Badia [2016b].

feedback not only needs to be related to the mental strategy used during training (e.g., reach-and-grasp), but it should also be consistent in delivering similar visual stimuli.

6.3.1.2 Effect of Multi-modal Feedback

To date, there is not a holistic approach in BCI-MI training that combines the advantages of different feedback modalities (e.g., immersive VR environment), and training approaches (e.g., motor priming preceding motor observation) and motivational mechanisms (game-like tasks) [Vourvopoulos and Bermúdez i Badia 2016b]. To address current limitations, we developed NeuRow, a novel BCI-VR training paradigm. NeuRow combines the advantages of different feedback modalities (immersive VR environment, vibrotactile feedback), training approaches (motor priming preceding motor observation), and motivational mechanisms (game-like tasks), while incorporating important design features from the aforementioned recommended guidelines [Lotte et al. 2013b].

Refined training in VR: The training protocol was re-designed and adapted based on the Graz-BCI paradigm [Pfurtscheller et al. 2003], substituting the standard feedback presented (directional arrows for left–right MI) by multi-modal VR feedback (movement of virtual hands). The first step of the training consisted of the acquisition of the raw EEG data to train a linear classifier to distinguish right and left imagined hand movements. Throughout the training

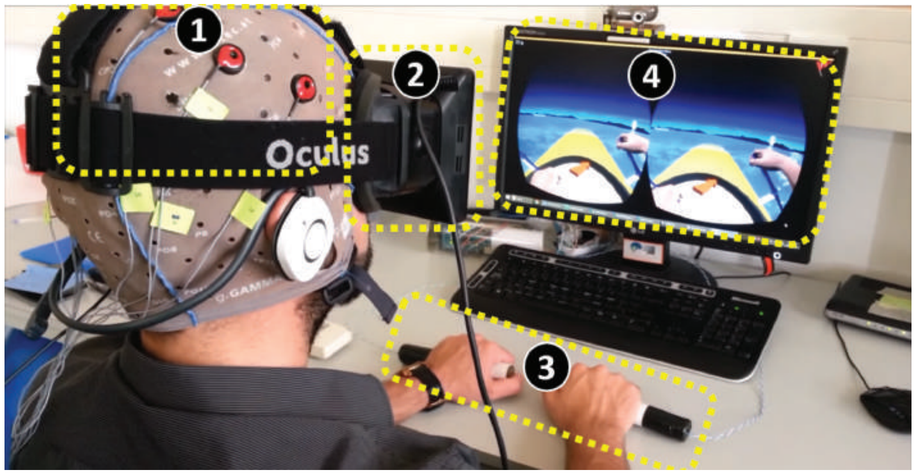

Figure 6.7 Experimental setup (1) EEG cap with eight active electrodes, (2) head mounted display (HMD), (3) vibrotactile modules, (4) VR feedback. Figure adapted from Vourvopoulos [2018].

session, the user performs mental imagery of the corresponding hand (based on the presented stimuli). For each hand, the user is stimulated visually (VR action observation), auditorily, and haptically through the vibration on the corresponding hand (Figure 6.7). The training session was configured to acquire data in 24 blocks (epochs) per class (right- or left-hand imagery) in a randomized order.

In terms of classification performance, an independent-samples *t*-test revealed that the NeuRow BCI training paradigm has a significantly higher score ($\mu = 76$, standard deviation [*SD*] $= 3$) compared to non-VR studies ($\mu = 68.2$, $SD = 7.7$) with similar feature extraction and classification configurations, $t(18) = 2.7195$, $p = 0.0141$ (Figure 6.8). These data support the hypothesis of a combined immersive VR and vibrotactile feedback, which also contributes to more distinct activation of sensorimotor areas of the brain. This in turn can also lead to increased performance and learning [Sigrist et al. 2013].

Although highly immersive, in current MI-BCI interaction users still have to undergo long, tiresome and complex periods of training, so that EEG classification score can reach acceptable performance rates. First time users, experience very low classification scores, being unable to have satisfactory control of the task in VR. Through immersive VR, we can increase performance in relation to abstract, non-VR feedback, but the learning curve remains long. In order to increase learning speed in first-time users, an adaptive middle layer was developed for filtering out misclassified behavior during interaction.

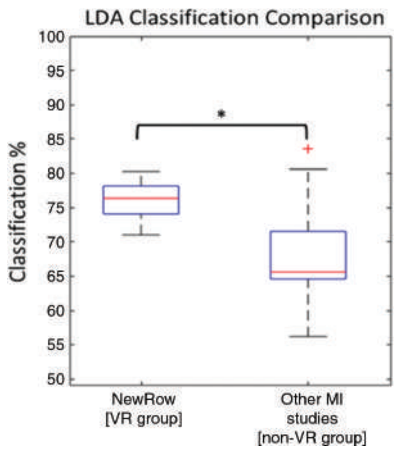

Figure 6.8 Significant differences of accuracy of performance in pure MI-based BCI studies using two classes (left- and right-hand imagery) with respect to LDA classification in VR and non-VR setup. VR group is consisted from data acquired through NeuRow [Vourvopoulos et al. 2016b], while non-VR groups from studies with reported classification performance [Obermaier et al. 2001, Garcia et al. 2003, Boostani and Moradi 2004, Solhjoo and Moradi 2004] (*$p < 0.05$).

6.3.2 System: Adaptive Technologies for Individualized BCI–VR Interaction

Moving to a second level, the main target is to increase the performance of first time users, with minimal exposure to BCI training. By following the next stage of NeuRow and immersive VR training, we created the Adaptive Performance Engine (APE) module. The APE aims at adapting the BCI interaction to each user in order to maximize the level of control on their actions, whatever their performance level is [Ferreira et al. 2015]. Hence, satisfactory performance rates can be guaranteed by softening decisions—making them probabilistic and non-time-constrained—depending on the confidence level on the user's training data.

The APE is composed by two main components: (a) a Bayesian inference layer (BIL) and (b) a finite state machine (FSM). The BIL was used to formulate the raw classifier input into a model, where we translate the continuous BCI classification data (e.g., hyperplane distance between two classes) into probability values (Equation 6.1). BIL was chosen since it is a simple computational approach and more efficient when compared to other supervised learning techniques such as ANNs. As for decision-making, an FSM was used because of its efficiency and non-linear properties (Figure 6.9).

$$P(i \mid LDAoutput) = \frac{MI_i(LDAoutput, \mu_i, \sigma_i) * P_i}{\sum_j MI_j(LDAoutput, \mu_j, \sigma_j)} \tag{6.1}$$

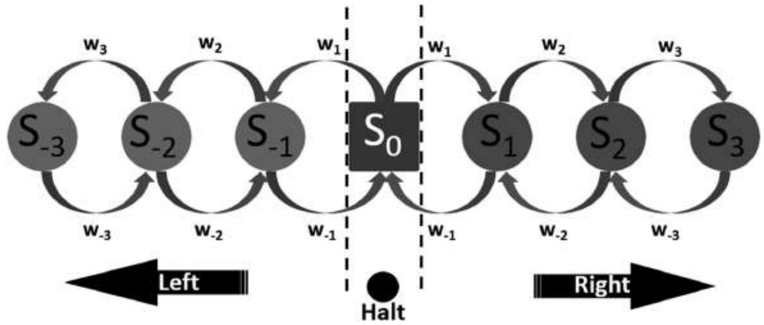

Figure 6.9 APE state transition diagram. Reproduced with permission of Springer Nature SwitzerlandAG from Ferreira et al. [2015].

The role of the FSM is to transform binary classifications—such as left versus right MI—into seven evidence-based states (S_i). It is composed of seven states, a neutral (S_0) and three for each class ($S_{1/-1}$, $S_{2/-2}$, $S_{3/-3}$). Each state has a transition threshold associated with it (w_1, w_2, w_3), and can only transition to one of the nearest neighbors, or stay in the same state (Figure 6.9).

APE's results compared with other classifier performance datasets have displayed an increase in performance of upto 20% when combined with LDA in a two-class MI paradigm [Ferreira et al. 2015]. By combining the use of immersive VR environment, sensory stimulation and adaptive performance, we can provide a holistic approach toward MI-driven BCIs for interactive systems, enhancing not only task performance but also sense of competence, which eventually could result in stronger learning [Vourvopoulos et al. 2019a].

Comparing the APE with simple LDA, we could identify a set of differences. In terms of control, Figure 6.10(i) illustrates the NeuRow boat trajectories resulting from the raw LDA control (blue) compared with the APE output (orange) for the same task, and with the same targets on fixed positions. The trajectory with APE is smoother than the raw LDA, while it is also visible in the APE trial, users could perform both left and right turns equally, while the raw LDA trajectory is generally dominated by one hemisphere, resulting in frequent rotation in one direction. Moreover, the improvement in control is also reflected by the number of sudden trajectory changes or "spins" during navigation, the game score and the reported sense of control by the users (see Figure 6.10(ii)).

Regardless the different feedback mechanisms and data processing pipelines, yet a major limitation with MI-BCI is based on a user level. In particular, the lack of the user ability to produce vivid MI and reliable EEG patterns, described as BCI illiteracy. This inability of the user to produce vivid mental images of movement results in poor BCI performance [Allison and Neuper 2010]. To date, most of the BCI

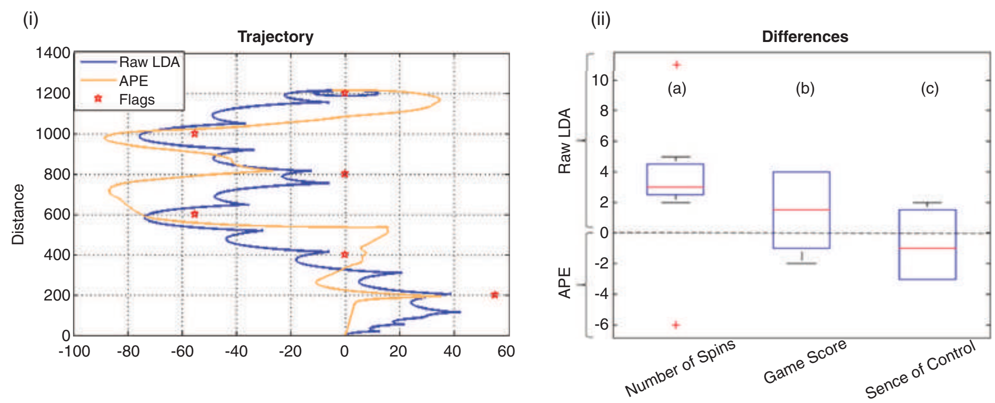

Figure 6.10 (i) Example of the boat trajectory during raw LDA classification output versus APE output, (ii) in-game data and self-report of control. (a) Number of boat spins (180° rotation), (b) game score in terms of flags captured, (c) reported sense of control. Reproduced with permission of Springer Nature from Vourvopoulos et al. [2019a].

studies have been focused on the signal processing and machine learning (ML) domain, not including the user in the loop. To address this, a set of studies was designed attempting to identify traits in the user profile and to ascertain if certain traits or prior experience or demographics can be reflected in BCI performance and influence EEG rhythms activation.

6.3.3 User: Understanding User Characteristics in BCI Interaction

To identify how different user profiles, impact BCI performance, this study investigated (1) the role of prior gaming experience [Vourvopoulos et al. 2016a] and (2) user profile and demographics [Vourvopoulos et al. 2017]. Our aim is to examine the effect that gaming experience has on brain pattern modulation capacity during MI training, and to identify the elements that contribute to high BCI control and how the user profile affects BCI performance.

6.3.3.1 Prior Gaming Experience

Past research has shown that users regularly exposed to video games have improved over time their visual and spatial attention, memory, mental rotation abilities [Green and Bavelier 2003, Feng et al. 2007], and enhanced sensorimotor learning thus, enabling better performance in tasks with consistent and predictable structure [Gozli et al. 2014]. Extensive video-game practice improves the efficiency of movement control brain networks and visuomotor skills of the users [Granek et al. 2010]. Based on these findings, our hypothesis is that experienced

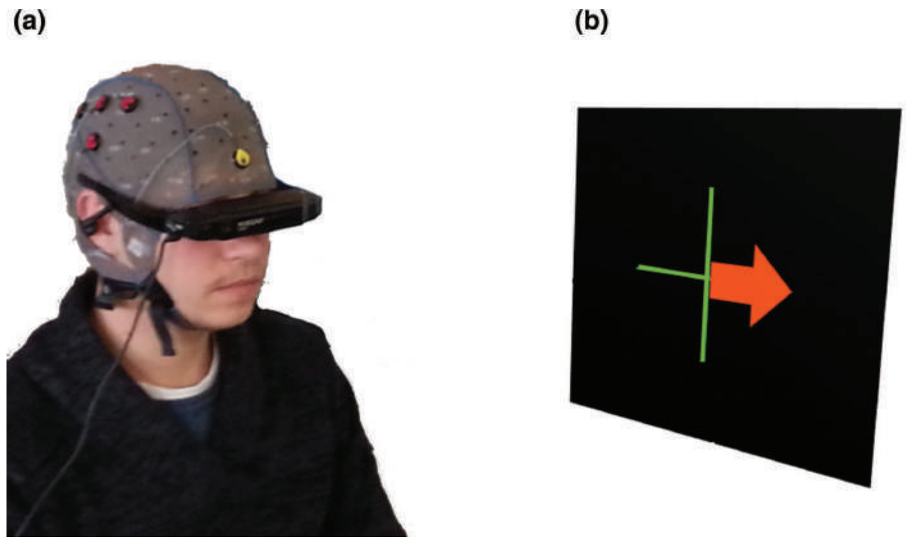

Figure 6.11 Headset setup and feedback. (a) User setup with a HMD and an EEG cap with the electrodes over the motor and sensorimotor cortices: Frontal-central (FC3, FC4), central (C3, C4, C5, C6), and central-parietal (CP3, CP4). (b) HMD is used for displaying the "Graz" paradigm. Reproduced with permission of Springer Nature from Vourvopoulos et al. [2016a].

gamers could have better performance in MI-BCI training due to enhanced sensorimotor learning derived from gaming [Vourvopoulos et al. 2016a].

To assess this, 20 participants were recruited and grouped based on their gaming experience, then clustered into "Hardcore" and "Moderate" gamers (Figure 6.11). Each group was exposed in BCI training using the Graz paradigm [Pfurtscheller et al. 2003] followed by an online session. The classic "Graz" MI paradigm consists of a fixation cross and two directional arrows, instructing the user to perform left or right MI after the cue. During training, and for each arrow, the EEG data are epoched (collection of time-locked events) for left or right MI trials followed by feature extraction, as mentioned in Section 6.2.3.2. After training, an online session was followed by acquiring real-time EEG data from the users for assessing how well the trained classifier performed with new data.

From the collected data, important user traits have been identified that can be utilized in the BCI training design within a gamified task. So far, findings have indicated (1) contrasts of different user-groups over time, and (2) the relationship between electro-physiological data with gaming experience, and demographic data.

From the demographic data, gender-related correlations can be identified, strongly associated with all EEG rhythms in both training and online tasks.

Handedness was related mostly with EEG activity modulation and asymmetry through the online session. A full correlations table can be found in Vourvopoulos et al. [2016a].

Users who prefer violent and/or action games have an increased ability to modulate all EEG rhythms in both training and online sessions. Competitiveness and preference to violent/action games were found to be significant predictors of the EEG rhythm modulation that is mostly activated during MI (i.e., α and β rhythms). Furthermore, mild video game addiction (those who play games over many hours on a daily basis) has been identified as a possible predictor of increased hemispheric asymmetry that could lead to increased BCI performance (Figure 6.12). The predictors table can be found at Vourvopoulos et al. [2016a].

Overall, it was revealed that the player's traits influence EEG rhythms activity patterns during an MI task, while highlighting the effects of video-game practice and player profile in BCI performance.

6.3.3.2 User Profile

In addition to the previous findings illustrating that prior game experience has an effect on faster learning, the impact of the user profile and user experience has so far been underexplored. Information about a user profile can be vital for understanding how a BCI system can be personalized and used for gaming and other purposes. Complementing previous findings, and based on previous research on realistic BCI feedback, the participant's role (students vs. employees) has been investigated, along with the way they perceived the task at hand, their gender, and time of the day in relation to their performance [Vourvopoulos et al. 2017].

In terms of gender, the sample was divided between the two genders, and the two conditions were assessed separately. Results showed differences on EEG patterns, being consistent with previous research [Davidson et al. 1976, Kober and Neuper 2011, Vourvopoulos et al. 2016a]. For the two different training conditions, females reported less concentration on the task.

In terms of feedback, although prior research illustrated the superiority of realistic feedback over a more abstract feedback in MI training [Vourvopoulos and Bermúdez i Badia 2016b], this study did not confirm whether video stimulation during MI training improves a user's performance over the abstract feedback. Findings showed that a reported loss of self-consciousness was experienced during the session, following the abstract feedback session (i.e., arrows), instead of the video feedback.

Concerning the difference between user roles (i.e., students vs. employees), current findings show that employees produced increased EEG activity during training (for α and θ bands). On the other hand, the reported workload during the game

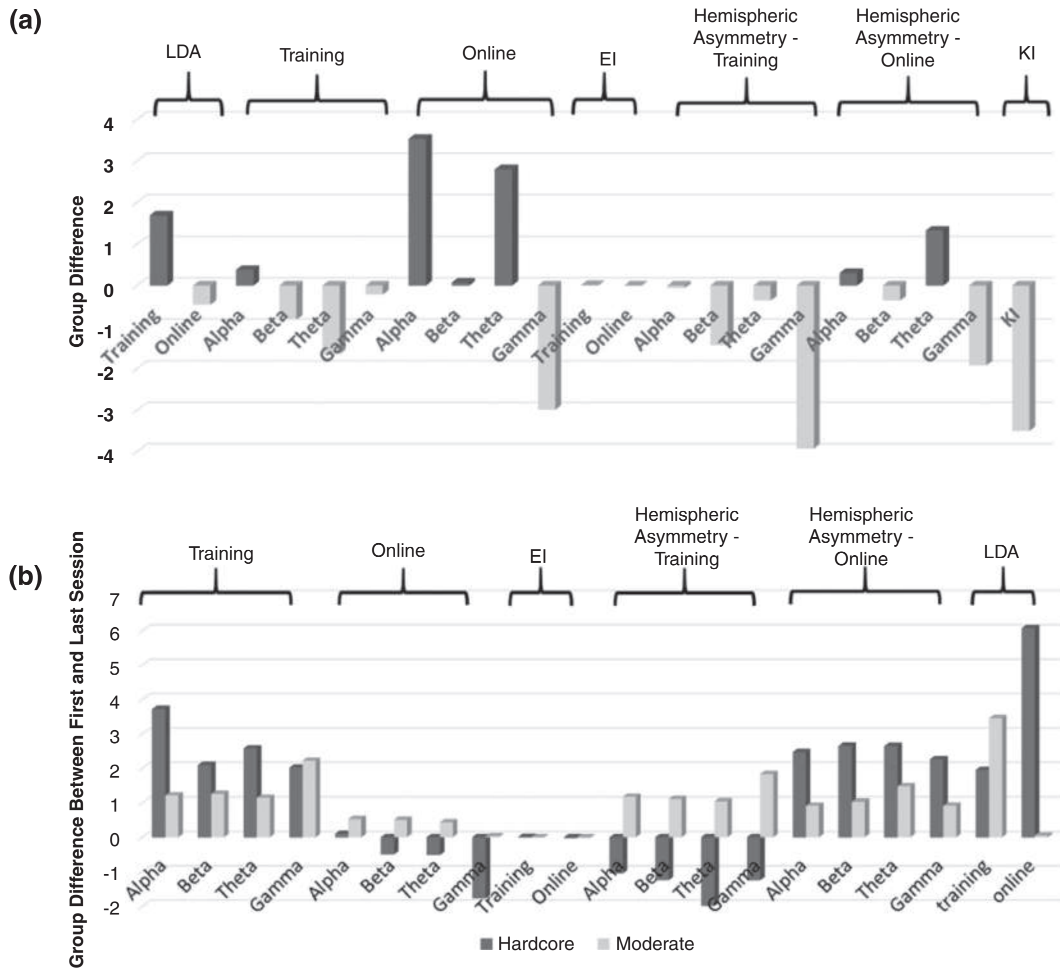

Figure 6.12 (a) Differences between "Hardcore" and "Moderate" groups in all EEG rhythms (for training, online task, hemispheric asymmetry), LDA classification performance, engagement index (EI) and kinesthetic imagery (KI). (b) Contrasts between first and last BCI session for both groups for the same type of data. Reproduced with permission of Springer Nature from Vourvopoulos et al. [2016a].

play was lower than that of students. Another important finding is the differences in time of the day in terms of the extracted EI and the γ band, concluding that time of the day influences engagement.

Finally, non-parametric Spearman correlations, revealed significant relationships in EEG bands (see Table 6.1). In particular, for α with the NASA Task Load Index (TLX): effort ($r_s = 0.348$, $p < 0.05$, $N = 34$), and Game Engagement Questionnaire (GEQ): unambiguious feedback ($r_s = -0.355$, $p < 0.05$, $N = 34$). θ is

Table 6.1 **EEG-band power correlations ($p < 0.05$). Adapted from Vourvopoulos et al. [2017]**

	TLX:Effort	GEQ: Unambiguous feedback	GEQ: Transformation of time	GEQ: Autotelic experience	PQ:How quickly did you adjust to the experience
α	0.348	0.355	–	–	–
θ	0.365	−0.348	0.344	0.348	–
γ	–	–	–	–	–
EI	–	–	–	–	0.466

related with TLX: effort ($r_s = 0.365, p < 0.05, N = 34$), GEQ: unambiguious feedback ($r_s = -0.348$, $p < 0.05$, $N = 34$), GEQ: transformation of time ($r_s = 0.344$, $p < 0.05$, $N = 34$), and GEQ: autotelic experience ($r_s = -0.348$, $p < 0.05$, $N = 34$). Finally, EI as extracted from EEG, is correlated only with the Presence Questionnaire (PQ): 7. "*How quickly did you adjust to the experience?*" ($r_s = 0.466, p < 0.05, N = 34$).

Overall, the results showcased that gender, role, and time of the day can have a significant effect not only on EEG modulation, but also on reported workload and loss of self-consciousness during game play. This demonstrates how sensitive BCI interaction can be, it is easily affected by insufficient attention due to user distraction or frustration.

6.4 Conclusions

The design of interactive systems which bypass the central nervous system—in the form of BCIs—has inherently major limitations due to its complexity. BCIs have arguably low usability levels, while they cannot be widely used like any other type of computer interface. In particular, this is due to their low robustness and reliability, as well as their often long calibration and training sessions, especially in the case of MI paradigms. Even though high satisfaction is reported with the currently available BCI systems—one could describe it as a novelty effect—a clear demand for BCI improvements is strongly reported by end-users.

Due to the noisy nature of EEG, ML leverages the potential of EEG-based BCI systems by giving them he ability to "learn" and progressively improve performance from non-stationary data. This data is then used to adapt the system to the specific brain signals of each user. In conjunction with ML, modern high resolution VR technology has a big impact in interactive systems. One could argue that the virtually or artificially perceived reality is resulting in higher levels of immersion and presence, that could change the way brain–computer interaction is used.

With immersive VR, more distinct brain patterns are evoked, resulting in better classification accuracy in ML algorithms by providing better features.

Altogether, through this chapter, an introduction to brain–computer interaction has been presented in an end-to-end approach for VR. We have illustrated our systematic approach towards enhancing BCI performance in interactive systems in terms of (1) feedback: illustrating the role of multimodal feedback and immersive VR; (2) system: incorporating adaptive performance for first-time users; and finally; (3) user profile: investigating the user's role (demographics, gaming experience, etc.) in the overall brain–computer interaction in a closed-feedback loop.

Building on top of these findings, researchers can incorporate not only guidelines for successful BCI interaction but also integrate their tools through the freely available open-source tools and proposed BCI paradigm derived from this research.

6.5 Follow-up Questions

For implementing an EEG processing pipeline and train BCI ML models as described in Section 6.2.3, multiple datasets can be used from the BCI competition database: www.bbci.de/competition/. The BCI competition datasets aim to provide high-quality neuroscientific data for open access to the scientific community. Moreover, it is considered a standard for testing methods and benchmarking ML algorithms for BCIs.

Based on the preprocessing and classification steps for MI classification as described in Section 6.2.3, explore the following:

1. How well does your classifier performance evolve when you train it with additional classes (e.g., 2 vs. 3 vs. 4)?
2. How well your model generalizes when you add more features (e.g., additional EEG bands)?
3. Are the MI EEG features the same for all users?
4. Can a classifier trained by multiple users data perform better than a classifier trained with individual training data?

6.6 Further Reading

For more on EEG background and measurement you can find it at Fernando Lopez da Silva et al. [2010], for EEG processing see Lotte [2014b] and EEG classification through OpenVibe see Bougrain and Serrière [2016]. More on BCI applications see McFarland and Vaughan [2016], BCI platforms see Brunner et al. [2013], Lindgren and Lécuyer [2016], BCI for interaction with games see Lécuyer [2016] and more on implementation of BCIs with VR for neurorehabilitation see Vourvopoulos et al. [2019b, 2019d]. Finally, for common implementation pitfalls in BCI design, see Chavarriaga et al. [2017].

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